When Does Recessionary Green Investment Make Economic Sense? Exploring conventional economic indicators for green infrastructure finance with machine learning

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A thesis submitted for the degree of

Doctor of Philosophy

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Abstract

Fiscal decision making—where and how to tax and spend—is complicated. It is especially complicated amidst rapid technological innovation and dramatic economic shifts to limit climate change. Despite efforts to integrate social and environmental criteria into fiscal decision making, many policy makers continue to rely mostly on conventional criteria—mainly, jobs and growth. This thesis meets these policy makers where they are by considering whether investments with positive climate mitigation characteristics might be superior to traditional investments, based solely on conventional metrics. In doing so, it investigates, critically analyses, and builds on the green growth literature using original datasets as well as novel applications of established and adapted methods.

Three papers are introduced, each providing a unique perspective on the economic characteristics of green investment using the coronavirus (COVID-19) economic shock as the instructive event. The first paper uses natural language processing methods to synthesise existing literature on the economic characteristics of green investment. The second paper surveys leading economists to understand how they perceive the characteristics of green investment. Supplementary analysis with machine learning provides further insights. Extending significantly from the first two papers, the third paper introduces two new datasets to understand sectoral and global variation in actual COVID-19 investment and the degree to which economic and other factors drove this variation. The datasets are validated with manual and machine learning methods.

Based on these papers, this DPhil answers three core questions. First, on conventional economic indicators, are climate mitigation investments attractive compared to alternatives: *yes, in many cases*. Second, are some measures better than others: *yes, but the most appropriate measures depend on the economic context and policy design*. Finally, does the answer change between economies: *yes, mitigation investments are promising in all economies, but the most attractive measures vary based on factors including level of development, human capital, existing economic structures, and present unemployment*. A discussion chapter synthesises findings, highlighting interdependencies and implications for research and policy.

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Supervisor: Professor Cameron Hepburn

In service of those, alive and not yet born, who face the greatest threats from climate change, and yet have no voice to stop it.

DPhil Papers

A **How Stimulating Is a Green Stimulus? The Economic Attributes of Green Fiscal Spending**
O'Callaghan, B., Yau, N., & Hepburn, C. *Annual Review of Environment and Resources*, Volume 47. (2022).
Manuscript: https://www.annualreviews.org/doi/10.1146/annurev-environ-112420-020640
Supplementary materials: https://www.annualreviews.org/doi/suppl/10.1146/annurev-environ-112420-020640

B **Will COVID-19 fiscal recovery packages accelerate or retard progress on climate change?**
Hepburn, C., O'Callaghan, B., Stern, N., Stiglitz, J. & Zenghelis, D. *Oxford Review of Economic Policy,* Volume 36, S359–S381 (2020).
Manuscript:
https://academic.oup.com/oxrep/article/36/Supplement˙1/S359/5832003
Supplementary materials:
https://academic.oup.com/oxrep/article/36/Supplement˙1/S359/5832003#supplementary-data

C **Reviewing the COVID-19 "Green Recovery": rhetoric or reality?**
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Draft manuscript: see Chapter 5.
Draft supplementary methods: see Appendix C.
Global Recovery Observatory dataset: http://dx.doi.org/10.6084/m9.figshare.20338395
Global COVID-19 Speech Database: http://dx.doi.org/10.6084/m9.figshare.20338533

Abstract

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List of Acronyms

Acronym	Meaning
ADB	Asian Development Bank
AER	Average Economic Regression
AEs	advanced economies
ARRA	American Recovery and Reinvestment Act of 2009
BERT	Bidirectional Encoder Representations from Transformers
CAGR	compound annual growth rate
CBLOF	cluster-based local outlier factor
CCS	carbon capture and storage
CEA	Council of Economic Advisers (USA)
CNN	convolutional neural networks
CO_2	Carbon dioxide
COVID-19	the severe acute respiratory syndrome coronavirus 2, SARS-CoV-2
CUREC	Central University Research Ethics Committee at the University of Oxford
DBSCAN	density-based spatial clustering of applications with noise
ELMo	Embeddings from Language Model
EMDEs	emerging market and developing economies
ESG	environmental, social, and governance
ETS	emissions trading scheme

EV	electric vehicle
GAN	generative adversarial networks
GDP	Gross Domestic Product
GETS	general-to-specific
GFC	Global Financial Crisis
GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit GmbH (German development agency)
GND	Green New Deal
GPT	Generative Pre-trained Transformers
GRO	Global Recovery Observatory
GUM	General Unrestricted Model
GVA	Gross Value Added
HBOS	histogram-based outlier score
HIC	high-income country
IIS	Impulse Indicator Saturation
IMF	International Monetary Fund
JAIC	United States Joint Artificial Intelligence Center
LDA	Latent Dirichlet allocation
LMIC	low- or middle-income country
LSA	Latent Semantic Analysis
LSTM	long short-term memory
ML	machine learning

MLP	multi-layer perceptron
MUM	Multitask Unified Model
NLP	natural language processing
NMF	non-negative factorization
OECD	Organisation for Economic Cooperation and Development
PCA	principal component analysis
pLSA	probabilistic Latent Semantic Analysis
pLSI	probabilistic Latent Semantic Indexing
ppm	parts per million
ppmv	parts per million volume
RNN	recurrent neural networks
SOGE	School of Geography and the Environment at the University of Oxford
t-SNE	t-Distributed Stochastic Neighbor Embedding
UNDP	United Nations Development Programme
UNEP	United Nations Environment Programme

1

Introduction

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1.1. Motivation

Relying solely on conventional economic indicators—domestic product, the rate of unemployment, and stock market trends, among others—is insufficient for directing fiscal policy. Security, health, social relations, freedom of choice, and natural ecosystem access are all obvious contributors to human wellbeing yet are not fully captured by conventional indicators (Millennium Ecosystem Assessment, 2005; Nelson *et al.*, 2013; Pecl *et al.*, 2017). However, despite efforts from some economists and advocates, many policy makers continue to rely mostly on conventional criteria for making investment decisions (Constanza *et al.*, 2009; Dynan and Sheiner, 2018; Hornsey and Fielding, 2019; Van den Bergh, 2009). This thesis meets these policy makers where they are by considering whether investments with positive climate mitigation characteristics might be superior to traditional investments based solely on conventional metrics.

The broadest purpose of this DPhil is to contribute to the understanding of environmental policy in a recessionary context. In doing so, it ponders well-established questions in the green growth literature with new data, adapted methods, and a new instructive event. It asks three major questions: (i) *if a government were to care only about conventional economic indicators, would it be rational to invest in climate solutions over traditional initiatives,* (ii) to this end, *are some climate solutions better than others*, and (iii) *does the answer change between economies?*

Existing literature provides a strong foundation for this work (see, among many others, Barbier, 1987; Barbier, 2014; Barbier, 2016; Bowen and Fankhauser, 2011; Dai *et al.*, 2016; Dercon, 2012; Fankhauser and

Jotzo, 2017; Fankhauser and Tol, 2005; Fankhauser *et al.*, 2013; Hallegate *et al.*, 2011; Hao *et al.*, 2021; Hepburn and Bowen, 2013; Jacobs, 2013; Jänicke, 2012; OECD, 2011; UNEP 2010; Stern *et al.*, 1996; van Vuuren *et al.*, 2017). Notably, some related questions are not considered. For instance, this thesis investigates "what to spend on" but not "how much to spend", nor "when to spend". It questions "what is possible", but not "what is practical in a socio-political context".

The unexpected and unprecedented economic shock of the SARS-CoV-2 coronavirus pandemic (COVID-19) is used as the instructive event for this DPhil. In times of recession, economic criteria are likely to elevate in priority for policy makers and manifest in fiscal distributions that more centrally target growth outcomes. In this way, analysis of the COVID-19 economic recovery provides a rare view on how policy makers use fiscal policy when conventional economic indicators and orthodox development criteria are prioritised. Additionally, the global nature of the COVID-19 shock allows for comparison of policy reactions between countries and consideration of what might drive differences in reactions. The focus on COVID-19 naturally brings focus to the characteristics of investment in a contractionary economic environment, but of course much of the discussion in this DPhil concerns fiscal trade-offs also relevant outside of those periods.

The complexity of the COVID-19 crisis, globally heterogenous patterns in fiscal response, and limited data availability demand appropriate tools for analysis. To that end, machine learning (ML) techniques are used as a unifying methodological theme across the DPhil, supporting traditional methods. Reinforced by ML tools, this DPhil

triangulates perspectives on the economic characteristics of green recovery by systematically assessing existing literature, undertaking a digital survey, collating data through policy scraping, and analysing empirical data with quantitative and econometric methods. Prominent ML tools used in the analysis include natural language processing (NLP), applications of recurrent neural networks (RNNs), deep learning for word embedding, and topic modelling, as well as ensemble modelling and clustering.

Analysing a new instructive event demands new data. In this DPhil, four new datasets are compiled. A global survey is presented with 231 responses from leading economists, an inventory of green investment literature is collated, a fiscal expenditure dataset is constructed with 8,001 policies from 88 countries, and a speech dataset is formed with 3,817 English transcripts using manual and computer-automated data scraping. Each dataset is verified using statistical methods and/or ML techniques.

The DPhil is structured in reference to three core papers. First, I use new and existing techniques in NLP to synthesise conclusions of existing literature on the economic characteristics of green investment. Second, I survey leading economists to understand the perceived characteristics of green investments compared to alternatives amongst *experts*. I include additional unpublished analysis to this paper using ML techniques. Third, I use results from the first two papers, with a new dataset and methods in deep learning and econometric model selection, to understand sectoral and global variation in actual spending habits and their drivers in response to the COVID-19 crisis. As detailed in Chapter 6.2, the third paper brings together many frameworks and ideas introduced in the first two papers to

provide a deep account and informed analysis of the fiscal response. Finally, I briefly synthesise the three papers as a collective body of work. Several additional essays, reports, and briefings contributed to the development of the three core papers, each focusing on different temporal, sectoral, and geographic components of the economic response to COVID-19. These are listed in Appendix E.

1.2. Definitions

1.2.1. What is "green"?

The terms *green investment* and *climate mitigation investment* are used interchangeably in this thesis to consider fiscal policies that are likely to reduce net greenhouse gas (GHG) emissions compared to scenarios in which the policies were not implemented. Despite the focus here on climate mitigation, other ongoing environmental crises including in biodiversity loss and pollution, are significant and must be considered in policy making. Additionally, the adaptation and resilience characteristics of investments must be prioritised.

The additional environmental impacts of policy, beyond climate change mitigation, are discussed at various points in this thesis and considered at length in supplementary works (listed in Appendix E). The primary reason for focusing on only one criterion here is to allow for singular categorisations of policy (*e.g.*, green vs neutral vs dirty; see extended data table 2 of paper C). The alternative, using multiple environmental criteria as in *Introducing the Sustainable Budgeting Approach* (see Appendix E), allows for a nuanced comparison of policy impacts, but is a significantly larger task. GHG impact is the focus of this thesis above other

environmental concerns due to (a) the immediacy of the climate crisis, (b) greater data availability and existing literature (necessary for paper A), and (c) better existing understanding amongst economists (necessary for expert elicitation in paper B).

Narrowing the focus of the DPhil to test only climate mitigation commensurately narrows the findings of the DPhil. While concepts of "green growth" and "greening" economies are introduced in their broad senses in the literature review to establish the broader context, subsequent discussion considers only their climate mitigation dimensions. Following Rockström *et al.*'s (2009) framing of nine planetary boundaries, it is clear that progress on climate mitigation is necessary but insufficient for attaining green growth—the non-mitigation components of green growth are left for future studies.

1.2.2. Does "fiscal" include taxation measures?

In this thesis, yes, the terms *fiscal policy*, *deficit spending*, *government investment*, and *government spending* are generally used interchangeably. In all three papers, I consider both spending-side and taxation-side measures. In my analysis of COVID-19 fiscal policies I identify trillions of dollars in taxation incentives of many different kinds and trillions associated with expenditure measures. When it comes to fiscal policy response in a recession, the choice between the two (taxation or expenditure) often appears to be one of mechanism rather than purpose. Certainly, the effectiveness of the initiative will depend on which mechanisms is used, with the preferred mechanism depending on the circumstances.

1.2.3. The stages of fiscal response

In this DPhil, three subcategories are used to describe different kinds of fiscal response to recession: *rescue*, *recovery*, and *reinforcement*. Rescue and recovery deficit spending are used here as subcategories to the traditional term *fiscal stimulus*. Both rescue and recovery measures should meet Elmendorf and Furman's (2008) definition to be "timely, targeted, and temporary". Reinforcement spending is that which is recurring and requires a permanent (or semi-permanent) increase in deficit spending.

Rescue and recovery spending are differentiated primarily by their economic and social intent. Rescue spending is that which intends primarily to protect businesses and people from the immediate impacts of the crisis—for instance, vaccine spending, food stamps, unemployment support, or business liquidity measures. Recovery spending is that used primarily to stimulate demand, address supply shocks, or otherwise reinvigorate an economy—for instance, new infrastructure investment, incentives to purchase priority goods or services, or cash payments with explicit intent to stimulate economic activity. There is clearly a degree of overlap between the rescue and recovery categories; they are not perfect and hence are often better considered collectively as "fiscal stimulus". Perhaps the overlap is most apparent for cash payments: during the Global Financial Crisis (GFC), a cash payment ('stimulus cheque') in Australia was described as an instrument to stimulate demand (Tienhaara, 2018), while a series of COVID-19 "welfare grants" in South Africa were described as an alternative to food stamps to protect welfare (Ohrnberger, 2022). While they might

have had different primary intent, both likely had some impact on protecting welfare and some impact on stimulating demand.

Reinforcement processes are used to integrate new recovery program trajectories into long-term development plans (see O'Callaghan and Murdock, 2021). For instance, actions that take temporary incentives for priority goods or services established in the recovery phase and make them permanent. A relevant example is recent attempts to make South Africa's COVID-19 welfare grant scheme permanent (Cele, 2022). If such a policy change were to be successful, by the definition in this DPhil, the ongoing costs of the welfare program would be considered reinforcement spending.

1.3. Context

1.3.1. Fiscal policy in response to climate change

For national governments, the imperative to reduce the magnitude and effects of climate change was formalised in a 1992 international treaty, the United Nations Framework Convention on Climate Change (UNFCCC, 1992). The directional consequences of increased atmospheric CO_2 concentrations were understood far earlier (Arrhenius, 1896; Foote, 1856; Fourier, 1822; IPCC, 1990; Tyndall, 1861). However, up until the UNFCCC, discourse on climate change was mostly limited to scientific domains. Subsequently, over three decades of subsequent annual diplomatic gatherings, and two additional treaties (Conference of the Parties, Adoption of the Paris Agreement; 2015; Kyoto Protocol to the United Nations Framework Convention on Climate Change, 1997), many national governments have made some progress on shaping domestic policy to address climate change (Lesnikowski, 2016; Schmidt and Fleig, 2018).

However, most policy interventions have not been commensurate with the scale of the problem and its related risks (Climate Action Tracker, 2021; Shukla *et al.*, 2022; UNEP and UNEP-CCC, 2021).

The negative externality of climate change requires the attention of policy makers in part because of its major harms to human wellbeing, in part because it erodes natural capital and associated ecosystem services, and in part because dealing with it on the requisite scale demands collective action. Significant literature details the impacts of climate change on human wellbeing, including through threatened food and water supplies (Godfray *et al.*, 2010; Helman and Bonfil, 2022; Hoegh-Guldberg and Bruno, 2010; Taylor *et al.*, 2013; Wheeler and Von Braun, 2013), higher exposure to extreme temperatures (Seneviratne *et al.*, 2021, pp. 1546-1553), wider exposure to and increased severity of environmental disasters (Easterling *et al.*, 2000; Seneviratne *et al.*, 2021, pp. 1567-1553; van Aalst, 2006), losses in economic productivity (Dunne *et al.*, 2013; Zander *et al.*, 2015; see related economic discussions in Fankhauser and Tol, 2005), greater contact with existing diseases (Wu *et al.*, 2016), increased risks of incubating new diseases (Parmesan *et al.*, 2022, pp. 233-246; Patz *et al.*, 1996), additional other risks to human health (McMichael *et al.*, 2006; Watts *et al.*, 2021), reduced nutrient density in food (Myers *et al.*, 2014), food system stress (Ciais *et al.*, 2005; Bezner Kerr *et al.*, 2022), increased rates of forced migration (Abel *et al.*, 2019; Warner *et al.*, 2010), loss of land and perhaps entire nation states (Barnett and Adger, 2003; Mycoo *et al.*, 2022), risk of social, political, and financial instability (Lamperti *et al.*, 2019; Scheffran *et al.*, 2012; Sofuoğlu and Ay, 2020), and loss of

environmental amenity (Cooley *et al.*, 2022; Parmesan *et al.*, 2022). Many of the processes that cause anthropogenic climate change bring additional associated impacts—for instance, burning biomass for heating and cooking can diminish respiratory health (Duflo *et al.*, 2008; Sigsgaard *et al.*, 2015), burning coal for electricity and oil in heavy vehicles both bring deadly air pollution (*e.g.*, Bai *et al.*, 2022; Beatty and Shimshack, 2011; Hendryx *et al.*, 2020), and the extraction of fossil resources is associated with polluted waterways, soil, and more (*e.g.*, Cravota and Brady, 2015; Crone and Tolstoy, 2010; Vidic *et al.*, 2013). The severity of all these potential impacts of climate change on humans has spurred significant concern from medical practitioners, social workers, economists, and others (for example, AAAS, 2009; Belkin, 2020; Cook *et al.*, 2013; Howard and Sylvan, 2021; Kotcher *et al.*, 2021; Lynas *et al.*, 2021).

If a fundamental role of government in crisis is harm minimisation to protect human wellbeing, then clearly there is a role for government to address and limit the impacts of climate change. Under a more expansive interpretation of the role of government, where it serves not just to protect human wellbeing but improve it, government might act to boost economic product through investment in climate-friendly industries (see Clements *et al.*, 2020, p. 11; Fankhauser *et al.*, 2013; Shah 2013).

Governments have several policy tools at their disposal that might be used for limiting and addressing climate harms, potentially creating wealth in the process. As detailed in paper B, these

include (a) monetary controls in the form of interest rates, reserve requirements, and quantitative easing (which is used relatively infrequently); (b) regulatory interventions to change incentives; and (c)

fiscal interventions in the form of changes to taxation and public expenditure.

(b) and (c) can be applied either to reinforce positive trends, particularly in support of new entrants and industries, or to counter negative trends, particularly against polluting incumbents with negative externalities. Fiscal policy can be a particularly powerful tool, if appropriately applied. Amongst other functions, it can support green innovation, seed and accelerate new low-carbon projects, signal long-term priorities in support of complementary business environments, spur early demand for new products, and reduce or remove inefficient subsidies that support the competitiveness of high GHG emissions industries (Coady *et al.*, 2017; Skovgaard and van Asselt, 2018; Parry *et al.*, 2021).[1]

There have been many examples of governments using fiscal tools to address climate change across nations and sectors. As one example, renewable energy generation has been supported by tax incentives of many varieties (Cansino *et al.*, 2010; Hymel, 2006), direct subsidies (Murray *et al.*, 2014; Nicolini and Tavoni, 2017; Yang *et al.*, 2019), indirect subsidies (*e.g.*, loan guarantees discussed in Yonk, 2021),[2] and more. However, climate-friendly fiscal investment has been minor compared to total government spending. The Climate Policy Initiative's annual *Global*

[1] Supporting innovation often comes in the form of direct grants or tax incentives. For seeding new projects, mechanisms include liquidity vehicles, guarantee efforts, and many varieties of fiscal incentive (*e.g.*, feed-in tariffs, subsides, tax incentives). Spurring early demand might be achieved directly by funding infrastructure projects or putting in place procurement standards, or indirectly by building new product or industry ecosystems (*e.g.*, hydrogen ecosystems). A helpful starting point for discussion on inefficient subsidies is Coady *et al.* (2017), Skovgaard and van Asselt (2018), and Parry *et al.* (2021).

[2] Unfortunately, fossil fuel subsidies are significantly more prolific than subsidies for renewable energy (Coady *et al.*, 2017; Skovgaard and van Asselt, 2018; Parry *et al.*, 2021).

Landscape of Climate Finance suggests that government budgets contributed only US$38 billion per year over 2019/20 to climate finance (Buchner *et al.*, 2021); this is equivalent to 0.25% of global government final consumption expenditure (World Bank, 2021a) and 0.04% of global gross domestic product (GDP) (World Bank, 2021b).[3,4] For comparison, road maintenance takes a budget of approximately 0.61% of GDP (Foster *et al.*, 2022, p.18)[5] and explicit fossil fuel subsidies are worth US$470 billion per year (3.1% of government consumption expenditure and 0.55% of GDP) (Parry *et al.*, 2021).[6] Compared to categories like military spending or public servant salaries, green fiscal allocations are minute. Certainly, public finance need not be the dominant form of climate investment in the same way that it is the dominant form of military finance. However, nevertheless, it can play a major role to accelerate private investment, particularly in nascent industries. This role can come both through "crowding-in" private funds to emerging sectors and by providing a favourable environment for green investment (Zenghelis, 2012). The total finance required to address climate change in the energy sector alone is estimated at US$1.6-3.8 trillion

[3] With a broader definition of climate finance, this figure is likely to be larger. The cited US$D38 billion in government budgets excludes the climate finance investments of development finance institutions (US$220 billion), multilateral funds (US$4 billion), state-owned enterprises (US$13 billion), and state-owned financial intermediaries (US$45 billion). Components of these investments originated in fiscal distributions.
[4] Final consumption expenditure (reportedly US$15.08 trillion in 2020, World Bank, 2021) includes all current expenditures by government on goods and services (including employees). It does not include capital formation. Global GDP was reportedly US$84.9 in 2020 (World Bank, 2021).
[5] Calculated from road funds expenditure as 0.52% of GDP and 85% of total road maintenance expenditure (Foster *et al.*, 2022, p.18).
[6] Implicit subsidies are an order of magnitude higher at US$5.4 trillion. This includes "undercharging for environmental costs and foregone consumption taxes" (Parry *et al.*, 2021).

per year (in 2010 dollars)[7]—compared to 2019/20 investments of just US$334 billion in low-carbon energy systems (Buchner *et al.*, 2021). There is clearly a long way to go.

One concern raised against government support of a green economy is that of economic harm. Some claim that the economic cost of progress on climate change exceeds the benefit—some because they deem the costs too high (*e.g.*, Lomborg, 2020), others the benefits too low (*e.g.*, Koonin, 2021). Joining a raft of precedent literature, this DPhil investigates the veracity of this negative perspective through the lens of traditional economic metrics including GDP growth and job creation during a period of economic contraction. The traditional lens excludes essential wellbeing benefits already highlighted on health, economic resilience, social stability, and more. These benefits are put aside for the purpose of engaging policy makers on the traditional criteria that they are familiar with and that tend to govern investment decision making (see Constanza *et al.*, 2009; Dynan and Sheiner, 2018; Hornsey and Fielding, 2019; Van den Bergh, 2009). Quite obviously, any serious real-world economic comparison should move significantly beyond traditional metrics and use holistic definitions for wellbeing that value human health and prosperity in their broadest sense.

1.3.2. Fiscal policy in response to economic contraction

In the 1930s, a prominent Cambridge economist, Lord John Maynard Keynes, challenged prevailing supply-focused economic theory on many

[7] As explained in Paper A, "Extrapolating funding requirements submitted to the UNFCCC (2021), non-Annex 1 nations might require US$11 trillion just to meet their Nationally Determined Contributions, most of which are not aligned with a safe climate trajectory".

topics including the role of fiscal policy through economic downturn (Keynes, 1936). Keynes provided arguments in support of government spending to restore consumer confidence, enable full employment, and thereby encourage an economy out of recession. Prior to Keynes, policies of low fiscal intervention, sometimes associated with economic liberalism, often dominated discourse in many nations.[8] Keynes' writings grew in popularity following the Great Depression. The United States and Sweden acted on his advice to aid their economic recoveries, and other nations followed later (Hall, 1989; Wier and Skocpol, 1985). Over proceeding decades, the popularity of Keynesian approaches to economic management ebbed and flowed; they featured in the fiscal approaches of several nations following the Second World War (Hall, 1989), and certainly in some nations in response to the GFC (Barbier, 2009; Robins *et al.*, 2009; Tienhaara, 2018), but in intermediate periods were challenged by neoliberal and monetarist ideas (Eatwell and Milgate, 2011).

What seems relatively consistent across economic ideologies, in all but the most apostate cases, is that there is some legitimate role of government to reduce extreme harm in the event of large-scale economic crisis (as is the case for response to large-scale crises of a non-economic nature).[9] What is not consistent is how to do so. It is helpful to consider

[8] That said, Lee (1989) comments that a "proto-Keynesianism" was very much a feature of heterodox thinking of the time, particularly in the United States, and is often forgotten (including in Keynes' own works). Lee refers to several works and statements from the times, including Frank Knight (in Davis, 1971), who purportedly said in relation to a significant 1931 government spending bill financed by borrowing "[a]s far as I know, economists are completely agreed that the Government should spend as much and tax as little as possible at a time such as this".

[9] Recessionary economic conditions are often associated with job losses and reduced social outcomes of many kinds (Di Tella et al., 2003; Kentikelenis, 2011), which can reduce

harm minimisation over three intervals: short-term *rescue* measures to protect lives and livelihoods from the immediate dangers of the crisis at hand (for instance, providing medical or unemployment support), medium-term *recovery* measures to reinvigorate economic growth once the crisis is contained, and long-term *reinforcement* measures to further bolster positive shifts in economic structures, investments, and behaviours set during the recovery phase. The recovery phase of a crisis provides the core opportunity for interventions with a Keynesian purpose.

The imperative for public investment in economic recovery introduces a question: *what to spend on?* In extended form, this question might be: *Which policy investments might best maximize future prosperity and minimize harms without introducing any new ones?* Future prosperity could include at least two aspects—one that relates to an immediate need for economic reinvigoration, defined by traditional economic metrics like a high fiscal multiplier for GDP growth, and another that relates to a long-term shift in national trajectories toward a more desirable form of economic growth, and therein increased wellbeing. Future prosperity is clearly not maximised by a stimulus that targets short-term factors at the expense of long-term wellbeing (for instance, measures that worsen other crises), nor by a stimulus that ignores the need to elevate an economy out of recession.

Green investments were touted in the first months of the COVID-19 crisis as a way to simultaneously meet emergency economic needs and

aggregate demand through several mechanisms and become reinforcing (Challe et al., 2017). Governments are concerned with alleviating these stresses and stabilising the economy—a historically practical mechanism for doing so is boosting economic outcomes and this is the stated prerogative of many governments (for example, see Council of Economic Advisers, 2022, p. 29-32; Elmendorf and Furman, 2008; The Commonwealth of Australia, 2020).

climate objectives (IRENA, 2020). Anecdotally, academic advisors began conceiving of and supporting these narratives as early as March 2020, with the first publication on the topic appearing in an academic journal on 8th May 2020 (*i.e.*, paper B of this DPhil). Again, anecdotally, enthusiasm for green fiscal measures as a form of COVID-19 response was organic and predated major public commentary in several countries. In other countries, enthusiasm was observed following the introduction of green recovery narratives into the public media; in these cases, it is unclear whether similar measures might have emerged organically without public pressure. It is fundamental that the political economy influences fiscal decision making,[10] and this was certainly the case for COVID-19 (see Paper C for brief discussion on the green political economy of the times). However, to some degree, questions of political economy are irrelevant to the academic queries of this DPhil. For impact comparison across fiscal policies, traditional academic analyses tend to discard political economy. This DPhil takes a mostly similar approach, only considering political economy in the *rhetoric or reality* discussion of Paper C.

The early calls for green recovery in response to COVID-19 followed exemplary climate investments made in response to the last major global economic crisis—the GFC. In nominal figures, recovery investment over that period saw approximately US$557 billion flow to green initiatives, including US$338 billion from Asia and the Pacific, US$147 billion from North America, and US$69 billion from Europe (figures adapted from

[10] Keynes mused in the *General Theory* that "the ideas of economists and political philosophers, both when they are right and when they are wrong, are more powerful than is commonly understood" (Keynes, 1936, p. 383).

Robins *et al.*, 2009, supplemented with missed policies). Several prominent authors provided support to these programs as well as later assessment of impact. Further details are included in the literature review and a summary historical account of fiscal responses to environmental threats, including over the GFC, is included in paper A.

1.4. Contribution

This thesis provides major contributions in six categories: new datasets, unique application of existing methods, new methods and structures, new evidence in support of green growth narratives and the core DPhil questions, evidenced policy recommendations, and suggestions for future research. Brief summaries of the first four contribution categories are provided below. Contributions to policy recommendations and a future research agenda are detailed in Chapter 6.4-6.5.

1.4.1. New datasets

Paper B, *Will COVID-19 fiscal recovery packages accelerate or retard progress on climate change?*, includes a survey of 231 leading economists, eliciting perspectives on the relative economic and climate potential of 20 policy archetypes. This represents the first known elicitation survey on the economic characteristics of green investment and one of surprisingly few that have surveyed leading economists on climate change topics. The resulting dataset includes 24,703 datapoints, of which 23,171 datapoints relate to fiscal policy options.[11] There are, of course, several limitations to the elicitation approach; these are discussed in the literature review.

[11] The dataset itself is of a personal and private nature, gathered with CUREC Ethics Approval (SOGE 1A2020-44) and cannot be shared.

Paper C, *Reviewing the COVID-19 "Green Recovery": rhetoric or reality?*, relies on progress made in Paper A and Paper B to consider actual spending in response to COVID-19. It introduces the world's largest database on recessionary fiscal investment, twice the size of the next largest contribution, and with significantly further geographic coverage and granularity. The Global Recovery Observatory (GRO) covers 88 countries, providing 8,001 policies and 58,704 datapoints. It has been made freely available, alongside an original fiscal taxonomy for categorising policies, a peer-reviewed assessment framework for understanding GHG emissions (see Paper C Supplementary Materials), and similar assessment frameworks for understanding other environmental and social impacts (see works in Appendix E). There are many potential use cases for the database, including for analysis of the environmental, social, and economic performance of countries in economic recovery. These analyses could, in turn, input to other scientific and environmental modelling—for instance, integrated assessment models (IAMs) for predicting climate change have previously not incorporated the potential impacts of fiscal policy due to a lack of categorised (labelled) data. To this end, the dataset could support development of new deep learning models, like that in Paper C, to quantify the potential future GHG emissions impacts of new fiscal policy. Beyond these applications, the dataset is already being used as a learning tool for policymakers who seek to understand options for green investment in different sectors (see *Introducing the Sustainable Budgeting Approach* in Appendix E) and as pertinent data for guiding business investment.

Paper C also presents the first database of COVID-19 speeches, including 3,817 speeches from heads of state and heads of government in 43 countries. It introduces many opportunities to study political rhetoric over the crisis and how this rhetoric relates to any number of events—including fiscal policy announcements. The dataset was developed using a combination of manual and automated web-scraping processes.

1.4.2. Unique application of existing methods

In paper A, established methods in NLP are applied, for the first time, to the green fiscal literature. The paper creates the second green dictionary for NLP that I am aware of (following Fisch-Romito *et al.*, 2021) and applies techniques that are now standard in the field of data science but largely foreign to the domain of economic policy. These techniques include Latent Dirichlet allocation (LDA), frequency collocation analysis, and t-Distributed Stochastic Neighbor Embedding (t-SNE) for visualisation.

In paper B, the elicitation survey is the first such inquiry to the economic characteristics of green investment and one of surprisingly few that have surveyed leading economists on climate change topics (and of even less that have done so with global respondents).[12] The paper's supplementary materials describe the approach methodology and helpful online tools with more detail than is available elsewhere, providing guidance for future studies. An additional note in supplement to paper B, conducts further analysis of the survey results using well-established supervised and

[12] Oppenheimer *et al.* (2016) note the underutilisation of elicitation methods for understanding climate change. See examples of economist elicitations on climate topics from Howard and Sylvan (2015 and 2020) and Pindyck (2019).

unsupervised ML approaches. As in paper A, these ML methods are by no means new. So far as I am aware, however, these approaches have not previously been applied to consider survey results from economist elicitations.

In paper C, a series of bidirectional Long Short-term Memory (LSTM) RNNs are used to validate the internal consistency of the GRO dataset. This application of RNNs is perhaps the first to categorise fiscal policy and the first to predict climate impact from policy descriptions (previous attempts, if any, were likely limited by a lack of adequate labelled training datasets—GRO fills this gap). Also in paper C, general-to-specific (GETS) econometric model selection is applied for the first time to fiscal spending questions and for the first time to the COVID-19 crisis. While the application in this paper uses only cross-sectional data, the data does allow for more advanced time series analysis (policy announcement dates are specified in the GRO dataset). Finally, paper C includes the first application of natural language processing to study the environmental content, or "green rhetoric" of head of state speeches. Prior conference proceedings from Gautrais *et al.* (2017) showed the progression of climate change as one of fifteen core topics in Trump-Clinton speeches, however this was not the focus of the paper.

1.4.3. New methods and structures

In systematic literature reviews, a topic-specific dictionary is needed to identify relevant papers. Paper A developed a novel iterative method with ML embedding models to build a domain-specific green dictionary. The method expanded an initial user-defined dictionary to include all related

domain-specific terms, where the domain was defined by the literature itself. The dictionary's function was as an input to identifying and then analysing green investment papers with NLP. The single pre-existing dictionary (Fisch-Romito *et al.*, 2021) was, unfortunately, deemed too rudimentary for the paper's objectives.[13] The new method is versatile and can be applied to any study which might require a topic-specific dictionary and has a significant text corpus. For example, it was applied to develop a green dictionary for head of state speeches in Paper C.

Paper C builds on intermediate work in Paper A and Paper B to describe a comprehensive *fiscal taxonomy for recessionary investment*. The taxonomy presents 42 fiscal policy archetypes and 221 subarchetypes, defined based on similarities in *both* economic and environmental characteristics. Archetypes intend to be collectively exhaustive in representing the full universe of available fiscal policy options and mutually exclusive in not overlapping with each other. Examples of fiscal archetypes include *job continuation support*, *education investment*, *clean transport infrastructure investment*, and *traditional energy infrastructure investment*. Each archetype contains a set of subarchetypes. These subarchetypes each describe a smaller set of fiscal policy options available within the family of their archetype. They too intend to be collectively exhaustive (subarchetypes together describe all options within an archetype) and mutually exclusive. For example, there are eight subarchetypes for clean transport, including *public transport systems or line expansions*, *EV*

[13] As discussed in the literature review (Chapter 2.3.1), the primary challenge with most dictionary-building methods is that they rely on expert elicitation, which can be inadequate for capturing the full range of relevant terms in a domain (Park *et al.*, 2021).

charging infrastructure, and *cycling and walking infrastructure.* Each of the 221 subarchetypes were assessed in Paper C for potential climate impacts using a 5-point Likert scale (very negative, negative, neutral, positive, very positive) over both short- and long-term time scales, where short term is the implementation phase and long term is operational life. These assessments drew directly on the machine-assisted literature review in Paper A, expert elicitation in Paper B, and a prolonged period of international peer review by over 20 leading experts. See Paper C's extended data table 2 for a full list of archetypes, subarchetypes, and their impact assessments.

Together, the taxonomy and assessments of GHG impact are a useful tool for interpreting the GHG characteristics of fiscal response to economic crisis. In Paper C, the taxonomy is used as a tool for categorising COVID-19 spending into the 221 subarchetype groupings, assessing potential climate impact at that granular level, and then aggregating to understand net finance in support of, or against, lowering emissions. This is but one demonstration for how the taxonomy might be used to interpret investment actions. With moderate tweaks, the taxonomy and assessments can be applied outside of economic crisis, i.e., to 'normal' budgetary processes too (see *Introducing the Sustainable Budgeting Approach* in Appendix E). Finally, the RNN models built for validation of the taxonomy in Paper C are themselves useful as a tool for automatically interpreting and assessing new fiscal policy announcements.

Previous taxonomies for recessionary spending are limited in that they generally consider only green spending (not neutral or dirty spending)

and a maximum of three categories and seven subcategories, essentially proxying for economic sectors (Robins *et al.*, 2009). Alternative non-recessionary fiscal taxonomies include those from the ESA (2010), IMF GFSM (2014), UN (2000), and EU (2020), although each was ostensibly developed by grouping similar policy types based on *either* environmental characteristics only (in the case of the EU taxonomy) or economic characteristics only. Further discussion on precedent literature is included in Chapter 2.2.

1.4.4. Findings on core DPhil questions and green growth

The central finding of this DPhil, triangulated with three papers, is that certain kinds of investments in a contractionary economic environment can possess strong economic, as well as climate, attributes. This conclusion supports the notion that absolute decoupling of GDP growth from GHG emissions is possible in a post-recession context of economic recovery. The policy observations of Paper C suggest that not only is it possible to achieve this, but that some governments in their responses to COVID-19 might have partially acted on this basis. For instance, GETS model selection suggests that one of the most critical predictors of green spending in the largest 50 economies was level of unemployment (i.e., nations with higher unemployment spent greener). While this result certainly doesn't prove causality, it suggests that there might have been some degree of conscious or unconscious prioritisation that led countries with higher unemployment to spend greener (see Chapter 6.3.1 for further discussion).

This thesis provides evidenced responses to three core questions on green investment during economic contraction:

- Using only conventional economic indicators (mainly jobs and growth), with appropriate policy design it can make sense to invest in many climate mitigation solutions over traditional initiatives in similar sectors,
- Some climate mitigation solutions have stronger economic characteristics than others, but which are superior depends on the economy and the specificities of policy design, and
- Investments in climate mitigation hold potential over traditional investments in all geographies, although the most attractive set of climate archetypes are likely to vary from economy to economy based on factors including level of development, human capital, present unemployment, and existing economic structures.

In support of existing green growth literature, the review of the literature in this thesis suggests that human wellbeing is not only driven by growth, good jobs, and innovation, but also by social and environmental factors like our relationship with nature, its ecosystems, landscapes, and nonhuman species. This is achieved first through Paper A's systematic literature review and next with Paper C's fiscal taxonomy, which details the climate mitigation characteristics of investment archetypes. Paper B's survey goes further, assessing the "overall desirability" of policy options and ascertaining that a component of this is driven by non-climate, non-economic factors.

Combining these two perspectives, this DPhil shows that in periods of economic contraction, relying on traditional economic measures can be

sufficient for prioritising green investments over others but is generally insufficient for directing fiscal policy.

Regarding the likely overall impacts of the COVID-19 fiscal response on GHG emissions, this DPhil provides a sobering assessment: an unprecedented US$18.2 trillion in deficit spending provided opportunity to meaningfully shift the carbon intensity of our economic systems, but this opportunity appears to have been mostly missed. That is not to say that all funds could have or should have supported explicitly carbon-negative initiatives, but certainly, more opportunities were missed than taken and climate finance gaps persist. On the positive side, governments announced up to US$978 billion in new spending that might reduce long-term GHG emissions. However, this was a relatively minor portion of total spending (5.4%) and there is evidence in existing literature to suggest that policies which might appear carbon-negative at the time of announcement, do not always achieve their imagined impact (see discussion in Chapter 2.2.2.2). For recovery type spending, where policy makers had greater discretion over which industries were supported, up to US$945 (31.1% of all recovery spending) might reduce GHGs in the long term. Less funds were directed to initiatives likely to increase long-term GHGs ($277.7 billion or 9.1% of recovery investment), but the fact that any public funds were spent on GHG-increasing projects at all is concerning given the herculean task of navigating towards net-zero emissions. Considering the short-term impacts of COVID-19 spending, the situation is even more dire; 71.5% of spending (US$13.0 trillion) is likely to increase GHGs in the short term, mostly due to the embedded carbon in new physical infrastructure as well as existing energy and resource inefficiencies in most sectors. While short-term

increases in emissions are not necessarily concerning for initiatives that might have a much larger long-term carbon-reducing impact, there are risks that poor implementation render those initiatives ineffective. Of course, the many initiatives that are not designed to lower long-term emissions then simply perpetuate the unsustainable economic status quo. When the actual fiscal response is compared to the green recovery scenarios of Forster et al. (2020), the chasm of opportunity becomes even clearer. As explored in Chapter 2.2.2.2, Forster et al.'s moderate green recovery scenario required 5 to 10 times more low-carbon investment than what we saw, as well as infinitely faster divestment of fossil fuels (governments increased support of fossil fuels through COVID-19 while divestment of 2-4 trillion was required), and significant supporting climate policies. It is only with ex-post assessment that we will come to fully understand the impacts of the COVID-19 fiscal response, but at the time of writing, the picture is not promising. Pairing this fiscal conclusion with the reality that COVID-19 weakened environmental regulation and did little to correct systematic mispricing of fossil fuels (in some cases exacerbating it) the overall impact of the COVID-19 policy response on emissions appears to have fallen well short of its potential.

1.5. Structure

The body of this DPhil is organised as follows. In Chapter 2, I review existing literature on green growth, counter-cyclical fiscal policy, and the core methods used in this DPhil.

Next, in Chapter 3, I append the paper *How Stimulating Is a Green Stimulus? The Economic Attributes of Green Fiscal Spending* and its

supplementary materials. Published in the *Annual Review of Environment and Resources*, this paper synthesises existing literature on the economic characteristics of green investment.

For the second paper, in Chapter 4, I append *Will COVID-19 fiscal recovery packages accelerate or retard progress on climate change?,* its supplementary materials, and an unpublished additional analysis using ML techniques. The paper was published in the *Oxford Review of Economic Policy* and uses an elicitation survey of leading economists to understand the perceived economic, environmental, and other characteristics of alternative fiscal responses to the COVID-19 pandemic.

For the final paper, in Chapter 5, I append *Reviewing the COVID-19 "Green Recovery": rhetoric or reality?,* its extended data tables and figures, and its supplementary materials. The paper, which has been, uses two manually-compiled datasets alongside methods in deep learning and econometric model selection, to understand sectoral and global variation in actual COVID-19 fiscal responses and their drivers.

Following the papers, a discussion chapter (Chapter 6) synthesises findings across the three works, noting areas of agreement, disagreement, and unanswered questions. The chapter also provides responses to each of the three core questions of the DPhil, ensuing policy recommendations, and an agenda for future research. A brief conclusion in Chapter 7 completes the thesis.

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2

Literature review

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This literature review first considers the theoretical basis of green growth, how it relates to concepts of decoupling and its applicability to emerging markets and developing economies. In the second section, the Keynesian neoclassical synthesis is introduced before its intersection with green growth is explored. In the third section, the field of machine learning is introduced, with particular attention to methods used in the papers of this thesis, including, natural language processing, clustering, ensemble models, and deep learning including neural network models. In the final section, other core methods for the thesis are briefly introduced, namely, survey methods and general-to-specific econometric modelling.

2.1. Green growth and its discontents

The threats of unfettered climate change demand a shift in human modes of production and consumption. The target is, of course, to reduce greenhouse gas emissions, which accumulate in the atmosphere and precipitate a "greenhouse effect" that traps in heat (Fourier, 1822; IPCC, 1990). At sufficiently high levels, this extra heat can have multifaceted and unpredictable consequences on atmospheric conditions, altering critical ecological processes and cycles, bringing extreme weather, and precipitating more frequent and severe natural disasters (Easterling *et al.*, 2000; van Aalst, 2006).

Opportunities to reduce emissions are plentiful and are necessary across most if not all sectors. One extreme pathway for reducing emissions could be to cut consumption to near zero and return human life to a more primitive form (Trainer and Alexander, 2019). However, this approach is unpalatable to most people and counters the human drive for improved

lives and livelihoods (see Panksepp, 2004). Another pathway might be to overhaul how goods and services, physical and virtual, are produced and consumed. This approach is technologically optimistic, suggesting that if adequately motivated, the *machine* of human innovation and creativity could develop new solutions to maintain and increase quality of life while reducing the GHG burden. It operates under the observation that humans have a history of innovating their way out of problems (Taalbi, 2017). Formulated in neoclassical economic terms, quality of life is proxied here by "growth" and, by convention, reducing GHG burden is often simply represented as "green", hence, "green growth".

It is important at this juncture to consider more deeply what is meant by *growth*. Growth of what? Conventionally, when used in the context of economic analysis, it is assumed that growth refers to the change in the market value of goods and services created in an economy over time, adjusted for inflation. The statistical convention is to measure gross domestic product (GDP), although similar alternatives like gross national product (GNP) and net national product (NNP) are sometimes used. GDP can be considered the "most widely accepted measure of a country's economic progress" (Constanza *et al.*, 2009) and "so often used as a measure of standard of living" (Dynan and Sheiner, 2018). As reported in Constanza *et al.*, (2009), the 2008 *Growth Report* of the World Bank asserts that the only way to solve global poverty is with persistently high GDP growth (World Bank, 2008). The United Nations has used GDP as its headline measure in the system of national accounts since 1953 (UN, 1953).

However, a well-established field of inquiry considers whether GDP is fit for purpose—whether it is appropriate to use GDP as a proxy for wellbeing. The argument stems from the person who developed the concept of GDP, Simon Kuznets. Kuznets explained in a 1934 report to the United States Congress "The welfare of a nation can, therefore, scarcely be inferred from a measurement of national income" (United States Bureau of Foreign and Domestic Commerce, 1934, p. 7). Why? It's quite simple—GDP does not measure many facets of what is valued by humans, including health outcomes, the environment, charity, art, integrity, and happiness. Indeed, history indicates that boosts in GDP can come at the direct expense of the features of life that humans value most (see Chapter 2.1.3 on decoupling). In most cases, adding in the non-growth benefits of environmentally-friendly investments would boost their policy appeal—assessing only GDP impacts understates what environmentally-friendly investment can contribute to the environment (IPCC, 2014; Nemet *et al.*, 2010), health (Carleton *et al.*, 2022; Scovronick *et al.*, 2019; Watts *et al.*, 2017), economic stability (Kahn *et al.*, 2019; Lamperti *et al.*, 2019; Stern, 2006), and more (Karlsson *et al.*, 2020). Senator Robert F. Kennedy, while campaigning for the Democratic nomination for President of the United States, famously remarked that GNP "measures everything… except that which makes life worthwhile" (Kennedy, 1968). Other major shortcomings of GDP include its inclusion of "bads" like war that clearly detract from wellbeing, its exclusion of value-adding services provided for free, and its tendency to

conceal inequality within an economic system.[14] Several alternative indicators have been proposed to replace GDP. Nordhaus and Tobin (1972) proposed the Measure of Economic Welfare (MEW) to adjust GDP to include environmental damage, leisure, and unpaid work. The United States and China both investigated greener accounting systems, respectively, the Integrated Environmental and Economic Accounts and Green GDP, but both ultimately failed under political pressure (Buckley, 2007; Landefeld and Howell, 1998).[15] More recent alternative proposals include GDP-plus approaches like the Genuine Progress Indicator (GPI)[16] and Genuine Savings (Hamilton and Clemens, 1999) that adjust GDP for missing environmental, financial, and social factors. The wealth-based approach advocated by the University of Cambridge considers a "wealth balance sheet" tracking all kinds of capital, including natural, human, and social capital (Agarwala and Zenghelis, 2021; Hamilton and Hepburn, 2014). Some welfare-based approaches use inequality indices as an adjustment factor (*e.g.*, Aitken and Weale, 2019). There are also considerable proposals for happiness-based indicators that rely on self-reported factors influencing

[14] This is not to say that GDP is a useless measure, far from it—high rates of GDP growth are understandably a key driver of public and private economic actions including foreign direct investment (Encinas-Ferrera and Villegas-Zermeñob, 2015) and increases in GDP have historically correlated strongly to healthcare and other drivers of wellbeing. The point is rather that GDP is not the only thing that matters. It is useful but insufficient.

[15] In China, Green GDP figures for 2004 suggested that pollution had contributed a wealth loss of 3.05% of GDP (Buckley, 2007). In the US, the Integrated Environmental and Economic Accounts suggested that mining companies had a far lower net wealth contribution than was suggested by GDP figures (Landefeld and Howell, 1998). However, a 2004 segment on National Public Radio (Wagner, 2004) noted that if the accounts had focused on forests instead of mining, the outcome might have been very different. The presenter explained that "natural re-growth of trees has increased the economic value of our nation's forests by approximately 2 to 3.5 percent annually over the last half century. So, in some instances, accounting for the environment might actually boost economic indicators".

[16] Developed from Daly and Cobb's (1989) Index of Sustainable Economic Welfare (ISEW).

wellbeing (Hervás and Vázquez, 2013; Ura *et al.*, 2012). Finally, there are a host of composite indexes that have been proposed including the Human Development Index (HDI) (Anand and Sen, 1994) and the Happy Planet Index (HPI) (Marks and Thompson, 2006).

Despite its shortcomings as a measure of wellbeing, and despite continued efforts to institute an alternative metric, GDP continues to be widely used by policy makers. For this reason, it remains an indicator worth considerable attention. The following sections investigate how green growth came to be, its begrudging use of traditional growth metrics to support progress towards environmental objectives, intersections with development, and the relevance of decoupling.

2.1.1. Introducing green economy and green growth

Economic interventions to support environmental objectives date back to at least Ancient Egypt when dry farming was used to stablise parts of the Levant as a response to localised drought (Finkelstein *et al.*, 2017). Many more environmental interventions followed over the proceeding centuries, several directed by public authorities.[17] The intersection of *global* environmental issues and the economy found strong attention with the 1972 Club of Rome report, *The Limits to Growth* (Meadows *et al.*, 1972). The report pronounced that the most probable outcome to the *human predicament*, without a substantial change in resource patterns of consumption, would be "a sudden and uncontrollable decline in both

[17] Paper A provides several additional examples through history. For instance, in response to the Great Depression, President Roosevelt's New Deal followed a Keynesian approach to establish the Civilian Conservation Corps, planting over 2 billion trees and employing up to three million men (Maher, 2008).

population and industrial capacity". *Blueprint for a Green Economy* (Pearce et al., 1989) adopted a practical lens, surveying the extent to which, and methods by which, environmental services were being valued at the time of writing and commenting on continuing gaps. The piece found strong attention for its demonstration, with practical policy examples, of how modern economies might be "greened". Other pivotal literature including the Brundtland Report (UN, 1987), work on the Environmental Kuznets Curve (including Grossman and Krueger's initial 1991 study), and the *Stern Review on the Economics of Climate Change* (Stern, 2006), continued to build discourse on the relationship between economic growth and GHG emissions, and how to change course.

The term, *green growth*, is relatively new to the economic vernacular, being introduced perhaps for the first time in the late 1980s by Colby (1989). It was used on a few occasions in the late 1990s, discussed at length in Paul Ekins' book *Economic Growth and Environmental Sustainability* (1999), and popularised in international economic fora including the 2005 Ministerial Conference on Environment and Development (MCED) in Seoul, South Korea (UN ESCAP, 2005) and especially the 2012 UN Conference on Sustainable Development (Rio+20) (Tienhaara, 2018). The term itself grew from themes discussed under the guise of *environmentally sustainable economic development* (for instance, see Barbier, 1987).

Green growth is defined by the Organisation for Economic Cooperation and Development (OECD, 2012) as,

fostering economic growth and development while ensuring that natural assets continue to provide the resources and environmental services on which our well-being relies.

The World Bank (2012), focuses to a greater degree on the interconnectedness of growth and resource use, specifying green growth to be growth which is

efficient in its use of natural resources, clean in that it minimizes pollution and environmental impacts, and resilient in that it accounts for natural hazards and the role of environmental management and natural capital in preventing physical disasters.

While many formal definitions for green growth consider all kinds of environmental impacts, some practitioners (particularly early practitioners) used the term entirely to focus on climate change mitigation (Jacobs, 2013). As explained in Chapter 1.2.1, this DPhil investigates only the climate mitigation component of green growth, acknowledging that for growth to be truly and completely green, it would need to avoid worsening infringement on any of the nine environmental factors identified in Rockström *et al.*'s (2009) planetary boundaries and others beyond that.

Beyond differences in what we talk about when we say "green" and when we say "growth", there are also differences in the strength of different green growth arguments. The *weak* version of green growth suggests that green interventions need not harm the economy in the long run while the *strong* version suggests that green interventions might actually advance the economic progress and could do so in the short term as well as the long term. These articulations build on the pure economic tradeoff of the cost of economic intervention compared to the cost of environmental damage. For the weak version of green growth, Jacobs (2013) describes two claims

argued for in the Stern Review (Stern, 2006). First, that the natural growth rate of an economy is not reduced to zero when the costs of environmental damage are considered. Second, that the economic consequences, measured in growth, of a deteriorating environment exceed the costs of acting. Jacobs explains that the strong version of green growth considers environmental sustainability is not only compatible with economic growth but can actively enhance it. Many arguments for Green Keynesianism in times of economic downturn fit this strong view (more on this in Chapter 2.2).

One argument for green growth builds from the observation that neoclassical growth theory largely ignores the natural environment (natural capital) as a factor of production. Solow's popularised growth theory (Solow, 1956) describes economic output (Y) as some function of physical capital (K), and labour (L), such that:

$$Y = f(K, L) \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (1)$$

With this model, $\frac{dK}{dt}$ and $\frac{dL}{dt}$ determine output growth $\frac{dY}{dt}$. Solow provided an extension to incorporate technology (A), where $Y = A \cdot f(K, L)$, which is often reformulated so that technology is labour augmenting, i.e., $Y = f(K, A \cdot L)$ (here $A \cdot L$ is referred to as "effective labour"). In Cobb-Douglas form, Mankiw et al. (1992) contributed human capital (H) into the function as an argument distinct from either physical capital or effective labour, in essence, $Y = f(K, H, A \cdot L)$.[18]

18 They go on to demonstrate that their augmented model explains most (78%) of the variation in income per capita across a set of 98 non-oil countries over the period 1960-1985.

Hallegate *et al.* (2011) contend that in these models, "the environment has no productive role, although it can enter in the utility function through its amenity value". However, Nordhaus and Tobin (1972), summarise that neoclassical theory considers human capital as a "near perfect substitute for land and other exhaustible resources". Constanza and Daly (1992) list objections to this perspective, summarising that the

> *assumption of near-perfect substitutability… has little support in logic or in fact. It was motivated more by mathematical convenience than anything else, except perhaps the hubris-driven technological dream of being independent of nature.*[19]

Green growth considers undervaluing of nature as a market failure, with observable consequences, including overexploitation of natural resources. Bowen and Fankhauser (2011) explain that green growth "promises to espouse a much wider and systematic view of market failures" than previously explored. The preponderance of subsidies for exploitation exacerbates these failures significantly (Coady *et al.*, 2017; Skovgaard and van Asselt, 2018). Commonly studied environmental market failures listed by Jacobs (2013) include (i) inefficient use of energy and other resources, (ii) underinvestment in activities that support productivity improvement due to not capturing spillover effects (including research and development), (iii) undervaluing the co-benefits of environmental policy on other externalities (like health costs from air pollution), and (iv) inefficiency in taxation systems.

[19] The helpful conclusion of Constanza and Daly (1992) is that a policy platform that maintains natural capital stocks, for instance through a natural capital depletion tax, can satisfy both technological optimists (because it incentivises innovation) and technological sceptics (because it protects natural capital even in the event of technological failure).

For green growth, policies that build or protect natural capital and correct environmental market failures can be growth generating by, for instance, boosting productivity in resource production, developing substitute products, repurposing saved natural capital for other functions that maintain their preservation (for instance sustainable tourism), and, through positive innovation externalities, spurring new and improved product offerings in other industries. Specific solutions identified in Jacob (2013) include pricing carbon, implementing minimum standards regulations, public spending to spur innovation, promoting research and development (R&D) on green initiatives including by building R&D ecosystems, and reducing income and labour taxes while increasing environmental taxes. Fankhauser *et al.* (2013) frame government policy in terms of a "green race", noting potential long-term economic gains that stand to be won by the nations who emerge ahead. Interestingly, one of their findings is that countries in their sample were not strategic in how they pursued green growth, inconsistently investing in green innovation. This seems to suggest that there might be opportunity for nations to shift more quickly to green industries as a vehicle for growth. Perhaps it also speaks to the enormous green financial flows observed in Paper C for 2020-21 (particularly relevant for high-profile technologies like green hydrogen).

Proponents of green growth generally recognise that the metric of GDP fails to capture the full benefits of many green interventions (Bowen and Fankhauser, 2011); indeed, this spurred the development of fields like natural capital accounting and gives credence to alternative measures of

wellbeing described in the introduction to Chapter 2.1.[20] As well as missing non-growth benefits of green initiatives, even a portion of the growth benefits can be missed by traditional economic methods which tend to miss second order and longer-term impacts. Fankhauser and Tol (2005) explain that traditional static approaches to growth accounting miss the dynamic effects of climate change. Nevertheless, following price reductions for many green technologies over the last decade, some contend that even with the handicap of lost value in the traditional focus on GDP, many green investments are still economically competitive—the papers of this DPhil form a part of that literature.

2.1.2. Green growth for development

Dercon (2012) asks, "Is green growth good for the poor?". In doing so, he draws attention to emerging market and developing economies with relatively low GDP per capita and high poverty rates. He assumes that "economic growth is essential for any large-scale poverty reduction" and then considers whether current conceptions of green growth can both satisfy development needs and maintain environmental priorities. By highlighting the unique aspects of poverty-sensitive growth opportunities, Dercon's sobering answer is *no*. He determines that for developing countries in particular, "trade-offs are bound to exist". However, several of Dercon's assumptions seem to have been time-bound and might no longer be appropriate. For instance, he reasons that environmental investment, while

[20] Natural capital accounting, now a significant field of research, grew from works including Hufschmidt *et al.* (1983), who provided early perspectives on how to consider an economic value of nature. Vardon *et al.* (2022) orient natural capital accounting with respect to economic crisis response.

having an ostensibly high economic impact on a per project basis, is not cost-effective (*i.e.*, the opportunity cost is too high) for both renewable energy and sustainable transport investment. Yet, renewable energy and battery costs have decreased logarithmically to the point that they are more than cost-competitive on a capacity basis to many fossil fuel alternatives (Way *et al.*, 2022) and with comparatively higher economic multiplier and job creation characteristics (Vivid Economics, 2022). Further, Dercon explains that while pricing measures might be theoretically efficient for the poor with redistribution, the practicalities of redistribution are too difficult to institute. Since then, we have seen China implement an emissions trading scheme, with a view to ensure that consumers do not end up in a worse position. Finally, Dercon considers adaptation investment, suggesting that proposed initiatives could reduce economic output for local residents. Fortunately, since his paper, there have been many works that indicate the comparative economic potential of adaptation initiatives compared to traditional alternatives, with favourable results (Vivid Economics, 2022; Chausson *et al.*, forthcoming).[21] None of this is to disagree with Dercon's overall perspective that the poor should not bear the costs of decarbonisation—indeed, this position is the foundation of the United Nations Framework Convention on Climate Change (UNFCCC) and the motivation of many green growth economists.[22]

[21] Bowen *et al.* (2012) preceded Dercon's work and also provides useful perspectives on how investment in adaptation might be "the right kind of growth" as it reduces exposure to large climate risks.
[22] Under the agreement, the incremental costs of both mitigation and adaptation initiatives should be met by developed countries.

Fankhauser and Jotzo (2017) provide a more recent analysis of green growth and development. Based on dramatic experience curves (Way *et al.*, 2022) and economies of scale for renewable energy technologies, the authors suggest that developing countries could pursue major structural change to leapfrog from low stocks of energy assets, over fossil fuel assets, and to "more productive" technologies. The proviso to this hopeful stance is that suitable policy and incentive frameworks are necessary and effective design of policy is somewhat hindered by gaps in knowledge on the interplay between low-carbon energy and development. Economy-wide transformations are difficult to achieve even for high-income nations.

This is reaffirmed in a subsequent paper, Fankhauser *et al.* (2019), where specific opportunities for low-carbon industry in emerging markets are considered. Using measures for low-carbon innovation and comparative advantage, the authors find that all countries in the region have opportunities for competitive low-carbon growth in one or multiple sectors and there are "very few sectors where the existing market structure might prevail".

Barbier (2014) highlights a set of climate mitigation policies that, if correctly designed, could stall poverty. These include innovation in several carbon-relevant sectors, avoided deforestation payments, and initiatives to reduce air quality like cook stoves (therein also boosting health outcomes). Some of these could simultaneously support growth. He also highlights climate mitigation initiatives that might have a negative effect on the poor, including poorly designed versions of the above positive policies. Barbier (2016) builds on Barbier (2014) by focusing on the prospects of green

growth to address two essential needs of many developing countries in their economic development: replacing earnings from the primary product sector and serving rural populations on suboptimal agricultural land. He uncovers several policy practices that might support green growth in service of these two needs. As one example, he observes that resource endowments have neither proven a curse nor a blessing for development and that instead, institutions and policies determine the likely success of long-term resource-driven development.

2.1.3. Decoupling

Understanding existing literature on decoupling is important for this DPhil as I investigate whether fiscal policy, in response to a recession, can support one form of decoupling, that is GDP growth from GHG emissions.

The notion of decoupling economic growth from environmental degradation is central to many conceptions of green economy, green growth, and green Keynesianism. While it was first formulated 35 years ago (UN, 1987), its feasibility remains highly controversial. Vadén *et al.* (2020) provide the helpful definition that decoupling is the process of delinking environmental bads from economic goods. It is often encountered in the form of decoupling economic growth (usually, controversially, measured in GDP) from GHG emissions (emissions decoupling), but can also be used to consider delinking growth from material resource use (resource or material decoupling) or from any kind of negative environmental consequence

(impact decoupling).[23] It can be expressed in terms of elasticities,[24] for instance GHG emissions and GDP growth as:

$$GDP\ elasticity\ of\ GHG\ emissions = \frac{\%\Delta GHG\ emissions}{\%\Delta GDP\ per\ capita} \quad . \quad . \quad . \quad . \quad (2)$$

The various decoupling phenomena are not necessarily positively correlated—for instance, it is possible to reduce GHG emissions without reducing material use (Vadén *et al.*, 2020). In this literature review, and in this DPhil more broadly, the focus is on emissions decoupling, but certainly other kinds of decoupling are essential for achieving completely green growth.

2.1.3.1. Frameworks for decoupling

There are two kinds of decoupling commonly discussed in the literature: *relative decoupling*, where environmental pressure decreases per unit of output, and *absolute decoupling*, where environmental pressure decreases absolutely. It goes without saying that absolute decoupling is significantly more difficult to achieve than relative decoupling, particularly over prolonged periods.

Yet, while decoupling is essential to sustainable growth (Jorgenson, 2014), even absolute decoupling is insufficient to meet GHG reduction needs for a sustainable climate. Maintaining the current rate of annual emissions would

[23] To this end, a range of environmental metrics are often proposed, including the ecological footprint (Wackernagel and Rees, 1998), but the ecological footprint and many of its alternatives might not be appropriate for measuring environmental damage (see Giampietro and Saltelli, 2014). A highly cited study for material use decoupling relies on the material footprint measure to show that while relative and absolute decoupling might have been demonstrated for GHG emissions, there is "no evidence of sustained absolute decoupling" so far (Hickel and Kallis, 2019).

[24] *Decoupling elasticities* are sometimes referred to as *decoupling indices*.

be wholly unsustainable as GHGs accumulate in the atmosphere; every year of additional emissions at the current rate increases the risk of exceeding environmental tipping points (Lenton *et al.*, 2011). Parrique *et al.* (2019) explain that decoupling needs not only to happen but to happen *sufficiently fast*, where *sufficiently fast* is defined as "before passing irreversible thresholds of damage such as the nine planetary boundaries". Of course, humanity has already passed Rockström's proposed planetary boundary for climate change (defined as 350 parts per million atmospheric carbon dioxide concentration) (Rockström *et al.*, 2009), but perhaps not yet the boundary that would set off a "Hothouse Earth" scenario of runaway climate change (Steffen *et al.*, 2018).

Tapio (2005) builds a framework for sub-categories of decoupling scenarios, based on the work of Vehmas *et al.* (2003). He divides the positive and negative decoupling spectrums based on elasticities. Under this framework, relative decoupling only occurs when $0.8 > elasticity > 0$.

When GDP growth is positive:

- If $elasticity > 1.2$, expansive negative decoupling;
- If $1.2 > elasticity > 0.8$, expansive coupling;
- If $0.8 > elasticity > 0$, weak decoupling; and
- If $0 > elasticity$, strong decoupling.

When GDP growth is negative:

- If $elasticity > 1.2$, recessive decoupling;
- If $1.2 > elasticity > 0.8$, recessive coupling;

- If $0.8 > elasticity > 0$, weak negative decoupling; and
- If $0 > elasticity$, strong negative decoupling.

2.1.3.2. How to decouple?

If green growth is possible then the question is *how to get it?* How might we achieve absolute decoupling? Neoclassical economists generally maintain that, for economic purposes, natural capital can be replaced by other forms of capital, including social capital and/or human capital. This view, known as "weak sustainability", contests that innovation can replace every scarce material. Weak sustainability contrasts with the "strong sustainability" view, which considers that other forms of capital might be complementary to natural capital but are not interchangeable with it. It is clear that the extremes of both ends of the spectrum are outrageous (Ayres, 2007). Barely anyone maintains a position of pure weak sustainability; practical economists don't suggest that absolutely every natural asset is replaceable with an alternative, but rather that many materials currently core to the economic system are. Robert Solow, commonly associated with weak sustainability, explains,

the claim that a feature of the environment is irreplaceable, that is, not open to substitution by something equivalent but different, can be contested in any particular case, but no doubt it is sometimes true,

for instance, the Grand Canyon (Solow, 1993, p. 171). To the extreme side of strong sustainability, even fossil fuels, long believed impossible to efficiently replace (Georgescu-Roegen, 1993), are already outcompeted by solar energy in many economically-valuable applications and firmed solar costs are set to fall further (Way *et al.*, 2022). The strong sustainability

arguments that solar energy was far too diffuse to cover its own material costs are clearly incorrect (see Ayres, 2007).

The UNEP's *International Resource Panel* has facilitated several reports on technologies and policy opportunities for decoupling. Their 2014 report, *Decoupling 2* (von Weizsäcker *et al.*, 2014) suggests that technological innovation is essential to resource and GHG decoupling. Technologies useful for this purpose include those that save energy, that save metals and minerals (including through higher economic circularity), and that save freshwater and biotic resources. To specific policy interventions, the study presents an overview of some past measures, structured in terms of (i) innovation enabling policies (for instance, skills development to increase capacity to innovate), (ii) policies to influence resource prices (like not charging prices below costs for government-controlled resources), (iii) new price-based instruments (including fees, taxes, and subsidies that appropriately account for negative and positive externalities), (iv) reform of existing taxes and subsidies (for example, removal of perverse subsidies that represent a drain on public finances and incentivise overuse of resources), (v) new market institutions (for instance, feed-in tariffs and tradable permits), (vi) bans and prohibitions, (vii) changes to consumption behaviours, and (viii) a generic "other" category that includes perspectives on labelling, norms, and procurement.

Hennicke *et al.* (2014) propose their own set of seven decoupling strategies: new types of knowledge (*e.g.*, sustainability research), capacity in skills and innovation (*e.g.*, awareness on material efficiency), policy (*e.g.*, setting clear and binding targets for emissions; creating an equal playing

field for eco-innovators), technologies (*e.g.*, new technologies to replace or substitute existing patterns of resource use, enabling technologies in advanced materials, and more), frugal innovations (*e.g.* low tech solutions, particularly in emerging markets), finance structures (*e.g.*, innovative financing schemes to enable new forms of innovation), and structural and behavioural changes (*e.g.*, to shift business perspective away from considering environmental damage an unimportant externality). They also note that policy mixes should be aware of possible counterproductive impacts (see below discussion on the *rebound effect*). Pao and Chen (2019) find that a policy environment which enables a transition to a diversified, sustainable energy mix can effectively enable absolute decoupling. This method is superior to one centred on energy efficiency measures. Using a study of 29 European countries over 18-years, Ko and Lee (2021) show that carbon pricing provides market incentives to reduce carbon use and hence drive decoupling. Similarly, Papież *et al.* (2021) note that energy policy in the EU was a core driver of accelerated decoupling in the region after 2005. In particular, the EU Emissions Trading Scheme (ETS) seems to have played a helpful role.

An important paradox, known as the rebound effect (or Jevons effect), explains one of the many difficulties that can come from relying solely on efficiency measures for environmental gains (Jevons, 1865). In brief, technological improvements that lead to higher efficiency might also bring a rebound effect of increased consumption since every unit of consumption is cheaper at a higher efficiency. Sorrell (2007) provides a comprehensive synthesis of works on the topic to 2007. The rebound effect

means that policies designed to reduce emissions through improved efficiency must heed caution based on, in part, preexisting consumer patterns and inherent appliance preferences (Kim *et al.*, 2006). They must also, in some instances, presume that any improvement in efficiency will be accompanied by an increase in appliance use and hence, to reduce net energy consumption, even more technological improvement might be necessary. Some scholars further assert that technological innovation is therefore on its own insufficient to achieve sustainability goals; institutional and behavioural change is also required (*e.g.*, Giampietro and Mayumi, 2018).

2.1.3.3. Existing empirical studies

In a significant review paper, Haberl *et al.* (2020) consider 835 peer-reviewed articles on decoupling, sourced from the green growth, degrowth, and other literature. In alignment with Vaden *et al.* (2020), explored below, they conclude that to date, reports of relative decoupling of GHG and CO_2 emissions are frequent and absolute decoupling rare.

Vaden *et al.* (2020) consider 179 articles to understand existing evidence for relative and absolute decoupling, with their main results reprinted in Table 1. They note that of the six articles presenting no evidence of CO_2 decoupling, five analyse a very limited geographical area and one (Moreau and Vuille, 2018) posits that prior studies fail to incorporate "deindustrialization and tertiarization [effects] which shifts energy consumption abroad and re-imports it as embodied energy in products". All other articles find evidence of absolute decoupling and/or relative decoupling. For studies on absolute decoupling, none explicitly

account for the impact of trade and outsourcing, weakening their potential applicability.

Table 1. Results from Vaden *et al.* (2020) review of studies on decoupling.

	No decoupling	Relative decoupling	Absolute decoupling
GHG decoupling	6	170	50
Other pollutant decoupling	0		6
Other impact decoupling	0		18
Resource decoupling	2		23
Total	**8**	**170**	**97**

Note: Total does not sum to the 179 articles reviewed since some articles provide evidence in multiple categories.

Sarkodie and Strezov (2019) provide a literature review for Environmental Kuznets Curves, finding some empirical support for an inverse-U-shaped relationship of per capita CO_2 to income, *i.e.*, CO_2 rises and then falls with GDP. They note that "effective institutional quality, awareness of environmental sustainability and high diffusion of technology and innovation… causes a decline in environmental deterioration". However, perspectives like that of Stern (2017), which followed pivotal prior work in Stern *et al.* (1996), note that many empirical studies on this topic make poor assumptions and employ "naïve econometric approaches". They don't usually consider that while income might be correlated to growth, it is non-income factors that "actually reduce pollution".

Other than those mentioned above, a few empirical studies are worth particular attention:

- Le Quéré *et al.* (2019) analyse 18 developed nations with falling GHG emissions, finding evidence of absolute decoupling, but

noting that even greater falls in GHG emissions are necessary to keep up with Paris reduction targets. The study finds that approximately half of the reduction in CO_2 in these countries came from reduced fossil fuel use in final energy consumption and a third from total reductions in energy use. This empirical evidence has been difficult to refute by detractors and is a significant step forward from authors like Hepburn and Bowen (2013) who had to rely on examples of massive technological shifts in non-climate sectors to make a case for absolute decoupling of GHGs from growth.[25]

- Fanning and O'Neill (2019) consider the relationship between carbon footprint and happiness, finding that happiness declines with reduced carbon footprint but not as rapidly as it declines with reduced consumption. Of course, there are questions as to whether the declines in consumption and carbon footprint in the study were forced (*e.g.*, by war or economic downturn) or came voluntarily. The authors posit that this adds support to calls for decoupling but note the obvious—that declining wellbeing is undesirable, and work must be done to reduce the carbon-happiness coupling.

- Chen *et al.* (2018) study CO_2 emissions over 2001-2015 in the OECD, finding evidence for strong (absolute) decoupling. They also consider drivers of the decoupling, finding that technical

[25] To this end, Hepburn and Bowen (2013) provide examples, "flint is no longer needed in axes, saltpetre for gunpowder, or guano for fertilizer".

factors (*e.g.*, emissions intensity, energy consumption structure) are more relevant than non-technical factors (*e.g.*, population size and distribution).

2.2. Countercyclical fiscal policy and its greening

2.2.1. Economic stimulus

During and around the time of the Great Depression, Lord John Maynard Keynes (Keynes, 1936) famously confronted conventional classical aggregate supply-focused thinking, which argued that expansionary fiscal policy would merely increase inflation without having any net-positive effects on growth or employment. As set out in the literature review of Paper A, "Keynes provided a new hypothesis to the following question: *How should the government act to get an economy out of a recession, restore consumer confidence, and enable full employment?* His answer: *spend*".[26] It should be noted that recessionary fiscal policy was only one topic of Keynes' many perspectives on the limitations of unbridled free-market economics and how policy interventions could correct and otherwise manage them. Indeed, post-Keynesians often argue that many of Keynes' core contributions, particularly for economies outside of downturn, are often missed or misrepresented (*e.g.*, Davidson, 2005; see Tienhaara, 2018). The specific flavour of Keynesianism to which recessionary Keynesian policy belongs was known as the neoclassical synthesis through the 1950s-70s (Samuelson, 1955, p. 250). Following the rise and fall of monetarist and

[26] Here we say, "spend", but mean either increase government expenditure or reduce taxation—both have the same effect of increasing aggregate demand and both are Keynesian, although the comparative effectiveness of each is heavily debated and likely depends on the application (Seidman, 2012).

neoliberal ideas in the 1980s (Eatwell and Milgate, 2011), it is now frequently considered a contributor to the new neoclassical synthesis, which underpins much of modern mainstream economics (Woodford, 2009).

As summarised in Paper A,

A Keynesian approach to demand management came into vogue for economies including the United States and Sweden following the Great Depression, aiding their economic recovery (Wier and Skocpol, 1985)… Keynesian approaches to fiscal spending were adopted by other nations including the United Kingdom, France, and Japan following the Second World War (Hall, 1989) but soon fell out of favor to neoliberal and monetarist ideas (Eatwell and Milgate, 2011) that reduced the role of government and emphasized the risks of inflation.

Hall's 1989 edited volume includes a helpful and detailed introduction to the political and practical history of Keynesian thinking to the 1970s (Hall, 1989). The volume presents a comparative study of various countries, exploring potential reasons behind the differing adoption of Keynesian ideas, with some nations embracing them while others resisted. For example, in his introduction, he compares France, where Keynesian ideas formed the platform for economic modernisation after World War 2, with West Germany, where Keynesianism only made an appearance after the country's 1965 recession, and even then, interest was muted. In France, Keynesian ideas

became the basis for a kind of national tutelle, designed to keep French industry competitive in an increasingly open international economy, and the source of a common language that allowed persons of quite different political sensibilities to rally around such a program (Hall, 1989, p. 20).

While in West Germany,

Free-market economists became influential after the war partly because more interventionist doctrines, including Keynesianism, were discredited through association with the Nazi regime (Hall, 1989, p. 23).

As the 1970s oil spike led to high inflation, an ostensibly Keynesian response precipitated stagflation; the response was met with harsh criticism and free-market ideologies began to dominate. It is a quirk of history that the policies of the time might have been Keynesian in name only (Davidson, 2009).

Perhaps the most important theoretical concept for recessionary fiscal spending is the idea of a national income (Keynesian) multiplier, which magnifies the economic impact of every dollar of fiscal investment. The size of the multiplier is generally accepted as higher directly after economic contraction. Sometimes, multipliers are *true Keynesian* in that they consider both private and public spending, but frequently they focus only on public investment and are better termed *fiscal multipliers*. As set out in Paper A,

> *In the simplest form, the direct job creation and consumption impacts of government spending are expected to induce additional consumption and investment, further adding to national income and creating a multiplier effect. Short- and long-run multipliers are both known to be higher in demand-deficient macroeconomic environments, for instance, during and directly following a recession (Auerbach and Gorodnichenko, 2013).*

Measuring the size of fiscal multipliers is notoriously difficult and there is no consensus within the economics profession on how to do so—amongst other things, there is disagreement on how to identify fiscal shocks, how to desasonalize observations, and over what time period to consider impacts (Ilzetki *et al.*, 2013). Parker (2011) explores the reasons for poor existing data on recessionary multipliers and provides three broad arguments. First, current methods struggle to disentangle the multiplier that comes in the depths of recession with that which comes during the proceeding expansion. Second, we lack methods to appropriately incorporate the non-linear dynamics of a crisis, which are of course essential. Third, there are relatively

few recessions and therefore relatively little data; this limits the statistical power of non-linear models. To the third limitation, Parker notes the potential that comes in estimating partial-equilibrium responses from data that is disaggregated.

Ramey (2011) provides a review of theoretical work and empirical estimates, concluding that the size of multipliers for debt-financed stimulus initiatives depends on the kind of investments that are made, but in aggregate across a package are likely to fall in the range of 0.8 to 1.5, although "reasonable people can argue… that the data do not reject 0.5 or 2.0". Interestingly, Ramey also notes that "there is still no consensus on the mechanism by which government spending raises GDP" (see the expectations versus direct effect discussion of fiscal austerity below). Several works since 2011 have moved beyond Ramey, including Barnichon *et al.* (2022), Caggiano *et al.* (2015), Candelon and Lieb (2013), Gechert (2015), Ilzetki *et al.* (2013), Leduc and Wislon (2012), and Qazizada and Stockhammer (2014), however the range in estimates for fiscal multiplier remains high. The work of Caggiano *et al.* (2015) is particularly noteworthy for its perspectives and measurement of non-linearities during recession.

Diving deeper, Paper A asks,

Which (fiscal) policy investments best maximize future prosperity and minimize harms without introducing any new ones?

and explains in response,

For some, including Elmendorf & Furman (2008), stimulus should be timely, targeted, and temporary—spending initiatives with the highest multipliers are technically strong, for instance, unemployment benefits where beneficiaries are likely to have higher marginal propensities to consume. However, others argue that recessionary investment is also a

valuable way to shift national trajectories toward a more desirable form of economic growth. Investment that comes with long-term debt servicing costs should incorporate corresponding long-lived assets; on this view, infrastructure investments, research and development (R&D) spending, and industry-building projects are attractive (Zenghelis, 2014; O'Callaghan and Murdock, 2021).

The sentiment to prioritise investment towards socially useful assets was shared by Keynes, who explained in a 1938 letter to President Franklin D. Roosevelt that priority investments should be in "durable goods such as housing, public utilities, and transport", noting that "the necessities for such developments were unexampled" (Keynes, 1938).

There are many documented criticisms of public spending to accelerate a recovery from recession. The vocality of their argument has ebbed and flowed over nearly a century of economic history, but broadly the criticisms can be grouped into three primary categories: inflation (*e.g.*, Cochrane, 2011), national debt (*e.g.*, Foster, 2009; Reinhart and Rogoff, 2010), and net (in)effectiveness (*e.g.*, Barro, 1974; Cochrane, 2011; Meltzer, 2011). Inflation arguments were uncommon in the first 6-12 months of response to the COVID-19 pandemic but emerged as advanced economy governments continued to spend on largely untargeted rescue measures in 2021 (for instance, the third round of US stimulus checks).[27] Inflation is a consequence of aggregate demand exceeding aggregate supply—the purpose of Keynesian stimulus is to restore demand to supply, not overshoot it (high inflation in 2022 might be partially described by an overshoot, but this

[27] The potential for rescue-type overheating, particularly in the US, was relatively clear around and perhaps a few months before January 2021. Indeed, many authors (including me) submitted perspectives on the topic at the time. Recovery-type initiatives tend to rely on a longer-term mechanism for disbursement with lower risk of short-term inflation.

remains to be verified). Dupor and Li (2015) demonstrate that post-war US government spending has not meaningfully contributed to inflation. Concerns over the national debt implications of large-scale spending tend to stem from a largely moral argument that future generations should not be burdened by spending for which they will see no benefit. Some counter that government debt is not the same as household debt and debt can be easily outgrown; therefore, governments should take budget surpluses during booms in order to service deficits during busts (Corden, 2010).[28] Another compelling counter is that fiscal policy should prioritise investments with long-term benefits that will benefit future generations. Arguments suggesting net ineffectiveness of stimulus policy come in several flavours. Meltzer (2011) provides four such arguments, suggesting that (a) more spending today requires higher taxes tomorrow (and that higher taxes, or the expectation of higher taxes, are a constraint on growth) (see also, Cochrane, 2011, who makes a similar argument), (b) directing more funds to those with high marginal propensities to consume (*e.g.*, the unemployed) has the long-term effect of taking funds away from productive investment, (c) new spending is often accompanied by new regulation (also a constraint on growth), and (d) all of the benefits are short term. Argument (a) misses the point of a Keynesian treatment of the economic cycle—countercyclical actions smooth the economic cycle, softening the booms and the busts (see

[28] Reinhart and Rogoff's (2010) *Growth in a Time of Debt* was another study that received strong public attention following the GFC. The paper claimed that, historically, as a nation's gross external debt grew above 60% of GDP, its annual growth was reduced by 2% and that after surpassing 90% it fell of a "cliff", being cut in half. However, the study was later discredited following the identification of several major errors, some mechanical mistakes (*i.e.*, spreadsheet errors) and others methodological oversights (Herndon *et al.*, 2014).

Seidman, 2012, p.283). Argument (b) is simply incorrect; the net effect of funds in the hands of those with a high marginal propensity to consume should be to boost the economic multiplier of the investment, ultimately meaning more funds in the hands of businesses. Seidman (2012) explains in response to a related argument in Cochrane (2011),

Cochrane ignores the simple, straightforward Keynesian explanation of how tax cuts and government spending increases are supposed to raise real output and employment when the economy is in recession—namely, that tax cuts and transfers enable consumers to spend more.

Depending on the political system, argument (c) perhaps holds practical credibility—it is true that US fiscal measures often come paired with regulatory measures, and these are sometimes dampeners on growth (Ash *et al.*, 2022; Ciccone and Papaioannou, 2007). However, the problem here is one of political system and political incentives, rather than stimulus policy. Finally, to argument (d), solving purely for the highest economic multiplier in policy design might lead to initiatives with relatively short-term benefits (*e.g.*, direct cash transfers), however, this is not necessarily the ideal stimulus—long-term growth aspects, as well as non-growth metrics, might be worth prioritising, even if for a small trade-off in immediate benefit. Indeed, Paper B of this DPhil explains

Recovery packages could exacerbate intergenerational inequities if they are focused on consumption, rather than productive investment delivering sustainable returns for future generations.

The alternative fiscal response to expansionary fiscal policy is often considered to be fiscal austerity (fiscal consolidation).[29],[30] With empirical study of two extreme cases of 1980s fiscal rectitude, in Denmark and Ireland, Giavazzi and Pagano (1990) suggested that contractionary policy can lead to higher growth. The suggested mechanism is one of expectations of confidence, wherein households and the private sector supposedly consider a reduction in fiscal spending as an indication of fiscal prudence. In this scenario, "households will revise upwards their estimate of their permanent income, and will raise current and planned consumption". This general argument is known as the expansionary fiscal contractions hypothesis. Alesina and Ardagna (2010) contribute supporting empirical work with simple regressions, noting "a 1-percentage-point higher increase in the current spending to GDP ratio is associated with a 0.75-percentage-point lower growth". However, many authors dispute these arguments. Guajardo *et al.* (2014) focus on changes in fiscal policy to reduce budget deficits rather than to respond to economic conditions, finding that for these cases, fiscal consolidation is contractionary. The authors then comment directly on the works of Giavazzi and Pagano, Alesina and Arda, and an earlier work (Alesina *et al.*, 2002), suggesting that their use of traditional

[29] This said, short-term stimulus does not preclude long-term austerity; the two are not mutually exclusive.

[30] A "do nothing" fiscal approach is usually broadly grouped with the austerity philosophy, although its motivations are often different. Kydland and Prescott (1977) argue, in essence, that policy makers have limited information and poor understanding of a complex system and are therefore unable to make optimal planning decisions. As such, every decision is suboptimal and can lead to economic instability. They go so far as to propose that the US Congress should "legislate monetary and fiscal policy rules and these rules to become effective only after a 2-year delay. This would make discretionary policy all but impossible".

measures for fiscal policy stance unacceptably biases their results. Jordà and Taylor (2016) consider consolidation during and outside of recession. Using a propensity-score method to separate fiscal consolidation episodes based on their explainability from observables (*i.e.*, correlation between outcomes and observables), they determine that "austerity is always a drag on growth, and especially so in depressed economies". Born *et al.* (2020) take a unique approach, showing empirically that contractionary policy while an economy is under fiscal stress leads to an increase in the sovereign default premium. The apparent implication is that the market perceives austerity measures to have a potentially negative impact on economic strength.

2.2.2. Green Keynesianism

In her thorough assessment of the GFC fiscal response, Kyla Tienhaara (2018, p.34) defines Green Keynesianism as "government intervention in the economy through public policies that aim to achieve full employment and environmental sustainability".[31] She notes that Green Keynesianism is best considered an economic philosophy that underpins policies like green stimulus and some versions of a Green New Deal. With Tienhaara's definition, it seems that Green Keynesianism represents one approach for greening an economy but is not necessarily a tool for green growth. While green growth explicitly elevates economic growth as a desirable outcome, the only economic focus of Tienhaara's Green Keynesianism is employment.

[31] There are relatively few recorded definitions for Green Keynesianism, indicating that its colloquial use, like that of Keynesianism, might be inconsistent with its theoretical definition. Tienhaara (2018) makes a similar observation.

However, others provide a different articulation. Jacobs (2013) considers Green Keynesianism as rooted in a strong green growth perspective.[32] Even Tienhaara (2018, p. 39) later explains that growth-GHG decoupling is commonly associated with Green Keynesian (see discussion in Chapter 2.1.3 for more on decoupling). Green Keynesianism is otherwise distinct from green growth as well as green economy as it significantly elevates the state's role.

Paper A explores the question "What sort of stimulus should governments use?", beginning,

The options vary dramatically in economic, social, and environmental characteristics. This variation is driven by policy archetype (e.g., infrastructure spending versus health care spending), policy mechanism (e.g., tax incentive versus direct subsidy), the national context in which the policy is applied (e.g., demographic structures, geography, level of economic development, and industrial composition), and other external factors.

The paper makes the case for green stimulus with a review of past green fiscal policy and its performance on traditional economic metrics, concluding that,

although the field is nascent, the overall economic characteristics of green fiscal investment appear positive and are likely superior to dirty investment options

and

The economic properties of recovery spending on the environment appear (on relatively weak evidence) to be relatively strong: Given that huge investments are required to achieve the world's climate and biodiversity goals, wise governments will seize the opportunity to progress two objectives with one intervention.

[32] A great many studies on green stimulus explicitly promote the growth characteristics of those initiatives. See paper A for an account of such studies responding to the GFC and COVID-19.

What is "green" when it comes to stimulus spending? This is a question of some debate. For many (including this DPhil), *green* is used as shorthand to represent a reduction in greenhouse gas emissions. This is usually not because other environmental impacts are considered less important, but to necessarily and transparently simplify analysis. For instance, it is quite clear that the impacts of emissions sometimes move in the opposite direction to other environmental impacts.[33] Even when considering how to define policies likely to reduce GHG emissions, there are different approaches. The 2009 study, *A Climate for Recovery*, from researchers at HSBC Bank (Robins *et al.* 2009), was influential in establishing what broad groups of fiscal measures were considered green during the GFC (Tienhaara, 2018, p. 33). The approach is built on the 18 climate change investing themes identified in HSBC's *Climate Change Index*, which are not themselves inappropriate but include little nuance and no obvious academic foundation. Tienhaara notes that the taxonomy subsequently filtered into some of the most notable works of the time, including from the Wuppertal Institute (Schepelmann *et al.*, 2009) and Edward Barbier (2009). New and emerging taxonomies provide significantly greater nuance, expanding to consider up to 221 subarchetypes. These are discussed in Chapter 2.2.2.2.

[33] For instance, the construction of a new train line might lead to reduced net GHG emissions, by displacing comparatively dirty road or air transport, but be detrimental to local natural capital reserves (especially where flora must be cleared and/or ecosystems permanently disrupted). O'Callaghan and Murdock (2021) incorporate natural capital considerations into their analysis (which builds on paper C). O'Callaghan (forthcoming) formalises this in a comprehensive trade-off methodology for 'normal' budgetary decision making, the *Sustainable Budgeting Approach*.

2.2.2.1. Understanding Green Keynesianism through history

Providing a historical lens on green stimulus, Paper A notes:

Some early recessionary spending programs included elements with positive climate outcomes. For instance, introduced in Roosevelt's New Deal, the Civilian Conservation Corps planted more than 2 billion trees, slowed soil erosion on 40 million acres of farmland, and in total altered more than 118 million acres of land, overall providing employment for up to three million young men at a time when unemployment was at 25% (Roosevelt, 1933; Maher, 2008)…

Stimulatory/expansionary fiscal policy saw somewhat of a resurgence following the GFC (Thorne, 2010). As governments attempted to restore their economies to growth, some adopted stimulatory economic policy, with a subset using fiscal investments to simultaneously address environmental harms. Leaders included the United States with the American Recovery and Reinvestment Act (ARRA), South Korea with its Green New Deal (GND), and China with a scattering of investments across several green sectors including green energy and sustainable transport. Various additional green policies were introduced by European Union (EU) member states, Canada, and Australia, among others (Robins et al., 2009). By cataloguing G20 fiscal stimulus policies following the GFC, Hepburn et al. (2020b) find that, by number, 32% of announced policies were green and Robins et al. (2009) determine that, by value, 15.6% of spending was green. Studies of GFC green investment mainly adopt a focus on the United States (Aldy, 2013; Council of Economic Advisors, 2016; Edwards et al., 2013; Elliott and Lindley, 2017; Mundaca and Richter, 2015; Steinberg et al., 2012; Vona et al., 2019;), South Korea (Jung, 2015; Mundaca and Damen, 2015; OECD, 2017), or China (Jaeger et al., 2020; Pollitt, 2011; Robins et al., 2009), or investigate across mixed/global economies (on Europe see Pollitt, 2011; see also Agrawala et al., 2020; Barbier, 2010a; Tienhaara, 2018), with findings explored below.

For the United States, it appears that the ARRA's clean energy package successfully stimulated the economy, creating jobs and catalyzing additional long-term green investment (Aldy, 2013; Council of Economic Advisors, 2016; Mundaca and Richter, 2015; Vona et al., 2019). US$21 billion in spending on renewable energy included production/investment tax credits, cash grants, tax credits for manufacturing, targeted loan guarantees, and traininggrants. Together, these likely increased renewable electricity capacity, lowered US emissions, and increased renewable energy patents in the medium term (Mundaca and Richter, 2015). The spending supported a significant immediate employment boost across the green energy supply chain, while also supporting long-term industry growth and associated opportunities for green labor (Council of Economic Advisors, 2016). Grants proved more cost-efficient than tax credits due to effective transaction costs, and grants and tax credits proved "significantly more effective than loan guarantees" in that they were more likely to be used by corporate actors (Aldy, 2013). Although the process of distributing funds was slowed by identifying suitable projects, new public investments paired

with private capital sustained aggregate demand as the economy moved out of the rescue phase (Aldy, 2013). Outside of renewable energy programs, the next largest green contributions were to energy efficiency, transit, grid modernization, and advanced vehicles, with lower support for green job training and early-stage carbon capture and storage (CCS) R&D (Tienhaara, 2018). Compared to non-green alternatives, ex post evaluations find high job and GHG impacts for spending on energy efficiency (see Steinberg et al., 2012; Tienhaara, 2018) and restoration of coastal habitats (Edwards et al., 2013). As they grew, green industries tended to increase their demand for medium-educated workers and lower their demand for lower-skilled workers (Elliott and Lindley, 2017), suggesting that it is important to pair green investments with the current or planned future skill base of the local economy (Popp et al., 2020). Across the board, evaluations of US GFC stimulus policies predominantly address one or two aspects of the green economy and focus on one or two policies, rather than the entire package.

The South Korean GND appropriated US$36.3 billion over four years, intending to create almost one million jobs in mass transit systems, fuel-efficient vehicles, energy conservation, and more (Barbier, 2010a). The package comprised ~69% of total South Korean crisis spending, reflecting a significantly higher ratio of green investment than other nations (Robins et al., 2009). However, although the economic returns of the package were high in terms of both jobs and economic growth (Mundaca and Damen, 2015; Pollitt, 2011), the net environmental impact of the spending remains unclear and might have been negative (Jung, 2015; Mundaca and Damen, 2015). Complications included insufficient renewable energy uptake, broad continued support of coal-powered electricity generation, increased energy intensity from new investments, export-led growth in energy-intensive sectors, and environmentally destructive waterway investments (Agrawala et al., 2020; Jung, 2015; Mundaca and Damen, 2015; OECD, 2017; Robins et al., 2009).

In China, approximately US$586 billion was appropriated for economic recovery, including US$221 billion for green purposes. However, of this, US$99 billion was for rail with unknown environmental consequences and unknown impacts on the displacement of automobile transport (Robins et al., 2009). In totality, although the literature is sparse, the stimulus might have supported a return of Chinese growth to precrisis levels (Jaeger et al., 2020, Pollitt, 2011).

Within the EU, up to US$54 billion worth of green stimulatory fiscal packages were introduced in total, at the supranational level and in member states (Robins et al., 2009). Focal green industries included energy efficiency, public transport, renewable energy, vehicle scrappage schemes, and green R&D (Pollitt, 2011). Green investments are likely to have delivered short-term multipliers similar to non-green investments (Pollitt, 2011) and employment opportunities to stressed sectors at low public cost (Pollitt, 2011; Robins et al., 2009). For instance, for the German Building Rehabilitation Program, when projects did not crowd out other investments, the net impact of spending was to reduce the public deficit due to increased income taxes and social security contributions (Kronenberg et al., 2012). Environmentally, the long-term net effects of spending were

generally favorable and are thought to have supported the long-term development of nascent green industries, particularly for energy efficiency and renewable energy investments (Pollitt, 2011).

Paper A also provides a literature review of the economic characteristics of green investment, considering job creation, time to achieve impact, and the fiscal multiplier. For job creation characteristics, the four findings are:

- *First, clean energy investments and energy efficiency retrofits can outperform traditional energy investments on direct and indirect job creation and labor intensity.*
- *Second, there is insufficient evidence to definitively comment on the comparative labor impacts of other green investments; however, emerging COVID-19 analyses suggest that these might also be more favorable than traditional alternatives. These investment archetypes require particularly urgent attention and include natural capital investment, green agriculture, sustainable transport, and clean R&D (particularly green hydrogen and CCS). Across each archetype, particular focus is required in emerging markets and developing economies.*
- *Third, the induced labor impacts of green investment are poorly understood and would benefit from more research.*
- *Fourth, minimal research has considered the key enablers of green job creation—namely, availability of sufficient and suitable green skills, existing baseline green business ecosystems and contractor capabilities, and appropriate absorptive capacity in R&D.*

For time to achieve impact, it finds:

Compared to employment impacts, research on the timeliness of stimulatory green fiscal spending is relatively shallow and skews to qualitative descriptions over technical analysis. Rather than quantifying the time spans over which economic benefits play out, most studies use broad descriptors, for instance, "fast," "medium," and "slow". Overall, a greater understanding of when different policy archetypes exhibit economic benefit will be beneficial to design balanced green stimulus packages that both provide an immediate economic boost and set the economy on a path toward long-term sustainability and prosperity.

For fiscal multiplier characteristics, it concludes:

- *First, all green policy archetypes identified in this review could benefit from further analysis, with particular consideration required for sustainable transport, natural capital investments, electric vehicles, energy efficiency programs, clean R&D, and green skill-building and retraining programs.*
- *Second, in the absence of long time-series data, which is often required for multiplier computation, unique methodologies in data collection and processing might be needed to reach empirical insights beyond Batini et al.'s (2022). Artificial intelligence solutions could unlock particularly promising opportunities.*
- *Third, new (non-Bayesian) modelling approaches should be considered to appropriately tackle distributional and parameter shifts, which are inherent in times of economic crisis.*

Fourth, multiplier assessment terms need to be better defined and linked to other assessments of economic impact, for instance, labor market impact. To enable comparison across studies and national contexts, a consensus is needed on definitions for short- and long-term multipliers, as well as definitions for green policy archetypes.

2.2.2.2. Interpreting the COVID-19 response

In one way or another, each of the three papers in this DPhil investigate the GHG characteristics of the COVID-19 fiscal response. The papers join a rich set of other works considering similar questions associated with incentivising a low-carbon transition in economic recovery. This associated literature considers the potential impacts of all kinds of policy, including fiscal policy, regulatory changes, structural reforms, and monetary policy, on GHG emissions. It is important to consider this DPhil in the context of this broader literature as it is not only fiscal policy that must be greened to precipitate a low-carbon economic transition. Barbier (2020), in review of the GFC fiscal response, explains that "Policies for a sustained economic recovery amount to much more than just short-term fiscal stimulus".

Clearly, carbon-reducing fiscal policy could be offset, partially or completely, by carbon-increasing fiscal, regulatory, or other measures. Included in this is systematic underpricing of fossil fuels[34] and failing to price carbon and pollution, which greatly slows the clean energy transition (Barbier, 2010b). As put by Meckling and Strecker (2022) in their defence of "regulatory sticks", "Public investment in clean technologies and infrastructure does not guarantee decarbonization outcomes." Another part of this, is that green spending measures do not always achieve their intended outcomes. For instance, Mundaca and Damen (2015) suggest that elements of the 2009 South Korean New Deal failed in their efforts to bolster the role of renewable energy in electricity production. When combined with a lack of complementary pricing reforms, they suggest that the New Deal was environmentally ineffective, at least in the short term. Beyond ineffective low-carbon policy and counterbalancing support of high-carbon policies, it is also worth considering that in some cases non-fiscal tools might simply be more economically efficient for achieving GHG reductions. For instance, there is a rich theoretical and empirical literature in support of carbon pricing as a first-best policy for incentivising renewable energy in high-income countries, better than subsidies (Borenstein, 2012; Gugler, 2021).[35] Paper A notes that policy tools for addressing economic crisis

34 The overwhelming size and distortionary impacts of explicit and implicit fossil fuel subsidies are explored in several places in this DPhil (see Chapter 1.3.1 *Fiscal policy in response to climate change* and Chapter 6.3.4. *What about green growth and COVID-19?*). See also, Parry et al. (2021), who estimate explicit annual global subsidies for fossil fuels of US$470 billion and implicit subsidies of US$5.4 trillion, Kotchen (2021), who highlight US$62 billion in direct *producer* benefits from inefficient fossil fuel pricing in the US, and IEA (2020), who highlight several continuing impediments to the energy transition from fossil fuel *consumption* subsidies and opportunities to address them.

35 Others argue that a combination of policies might best accelerate decarbonisation in these scenarios (Hepburn et al., 2020a).

include monetary controls, regulatory interventions, and fiscal interventions. Covering each of these tools, Agrawala et al. (2020), Barbier (2020), and Jaeger et al., (2020) identify a range of policy types that could be considered for accelerating a low-carbon transition through and after economic recovery. These include deficit spending, pricing carbon and pollution (which has the added benefit of raising new funds to finance other measures), removing fossil-fuel subsidies, upholding environmental regulations, supporting "technology-push policies" (like R&D subsidies and protecting intellectual policy), ensuring that crisis response measures do not inadvertently exacerbate environmental harms, and prioritising green sectors in quantitative easing (QE) programs. Jaeger et al. go on to explain that despite significant green public spending in response to the GFC, GHG emissions increased at pace following the recession. They posit that an absence of sufficient structural reforms plus significant fiscal support of high-emitting sectors exacerbated this rise.

Turning to the COVID-19 response, so far as I am aware, the first published COVID-19 fiscal tracking dataset appeared with Paper B in May 2020. In its original format, this dataset covered barely two months of spending announcements and only G20 nations and Spain. The dataset was continuously updated on a public server from June 2020, growing to include 50 countries by August of 2020, and expanding to 88 countries plus the EU in 2021. In March 2021, it was relaunched as the *Global Recovery Observatory* (GRO) with the United Nations Environment Programme (UNEP), United Nations Development Programme (UNDP), International Monetary Fund (IMF), and German development agency (GIZ). Over the

period 2020-2022, the fiscal taxonomy for categorising policies was updated several times, corresponding with the development of each DPhil paper. Analysis of GRO data is included in Paper C. The methodology of Paper C advances on the approaches of GFC trackers in several ways: (i) by moving from one (sectoral) level of classification to two levels (sector and policy-target/subarchetype), (ii) by considering immediate and long-term impacts separately, and (iii) by making impact assessments based on rigorous literature review, a survey, and extensive peer review.

Several other COVID-19 fiscal policy tracking initiatives emerged alongside GRO in early 2020, including, from the IMF (2020), Vivid Economics (2020), and Yale's Program on Financial Stability (Yale, 2020). Additional researchers began yet more tracking efforts as the pandemic progressed, leading to output from CarbonBrief (2020), Covid Money Tracker (Committee for a Responsible Federal Budget, 2021), Energy Policy Tracker (IISD et al., 2020), Green Recovery Tracker (2021), IEA Sustainable Recovery Tracker (2022a), the OECD (2020), and most recently, Nahm et al. (2022). Each of these trackers were developed to serve slightly varied functions and as a result, each cover a different subset of countries, sectors, policy granularity, and time periods. Table 2 provides a summary.

Table 2. Simplified comparison of fiscal policy trackers. Excerpt from supplementary materials of Paper C. Several columns removed for simplicity. These include "geographic coverage", "data available to download?", and "data sources".

	Number of fiscal policies	Sectoral coverage	Granularity of coverage	Academic method available?	Approach to categorising policies	Approach to assessing GHG impact
Global Recovery Observatory (Paper A)	8,001	All sectors	Policy level	Yes, both for policy categorisation and GHG impact assessment	Original environmental-economic taxonomy with 42 archetypes and 221 subarchetypes, all mapped to sectors	Archetype-based 5-point Likert scale; both short- and long-term impact; assessments based on literature, experts, and Hepburn *et al.* (2020b) survey
CarbonBrief Green Recovery Tracking (CarbonBrief 2020)	204	Green initiatives only	Inconsistent; some policy level and some package level	No	9 sectors and 22 green subsectors	All policies in database considered relevant to GHGs, but no assessment provided
Covid Money Tracker (Committee for a Responsible Federal Budget, 2021)	2,808 (including some sub-policies)	All sectors	Sub-policy level. N.B. appears to include some allocations that might not be incremental above pre-COVID-19 levels	No; provided methodolo-gy does not relate to categorisation or GHG assessment.	24 recipient industries	**GHG impact not considered**
Energy Policy Tracker (IISD et al., 2020)	1,725	Energy producti-on and consumpt-ion only	Policy level	Yes, both for policy categorisation and GHG impact	Original energy taxonomy with 17 energy types and 9 energy stages	Archetype-based 4-point Likert scale; long-term impact only
Green Recovery Tracker (E3G and Wuppertal Institute, 2021)	1,184	Only policies that impact GHG emissions	Inconsistent; some policy level and some package level	No; brief note available for GHG impact	7 sectors	Broadly follows EU standards with notes on "controversial cases"; long-term impact only
IEA Sustainable Recovery Tracker (IEA, 2022)	1,188	Only clean energy measures	Policy level	Yes, both for policy categorisation and GHG impact assessment	Original energy taxonomy with 7 archetypes and 44 subarchetypes	World Energy Model provided CO_2 impact assessment
IMF Fiscal Policy responses to	~850	All sectors	Package level	No	6 broad economic categories	**GHG impact not considered.** N.B. the October 2020

	Number of fiscal policies	Sectoral coverage	Granularity of coverage	Academic method available?	Approach to categorising policies	Approach to assessing GHG impact
COVID-19 (IMF, 2020)						Fiscal Monitor includes a useful box (1.1) covering ~100 green policies
G20's US$14-trillion economic stimulus (Nahm *et al.*, 2022)	366	All sectors	Mostly package level	No; supplementary materials only provide definitions	None	Bottom-up (policy-by-policy) 3-point Likert scale; no consistent assessment categories; short- and long-term impact
OECD Green Recovery Database (OECD, 2020)	1,494	Only recovery policies with "environmental relevance"	Inconsistent; some policy level and some package level	No; brief note available for GHG impact	14 sectors and 7 policy types	Bottom-up (policy-by-policy) 3-point Likert scale; no consistent assessment categories; long-term impact only
Vivid Economics Greenness of Stimulus Index (Vivid Economics, 2020)	~1,500	All sectors	Inconsistent; some policy level and some package level	Yes; for categorisation; No for GHG impact	Original environmental taxonomy with 43 archetypes, all mapped to sectors	Archetype-based 5-point Likert scale; long-term impact only; no apparent assessment method for archetypes
Yale COVID-19 Response Tracker Visualisation (Yale, 2020)	3,492	All sectors	Inconsistent; some policy level and some package level	No	27 policy tools, 59 ultimate beneficiaries, 65 target subsectors, and 48 conduits	GHG impact not considered

Apart from the Yale, IMF, and Covid Money trackers, all other tracking initiatives consider the positive and/or negative GHG characteristics of recorded policies. Some use transparent taxonomies while others make case-by-case assessments with unclear methodologies (and everything in between). In their sixth and final report, released in July 2021, Vivid Economics (2021) suggest that 15 of the G20 economies had stimulus packages with a net negative environmental impact. Out of

US$17.2 trillion of tracked spending, they find that 28% (US$4.8 trillion) will flow into "sectors that impact climate change, biodiversity or local air quality" and US$1.8 trillion to "green" initiatives, which are those that have a net positive performance on "multiple environmental performance indicators". Vivid Economics also incorporated some environmentally-relevant regulatory changes into their Index, commenting that

Environmental deregulation has been used as a stimulus measure in some countries, on the basis that this relieves regulatory burdens for businesses. However, others have reinforced environmental regulation, for example introducing wildlife trading bans, and proposing to expand the coverage of the EU Emissions Trading Scheme (EU ETS) to other sectors.

Nahm et al. (2022) consider spending in G20 nations over the period 2020-2021, finding that 8% of global spending is directed to "areas that will also cut emissions" and 3% will likely increase global emissions. However, there are a few reasons to question these estimates. Unlike most trackers, the Nahm et al. dataset considers spending at the package level rather than the policy level, resulting in a comparatively broad analysis.[36] This means, for example, that instead of analysing every policy in Japan's various Coronavirus packages, the full $US1.1 billion is treated as a single item and deemed "neutral". This is despite the package including large measures in support of solar energy. Focusing at the package level also makes one vulnerable to double counting initiatives that are not truly new spending but rather repeated mentions of prior announcements (we saw this frequently in our own tracking). Important nuance is therefore lost before

36 A seemingly unpredictable set of packages are analysed at the policy level, including Germany's 3rd of June 2020 Recovery Package and portions of South Korea's 14th of July 2020 New Deal.

analysis even begins. Beyond issues in tracking at the package level, there are other apparent inconsistencies in the dataset. Unfortunately, several large packages appear to be missing, including the US Bipartisan Infrastructure Bill of 2021, which totalled nearly US$ 600 billion in new spending (this is included in all other trackers). For unknown reasons, a set of monetary policy measures are also included in the Nahm et al. database (for instance "Quantitative Easing" totalling GBP250 billion in the UK). Unlike other trackers, no apparent archetyping methodology is used for determining the likely GHG impact of measures, so it is difficult to understand where differences in impact assessment, compared to other trackers, might have emerged from. This is particularly so as the authors don't provide reference to any tracking initiatives after Andrijevic (2020) in August 2020. Despite the potential flaws in method, the authors' elevation of discussion on carbon-increasing investments is useful and speaks to their third proposed lesson: we must build "institutions to make economies more resilient to further shocks, and to help those who rely on fossil-fuel-based industries to transition to new livelihoods".

In a 2022 analysis, released in Climate Action, developers of the Green Recovery Tracker consider a more nuanced question, asking how COVID-19 fiscal policy responses might "differ in terms of their causal effect on GHG emissions" (Hans et al., 2022). Considering spending from January 2020 to May 2021 in a set of 26 countries, referred to as "key emitters", the authors first categorise policies by potential impact on GHGs and then by "impact type" (direct, enabling, and catalytic measures). Combining these

two categorisations in matrix form, the authors identify first that 27% of total spending has the potential to meaningfully impact GHG emissions. Next, they indicate that 6% of total spending (22% of GHG-relevant spending) is likely to reduce GHG emissions and that 36% of this figure might have a direct impact, 54% an enabling impact, and 10% a catalytic impact. By contrast, 1% of total spending is likely to increase GHG emissions, with 42% having a direct impact and 58% an enabling impact. In identifying that ~2/3rds of low-carbon spending is likely to have an enabling or catalytic impact, they suggest that most of the COVID-19 fiscal policy impacts on emissions will unfold only over the long term.

Andrew et al. (2022) use the Energy Policy Tracker (EPT) dataset to analyse the characteristics of 2020-2021 energy-related fiscal measures. The EPT's close focus on energy industries, where policies have much clearer GHG outcomes, allows for a deeper analysis on potential impact than other studies. They find that 30% of spending in energy-related sectors supports a low-carbon transition, with most positive spending in the building and transit sectors. Like Vivid Economics, Andrew et al. build an index to account for both "green" and "brown" stimulus measures and assess the net performance of countries. They analyse this index with simple regression to identify that wealthier and lower emissions intensity countries tend to have stronger low-carbon characteristics in their fiscal policy.

Andrijevic et al. (2020), although only considering the period to August 2020, also provide helpful insights to energy-related spending. They suggest that early COVID-19 fiscal policy priorities clearly did not align with clean energy investment needs. Considering spending in 149 countries,

the authors highlight that annualised COVID-19 spending was already double the annual investment needed to orient the world to achieve an energy system of zero GHG emissions—after their study, spending increased by an additional 50%. The authors also introduce a helpful concept of "annual investment shifts" to remind us that green investment needs must be paired with divestments from pollutive energy, which were themselves entirely absent from fiscal announcements. In their concluding remarks, the authors expand their consideration beyond the immediate financial incentives of fiscal announcements, suggesting that announced green recovery packages can also provide a clear signal to investors to reduce their own exposure to stranded assets, with polluting packages having the opposite effect.

Several studies have considered the GHG impacts of non-fiscal policy measures in response to COVID-19. Helm (2020) highlights weakened environmental regulations in the US and suggests that enforcement of existing regulations likely fell over lockdown periods. Helm also argues that quantitative easing inflates asset prices, leading to increased land use and economic production, raising GHG emissions. However, he moderates this assessment by explaining that increased QE reduces the cost of capital and therefore supports capital-intensive industries, including renewable energy, as well as nuclear and oil production. He concludes with arguments that might ultimately suggest that QE will reinforce the environmental characteristics of the investment pathways supported by governments—either positive or negative. The IEA (2022b) suggests that a lack of pricing reforms and a rebounding global economy led to significantly increased

fossil fuel consumption subsidies in 2021 (US$697 billion), exceeding pre-pandemic levels. Corker et al. (2022) submit that COVID-19 regulatory restrictions precipitated an increase in pro-environmental behavioural changes, at least in case study European countries, and that some of these benefits might be sustained over the long term.

A small set of studies have attempted to calculate the net impact of COVID-19 on actual GHG emissions. Le Quéré et al. (2020) and Liu et al. (2020) estimate the impacts of early lockdowns on emissions. Forster et al. (2020) go further, providing emissions forecasts for a status quo economic recovery (0.01˚C reduction in warming by 2030) compared to a fossil heavy recovery (0.03˚C increase in warming by 2050), a moderate green stimulus (0.2˚C reduction in warming by 2050; net zero by 2060), and a strong green stimulus (0.3˚C reduction in warming by 2050; >50% chance of preventing temperature rise to exceed 1.5˚C greater than levels of pre-industrial times). The moderate strength green recovery scenario requires an increase in annual green investment of 0.8% of GDP (US$1.06 trillion), a reduction in fossil fuel investment of 0.3% of GDP (US$400 billion), and supporting climate policies, all to continue without pause to 2050. While green spending approached US$1 trillion in the Paper C analysis, most of this spending has a disbursement timeline in the range of 5-10 years, implying that green investment was 5 to 10 times lower than that required for Forster et al.'s "moderate green stimulus" scenario. By these measures, the COVID-19 response was a non-starter on climate. For fossil fuel divestment, the result was considerably more dismal.

Looking forward, Meckling and Strecker (2022) suggest that the high public investment in clean technologies and infrastructure over the COVID-19 period creates a "political opportunity of government leverage" to introduce immediate "green bargains". These bargains could be either in the form of conditionalities or regulatory reforms in exchange for funds which have already been allocated. Barbier (2020) argues that immediate investments should be backed by long-term commitments of public spending, funded through pricing reforms. Andrijevic et al. (2020) supports this posit explaining that longer-term measures should include "incentives, policies, taxes or rebates, mandates, and other supportive regulations that facilitate the achievement of long-term climate goals". They warn that government failure to embed fiscal policy into a clear long-term vision for low-carbon transition risks additional economic disruption and hardship. As just one example, they cite the need for workforce reorientation programs paired with fiscal support for polluting sectors to transition. To future crises, Hans et al. (2022) suggest that policy makers should soon consider, ahead of future crises, putting in place regulatory frameworks to define key priorities in recovery and build capacities to execute these priorities.

2.3. Machine learning methods for policy and climate

This DPhil uses ML techniques as a common methodological thread between papers. Applications of ML tie together several other quantitative methods used in the DPhil to triangulate the economic characteristics of green investments compared to traditional investments.

ML is a field of inquiry that uses computer algorithms to iteratively understand and learn from patterns in data, gradually improving its accuracy as it does so. It is a subfield of artificial intelligence and a commonly used tool in data science. ML is already ubiquitous to modern life, with commercial, social, and research applications across sectors (Jordan and Mitchell, 2015), yet technologically speaking, it is only its infancy. In their seminal 2015 review of trends in ML, Jordan and Mitchell explain,

Despite its practical and commercial successes, machine learning remains a young field with many underexplored research opportunities.

Compared to other domains, the adoption of ML has been slower in economics and public policy, perhaps due to poor *explainability*, a lack of knowledge, and strong prior theoretical norms amongst other factors (Amarasinghe *et al.*, 2021; Athey and Imbens, 2019; Einav and Levin, 2014; Taylor *et al.*, 2014). Nevertheless, as this DPhil demonstrates, ML can be a valuable tool for economists and policy makers alike, both for independent analysis and in support of traditional methods.

For the most basic applications, ML can be grouped in three major types: supervised, unsupervised, and reinforcement learning. In the case of supervised learning, pre-labelled input and output data train the model (or multiple models)—once a model is trained, it can be used to classify new, unseen data. Unsupervised learning uses raw (unlabelled) data to train its model—this allows for the identification of patterns and trends but no understanding of the factors driving those patterns and trends. Reinforcement learning uses a trial-and-error method to discover

approaches to meeting a user-defined goal. It does not require labelled data, instead learning based on its own prior actions. In practical terms, each typology is not mutually exclusive of the other and there are ML methods which can be relevant to multiple typologies. For instance, semi-supervised approaches use some unlabelled data alongside some labelled data, balancing human effort with accuracy (van Engelen and Hoos, 2020; Zhu, 2005). Self-supervised approaches build their own data labels (pseudolabels) and use these to complete their tasks, allowing for potentially greater robustness than unsupervised approaches, but this depends on the application (Hendrycks *et al.*, 2019; Jaiswal *et al.*, 2021). The rationale for applying one typology over another is usually influenced principally by whether available data is labelled, but also, practically, by how much resources are available for processing data and the availability of existing pre-trained models. In the case that available data is not labelled, adding labels can be prohibitively resource intensive.

Deep learning is a class of machine learning that imitates human brains by treating pieces of data as neurons and building neural networks with multiple layers of data processing (see LeCun *et al.*, 2015). The learning is "deep" because of the multiple layers. It can be used in supervised, unsupervised, and reinforcement applications. Deep learning has garnered widespread attention for its usefulness across a wide range of applications extracting progressively more complex features from input data. It is explored in greater detail in the below section on RNNs, which are just one method in deep learning.

Several subdisciplines of ML are explored in the papers of this DPhil including NLP (in supervised, semi-supervised, and unsupervised applications), clustering and ensemble methods (respectively, unsupervised and supervised), and RNNs (supervised). Figure 1 illustrates the methods used in this DPhil and their relation to supervised and unsupervised machine learning paradigms (reinforcement learning is not used). Details of each subdiscipline, and its alternatives, are discussed in the following subsections.

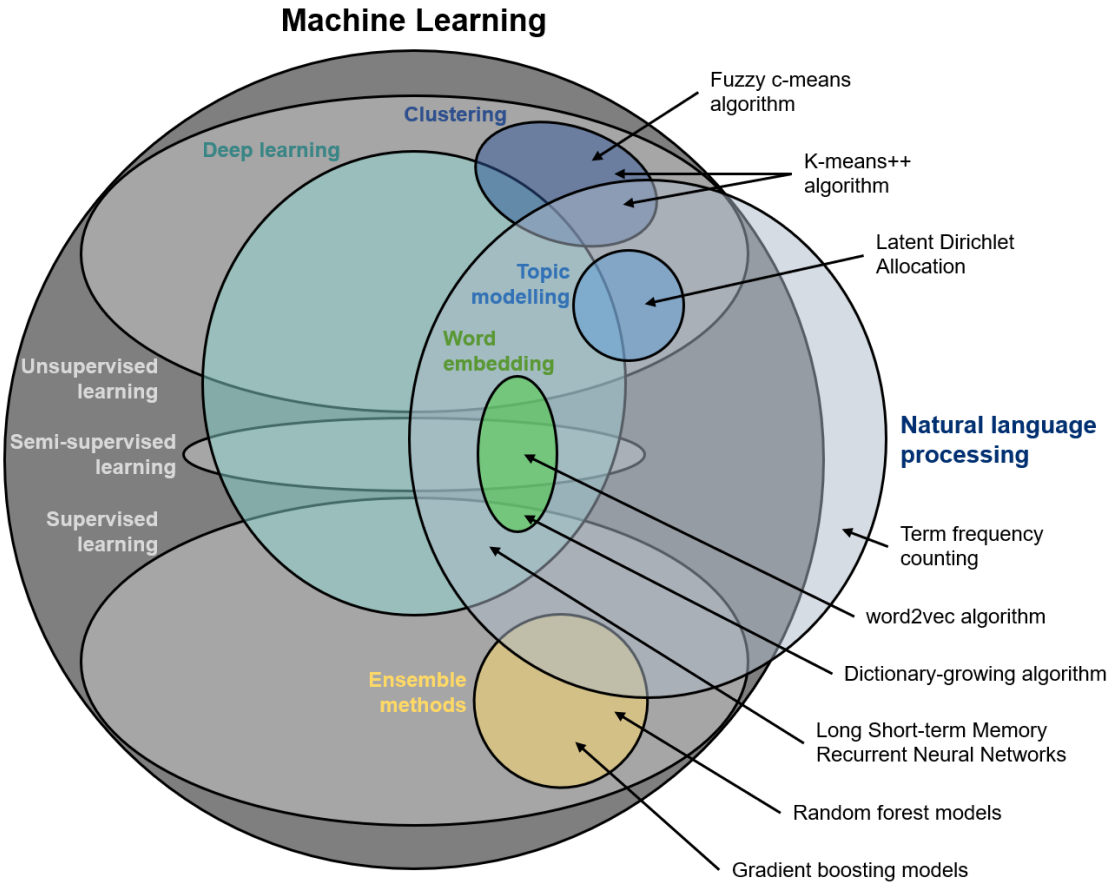


Figure 1. Venn diagram of ML methods as applied in this DPhil.

2.3.1. Natural language processing

NLP describes a family of AI methods that analyse features and patterns in human language. Early NLP approaches, beginning in the 1940-1950s,

were mainly attempts at machine language translation (usually English-Russian for intelligence gathering during the Cold War) (Jones, 1994, p. 4). With the intersection of NLP and ML, and later with deep learning models, NLP capabilities have significantly advanced such that they are now applied in tasks ranging from chatbots (including Google's Alexa) to search engines and resume filtering for recruitment.

ML-powered NLP is a significant step up from prior methods. It enables enormous text corpuses, sometimes with trillions of words to be analysed and learnt from (Brants *et al.*, 2007). Traditional, non-ML, methods, including atomic representations, can be useful for simpler analyses, but are simply inappropriate for complex analysis (see Brown *et al.*, 1992; Ullmann, 1977). Traditional methods are resource intensive (implying restriction in the quantity of data that can be efficiently processed)[37] and limited in their analytical capability (Cambria and White, 2014, p. 49).

2.3.1.1. Word embedding

In modern applications, a text corpus is tokenised into stems, words, and/or n-grams (*i.e.*, a continuous sequence of n words), and analysed based on how those tokens are used in relation to each other. The method of analysis can vary substantially between ML methods, but generally includes a crucial word embedding step (or a sentence embedding step). In this step, tokens are vectorised into a vector space of n dimensionality. In a sense, it is a method to understand how any single token is used in relation to all

[37] For example, Haddaway and Westgate (2019) and Michelson and Reuter (2019) provide perspectives on the high resource intensity of manual literature reviews compared to NLP alternatives.

other tokens in the vector space. For a general corpus, we would expect "dog" to appear relatively close in the vector space to a related term like "puppy", and relatively far from an unrelated term like "aluminium". Vectorised tokens can also have meaningful arithmetic applications. A common example is that of "King", "Man", and "Woman"; in vector space, with high dimensionality, we could see King + (Woman - Man) = Queen (Mikolov *et al.*, 2013a).

For several years, the word2vec algorithm was the forefront of word embedding, operating more efficiently than previous methods, particularly at high vector dimensionality (Mikolov *et al.*, 2013b). The model is relatively straightforward to understand and apply, being used to support a myriad of processes (Acosta *et al.*, 2017; Chung *et al.*, 2016; Li et al 2019; Ma and Zhang, 2015; Sivakumar *et al.*, 2020). Other context-independent embeddings like GloVe (Pennington *et al.*, 2014) came later but operate with relatively similar method.

One major complication in context-independent embedding is that it is difficult to adequately capture words that are polysemous or homographs (*i.e.*, words that have multiple senses). For instance, "man" can be used in the sense of describing a human's sex, a male's adulthood, the human species as distinct from other species, a person's affiliation to an institution (*e.g.*, an Oxford man), as a verb to operate a vehicle (*e.g.*, "man the ship"), as a functional apparatus (*e.g.*, "man the shopping counter"), and more. For most multi-sense tokens, the sense which appears with the highest frequency tends to dominate the other senses. If the downstream application

relies on vector arithmetic, the number of wildly inappropriate cases is likely to be low and errors identifiable with small output datasets (for instance, Paper B). Hover, for training classifiers (as seen in Paper C), word sense can be far more important because once-off errors can be hard to identify and lead to misclassification. To deal with the issue, Multi-Sense Skip-Gram defines different senses for each token (Neelakantan *et al.*, 2015), and an alternative approach, context-dependent embedding methods rely on the unique context of a token in a sentence to understand its unique sense (*e.g.*, Devlin *et al.*, 2018; Le *et al.*, 2017; Yuan *et al.*, 2016). To this end, BERT (Devlin *et al.*, 2018) and GPT (Radford *et al.*, 2018) are particularly attractive pre-trained models (see Chapter 2.3.4). As well as being context-dependent, these models also learn representations of word pieces rather than words (*e.g.*, "subword" can be separated and then independently analysed as "sub" and "word"), meaning that they can interpret new words (out-of-vocabulary words) that do not appear in the original corpus.

2.3.1.2. Dimensionality reduction

Since word embeddings are generally computed at high dimensionality (often over 100 dimensions), visualisation of embeddings requires dimensionality reduction. Many techniques are available for this, including, (i) linear unsupervised reductions like principal component analysis (PCA) (Pearson, 1901; Hotelling, 1936), as used in Paper B's additional analysis, (ii) non-linear unsupervised reductions like t-distributed Stochastic Neighbor Embedding (t-SNE) (van der Maaten and Hinton, 2008), as used in Paper A, and (iii) ML techniques like autoencoding (Rumelhart *et al.*,

1987; see also Hinton *et al.*, 2006). PCA finds the component axes to a dataset of infinite dimensionality that maximises variance between datapoints, with the first axis providing the greatest variance, the second providing the second most variance, and so on. While PCA tries to preserve the global structure of data on redefined axes, t-SNE preserves structure at the local cluster level. As a non-linear approach, t-SNE considers each datapoint for its similarity to every other datapoint, creating an entirely new 2-D or 3-D space on which to remap datapoints and minimise gaps between them. Several metrics can be used for similarity, including Euclidean distance, Manhattan/cityblock (*i.e.*, sum of absolute distances), and the cosine method (*i.e.*, one minus the included angle cosine between a centroid and two points). The choice of similarity metric depends in part on the desired application, although it is best practice to trial multiple metrics in a study. The user is able to manipulate hyperparameters to influence the display characteristics of a t-SNE model, often with the effect of highlighting clusters in data—it is important that care is taken in any such exercise as clusters might be artificial and sometimes genuine clusters might not emerge at all (Yang *et al.*, 2021). See Chapter 2.3.2 for further discussion on clustering. When deciding between PCA and t-SNE applications, for small datasets where a global treatment of data is desirable, PCA might be sufficient. For larger datasets, t-SNE and ML approaches can be useful alternatives to PCA given their lower computational requirements (higher efficiency), ability to handle outliers, and available hyperparameters.

2.3.1.3. Topic modelling

Topic modelling is an unsupervised NLP method for understanding the relative incidence of the most significant themes in a text without prior knowledge of what those themes are. In recent years, Latent Dirichlet allocation (LDA) (Blei *et al.*, 2003) has been cited as a popular method in topic modelling, well suited to refined texts like journal articles (Guo *et al.*, 2016), although the field is rapidly advancing. LDA uses a hierarchical Bayesian model to infer the topics in a corpus, essentially based on the probability that any word is associated with a set of iteratively refined trial topics. As such, LDA, like its predecessors, Latent Semantic Analysis (LSA) and probabilistic Latent Semantic Analysis (pLSA), assumes the distributional hypothesis. The distributional hypothesis holds that similar topics are made up of similar words. Of course, this hypothesis is not completely practical, as some words have multiple senses and word context significantly impacts meaning (*i.e.*, syntactic information is important). Distinct from LSA, LDA also assumes that the distribution of words in a topic, and topics in a text, abide by Dirichlet distributions. In other words, LDA is a Bayesian incarnation of pLSA. This allows for better generalisation of terms based on prior distribution. A more recent contribution, Moody's (2016) lda2vec model, overlays LDAs on top of word embeddings, allowing for document-specific variability in word use to be incorporated into topic models. Another method, ULW-DMM (Yu and Qiu, 2018), advances on LDA with a Dirichlet multinomial mixture for better performance on short texts, which is commonly a weakness of LDA. The probabilistic Latent Semantic Indexing (pLSI) method is also an interesting alternative that uses a statistical foundation to overcome the scaling

constraints that come from the linearity of LDA (Onan *et al.*, 2016). Other recent contributions include Chen *et al.* (2017), Cigarrán *et al.* (2016) and Jiang *et al.* (2018), although none have received particularly high academic attention, perhaps indicating limited marginal value compared to LDA for typical applications. For applications where scaling is not an issue and texts are longer than a few sentences, LDA continues to be widely used. Topic modelling is employed as a supplementary tool in paper A and paper C. Two other families of NLP methods used in this DPhil are discussed at length in dedicated sections below (ensemble modelling and neural network classification).

2.3.1.4. Applications of NLP to policy and the environment

NLP has been used in several, although not many, public policy applications. For instance, it has shown how both macro and micro decision making could be informed by past and present discourse amongst constituents. Examples include predicting citizen satisfaction for new policies based on old policies (Rezk *et al.*, 2018), interpreting e-petitions (Hagen *et al.*, 2015), informing restaurant hygiene inspections (Kang *et al.*, 2013), enabling biosurveillance through social media (Erraguntla *et al.*, 2019), interpreting policy advice and its possible political influences (Jelveh *et al.*, 2014), understanding consumer experiences with vehicles (Ha *et al.*, 2021), and understanding consumer experiences with city logistics (Tamayo *et al.*, 2020). NLP has also been used to classify demographic factors, including poverty exposure (Muñetón-Santa, 2022). It has been used to consider the political economy of decisions through analysis of the social media actions of US legislators in response to the COVID-19 pandemic

(Guntuku *et al.*, 2021) and policy and scientific discourse on the Sustainable Development Goals (Smith *et al.*, 2021). It has demonstrated how to simplify resource-intensive tasks of checking for conflicts in policy programs, for instance between Department of Defence directives (JAIC and Advana, 2022). For tracking, it has provided examples to classify policy decisions, for instance, incentive programs in forestry (Firebanks-Quevado, 2022) and loan agreements of the International Monetary Fund (Åkerström *et al.*, 2019). Finally, for communications purposes, it has demonstrated how to counter misinformation on public policy (Suter *et al.*, 2022). These are significant studies, and their completion indicates that there is some interest from NLP communities to assist policy making, however, NLP applications for public policy are significantly less frequent than for other domains. To this end, Zwilling (2022) notes, using an NLP analysis, that there is a lack of social science students with sufficient training in big data and ML, and that this could negatively influence decision-making processes in public policy.

NLP has only recently gained attention for its potential to guide environmentally relevant topics. For example, NLP techniques have been applied to understand environmental, social, and governance (ESG) reporting in public financial documents (Luccioni *et al.*, 2020), social media sentiment on climate change and related topics (Bennett *et al.*, 2021; Chen *et al.*, 2019; Effrosynidis *et al.*, 2022; Loureiro and Alló, 2020; Lydiri *et al.*, 2022; Stutzer *et al.*, 2021), non-social media discourse on climate change (Benites-Lazaro *et al.*, 2018), the strength of corporate climate disclosures (Bingler *et al.*, 2022), UNFCCC National Communications (Biesbroek *et*

al., 2022), coordination (or lack thereof) in strategy on climate action (Hsu and Rauber, 2021), consumer experiences with electric vehicles (Ha *et al.*, 2021), the prominence of climate misinformation in philanthropy (Farrell *et al.*, 2019), the changing meaning of the term 'resilience' (Selles and Rissman, 2020), trends in adaptation and climate research (Fisch-Romito *et al.*, 2021; Sietsma *et al.*, 2021), and more. Planas *et al.* (2022) present an early-stage proposal for an integrated knowledge management framework to track, interpret, and perhaps influence environmental policy. Swarnakar and Modi (2021) introduce NLP applications for climate policy. To methodology, Alashri *et al.* (2016) discuss the detection of different climate change framings with a useful corpus of over 45,000 sentences related to climate change and Alashri *et al.* (2018) describe a system to generalise concepts related to climate change. Regarding environmental topics in policy speeches, paper C provides additional detail. Of most importance, it notes a non-negative factorization (NMF) model in conference proceedings that shows climate change as one of fifteen core topics in Trump-Clinton speeches (Gautrais *et al.*, 2017) and identifies an analysis by Willis (2017) on political speeches related to the *2008 Climate Change Bill* in the United Kingdom.

2.3.1.5. Limitations and latest developments

The field of NLP is defined by rapid innovation, likely to continue at a fast pace in the years ahead. Several major limitations in text processing persist at the time of writing, but progress in addressing these is already strong. Essential limitations, with relevance to this DPhil, include (i) interpreting ambiguities and errors in texts, wherein everything from unclear sentence

structure (semantics) to misspelling and slang can challenge standard techniques, (ii) single domain-specific modality, which limits the usefulness of applying one learning model to another, (iii) initialising a starting dictionary with unlabelled data, and (iv) low explainability of some results.

The simplest method for addressing limitation (i) is to make automated corrections in preprocessing, using purpose-built algorithms and/or reference dictionaries (*e.g.* Garbe, 2022; Neethu and Rajasree, 2013; Wilson *et al.*, 2020). This has the advantage of being relatively simple as a fix but can be expensive in compute and is limited by reference dictionaries. Alternatively, a subword approach can efficiently associate misspelled words with known constituent subwords (Edizel *et al.*, 2019). This allows misspellings to be embedded nearby to correctly spelled words but does not assume equivalence. However, both preprocessing interventions and subword methods deal with the limitation at the symptoms level rather than considering its origins. An alternative approach, pre-trained contextual language modelling through transformer models like BERT and ELMo, relies on the context of all words to address ambiguity (which the pre-described methods cannot do). Sun *et al.* (2020) note the importance of appropriate pre-training to reduce the influence of misspellings.

For limitation (ii), emerging multimodal neural networks like DeepMind's Gato (Reed *et al.*, 2022) can learn multiple tasks at the same time (Heikkilä, 2022). Gato, which is processed with a transformer learning model (Vaswani *et al.*, 2017; see Chapter 2.3.4), is unique in its ability to learn a task without forgetting how to do other tasks that it has previously learnt. It is an early step to a future model that can learn how to do one

task based on how it does another task (*i.e.*, learning through prompting rather than by training a new model from scratch). It should also be said that domain-specific NLP learning models can use a pre-trained model for fine tuning—the issue is that even the fine-tuning will generally require thousands of labelled examples, and this fine-tuning is not usually helpful to other domains (Brown *et al.*, 2020). The Generative Pre-trained Transformer 3 (GPT-3) model (Brown *et al.*, 2020) is a recent, largely successful, approach for generalising a language model by using an unprecedented amount of learning data—large context (2048 tokens) and many parameters (175 billion) (see Chapter 2.3.4 for further discussion).

For limitation (iii), supervised NLP approaches often require a well-defined dictionary to query a particular subset of tokens or ideas. However, it is notoriously difficult to identify a full set of relevant terms to a particular domain. Typical approaches rely on subject matter experts, but the resulting dictionaries can often be inadequate, with many gaps (see Park *et al.*, 2021). For instance, the only known literature applying a green dictionary to the analysis of literature (Fisch-Romito *et al.*, 2021), used only 41 inclusion terms and 3 exclusion terms in the dictionary. Some emerging active unsupervised learning methods, which rely on iterative user guidance, provide some advances, but struggle to eliminate reliance on input dictionaries defined by the user (van de Schoot *et al.*, 2021). Paper A provides an alternative dictionary-growing approach which seems to significantly reduce missed terms.

Finally, for limitation (iv), low explainability (interpretability) of some deep NLP model output can reduce their practical usefulness (see

Belinkov *et al.*, 2020). Low explainaibility describes the situation where a model might demonstrate a relationship between terms, or sets of terms, but be unable to explain what is driving that relationship. Poor explainability can lead to distrust and limited use of model output. The issue is common across many ML applications and is discussed in greater detail in Chapter 2.3.4.

2.3.2. Clustering

Clustering is a family of methods for identifying prominent groupings in data when the title or description of the group is not known ex-ante and, sometimes, cannot be known. Big data clustering, both for NLP and other fields, has been enabled by efficient ML algorithms which can compute high-dimension calculations quickly. Although basic clustering approaches were first investigated in a general sense in the 1930s for analysing cultural groupings (Driver and Kroeber, 1932), and the k-means method developed in the 1950s (Forgy, 1965; Lloyd, 1982; MacQueen, 1967), their widespread use for big data applications has only come relatively recently with improved ML techniques (Jain, 2010).

2.3.2.1. Inherent limitations

In the past, clustering methods have been subject to several significant limitations, however some of these have partial remedies. Amongst the most important limitations are a tendency to identify relationships that do not exist, the assumption that all clusters are of a similar type (but clusters might have varied characteristics from each other), and the fact that it is difficult to deal with special patterns in datasets (*e.g.*, mixing zones, outliers). To false relationships, most modellers who have used clustering

tools have likely observed that clusters can often appear artificial and tuning of parameters can significantly change apparent relationships. Yang *et al.* (2021) show what should be obvious—sometimes genuine clusters might not exist at all. Part of the difficulty in identifying clusters (for non-hierarchical clustering) is determining how many to search for. To this end, Pelleg and Moore (2000) provide the X-means algorithm to optimize the number of clusters and their locations for a selected information criterion,[38] Tibshirani *et al.* (2001) propose "the gap statistic" to compare dispersion within trial clusters to what would be expected with a null reference distribution,[39] and others rely on a simple graphical (elbow) method, trading change in number of clusters for change in within-cluster variance. These are all useful tools; however, it is not clear that they fully address the limitation. To the final limitation, which describes the difficulty of incorporating complex patterns into clusters, several tools have been developed. For instance, density-based spatial clustering of applications with noise (DBSCAN) from Ester *et al.* (1996), cluster-based local outlier factors (CBLOFs) (He *et al.*, 2003), histogram-based outlier scores (HBOSs) (Goldstein and Dengel, 2012), and more. All in all, the limitations associated with clustering are significant and suggest that use of clustering methods should be accompanied by healthy scepticism. Results should be queried and not over interpreted. Ideally, clustering should be supplemented with other methods.

[38] In their paper, Pelleg and Moore (2000) focus on the Bayesian and Akaike criterion.
[39] Conveniently, this method can also determine whether perhaps there is no optimal set of clustering at all, *i.e.*, the dataset is relatively homogenous.

2.3.2.2. Clustering types

In computational complexity theory, several popular approaches to clustering, like k-means, are categorised with nondeterministic polynomial-time hardness (NP—hard). Simply put, this means that solving for the most efficient cluster set is more difficult (time consuming) than a problem that can be solved in polynomial time,[40] and perhaps has no solution at all. Any given set of clusters can easily have their effectiveness verified and most approaches to solving clustering problems use this characteristic to iteratively search for local optima. In doing so, any given clustering algorithm trades-off accuracy in clustering for computational efficiency (i.e., by using trial and error rather than first principles computation).

The k-means++ algorithm, from Arthur and Vassilvitskii (2007), is one of the most popular *hard* clustering methods. It is termed "hard" because every data point has a binary cluster classification—it is either included in a cluster or not. In contrast, fuzzy clustering assigns each data point to all clusters to varying degrees, depending on how strongly it associates with each cluster. Both hard and soft clustering are useful for visualisation, although hard clustering is usually preferred for determining whether there are clear clusters in a dataset. The attraction of k-means++ is in part that it identifies intelligent initial locations for cluster centroids (seeds), thereby reducing sub-optimal clustering that sometimes comes

[40] A problem is solvable in polynomial time if the number of steps required is $f(n^k)$ where n is a parameter related to the length of the algorithm (input size, *e.g.*, number of nodes in a graph), and k is a constant that varies with the class of the problem (*e.g.*, $k = 1$ for the Knuth-Morris-Pratt pattern searching algorithm [Knuth *et al.*, 1977]). As such, the number of steps required varies with k. It contrasts to, for instance, exponential time, where the number of steps required to solve the problem grows with complexity, *i.e.*, $f(k^n)$.

using heuristic algorithms (i.e., trial-and-error methods). K-means is, generally, a strict partitioning method, wherein every data point must belong to a cluster—in other words, there are no outliers. There are several alternatives to strict partitioning (subspace, overlapping, hierarchical, and more) and these should be considered if clear clusters emerge in the dataset. K-means attempts to minimise the function J_m as in equation (11), where k is the number of data points, n the number of clusters considered, x_i the considered data point, and c_j the mid-point of the j^{th} cluster.

$$J_m = \sum_{i=i}^{k} \sum_{j=1}^{n} \overrightarrow{|x_i - c_j|}^2 \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (3)$$

The specific heuristic contributed by the k-means++ algorithm to identify starting centroids initially selects a random data point x in X as the first centroid c_1, next calculates the distance between each observation and the centroid $d(x_{obs},c_j)$, where j is 1, then selects a second centroid, c_2, randomly and finds the distance from each observation and the new centroid $d(x_{obs}, c_j)$, where j is 2. From here, each observation is assigned to its nearest centroid and the next centroid is selected at random with probability defined by equation (12), repeating the process for each additional centroid until k centroids are selected. k is defined by the user. C_p denotes the set of observations that are closest to c_p. In essence, we are choosing starting centroids that are furthest from each other.

$$\frac{d^2(x_{obs},c_p)}{\sum_{h\,;\,x_h \in C_p} d^2(x_h,c_p)} \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (4)$$

Basic k-means analyses have assisted various environmental investigations over several decades, particularly for categorising geographic

zones (*e.g.*, Carvalho *et al.*, 2016; Fovell and Fovell, 1993; Santos *et al.*, 2005). The k-means++ algorithm has been used on several occasions for environmental problems (*e.g.*, Ansari *et al.*, 2021; Fairley *et al.*, 2020; Froemelt *et al.*, 2018; Harrou *et al.*, 2018; Panapakidis *et al.*, 2014; Taherkhani *et al.*, 2020), although on significantly fewer occasions than the basic k-means analysis—presumably due to low social scientist familiarity with ML.

Similarly to the k-means++ approach, fuzzy c-means (built from Bezdeck, 1981) attempts to minimise the function J_m (equation 13), where m (m>1) is the fuzzy partition matrix exponent (higher exponent brings borders between clusters with higher fuzziness) and u_{ij} is the degree to which x_i is a member of the j^{th} cluster. For any datapoint, the sum of membership to all clusters is one.

$$J_m = \sum_{i=i}^{k} \sum_{j=1}^{n} u_{ij}^{m} \overrightarrow{|x_\iota - c_j|}^{2} \quad . \quad . \quad . \quad . \quad . \quad . \quad (5)$$

Examples of c-means in environmental studies include for categorisation of weather regimes (Goyal and Gupta, 2014), for defining land facets based on topography (Brost and Beier, 2012); for understanding the climate sensitivity of varied tree species (Carrer et al, 2012), for optimising solar photovoltaic (PV) placement (Ansari *et al.*, 2021), and for estimating evapotranspiration (Duo and Yang, 2018).

Applied with ML, both k-means and fuzzy c-means approaches use iterative convergence algorithms to minimise distances between elements and cluster centroids. As is evident in the math, they are distinct from each other in that k-means clustering minimises internal cluster variance (*i.e.*,

between elements and their closest cluster centroid) while fuzzy c-means minimises overall weighted variance (*i.e.*, between elements and all centroids with a weighting for the degree to which elements are associated with each cluster).

2.3.3. Ensemble models

Ensemble models are a form of data mining useful for understanding correlations in datasets using advanced learning algorithms. Learning algorithms extract patterns from data. Ensemble models are characterised by their melding of multiple learning algorithms together to predict results from input data. As Dong *et al.*, (2020) explain, they use "various voting mechanisms to achieve better performances than that obtained from any constituent algorithm alone".

To some degree, they hold a similar function to methods in econometric model selection (like GETS)—both methods aim to understand the degree to which certain independent variables predict a dependent variable. They differ in that (a) ensemble models assume that all independent variables are at least somewhat relevant while econometric model selection attempts to eliminate some variables entirely and (b) GETS is concerned with the nature (the how) of the relationship between variables (*e.g.*, linear, logarithmic, multi polynomial) while ensemble models care only of the strength of the relationship (magnitude only).

Since their algorithms are black-box estimators, ensemble methods are in some respects most valuable for blind prediction of the future where the user is confident that the past predicts the future. That said, ensemble

methods are more transparent (less black box) than alternative ML techniques like relevance vector machines, support vector machines, and even multilayer perceptrons, which can be used in similar situations (Verikas *et al.*, 2011). These alternatives, while of high predictive power, tend to predict outcomes without indication of the relative importance of different independent variables. For use cases where training data will not adequately represent future scenarios, network-based ML methods, or non-ML methods, might be a superior alternative to ensemble models.

Differences between supervised ensemble methods include which learning algorithms and classifiers are used, what bagging/boosting/stacking approach is used to combine models, what voting mechanism is used to weight models, and interactions between each of these features. The bagging approach to combining models applies each model independently, learns from the data, and then combines them with deterministic averaging. The boosting approach learns each algorithm sequentially, adapting as it goes, and then combines them with some kind of deterministic strategy. Both are *homogenous* in that they consider the same ML model built many times from a single algorithm and the same data, but with different structures. By contrast, the stacking approach uses different ML models (*heterogenous*), before applying each model independently and then combining them by training an entirely new meta-model.

Some of the supervised ensemble methods that have been used most frequently in prior decades include random forest (Breiman, 2001 built from Ho 1998), Adaptive Boosting (Freund and Schapire, 1997), and gradient

boosting (Friedman *et al.* 2000, Friedman 2001). The relative value of each method depends on the use case, and even then, is debatable. David Wolpert and William Macready famously explained that there is "no free lunch" when it comes to building all-purpose optimisation programs and certainly no optimisation methodology is going to be appropriate to every dataset (Wolpert and Macready, 1997). Kern *et al.* (2019) provide a helpful introduction to tree-based learning, including those methods mentioned above. Best *et al.* (2022) provide a useful example on how ensemble methods can be applied to survey data. Other prominent applications to policy problems are not reviewed here but include Alves *et al.* (2018) and Huber and Imhof (2019). Cutler *et al.* (2007) give an account of applying random forest models to a classification problem in ecology, along the way discussing the advantages and disadvantages of the method. Other prominent applications to climate-relevant topics are not reviewed here but include Bunn *et al.*, (2015), Jung *et al.* (2010), and O'Gorman and Dwyer (2018).

2.3.4. Deep learning: RNNs to Transformers

Deep learning is a class of machine learning that imitates the human brain. It treats pieces of data as neurons and builds networks of neurons (i.e., neural networks) by connecting neurons across multiple layers based on its interpretation of a training data set (see LeCun *et al.*, 2015). The learning is "deep" because of the multiple layers. Despite a long history, with a base framework conceived as early as 1962 (Tappert, 2019), deep learning continues to be at the forefront of ML today. More and more advanced

deep learning tools can more and more effectively recognise patterns in data and apply understanding of those patterns to novel problems. Deep learning has already radically changed the world by enabling technological progress in advanced robotics, autonomous vehicles, predictive algorithms for most of the world's most-used websites, and much more. It is certain that further developments in deep learning will bring progress on many more of humanity's hardest problems—including, perhaps, climate change.

Every deep neural network consists of neurons, synapses, weights, biases, and an activation function. *Neurons* are the nodes of the network, organized in layers. Generally, there is:

- an input layer made up of input neurons—each input neuron receives information,
- any number of hidden layers made up of hidden neurons—each hidden neuron processes information, and
- an output layer made up of output neurons—each output neuron presents a conclusion.

Neurons communicate through *synapses*, where the strength of each synapse connection is defined by its *weight*. The weightiest synapses will dominate information flow to the next neuron. The weights are optimised through the learning process. To calculate an output, the input is multiplied by the weights of the synapses through each layer, and then passed through an activation *function*. Common activation functions include:

- linear, $f(x) = x$,

- sigmoid (logistic), $f(x) = \frac{1}{1+e^{-z}}$,
- hyperbolic tangent (Tanh), $f(x) = \tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$,
- rectified linear unit activation function (ReLU),

  $(x) = \begin{cases} x & if\ x > 0 \\ 0 & if\ x \leq 0 \end{cases}$, and
- exponential linear unit (ELU), $f(x) = \begin{cases} \alpha(e^{x} - 1) & if\ x \leq 0 \\ x & if\ x > 0 \end{cases}$

  where α is a parameter.

Most artificial neural networks also have bias neurons, which exist in parallel to hidden and output layers and allow for variations of the synapse weights to be stored. Put simply, they act as a constant to the activation function.

There are many classes of artificial neural networks including basic multi-layer perceptrons (MLPs), recurrent neural networks (RNNs), generative adversarial networks (GANs), convolutional neural networks (CNNs), and a recent addition, transformers. I focus here first on RNNs, which have until recently been the dominant approach to interpreting sequence data and second on transformers, which are taking the crown of RNNs. CNNs excel in analysis of spatial data, for instance in image recognition, while GANs shine in generating new data based on input data (Goodfellow et al; 2014).

The RNN architecture adds a loop to hidden neurons, allowing for learning from memory. During the training phase, the characteristics of synapses between neurons are considered in both directions (forward and

backward); this is essential for text data as the order of words matters (*i.e.*, to understand the meaning of a target word, the word(s) before and the word(s) after are both important). RNNs remember what has happened in the past, while alternative feed-forward networks do not. RNNs have been widely in the data science literature, amongst other things to diagnose cancer (Munir *et al.*, 2019), detect anomalies in aircraft data (Nanduri and Sherry, 2016), and identify hate speech on Twitter (Pereira-Kohatsu *et al.*, 2019).

As a widely studied neural network architecture, there have, unsurprisingly, been many models built on the base RNN architecture. These variants most commonly work to improve speed and address major limitations including the vanishing gradient problem (described in Bengio *et al.*, 1994). Long short-term memory (LSTM) networks (Hochreiter and Schmidhuber, 1997) are a particularly strong approach, which up until recently were breaking many records in machine learning (including for translation, speech recognition, and more). LSTMs use input, output, and forget gates as additional neural network layers to address the vanishing gradient problem. What this means is they have a longer-range memory, being able to, for example, relate words from much earlier in a text to the target word.

Seemingly, RNNs have been used on relatively few occasions for public policy queries. Some examples include predicting dengue outbreaks (Bomfim *et al.*, 2020), predicting inflation (Binner *et al.*, 2006; Šestanović and Arnerić, 2021; Zahara *et al.*, 2020), identifying vulnerable groups within a community (Mossie and Wang, 2020), and forecasting economic growth

(Chen and Xu *et al.*, 1998). It is possible that they have never (prior to this DPhil) been used for applications in fiscal policy.

For environmental questions, RNNs have seemingly been used slightly more frequently, but by no means often. Some examples include predicting particulate and other matter in the atmosphere (Ong *et al.*, 2016; Feng *et al.*, 2019), infilling of missing weather records (Coulibaly and Evora, 2007), classifying land use (Campos-Taberner *et al.*, 2020), and predicting environmental changes inside a greenhouse (Jung *et al.*, 2020). At the intersection of climate and public policy, Manowska *et al.* (2020) forecast electricity demand in Poland, McDonough MacKenzie *et al.* (2020) present the perspectives of citizens on natural monuments in the US, Llanos *et al.* (2022) report how energy consumption and CO_2 emissions can effect GDP, Han *et al.* (2020) investigate optimal control management strategies for EVs, and Huntingford *et al.* (2019) broadly discuss the use of artificial neural networks for climate change research.

Transformer models entered the public domain in 2017, led by a team from Google Brain (Vaswani *et al.*, 2017). They are emerging as the predominant model for many NLP and other problems, although for practical work with smaller datasets LSTM temporarily remain the preferred model (Ezen-Can, 2020). What sets the transformer architecture apart is its application of *self-attention* to assign varying levels of importance to different elements of the input data and process all the input at once, instead of sequentially. The attention factor provides simultaneous context to all tokens in an input sequence, allowing for better context learning than LSTM. The value of processing all the input at once is also

that the process can be better parallelised, allowing for quicker and more efficient training. Quicker and more efficient training means that larger datasets can be processed, and more comprehensive models built.

Bidirectional Encoder Representations from Transformers (BERT) (Devlin *et al.*, 2018) and Generative Pre-trained Transformers (GPT) (Radford *et al.*, 2018) were the two early major pre-trained transformer models, created respectively by researchers at Google and OpenAI. Although both built on the transformer architecture, the core difference between the two is that GPT uses only *decoder* blocks, learning only from the words in a sentence that occur before a target word while BERT uses only *encoder* blocks, learning from the entire sentence in which a word occurs. To address the target leakage problem, where an algorithm starts to rote learn entire sentence structures, BERT hides 15% of every sentence. In summary then, GPT learns only from words before the target word and BERT learns from a random 85% of the sentence, including words both before and after the target word. Many variations on these two models exist, including RoBERTa, ALBERT, DeBERTa, KnowBERT, XLNet, GPT2, GPT3, Gopher, Chinchilla, and Bort.

Google's introduction of the Multitask Unified Model (MUM) in mid-2021 could challenge the dominance of BERT and GPT (Nayak, 2021). Also using a transformer architecture, MUM uses both encoder and decoder pathways. With this, it can simultaneously predict what an input *really means* and search for relevant answers. It advances from the T5 Text-To-Text framework (Raffel *et al.*, 2020), which proposes outputting text, rather than a class label, from text input. Furthermore, it is multi-modal, able to

simultaneously process text, images, and soon, video and audio. Although a comprehensive research paper has not yet been released, Google claims that MUM is able to do BERT-like tasks with 1000x the power.

ClimateBert is a new pretrained model with intrigue for NLP environmental analyses (Webersinke *et al.*, 2021). Environmental texts can often incorporate domain-specific jargon and use certain framings in a way that is distinct from typical texts. Addressing this issue, ClimateBert was trained on over 1.6 million paragraphs of climate-related texts and is already seeing application to practical climate change questions (Bingler *et al.*, 2022). Ha *et al.* (2021) demonstrate early usefulness of BERT for climate change, studying consumer experiences with electric vehicles.

Given that transformer models are themselves relatively recent additions to the ML landscape, discourse on "what comes next" is limited. That said, Chernyavskiy *et al.* (2021) note a few desirable features for future techniques, including hybrid symbolic-distributed representation to ensure that some specific symbols/tokens have defined meanings amongst the general case of distributed representations. They also suggest that a target length feature should be incorporated to inform the model on expected length of output.

Future innovations in deep learning might not be limited to the technological. For instance, discourse on the ethics of AI is notorious for the division it exposes amongst technologists, policy makers, ethicists, and others. The debate is particularly relevant for deep learning, where the optimum technological solution resembles the human brain in function but exceeds it in performance. Further discourse in this area might influence

the path of technological change, perhaps leading to the introduction of additional safeguards in model design.

2.4. Other core methods

2.4.1. Survey-based expert elicitation

Check and Schutt (2012, p. 160) provide a definition for "survey research", considering it to be "the collection of information from a sample of individuals through their responses to questions". Surveys can contain any number of survey questions and, if appropriately used, can be a useful tool for eliciting and recording the perspectives of a target group of people. Survey questions are often classified as quantitative (*e.g.*, requiring the respondent to rate items), qualitative (*e.g.*, allowing for open-ended responses), or mixed (Ponto, 2015). Web-based surveys are particularly attractive for their low cost, speed, and economies of scale benefits compared to phone and other methods (Dillman *et al.*, 2014, p. 301; Toepoel, 2017). While web surveys tend to deliver lower response rates than alternatives, they generally achieve higher data quality, measured by length of responses and other measures (Vehovar and Manfreda, 2008). Expert elicitation is a particular kind of survey which targets a group of experts for their unique knowledge or perspectives (Morgan, 2014).

About expert elicitation for public policy, Morgan (2014) explains,

Done well, expert elicitation can make a valuable contribution to informed decision making. Done poorly it can lead to useless or even misleading

results that lead decision makers astray, alienate experts, and wrongly discredit the entire approach.[41]

Past expert elicitation in the field of economics can be categorised into repeated surveys for economic forecasts and once-off surveys on targeted research questions. Major repeated surveys include initiatives like *Blue Chip Economic Indicators* which regularly poll top economists for forecasts on U.S. economic growth, interest rates, inflation, and more (Wolters Kluwer, n.d.). Core examples of expert elicitation for economic research questions include Drupp *et al.* (2018) on the risk-free social discount rate, Enders and Hoover (2006) on academic plagiarism, Howard and Sylvan (2015, 2020) and Pindyck (2019) on economist perspectives about climate change, and Necker (2014) on research norms including data fabrication and plagiarism.

There are at least six steps to designing and running a digital survey, which form a helpful structure for discussion:

2.4.1.1. Determining to use a survey method

The elicitation method can be particularly useful for scenarios in which requisite data is not available for a direct empirical study[42] or otherwise such a study is not possible due to time constraints (*e.g.*, to answer an urgent policy question). Where alternative approaches are available, some suggest that economists prefer not to use questionnaire surveys (McCloskey, 1983), however, Boulier and Goldfarb (1998) argue that economists use the

[41] Morgan (2014) provides theoretical and practical perspectives on expert elicitation based on the many elicitations performed by himself and his colleagues. The work contains many helpful tips worth noting for researchers interested to conduct their own elicitations.

[42] I specify "direct empirical" as surveys are themselves empirical, but with a different field of observation.

technique more frequently than is commonly suggested.[43] Boulier and Goldfarb go on to suggest that survey methods can have many useful and legitimate purposes in economics research—it might be the case that the issue is less with what is asked and more with how it is asked, to which end the authors propose several recommendations. They distinguish (p. 10) between using surveys for (i) "hypothesis formation", (ii) "participant or observer evaluations as idea generation", (iii) "confronting theory with evidence: theory testing and anomaly generation", and (iv) "measurement", all of which are legitimate applications. Kelly *et al.* (2003, p. 266) imply that if survey approaches are "quick and dirty", they haven't been done correctly and shouldn't be considered in the same family as well-designed and executed surveys, which can take considerable time. Blinder (1991) suggests that imperfect knowledge from a survey approach must be compared to the counterfactual, which is also imperfect knowledge, often obtained from theoretical deduction or econometric analysis.

Survey methods have several important limitations that are worth briefly discussing. First, for contested topics, particularly in the social sciences, it is unclear whether the perspectives of supposed experts are more valid than others or even whether genuine experts exist (Morgan, 2014). DellaVigna and Pope (2018) find that PhD students outperform "expert" academics on forecasting a series of piece-rate and behavioural treatment

[43] It strikes me that many of the traditional hesitations cited for questionnaires might be less relevant for use of digital surveys. For instance, the less formal environment for posing questions, and greater certainty of anonymity might reduce the risk of "billiard player" actors famously used by Friedman (1953) to justify never asking businessman (or perhaps anyone) how they act or think.

impacts (although the experts do outperform undergraduate and MBA students). That said, policy experts lean heavily on experiential learning (see Dolowitz and Marsh, 2000) and economists frequently make legitimate inferences from a set of knowns to an unknown (or set of unknowns). Second, bias is not only possible but inherent. This somewhat distinguishes elicitation methods from direct econometric studies. Biases might have to do with representation issues in expert selection (see below), the ordering of survey questions (Bradburn and Mason, 1964; McFarland, 1981), the content of survey questions (and their politicisation or sensitivity; Blair *et al.*, 2020), the wording of survey questions (Warnecke, 1997), the mechanism by which survey questions are asked (*e.g.*, social desirability bias in Jones *et al.*, 2016), response patterns (see nonresponse bias in Rüdig, 2010), and more. Tversky and Kahneman (1974) describe representativeness as a particular heuristic relevant to expert elicitation, wherein experts make a judgement on a new scenario based on observations of a past potentially similar scenario, sometimes believing with too high a confidence that one represents the other and neglecting other factors. It is the job of the researcher to minimise bias in every way they can and to identify and possibly quantify enduring biases. For expert elicitation, Kynn (2008) suggests that this is very much possible. Third, since survey data is often treated as personal and confidential, there can be less opportunities for third parties to view the unaggregated data and validate findings without repeating the test entirely.

2.4.1.2. Tool selection and approvals

There are many options for disseminating and presenting an online survey. These include embedding the survey directly into an email, using a survey app on a mobile phone, circulating fillable PDFs, or using a browser-based survey, for which there are many options (Dillman *et al.*, 2014, p. 305). There are advantages and drawbacks to each, with the main axes being accessibility, simplicity, cost, functionality, and perceived ease of use for the respondent. Dillman (2014) provides further details.

It is also worth considering the mechanics of the systems that might receive the survey requests. For instance, spam filters can prevent survey requests from reaching their destination, particularly if the intended recipient happens to be a member of a foreign government.[44] The complexity here is that the sender is unlikely to know whether emails were received at all and so response statistics might prove unreliable. To mitigate risks of spam, bulk emailing to a small set of domains should be avoided, credible university (or other official) email addresses should be used for sending, and spam testing should be considered using tools like *mail-tester.com* (*Newsletters spam test*, n.d.) and *Glock Apps* (Glock Apps, n.d.).

It is important to ensure that the desired survey tools are approved by the researcher's institution for use. As a part of this, data storage

[44] Perhaps an unusual example came in attempts to circulate the online survey for Paper B. An entertaining exchange with the digital security team of an unnamed central bank highlighted that our bulk emails had set off security alerts. After manual review, their conclusion was that there was no way to prove that we were not scammers and so the emails could not be delivered.

protocols should be closely considered and communicated (Management and Protection of Data Collected for Research Purposes, 2020).[45]

2.4.1.3. Expert selection

Selecting a representative pool of experts can be challenging, particularly in domains which are understudied. The first task is to identify the categories of experts that might be suited to respond, for instance, academics, policy makers, business and third sector subject matter experts, and representatives of multilateral institutions. Then, for each expert category, several selection approaches appear in the literature. These are explored in the Supplementary Materials of Paper B,

For selection of academic experts, at least four methods have been used. The first and most rigorous approach, as used prominently by Drupp et al. (2018), is expert identification by publication record.[46] In this case, elite academics are selected based on the strength and relevance of their research output using stringent filtering rules. See also Howard and Sylvan (2015 and 2020) who used a working paper version of Drupp et al. (2018) as the basis for their methodology. A second, similarly useful but arguably more biased approach is identification using peer nomination (Christensen et al., 2018). Here, a broad group of peers nominate experts to a topic area and vote to distinguish those they deem most appropriate for sampling. However, this process is unlikely to be purely meritocratic or representative. Peers are likely to nominate colleagues with whom they have positive personal relationships and/or who have perspectives similar to their own. A third common approach is using conference attendance as an indicator of elite expertise, as in Necker (2014). While this may be an effective means of identifying academics with research interests in a particular field, it is likely to over-index on junior researchers and is not collectively exhaustive. It also excludes prominent leaders who are not in attendance at the selected conference. The final approach is expert selection through personal relationships, as used by Nordhaus (1994). This approach, while simple,

[45] It goes without saying that prior to proceeding with any contact of potential survey participants, it is important to ensure that all necessary ethics approvals are in place. If the researcher is not associated with a research institution, independent ethics committees can be considered.

[46] A helpful resource, with precedent for identifying highly regarded economics publications in survey studies (Drupp *et al.*, 2015), is Combes and Linnemer (2010). For identifying multinational development banks by prominence, Faure *et al.* (2015) is helpful. For think tanks, McGann's *Global Go To Think Tank Index* (McGann, 2020) and IDEA's *Top 25% Think Tank Ranking* (Zimmermann 2020) are both helpful.

time-efficient and in some cases useful for directional understanding, lacks rigour in representation and bias-control.

Including a diverse set of voices can be important in expert surveys as often perspectives include a degree of subjective opinion, which is influenced by the respondent's social, cultural, and other background (Moussaïd *et al.*, 2013).[47] While Necker (2014) and Drupp *et al.* (2018) both consider the representativeness of respondents to the selected expert pool (which is certainly helpful for correcting one level of bias), it is unclear whether their selected pools were themselves representative of the sampled professions and it seems near certain that they were not representative of the general population (driven by the non-representativeness of the economics profession writ large).

2.4.1.4. Survey design

There exists a rich literature on how to effectively design survey questions to maximise attention, maximise comprehension, and avoid biasing the results, all to ensure that survey answers address what the researcher seeks to measure. Fowler (2014a, p. 75) defines, "Good questions are reliable (providing consistent measures in comparable situations) and valid (answers correspond to what they are intended to measure)". In his textbook on the subject, he goes on to provide helpful guidance on how the researcher can increase the reliability of answers by simplifying and otherwise optimising wording and ensuring consistent meaning to all participants. He provides further guidance on selecting the most

[47] See also Timpte *et al.* (2016) on the value of diverse expertise for environmental assessments.

appropriate type/measure of question (*e.g.*, open ended, Likert), how to facilitate answers about subjective states, and more.

Presser *et al.* (2004) discuss manual methods for pretesting survey questions. Fernández-Fontelo *et al.* (2021) discuss machine learning tools useful for understanding which questions in any given survey cause the most confusion, and introduce a new method based on the pattern of respondent mouse movements to ascertain the same, but with higher effectiveness.

Beyond question design, other design attributes for online surveys include the length of the survey, question sequence, response styles (*e.g.*, plain text compared to radio button and sliding scale), text presentation (*e.g.*, fonts and size), and page presentation (*e.g.*, colours, image, graphics, branding). To survey length, generally speaking, longer surveys suffer from lower response rates (Heberlein and Baumgartner, 1978; Sheehan, 2001) and *roll-off*, where respondents leave the survey midway through (Best and Krueger, 2008). To question sequence, a long history of works demonstrates that order can matter (McFarland, 1981), although sometimes it might not (Bradburn and Mason, 1964). Several related biases have been explored, including assimilation and contrast effects (Herr *et al.*, 1983; Lord *et al.*, 1979). On survey formatting, there is some literature providing guidance (*e.g.*, Best and Krueger, 2008; Dillman *et al.*, 2014).

2.4.1.5. Expert contact

Survey responses (response rates and answers) can be influenced by how the survey is delivered and what (if any) inducement is used. For instance, seemingly minor changes like adding a signature to a cover letter (Dodd

and Markwiese, 1987), changing the sponsor of a request (Bachman, 1984), providing a pre-letter to a secretary (Furst and Blitchington, 1979), and changing the background colour of a questionnaire to pink or purple (Brennan and Charbonneau, 2005; Etter *et al.*, 2002), can increase response rates. Providing inducements can also increase response rates but might impact the precision of results through systematic bias (Jones and Lang, 1980).

2.4.1.6. Results analysis

There are an infinite set of methods and sub methods available for analysis of survey responses, with the best method depending on the type of question and the research purpose. Survey responses can be qualitative, ordinal, categorical, interval, ratio, or other. In any case, it is important for the researcher to first deal with question non-response, adjust for probabilities of selection (who completed the survey), calculate sampling errors, and then finally consider patterns in response and the statistical significance of those patterns (Fowler, 2014b). Data mining techniques can be used to discover new relationships while model-based techniques can be used to test theorized relationships. Machine learning techniques are emerging as useful tools for analysis of both quantitative and qualitative survey responses. A very early introduction to machine learning applications for survey analysis is provided by Buskirk *et al.* (2018).

A common metric for understanding survey engagement is the response rate, calculated by dividing the number of completed surveys by the total number of individuals invited to participate. Generally, in survey

analysis, partially completed surveys are discarded and not counted as a response. As discussed in the Supplementary Materials of Paper B,

> *Previous surveys of expert academic economists have achieved response rates of 33% (Howard and Sylvan, 2015), 30% (Drupp et al., 2018), 17% (Necker, 2014), and 7% (Enders and Hoover, 2006). Surveys of finance officials and central bank executives are rare in the academic literature. No comparable study was found in the literature outside of a select group of opaque corporate surveys (Barontini and Holden, 2019), which does not provide data on response rates.*

2.4.2. General-to-specific model selection

GETS model selection is used to select useful empirical models from general input sets (Hendry and Richard, 1983; Campos *et al.*, 2005). As suggested by its name, GETS starts with a broad (general) set of inputs and eliminates less-relevant inputs to define a more specific model. It first identifies the most general model (the General Unrestricted Model, GUM) that is also appropriately specified, valid, and parsimonious (therefore, congruent) and then tries to simplify the general model in the most efficient way possible, strategically eliminating variables using complex conditioning while trying to maintain high explanatory power. To arrive at useful empirical models, GETS selection relies on the theory of reduction, which explains that empirical models describe the reduced form of the actual mechanisms that demonstrate economic outcomes (Cook and Hendry, 1994). GETS selection takes a base general model, that incorporates the core features of the underlying dataset, and applies the theory of reduction to eliminate statistically insignificant variables and determine those factors most important for predicting outcomes (Hendry and Richard, 1983; Campos *et al.*, 2005). When two competing explanations have equivalent explanatory power, the simpler model is selected. In this way, it finds the

most appropriate model that fits the data by trading off the number of selected regressors with the model's explanatory power, relating the two with an information criterion (*e.g.*, the Akaike, Bayes-Schwarz, Chow, Schwarz, Shibata, Theil, or another criterion). Helpful outlines of the GETS approach are provided by Campos *et al.* (2005) and Hendry and Richard (1983). The approach has been applied empirically to numerous policy and related questions (see, amongst others, Bauwens and Sucarrat, 2010; Cairns *et al.*, 2011; Campos *et al.*, 2005; Engle *et al.*, 2021; Hasanov *et al.*, 2022; Hoover and Perez, 1999; Pandey and Jessica, 2020; Ryan-Collins *et al.*, 2016), although never to fiscal spending questions, nor to the COVID-19 crisis.

Introductory perspectives on the relative strengths and limitations of the approach are included in Campos *et al.* (2005) and Castle *et al.* (2011). One of the most prominent criticisms is that the method is a form of data mining. But is all data mining bad? Or does it depend on method and purpose? Castle and Hendry (2014) argue,

Appropriately conducted, data mining can be a productive activity even with more candidate variables than observations. Omitting substantively relevant effects leads to mis-specified models, distorting inference, which large initial specifications should mitigate. Automatic model selection algorithms like Autometrics offer a viable approach to tackling more candidate variables than observations, controlling spurious significance.

GETS has been classified as "strong data mining" (Gilbert, 1986), meaning that it is an approach to identify the best model from available data rather than "weak data mining" which looks for the best data to confirm prior beliefs (Hendry and Kolzig, 2004). Most certainly, the method can lead to incorrect models, especially for small sample sizes, although software

packages attempt to reduce spurious selection of regressors. It is up to the modeller to ascertain whether selected models are theoretically coherent. In a colourful defence, Castle and Hendry (2014) explain,

That an activity can be done badly does not entail that all approaches are bad, as stressed by Hoover and Perez (1999), Campos and Ericsson (1999), and Spanos (2000)—driving with your eyes closed is a bad idea, but most car journeys are safe.

The function of GETS model selection is to identify the most appropriate model to explain data. There are, however, alternative approaches to achieving a similar purpose; here I discuss the traditional Average Economic Regression (AER) approach and alternative machine learning techniques for data mining. Whereas GETS is general-to-specific, AER is specific-to-general. In practice, AER begins with the simplest theoretical model (*i.e.*, $y = \beta x + \varepsilon$), estimates the model with defined regressors, performs diagnostic testing, and respecifies until an acceptable model, aligned to original hypotheses, is reached. Gilbert (1986) provides a helpful account of the values and limits of AER. Most notably, he explains that AER's problem is that it *illustrates* theories that are independently believed by the researcher—models with "errors" (*e.g.*, wrong signs and insignificant coefficients) are respecified until all pathological problems are addressed. This contrasts to the mode of econometrics (exemplified by GETS) which focuses on *discovering* which views of economic and business systems are tenable. The comparative value of the two approaches is described by Gilbert (p. 287),

The difficulty with this (AER) approach is that, if two investigators start from different simple hypotheses… there is no reason to suppose that they will converge on the same final equation and even with the same starting

point, investigators may diverge if they adopt different respecifications. The general-to-simple [e.g., GETS] methodology is less vulnerable to this objection.

Machine learning techniques are an alternative form of data mining. These too are "strong" in that they attempt to identify the clearest relationships in data. However, they trade lower interpretability for higher accuracy in predicting outcomes. Some forms of machine learning, like ensemble modelling, do have some level of interpretability given a set of predefined variables—they explain the degree to which defined independent variables predict dependent variables—while others, like many neural network models have very low interpretability. Compared to machine learning alternatives, which care more about the strength of the relationship between variables, GETS is more concerned with the nature (the how) of the relationship. In other words, so far as data mining techniques go, GETS is better suited to explaining relationships. It is far more interpretable than ensemble output, which is in turn more interpretable than neural network output.

PcGive, a part of the OxMetrics package (Doornik, 2018; Hendry and Doornik, 2014), seems to be the most widely studied GETS computer automated program (Doornik, 2001; Hendry and Krolzig, 2001). There is considerable literature on the virtues and potential deficiencies of PcGive, summarised in part by Campos *et al.* (2005). The functionality of the program allows for time series investigations with shifts, as well as more basic applications like cross-sectional analysis. The method uses the Schwarz information criterion for relating regressors to explanatory power. Model runs provide the user considerable modelling flexibility, allowing for

several model selection methods, an unlimited continuous spectrum of model sizes, several estimation options, many statistical test parameters, options for outlier detection, and more. For statistical testing, the software automatically checks, in the most basic cross-sectional case, for normality with $\chi 2$ tests (two-sided) and for heteroscedasticity, White tests (both with and without cross products), and Regression Specification Error Tests (RESET tests) to identify misspecification (see Ramsey, 1969). The results of these tests provide the modeller with the necessary information to refine the model.

Outlier detection warrants extended comments as this is itself a contentious field. Paper C notes,

> *Hendry's (1999) Impulse Indicator Saturation (IIS)…is a general-to-specific approach which, for cross-sectional analyses, aims to identify an unknown number of outliers with unknown magnitudes. The method introduces impulse dummy variables for every observation in a sample, allowing the model to be saturated by dummy variables—the general-to-specific model selection then selects the dummy variables (and therein outliers) that matter. As such, IIS is a natural fit for general-to-specific applications.*

In simple language, IIS penalises the model for any outliers by counting them as additional variables in the information criterion trade off. IIS applications have featured in several empirical works, including Castle *et al.* (2012), Ericsson (2017), Ericsson and Reisman (2012), Hendry and Mizon (2011), Hendry and Pretis (2013), Pellini (2021), Pretis *et al.* (2018), and Reade and Volz (2011). It has been defended against critiques for two decades (Castle and Hendry, 2019).

Given the other methods explored in this literature review, it is worth noting that the field of machine learning has made significant progress in

theories and methods for outlier detection. For one, the field classifies anomalies into point, contextual, and collective anomalies, whereas most econometric applications consider only point anomalies.[48] Chalapathy and Chawla (2019) provide a survey of deep learning methods for outlier detection. Lai *et al.* (2021) compare classical machine learning outlier algorithms for time series applications (some of which are rooted in econometric methods) to deep learning approaches, finding that some classical algorithms "surprisingly" remain comparatively strong.

[48] Point anomalies are those which represent a general irregularity without clear reason. Contextual anomalies are anomalous to a particular context (*e.g.*, to contexts in time and space, perhaps a sub part of a series). Collective anomalies are a set of data points which, when considered collectively, are anomalous. For instance, a set of fraudulent credit card transactions that each have small values but collectively total a large value (Chalapathy and Chawla, 2019).

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3

How Stimulating Is a Green Stimulus? The Economic Attributes of Green Fiscal Spending

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3.1. Abstract

When deep recessions hit, some governments spend to rescue and recover their economies. Key economic objectives of such countercyclical spending include protecting and creating jobs while reinvigorating economic growth—but governments can also use this spending to achieve long-term social and environmental goals. During the COVID-19 (coronavirus disease 2019) pandemic, claims have been made that green recovery investments can meet both economic and environmental objectives. Here, we investigate the evidence behind these claims. We create a bespoke supervised machine learning algorithm to identify a comprehensive literature set. We analyze this literature using both structured qualitative assessment and machine learning models. We find evidence that green investments can indeed create more jobs and deliver higher fiscal multipliers than non-green investments. For policymakers, we suggest strong prioritization of green spending in recovery. For researchers, we highlight many research gaps and unalignment of research patterns with spending patterns.

3.2. Main paper

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How Stimulating Is a Green Stimulus? The Economic Attributes of Green Fiscal Spending

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economic stimulus, green recovery, green growth, natural language processing, coronavirus disease 2019, COVID-19

Abstract

When deep recessions hit, some governments spend to rescue and recover their economies. Key economic objectives of such countercyclical spending include protecting and creating jobs while reinvigorating economic growth—but governments can also use this spending to achieve long-term social and environmental goals. During the COVID-19 (coronavirus disease 2019) pandemic, claims have been made that green recovery investments can meet both economic and environmental objectives. Here, we investigate the evidence behind these claims. We create a bespoke supervised machine learning algorithm to identify a comprehensive literature set. We analyze this literature using both structured qualitative assessment and machine learning models. We find evidence that green investments can indeed create more jobs and deliver higher fiscal multipliers than non-green investments. For policymakers, we suggest strong prioritization of green spending in recovery. For researchers, we highlight many research gaps and unalignment of research patterns with spending patterns.

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1. INTRODUCTION

Recession: a contraction in an economy's output or gross domestic product over two consecutive quarters

Green spending: public fiscal expenditures that are likely to reduce net greenhouse gas emissions, reduce air pollution, and/or strengthen natural capital, compared to a scenario in which the expenditure was not made

Rescue measures: policies used to protect lives and livelihoods in times of economic crisis

Recovery measures: policies used to reinvigorate economic activity following economic crisis

In 2020, two global crises converged. The coronavirus disease 2019 (COVID-19) pandemic crippled global health systems and economies, precipitating lockdowns and a global recession. The severity of the climate and nature crises became more obvious, with record-breaking floods and wildfires (e.g., 1). The co-occurrence of the two crises led to debates on the prospects of using green fiscal spending to simultaneously address both economic and environmental challenges. Proponents of a so-called green recovery claimed that public green investment could create jobs and grow national economies while reducing global net greenhouse gas (GHG) emissions and addressing other environmental and social priorities.

The intersecting themes of economy and environment were also present during the very different 2008–2009 Global Financial Crisis (GFC). These themes will likely be relevant in every economic crisis in the coming decades, irrespective of its cause and structure. This article reviews and synthesizes the current evidence on green spending, with a view to understanding the benefits and trade-offs associated with environmentally focused fiscal stimulus for when the next crisis hits. By green spending, we mean public expenditure that is likely to reduce net GHG emissions, reduce air pollution, and/or strengthen natural capital, compared to a scenario in which the spending did not occur. This can include investment in established, emerging, or nascent green industries. The most common archetypes are set out in **Table 1**. Domestic fiscal incentives include direct investments, grants, loans, guarantees, and tax measures.

Harm minimization is the predominant objective of government in response to an economic crisis. This comes over three intervals: (*a*) short-term emergency rescue measures to counter the immediate direct and indirect impacts of the economic crisis and related crises, (*b*) medium-term recovery measures to spur economic reinvigoration once the root causes of the crises have been sufficiently countered, and (*c*) long-term reinforcement measures after the crisis to fortify and ensure permanent shifts of investments and behaviors (2, 3). The appropriate policy tools to employ depend on the nature of the crisis and the capacities of the nation. Policy tools include (*a*) monetary controls in the form of interest rates, reserve requirements, and quantitative easing; (*b*) regulatory interventions to change incentives; and (*c*) fiscal interventions in the form of changes to taxation and public expenditure. In the context of the COVID-19 pandemic, loose monetary positions

Table 1 Green recovery policy archetypes used in this article, adapted from the O'Callaghan et al. (30) fiscal archetype taxonomy

Policy archetype	Description
Electric vehicle incentives	Support for vehicle production and consumption, including vehicle scrappage schemes or "cash-for-clunkers" schemes, cash and tax rebate support for purchases of electric vehicles, and electric vehicle production tax incentives
Green worker retraining and job creation	Retraining members of current or soon-to-be displaced workforces with new skills suitable for future industries, including green ones
Clean transport infrastructure	Investment in low-carbon public transport solutions, such as buses, trams, and metro infrastructure, as well as electric vehicle charging networks and pedestrian/bike infrastructure
Clean energy infrastructure	Clean electricity and fuel generation, transport, and storage, including WWS, hydrogen, and transmission
Buildings upgrades and energy efficiency infrastructure	Increasing thermal efficiency through improved insulation, improved energy efficiency of appliances, clean heating (e.g., heat pumps, heat networks), and/or household energy generation
Natural infrastructure and green spaces	Environmental (re)building initiatives, including afforestation, reforestation, and environmental rehabilitation, and environmental protection initiatives, including conservation, natural infrastructure resilience, and improving green spaces
Clean R&D	Cash support for R&D in emerging green technologies, including hydrogen electrolysis, energy storage, alternative proteins, and greenhouse gas removal (such as CCS)

Abbreviations: CCS, carbon capture and storage; R&D, research and development; WWS, wind, water, and solar.

entering the crisis meant that new stimulatory monetary interventions were unable to play a leading role. A need for expeditious protection of lives and livelihoods meant that only the fastest-acting fiscal and regulatory interventions were relevant. Overwhelmingly, governments have focused on fiscal tools, and mostly public expenditure, to minimize harms over the COVID-19 crisis.

Countercyclical fiscal policy—where governments step in to compensate for the private sector stepping back in a crisis—has been well studied since Keynes (4) and popularized in multiple forms, even including by analogies about baby-sitting clubs (see 5, 6). But whether and when a public spending stimulus is appropriate depends on the circumstances. The recession induced by COVID-19 was not a conventional demand slump caused by a financial shock, or a collapse in private sector confidence, but rather the result of enforced shutdown of economic activity by governments to protect human life and to manage pressure on healthcare systems. During lockdowns, economic activity was muted by design. However, once government rescue packages, such as furlough schemes and other social safety nets, had played their role, further recovery measures were considered desirable to return economies to healthy levels of employment and growth.

What sort of stimulus should governments use? The options vary dramatically in economic, social, and environmental characteristics. This variation is driven by policy archetype (e.g., infrastructure spending versus healthcare spending), policy mechanism (e.g., tax incentive versus direct subsidy), the national context in which the policy is applied (e.g., demographic structures, geography, level of economic development, and industrial composition), and other external factors. Which policy investments best maximize future prosperity and minimize harms without introducing any new ones? For some, including Elmendorf & Furman (7), stimulus should be timely, targeted, and temporary—spending initiatives with the highest multipliers are technically strong, for instance, unemployment benefits where beneficiaries are likely to have higher marginal propensities to consume. However, others argue that recessionary investment is also a valuable way to shift national trajectories toward a more desirable form of economic growth. Investment that comes with long-term debt servicing costs should incorporate corresponding long-lived assets; on

Reinforcement measures: policies used to embed new economic trajectories formed through recovery investment into long-term growth plans or development plans

this view, infrastructure investments, research and development (R&D) spending, and industry-building projects are attractive (8, 9). Approximately US$100 trillion of investment in assets like these will be required to deliver a net-zero emissions economy in the coming decades (10).

Machine learning algorithm: computer algorithms that automatically create models from data, iteratively improving themselves based on training data, sometimes with human supervision

The objective of an economic stimulus in a crisis may seem obvious enough: gross domestic product (GDP) growth needs to be restored and the economy returned to healthy full employment. But growth within our current model of economic production and consumption has devastating and terrifying consequences for natural ecosystems, nonhuman life, and indeed human life. The economy and the environment are inexorably intertwined: All economic production requires natural resources, and economic prosperity requires ecosystem services, including climate stability. More broadly, human wellbeing is not only driven by innovation, good jobs, and growth but also by our relationship with nature itself, its ecosystems, landscapes, and nonhuman species.

As such, a stimulus that targets short-term GDP growth but simultaneously undermines the very basis for human existence (hence also undermining medium-term growth) is counterproductive. Even if decoupling environmental damage from GDP is theoretically possible (11), it is clearly not occurring fast enough in reality (12, 13). Given these trends, GDP is even less suitable as a proxy for wellbeing (14–16), especially in developed economies. The deeper objective of economic policy is societal wellbeing, of which material prosperity is merely one (important) component. Environmental considerations take a more central position within ecological and steady-state economics (see 17, 18), the degrowth movement (19), the economics of wellbeing, and so-called doughnut economics (20). Although the environment has become a more mainstream political and economic issue in recent decades, most economic policy decisions, especially in a crisis, remain focused on jobs and GDP, which are admittedly more closely correlated with economic wellbeing in a recession than in normal times. Here, we focus instrumentally on the relationship between green stimulus and GDP. We stress that in most cases, factoring in the nongrowth benefits of green investments would significantly improve their policy appeal compared to other investments—examining only the impacts on GDP understates benefits of green investment spanning health (21–23), the environment (24, 25), economic stability (26–28), among others (see 29).

Even with a narrow, orthodox lens, the response to the COVID-19 pandemic arguably represented the single biggest opportunity to date to decouple fossil emissions from economic growth and keep within Paris climate targets (2). **Table 1** outlines key investment archetypes used in analyzing COVID-19 spending.

Just how stimulating is a green stimulus? In this article, we review the economic characteristics of stimulatory green fiscal spending, identify misalignments between research and public spending in the first 18 months of the COVID-19 pandemic, and synthesize recommendations for policymakers. In Section 2, we narrate an abridged history of green stimulus spending, beginning in ancient Egypt and exploring modern patterns. In Section 3, we create a bespoke machine learning algorithm to systematically identify and understand green investment literature. In Section 4, we build on the quantitative analysis to provide a comparative account of the literature on the speed of implementation, job creation, and national income multiplier characteristics of green fiscal spending. We identify the most pressing gaps in the literature. In Section 5, we provide recommendations to policymakers and priority areas for future research.

2. HISTORY OF GREEN RECOVERY SPENDING

2.1. Green Fiscal Spending Before 2008

Human civilizations have long used public interventions to mitigate and adapt to localized climatic change. Archaeological evidence suggests that local governors in the ancient Egyptian

imperial economy used dry farming to stabilize areas of the Levant in response to localized drought (31). Although the source of finance is unknown, there is evidence that communities in ancient Arabia responded to changes in climate through water resource management and by diversifying construction practices, using economic intensification (32).

In the 1930s, John Maynard Keynes (4) challenged the prevailing classical aggregate supply-focused thinking that suggested stimulatory/expansionary fiscal policy would only lead to higher inflation, without net-positive growth or employment impact. Keynes provided a new hypothesis to the following question: How should the government act to get an economy out of a recession, restore consumer confidence, and enable full employment? His answer: Spend.

A Keynesian approach to demand management came into vogue for economies including the United States and Sweden following the Great Depression, aiding their economic recovery (33). Some early recessionary spending programs included elements with positive climate outcomes. For instance, introduced in Roosevelt's New Deal, the Civilian Conservation Corps planted more than 2 billion trees, slowed soil erosion on 40 million acres of farmland, and in total altered more than 118 million acres of land, overall providing employment for up to three million young men at a time when unemployment was at 25% (34, 35).

Keynesian approaches to fiscal spending were adopted by other nations including the United Kingdom, France, and Japan following the Second World War (36) but soon fell out of favor to neoliberal and monetarist ideas (37, 38) that reduced the role of government and emphasized the risks of inflation.

Stimulatory/expansionary fiscal policy: policies that inject government funds into the economy, or reduce tax receipts, with the purpose of restoring or accelerating economic growth

Keynesian: a macroeconomic theory that suggests, in the context of economic recovery, increased government spending in times of crisis to boost economic growth

2.2. The 2008–2009 Global Financial Crisis and Great Recession

Stimulatory/expansionary fiscal policy saw somewhat of a resurgence following the GFC (39). As governments attempted to restore their economies to growth, some adopted stimulatory economic policy, with a subset using fiscal investments to simultaneously address environmental harms. Leaders included the United States with the American Recovery and Reinvestment Act (ARRA), South Korea with its Green New Deal (GND), and China with a scattering of investments across several green sectors including green energy and sustainable transport. Various additional green policies were introduced by European Union (EU) member states, Canada, and Australia, among others (40). By cataloging G20 fiscal stimulus policies following the GFC, Hepburn et al. (2) find that, by number, 32% of announced policies were green and Robins et al. (40) determine that, by value, 15.6% of spending was green. Studies of GFC green investment mainly adopt a focus on the United States (41–47), South Korea (48–50), or China (40, 51, 52), or investigate across mixed/global economies (see 52 on Europe; see also 53–55), with findings explored below.

For the United States, it appears that the ARRA's clean energy package successfully stimulated the economy, creating jobs and catalyzing additional long-term green investment (41–44). US$21 billion in spending on renewable energy included production/investment tax credits, cash grants, tax credits for manufacturing, targeted loan guarantees, and training grants. Together, these likely increased renewable electricity capacity, lowered US emissions, and increased renewable energy patents in the medium term (42). The spending supported a significant immediate employment boost across the green energy supply chain, while also supporting long-term industry growth and associated opportunities for green labor (43). Grants proved more cost-efficient than tax credits due to effective transaction costs, and grants and tax credits proved "significantly more effective than loan guarantees" in that they were more likely to be used by corporate actors (41). Although the process of distributing funds was slowed by identifying suitable projects, new public investments paired with private capital sustained aggregate demand as the economy moved out of the rescue phase (41). Outside of renewable energy programs, the next largest green contributions

were to energy efficiency, transit, grid modernization, and advanced vehicles, with lower support for green job training and early-stage carbon capture and storage (CCS) R&D (55). Compared to non-green alternatives, ex post evaluations find high job and GHG impacts for spending on energy efficiency (see 45, 55) and restoration of coastal habitats (46). As they grew, green industries tended to increase their demand for medium-educated workers and lower their demand for lower-skilled workers (47), suggesting that it is important to pair green investments with the current or planned future skill base of the local economy (56). Across the board, evaluations of US GFC stimulus policies predominantly address one or two aspects of the green economy and focus on one or two policies, rather than the entire package.

The South Korean GND appropriated US$36.3 billion over four years, intending to create almost one million jobs in mass transit systems, fuel-efficient vehicles, energy conservation, and more (53). The package comprised ∼69% of total South Korean crisis spending, reflecting a significantly higher ratio of green investment than other nations (40). However, although the economic returns of the package were high in terms of both jobs and economic growth (48, 52), the net environmental impact of the spending remains unclear and might have been negative (48, 50). Complications included insufficient renewable energy uptake, broad continued support of coal-powered electricity generation, increased energy intensity from new investments, export-led growth in energy-intensive sectors, and environmentally destructive waterway investments (40, 48–50, 54).

In China, approximately US$586 billion was appropriated for economic recovery, including US$221 billion for green purposes. However, of this, US$99 billion was for rail with unknown environmental consequences and unknown impacts on the displacement of automobile transport (40). In totality, although the literature is sparse, the stimulus might have supported a return of Chinese growth to precrisis levels (51, 52).

Within the EU, up to US$54 billion worth of green stimulatory fiscal packages were introduced in total, at the supranational level and in member states (40). Focal green industries included energy efficiency, public transport, renewable energy, vehicle scrappage schemes, and green R&D (52). Green investments are likely to have delivered short-term multipliers similar to non-green investments (52) and employment opportunities to stressed sectors at low public cost (40, 52). For instance, for the German Building Rehabilitation Program, when projects did not crowd out other investments, the net impact of spending was to reduce the public deficit due to increased income taxes and social security contributions (57). Environmentally, the long-term net effects of spending were generally favorable and are thought to have supported the long-term development of nascent green industries, particularly for energy efficiency and renewable energy investments (52).

2.3. The COVID-19 Recession

The overall fiscal response to the COVID-19 crisis has set new records for countercyclical spending. This time, the economic contraction came more severely and with greater geographic coverage, precipitated by synchronized demand- and supply-side shocks (2). Over the first year of the pandemic, governments with the capacity to spend on rescue measures often did so to protect lives and livelihoods. In many nations, trillions in recovery-type investment quickly followed rescue measures. Compared to the GFC period, debate on the role of stimulus spending has been muted in most countries, with discourse instead focusing on the volume of spending and its recipients. For instance, analysis in France finds that public discourse has shifted against austerity narratives (58). With already loose monetary policy moving into the crisis, and negative effective monetary interest rates in several advanced economies, governments have felt it necessary to spend and had the public license to do so.

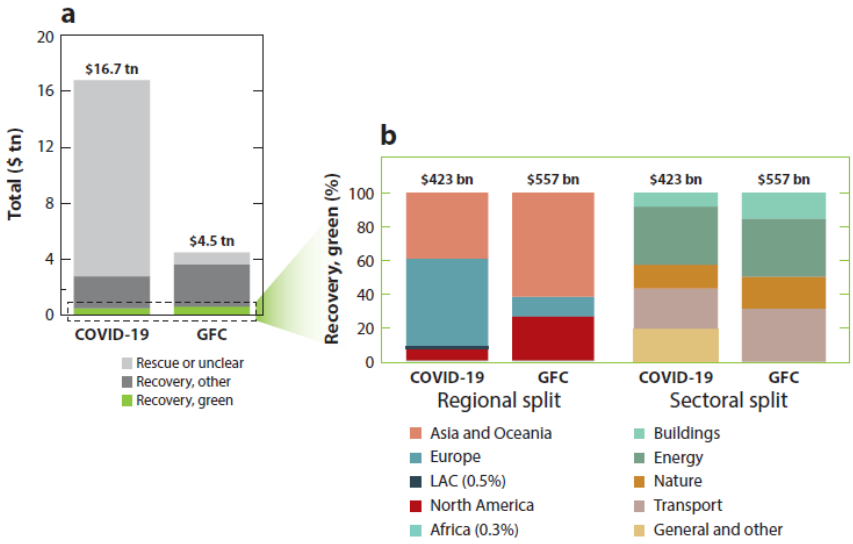


Figure 1

(*a*) Green characteristics of total COVID-19 and GFC investment (US$, real values). (*b*) Regional and sectoral/archetype characteristics of total green COVID-19 and green GFC investment (US$, real values). Nature includes water and waste. Energy includes CCS. Sources: COVID-19 data to October 2021 from the Global Recovery Observatory (59); GFC data adapted from Robins et al. (40), supplemented with missed policies and adjusted for real values. Abbreviations: CCS, carbon capture and storage; COVID-19, coronavirus disease 2019; GFC, 2008–2009 Global Financial Crisis; LAC, Latin America and the Caribbean.

By October 2021, total COVID-19 spending was already 3.7 times GFC spending in real terms (59) (**Figure 1**), with more to come. Yet, despite this, on green investment, compared to the GFC, COVID-19 initiatives are lower in value and as a proportion of total spending (53, 59). The biggest green spending nations so far are Spain (US$63.5 billion), Japan (US$61.8 billion), and France (US$53.9 billion), with the highest proportionate green spending coming from Denmark (62.6% of recovery spend), Finland (58.3%), and Belgium (58.3%) (59).[1] Green investment allocations have been made in every region and for almost every emerging mainstream green industry (8, 59–61); however, the scale of spending is much lower than the need. The International Panel on Climate Change (62) found that to meet a 1.5-degree Celsius trajectory, it would take total investment of US$1.6–3.8 trillion per (in 2010 dollars) year to 2050 from public and private sources to transition just the world's supply-side energy system, let alone the various transitions required in industry and agriculture. Extrapolating funding requirements submitted to the UNFCCC (63), non-Annex 1 nations might require US$11 trillion just to meet their Nationally Determined Contributions, most of which are not aligned with a safe climate trajectory. By every measure, the scale of green public and private investment will need to increase many times over to meet the needs of a sustainable climate.

Our understanding so far of the impacts of the green stimulus in response to COVID-19 is necessarily limited, as the crisis is still in motion at the time of writing and most funds are yet

[1]Only nations that have spent >1% of GDP on recovery initiatives are considered in leadership rankings. Other nations, including Turkey, Mauritius, Bangladesh, and Burkina Faso, might have high levels of green spending as a proportion of total spending but low levels of overall recovery spending.

to be disbursed. However, ex ante studies suggest high potential positive economic impacts of green stimulus across regions and sectors, using macroeconomic and general-equilibrium modeling (64–67), employment multiplier modeling (68), input-output modeling (66, 69, 70 forthcoming), and surveys or other approaches (2, 66). This is also supported by Batini et al. (71), who use multi-decadal data to ascertain directional green multipliers and support ex ante statements on the strength of a green COVID-19 response. Studies currently continue to commentate on these impacts through a variety of analytical approaches (72–74), but the full impacts of green COVID-19 spending will remain unclear until ex post studies can be completed, with the validity of studies governed in large part by data collection and strengthened by government commitments to policy experimentation (61, 75). Fortunately, much can be learned from nonstimulatory or so-called peace time literature and applied with caveats to periods of economic contraction. These might also be relevant to "reinforcement measures" in years to come. The next section reports on a comprehensive review of the literature using a novel approach.

Neural network models: machine learning algorithms designed to recognize patterns and in so doing, cluster and classify data, ideas, and concepts

Latent Dirichlet Allocation (LDA): a natural language processing method that uses statistical analysis to identify and categorize similarities in terms within a corpus

t-Distributed Stochastic Neighbor Embedding (t-SNE): a statistical method used to visualize data through connecting similar objects and separating dissimilar objects

3. QUANTITATIVE LITERATURE ANALYSIS WITH MACHINE LEARNING

We present a bespoke supervised machine learning algorithm based on the word2vec neural network model (76) to identify the academic literature on green public expenditure and all English language gray literature in the Web of Science collection (**Table 2**). This provided a corpus of 908 texts for quantitative analysis, across three categories: premier journals (190 texts), secondary journals (514 texts), and Web of Science gray literature (204 texts) (see definitions in the **Supplemental Appendixes**). For the cumulative corpus, we analyzed collocation of economic and environmental terms, applied unsupervised topic modeling with Latent Dirichlet Allocation (LDA), and visualized word relationships using t-Distributed Stochastic Neighbor Embedding (t-SNE) (77, 78; also see the **Supplemental Appendixes**).

3.1. Literature Identification

For traditional systematic review processes, scholars face a trade-off between precision and breadth; the manual review of all facets of a topic of literature is too labor intensive to be feasible (79, 80). Traditional reviews either risk errors, omissions, and bias (81) or are excessively time- and

Table 2 Descriptive characteristics of the literature identified by application of a bespoke algorithm based on the word2vec neural network model[a]

Iteration number	Terms added to dictionary set (*words*, *bigrams*)	Papers added to review set				New unique words in review set, postprocessing (*lemmatized*)	Total words in review set [preprocessed millions (M)]	Total words in review set [postprocessed millions (M)]
		Premier journals	Secondary journals	Gray literature	Total			
Initial	154 (*13*, *141*)	158	434	174	766	20,898 (*16,950*)	6.42 M	3.48 M
First review	70 (*4*, *66*)	29	75	28	132	3,584 (*2,981*)	1.85 M	1.03 M
Second review	9 (*1*, *8*)	3	5	2	10	157 (*137*)	0.09 M	0.05 M
Third review	1 (*0*, *1*)	0	0	0	0	0 (*0*)	0	0
Total	**234**	**190**	**514**	**204**	**908**	**24,639 (*20,068*)**	**8.36 M**	**4.55 M**

[a]Rows might not sum to total due to rounding.

cost-intensive (82, 83). Automated text analysis can help to address these issues (79, 81, 83, 84); however, such analyses also face several practical and technical constraints (84). Automated models for literature identification often rely on domain-specific dictionaries, and subject matter experts can fail to provide adequate dictionaries for complete reviews (85). Emerging active unsupervised learning methodologies, which use iterative user guidance to sort relevant literature and identify the pieces of highest relevance for manual review (79), also rely on input dictionaries defined by the user. Recent supervised machine learning approaches in reviews on climate policy represent an important advance in the field but also rely on relatively small dictionaries, potentially resulting in missed works (86).

In contrast, here we employ embedding models to expand an initial user-defined dictionary to include all related domain-specific terms, whereby the domain is defined by the literature itself (see the **Supplemental Appendixes**). Such embedding models operate by identifying how terms in a corpus relate to each other and vectorizing the terms into a n-dimensional space (alternative tools are discussed in the **Supplemental Appendixes**). Here, we use the word2vec embedding model (76) of dimension 100 with a minimum count of three in order to expand our user-defined dictionary to capture groups of related terms (rather than synonyms) that convey similar concepts.[2] **Figure 2** describes the methodology for literature identification: The algorithm finds related words to an input dictionary set, uses these new words to identify additional literature, updates the corpus with this new literature, and repeats until no new words or papers are identified. Related words are identified by cycling through each potential term pairing in every dictionary category, taking the average of the term vectors, and finding the closest term to this vectorized location. The cycle repeats by pairing the new term vector with every existing term vector in the dictionary category until the closest term vectors to the average of the pair vectorization are the input word pair. Papers are identified based on dictionary search terms used with the Web of Science Topic Search function, which considers titles, abstracts, keyword fields, and KeyWords Plus fields. Manual postprocessing is applied on every iteration of the cycle to filter out unrelated papers.

Our initial term set was significantly larger than that used by others (86), and even still, the algorithm was able to identify 18.5% additional highly relevant papers that would have been missed without the embedding model. Descriptive dictionary and literature statistics are included in **Table 2**.

3.2. Thematic and Quantitative Analysis

For a preliminary understanding of literature coverage, themes, and gaps, we first applied established LDA and t-SNE methods (see the **Supplemental Appendixes**) before analyzing co-occurrence of environmental and economic terms across predefined categories. To distinguish between literature types, the analysis was repeated for groups 1, 2, and Web of Science gray literature, with results included in the **Supplemental Appendixes**.

As a form of topic modeling, LDA is highly suited to drawing unknown themes from well-constructed texts like journal articles (87). In our study, optimizing for low perplexity with a 90% train, 10% test model suggested a 15-theme analysis to balance theme quality and theme redundancy. Analyzing the full 908 paper corpus reveals prominent environmental themes including

[2]For instance, in our specific literature domain, the algorithm found "emissions" to be related to "clean," but these are clearly not synonyms. Beyond related words, the approach also identifies related N-grams; for instance, "spending policy" was considered related to "fiscal recovery" and "economic stimulus." Importantly, acronyms are included in the word vectorization; for instance, "ghg" was identified as a key missing term by the algorithm.

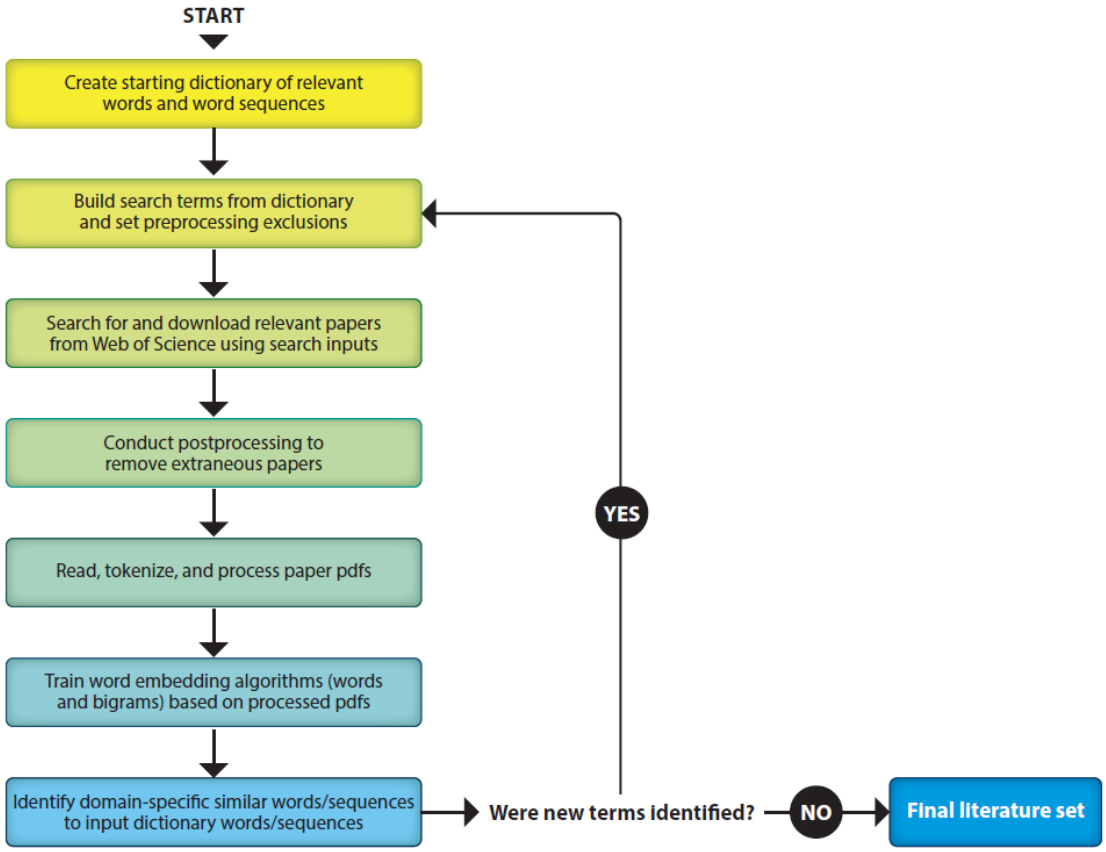


Figure 2

Process of literature identification using iterative machine learning model. Dictionary for identification defined internally with word embedding. Method malleable to any literature set across disciplines.

clean energy, green jobs, and forest services, as well as economic themes, including economic growth impact, productive labor, and development outcomes (**Figure 3**). t-SNE dimensionality reduction (88) of the final corpus word2vec word embedding model was used as an alternative visualization to observe relationships between terms within the corpus. The *k*-means algorithm (89) with the squared Euclidean distance metric proved the most informative for visual comparisons.

To understand coverage of the economic characteristics of environmental topics, we developed a collocation frequency analysis with four economic categories and eight environmental categories, defined by a total of 614 terms. This term list is an expansion from the dictionary outputs found through the learning process described in Section 3.2. The economic categories are employment, economic growth, investment as stimulus, policy implementation speed, and economic impact assessment. The environmental categories align with the previously discussed set of green recovery archetypes (30): clean energy, natural infrastructure and green spaces, green transport infrastructure, buildings upgrades and energy efficiency, clean R&D, CCS (as a subset of clean R&D), electric vehicles, green worker retraining, electronic appliances, and other environmental,

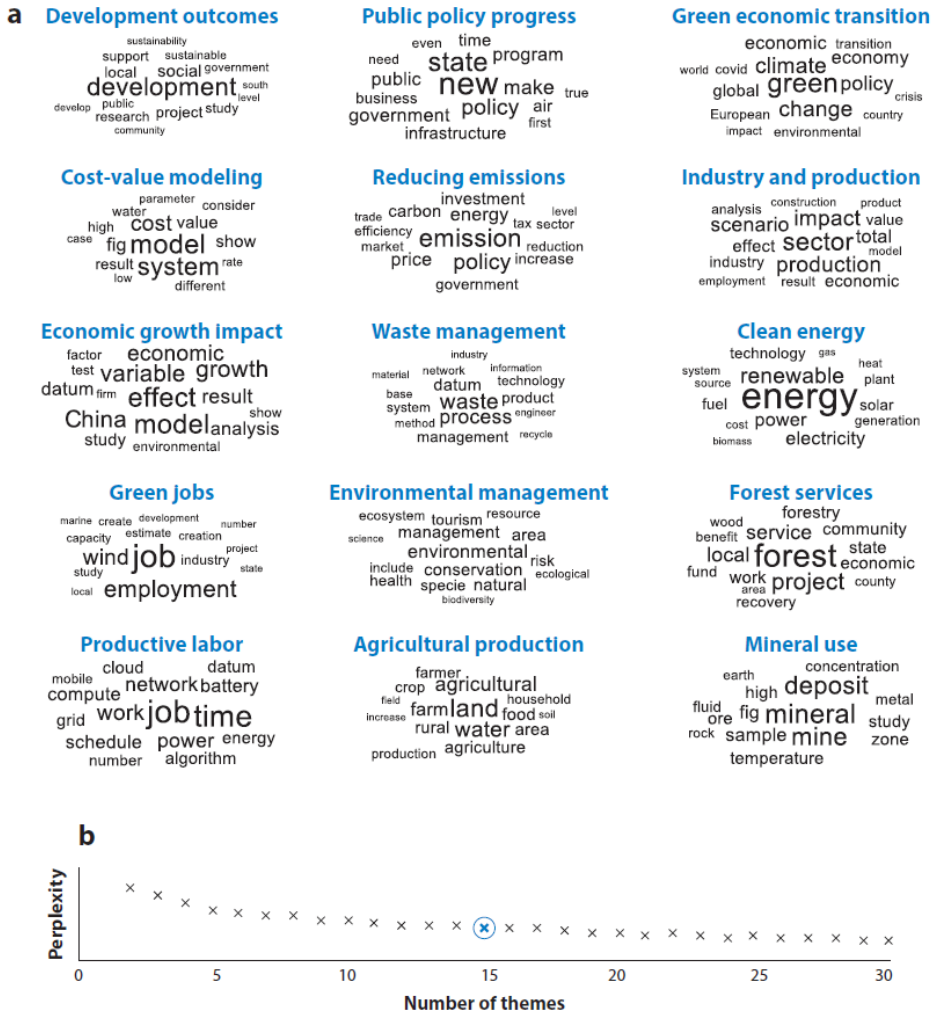


Figure 3

(*a*) 15-theme Latent Dirichlet Allocation analysis for the full corpus of the economic literature on green investment (lemmatized). Labels defined manually. Topic mixtures across papers are included in the **Supplemental Appendixes**. (*b*) Relationship between the number of themes and perplexity for the full corpus, derived through iterative testing.

which incorporates green market creation and general environmental commentary. Green rescue type terms were excluded. The collocation process considers the occasions that an economic term and an environmental term (or their derivatives) occur close to each other, for instance, "job creation" and "solar energy." Observed trends were persistent across all "close proximity" scenarios, where context varied from 100 to 500 characters in either direction.

80.8% of all economic-environmental term pairs related to employment topics, with the balance of economic themes covered by growth terms (8.0%), investment as stimulus terms (7.6%), economic policy assessment terms (2.9%), and policy implementation speed terms (0.8%) (all

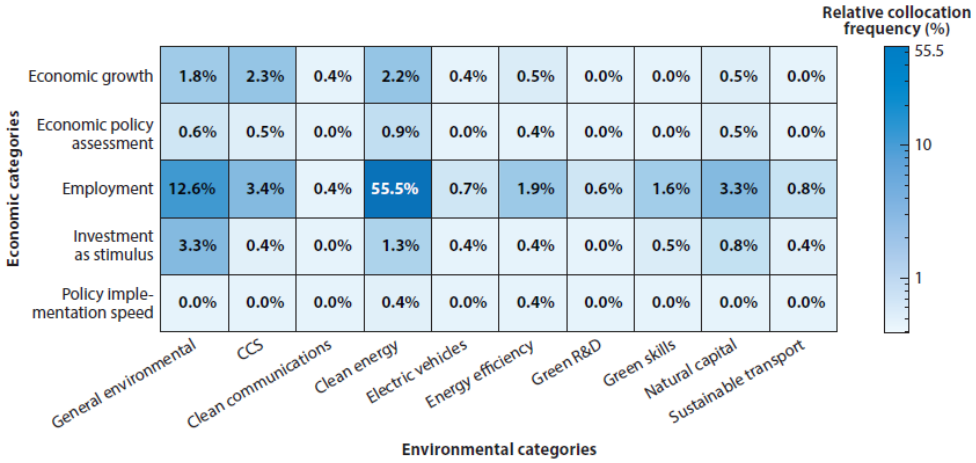


Figure 4

Relative collocation frequency of economic and environmental categories. Results for full corpus (908 papers) and context = 100 scenario. Collocation frequency for the subset of premier journals is included in the **Supplemental Appendixes**. Abbreviations: CCS, carbon capture and storage; R&D, research and development.

figures from the context = 100 scenario; see **Figure 4**). Relative to other economic terms in the category, employment coverage was particularly high for green R&D topics (100.0% of economic coverage), green energy (92.1%), and green skills (76.3%). Meanwhile, economic growth emerged more prominently for clean communications (49.0%), CCS technologies (34.3%), and electric vehicles (26.5%). The greatest proportional coverage of investment as stimulus topics came from sustainable transport (35.8%) and electric vehicles (28.1%).

Coverage of environmental topics was dominated by clean energy, which represented 60.2% of all environmental terms used in proximity to economic terms, followed by general environmental (18.3%) and CCS technologies (6.6%). This trend was particularly strong in employment topics (68.7% of collocated mentions were with green energy); for investment as stimulus topics, general environmental (43.1%) and clean energy (17.2%) were the most prominent topics. Within the clean energy category, general terms dominated occurrences, accounting for 53.3% of all clean energy mentions in proximity to economic terms; however, wind energy and bioenergy were also major subcategories (20.0% and 17.0%, respectively).[3]

The comparative coverage of environmental categories in the surveyed literature is wildly misaligned with government recovery expenditure observed during the GFC and so far during the COVID-19 pandemic (**Figure 5**). This trend is similar but less pronounced in premier journals, which deliver a higher proportional coverage of environmental topics outside of clean energy (see the **Supplemental Appendixes**). In part, these findings are unsurprising because they are backward-looking. Logically, established technologies and practices have garnered comparatively greater research interest than nascent and emerging technologies, particularly for a sector as large as energy. Nevertheless, low research attention for initiatives receiving billions of dollars in taxpayer support is concerning. These findings align with commentary that the field of

[3]We note that bioenergy terms are frequently used by researchers when clarifying the definition of renewable energy used in their analysis and do not necessarily relate to specific investigations.

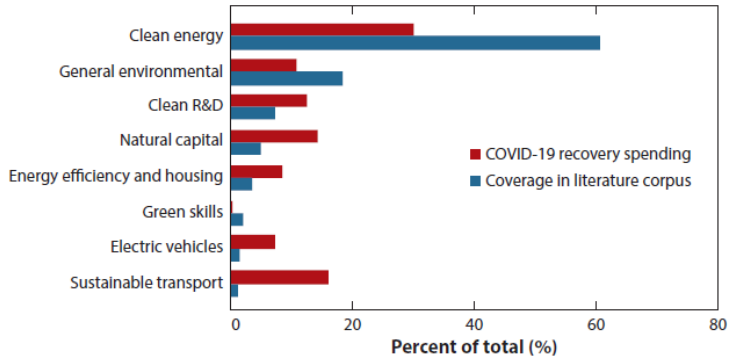


Figure 5

Research spread versus green stimulatory investment patterns. CCS combined with R&D for comparison. Clean energy includes relevant market creation initiatives. Source: literature data from this article; COVID-19 data to October 2021 from the Global Recovery Observatory (59). Abbreviations: CCS, carbon capture and storage; COVID-19, coronavirus disease 2019; R&D, research and development.

environmental economic research has not directed sufficient attention to the fastest growing areas of public climate investment, including in so-called hard-to-abate sectors (90, 91).

4. MACROECONOMIC IMPACTS OF GREEN STIMULUS

This section builds on the quantitative analysis above to provide an assessment of the literature on the economic characteristics of green fiscal spending in terms of speed of implementation, job creation, and national income multipliers. Overall, although there are some quality studies offering initial guides on the characteristics of stimulatory green investment, there are also large gaps in the literature where progress appears both valuable and possible.

The characteristics of green fiscal spending could be evaluated across at least eight important dimensions, namely (*a*) boosting employment and doing so in areas of greatest need, (*b*) optimizing the time of action, (*c*) maximizing the economic multiplier, (*d*) ensuring fiscal affordability, (*e*) reducing inequality and meeting other social prerogatives, (*f*) supporting the natural environment, (*g*) achieving simplicity for implementation, and (*h*) political considerations. This review focuses on the first three listed objectives, each of which is an essential economic consideration for policymakers.

4.1. Job Growth

Perhaps the most oft-cited objective in stimulatory/expansionary fiscal policy is job protection and creation, as contractionary economic periods tend to induce unemployment. It is unsurprising then that the employment characteristics of green investment receive disproportionately higher coverage in the literature than studies of timeliness or Keynesian multipliers, as seen in Section 3.[4] In this section, we focus on modeled and measured green job creation effectiveness and job multipliers from public green investment programs. A complementary and growing literature investigates green job potential from all kinds of investment (96, 97).

[4]Job creation is often reported as full-time equivalent (FTE) jobs or job years (92–95), to standardize across full time and part time jobs and to account for the temporary nature of some types of employment (e.g., in the construction sector) compared to the more permanent employment generated in roles like maintenance and research. In this study, jobs refers to FTE jobs and job years to FTE job years.

Spillover effects: effects of an economic event on third parties, including benefits and harms

One class of literature focuses on absolute job creation. Blanco & Rodrigues (98) assess job creation from nascent wind energy deployments in the EU, finding that early investments created many jobs as other segments of the energy sector were shrinking. Scholtens (99) estimates that the Netherlands' Green Projects Facility created approximately 21,500 FTE job years. Pollitt (52) and Mundaca & Damen (48) respectively present figures for post-GFC measures in EU member states and South Korea, again demonstrating strong job creation characteristics. In the US, ARRA renewable energy investments were identified as particularly strong for job creation (41–43, 45, 56). For example, Steinberg et al.'s (45) analysis shows that $US 9 billion in incentives under the Section 1603 Grant Program of the American Recovery and Reinvestment Tax Act generated 150,000 to 220,000 job years just in renewable energy construction, and a further 5,100 to 5,500 job years in operation. Popp et al. (56) consider total jobs rather than job years, finding that every $US 1 million in green ARRA spending created 15 new jobs. For COVID-19, ex ante models also predict strong employment impacts from green investment across geographies (see 68 for global coverage, 70 for ten case study countries, and 66, 69 for South Africa).[5]

Without a counterfactual, the relative job creation potential of green investment is difficult to ascertain. Kammen et al. (100) perform a meta-analysis of 13 studies, concluding that renewable energy policy portfolios generate more jobs than fossil fuel–based portfolios, per unit of energy delivered. Wei et al. (92) build on this, including more studies to find that clean technologies, from renewable energy and energy efficiency to CCS, can form energy portfolios with considerably more FTE jobs per unit energy than coal and natural gas. Blyth et al. (93) estimate that a shift toward renewable energy and energy efficiency investment can increase the labor intensity of energy by up to 1 FTE job per annual gigawatt hours above the previous average of 0.4.

Other studies use jobs per unit capital investment and direct job multipliers to compare the economic advantages of green spending against other investments. Spencer et al. (101) use French data to show that a million Euro of expenditure created 17 jobs in energy efficiency and 10–14 jobs in renewable energy, versus 2.4 in oil and 3.6 in gas. Using an input-output model, Garrett-Peltier (102) finds that, in the United States, US$1 million in spending creates 7.49 jobs in renewable energy, 7.72 in energy efficiency, and 2.65 in fossil fuels. However, Huntingdon (103), including data from Kammen et al. (100) and others, finds that green job creation is only cheaper where there are pre-existing advantages for green power sources, such as a facility located close to the power grid. Huntingdon concludes on average that, up to 2009, green jobs were not clearly cheaper than conventional energy jobs; however, Huntingdon does not consider spillover effects and refrains from commenting on possible future job multipliers. Additional commentaries point to the sizeable risks of offshoring capital to fund import-heavy renewable technology while losing corresponding fossil energy jobs (104).

Induced jobs and other employment spillover effects on green investment are considered by a small group of authors, including Nair & Rutt (94), who estimate that one additional job in forestry generates an additional 1.5 to 2.5 FTE jobs in the wider economy. Vona et al. (44) find that one additional green job is associated with 4.2 new local jobs in nontradable, non-green activities, only falling to 2.2 in crisis periods—this is considerably higher than previous studies. Houser et al. (95) partly associate these benefits with savings in energy costs—every US$1 billion on building efficiency is estimated to create 30,100 FTE jobs and save US$450 million in energy costs, of which approximately 50% is reinvested in the economy and creates further jobs. Kronenberg

[5]Higher modeled employment benefits of green spending might be explained by technological progress, a more complementary macroeconomic environment, and/or better data availability. In the case of technological progress, lower costs for green technologies might lead to a smaller portion of investment spent on materials and a higher portion on labor.

et al. (57) further consider the significant avoided cost of unemployment, in the example of a German building rehabilitation program. O'Callaghan et al. (69) note that the mutually supportive characteristics of green industries are difficult to account for in modeling—consider, for example, the role of cheaper electricity in strengthening the economic appeal of consumer products like electric vehicles and emerging innovations like artificial proteins.

There are also negative effects to consider. For instance, although renewable energy spending boosts employment while the asset is being built, in the longer run, keeping net capacity equal, the transition from fossil electricity to renewable electricity could reduce total direct employment, as renewable infrastructure has comparatively minor maintenance requirements (105, 106). Indirect effects may be significant, however: Energy savings from cheaper renewable electricity could be reinvested into the wider economy, leading to job growth, as Houser et al. (95) suggest. Jacobson et al. (107) calculate private energy cost savings of US$10.9 trillion a year (61%) across 143 countries, from an energy transition of this kind. If reinvested, this could bring many new jobs globally. More widely, it remains imperative that green fiscal stimulus programs are tailored and well implemented to minimize harm to overall employment—policy design remains crucial (2, 108, 109).

There is an older and relatively limited literature critiquing green jobs (e.g. 110–114), drawing attention to definitional issues and data comprehensiveness, querying the public expense of such job creation, and observing that labor-intense output is not necessarily economically superior to output that involves higher labor productivity (and hence fewer jobs). These specific critiques and questions are useful. Overall, however, the literature examining the role of green job creation during an economic recession remains limited and partial at best. Álvarez et al. (106) claim that green jobs investment in Spain destroyed nine jobs for every four created, before accounting for the opportunity cost of the investment. This work is directly countered by Lantz & Tegen (115), who identify inappropriate use of metrics and failure to account for economic variability, among other critiques. Marsh & Miers (116) find that, in the United Kingdom, 3.7 jobs are foregone for every job created in renewable energy. Böhringer et al. (117) observed a similar decline in overall labor force participation because of Ontario's feed-in tariff policy to promote renewable energy. This finding opposes other studies conducted in Germany (118, 119), and the EU more widely (120). Hillebrand et al. (121) suggest that short-term gains in net employment are eventually offset by falls in domestic production if energy costs rise, leading to a negative employment balance in the long run. Yet even this is of limited relevance today, 15 years later, where the levelized cost of energy of solar has fallen 89% and onshore wind 55% (globally representative figures) (122, with data from 123 and 124). Broader, elemental criticisms from the literature question the political fixation on jobs—they contend that if the objective is to spend efficiently then perhaps the focus should be to minimize costs rather than create jobs. Some suggest that the goal should be more productivity rather than more jobs (113), whereas others warn against conflating labor-intensive energy provision with efficient climate protection (104).

Four clear findings emerge from the literature on job creation through stimulatory green investment:

- First, clean energy investments and energy efficiency retrofits can outperform traditional energy investments on direct and indirect job creation and labor intensity.
- Second, there is insufficient evidence to definitively comment on the comparative labor impacts of other green investments; however, emerging COVID-19 analyses suggest that these might also be more favorable than traditional alternatives. These investment archetypes require particularly urgent attention and include natural capital investment, green agriculture, sustainable transport, and clean R&D (particularly green hydrogen and CCS). Across each archetype, particular focus is required in emerging markets and developing economies.

- Third, the induced labor impacts of green investment are poorly understood and would benefit from more research.
- Fourth, minimal research has considered the key enablers of green job creation—namely, availability of sufficient and suitable green skills, existing baseline green business ecosystems and contractor capabilities, and appropriate absorptive capacity in R&D.

For findings two, three, and four, US$470 billion (and growing) in COVID-19 investment that is geographically and sectorally spread provides the ideal testbed for future research. In this, it will be important for researchers to coalesce on consistent definitions and methodologies in green job impact assessment.

4.2. Time of Action

A key attribute of fiscal stimulatory spending is its timeliness—governments aim to deploy investment rapidly to reduce economic harms (125). Quickly deployed stimulus can counter consumer and business uncertainty, acting to restore aggregate demand and make use of idle labor in the period of higher unemployment associated with recession (4). If fast enough, spending can also arrest a fall in jobs by replenishing revenue for companies in target sectors with new contracts, allowing them to meet wage obligations (126). If dispersed in a favorable low-interest rate environment, which might follow a period of economic contraction, well-timed investment could also more easily catalyze business investment and thereby support higher economic multipliers (4, 9, 127).

But faster is not necessarily better—combining policies of varied timeframes into a policy portfolio might enable a smoother recovery path. Rapid measures can bring forward established consumer demand without necessarily increasing total demand over the medium term (128, 129). This possibility raises concerns about arrested growth or industry slowdown in the period following the stimulus action but also might resolve concerns about excessive overheating and inflation in the event of a strong rebound.

Incorporating policies with medium-term effects into stimulus packages can complement rapid action measures. Such policies can deliver a permanent upward shift in the demand curve to establish new industry and long-term jobs. However, any medium-term spending must be considered for its impact on the national debt and resulting effects (positive or negative) on business confidence. Reduced business confidence in a high-debt environment could feasibly constrain private investment, increasing long-term interest rates and countering the intended effect of the stimulus program (see 125). As economic recovery itself takes place over several stages, packages incorporating policies that exhibit economic benefit at different stages of recovery could ensure that this takes place completely and gradually.

Pollitt (52) conducts a high-level analysis of the timeliness of recovery packages from EU member states, the United States, Australia, China, and South Korea following the GFC. Pollitt concludes that stimulatory green investments have generally been timely, although as in the Australian roof insulation experience, attempts to take shortcuts can have severe negative consequences. He finds that energy efficiency investments, including building retrofits, are particularly quick—this finding is supported across the literature (see 95, 101, 130–132). However, this is contingent on overcoming barriers such as up-front costs, cost of finance, and informational barriers (55). These policies can be particularly fast-acting when supported by direct loans (101). Alberini et al. (133) may offer some explanation for the speed of these policies, demonstrating that in addition to having low planning requirements, a successful Swiss retrofit program was spurred by high levels of household responsiveness to simultaneous cost, comfort, and climate benefits from retrofitting.

Depending on the type of program, natural capital investments can also be relatively fast-acting (130). Some jobs in ecosystem services are considered lower-skilled, meaning project lead times can be shorter than in other industries if skilled labor is scarce. Additionally, as these projects often rely on primary goods and domestic supply chains, input material sourcing can be comparatively streamlined. However, without apt consideration of biodiversity, local populations, and other practical needs, rapid and poorly planned investment in natural capital risks inadvertent but severe human and environmental externalities (134).

Biodiversity: the diversity in types of life forms and systems of life forms, including species, ecosystems, and livable habitats

Whereas energy efficiency and natural capital investments stand out as fast-acting policies, clean energy infrastructure and clean transport infrastructure investments are typically considered to be slower-acting policies (101, 130). The speed of action in these investments depends on the availability of so-called shovel-ready projects, particularly those that have already passed planning and approval processes, or perhaps are already underway and would benefit from acceleration (131). The prioritization of shovel-ready projects in the ARRA during 2009 allowed for rapid US deployment of both the Weatherization Assistance Program and tax credits for wind and solar (43). In some nations, provided that appropriately skilled labor is available, a backlog of existing shovel-ready projects might guide investment—for instance, ecological conservation projects and local bike infrastructure projects in the United Kingdom following COVID-19 (135).

Despite the labor intensity of many rapid action projects, and the relatively low training requirements of associated jobs, induced labor demand from significant fiscal investments is often not fulfilled (132). Instead, the wider economic impacts of targeted worker retraining programs are likely to only be fully realized in the medium and long run. This is because maintenance demands increase over time, while dynamic innovation effects and skill-biased technical change creates jobs through R&D (136). Relatedly, stimulus through clean R&D investment is expected to have a delayed effect. In the past, depending on the industry, regulatory hurdles and scaling timelines have seen new fiscal allocations dispersed to research teams two or more years after initial funding (95, 130, 137).

Compared to employment impacts, research on the timeliness of stimulatory green fiscal spending is relatively shallow and skews to qualitative descriptions over technical analysis. Rather than quantifying the time spans over which economic benefits play out, most studies use broad descriptors, for instance, "fast," "medium," and "slow" (9, 52, 95). Overall, a greater understanding of when different policy archetypes exhibit economic benefit will be beneficial to design balanced green stimulus packages that both provide an immediate economic boost and set the economy on a path toward long-term sustainability and prosperity.

4.3. National Income Multipliers

Comparing the economic benefit of fiscal investment alternatives is traditionally completed with reference to national income multipliers or so-called Keynesian multipliers (4, 9, 138, 139). Sometimes these are "true" Keynesian in that they consider both private and public spending, but frequently they focus only on public investment and are better termed fiscal multipliers. The intertwined nature of economy and environment in our current system of production questions whether economic growth should be analyzed in isolation from its environmental consequences. Yet, mainstream policy discourse continues to consider the two as separate today (2, 52, 71, 101, 108). In the simplest form, the direct job creation and consumption impacts of government spending are expected to induce additional consumption and investment, further adding to national income and creating a multiplier effect. Short- and long-run multipliers are both known to be higher in demand-deficient macroeconomic environments, for instance, during and directly following a recession (140). This being said, fiscal multipliers are notoriously difficult to estimate, and green multipliers represent a particularly understudied area (9, 71, 138).

Given a lack of appropriate data, various directional estimates of green multipliers have informed policy decision making. Estimates employ three-point scales, judging multipliers from high to low or best to worst. In these schemes, policies including energy efficiency retrofits, CCS programs, vehicle scrappage schemes, and afforestation are reported to have high fiscal multipliers (101, 130, 141). Conversely, smart metering stands out as a policy considered to have a particularly low multiplier (130). The multiplier potential of renewable energy promotion and capacity construction is debated, with some studies claiming both high absolute multipliers and high multipliers relative to other green technologies (130), and others estimating high absolute but low relative multipliers (101, 141).

Batini et al. (71) provide a direct analysis of green national income multipliers, using factor-augmented panel vector-autoregressive models to interpret the impact of clean energy spending and biodiversity conservation spending on GDP. They find that the output response of green investments is much more persistent when compared to their non-green direct corollaries (e.g., dirty energy and industrial farming, as Batini et al. describe). In their model, whereas the output response of non-green spending dies within five years, the green spending response continues beyond five years. This translates to an impact multiplier of 1.19 for clean energy (five-year multiplier of 1.11), compared to 0.65 for dirty spending (five-year multiplier of 0.52). The authors explain the following:

> In other words, when an additional dollar of public or private money is spent to build more fossil fuel energy infrastructure and power generation plants, this expenditure crowds out some other component of GDP (investment, consumption, or net exports) by 48 cents in the medium run. When the same dollar is spent on solar, wind or geothermal, 11 cents are instead crowded in. (71, p 24)

On biodiversity conservation, the study is unable to derive a statistically significant short-term impact multiplier. However, at the five-year horizon, biodiversity conservation is shown to be even more persistent in its output response with a growth multiplier of 6.67. This compares to a five-year multiplier of 0.94 for industrial farming.

Hasna (142) estimates local green energy multipliers in the United States using state-level annual data over 16 years. Hasna finds a multiplier of 1.1 contemporaneously, 2.5 within one year, and up to 4.2 within two years of implementation. These figures are significantly higher than comparable traditional energy investments. Hasna (142) shows that 86% of the variation between the green and non-green multipliers is due to differences in the initial stock of public capital, with green "further away from the steady-state."

Pollitt (52) provides a quantitative estimate for domestic short-term green multipliers for EU member states, using the E3ME macroeconometric model. Pollitt concludes that green multipliers range from 0.5 to 1.1 domestically and that multipliers vary more between countries than they do between green policy types. Notedly, Politt shows that whereas average multipliers might be 0.75 when measured at a national level, at the regional EU level they can be as high as 1.5 due to captured imports and the integrated nature of the Union. At the national level, spending on buildings is estimated to be slightly higher than 1 due to the domestic nature of construction. For other green initiatives, trade and importing impact national fiscal multipliers to a greater extent.

A valuable case study in the variability of green fiscal multipliers is that of vehicle scrappage, or "cash-for-clunkers" programs. Although, theoretically, these initiatives might bring large economic returns on account of their propensity to mobilize private savings (52), the size of impact depends on how these private funds might otherwise have been used to purchase another, perhaps less expensive, vehicle, or any other good or service. Ex post analyses return mixed findings. Analysis of the US Car Allowance Rebate System program suggests high economic effectiveness,

wherein the probability of a household exchanging their old vehicle for a new one increased by a factor of four and the average spent on a new vehicle increased by US$320 (143). However, analysis of a German vehicle scrappage program identified high leakiness on the account of rapidly increased Czech automobile imports (144). Additionally, relevant for all cash-for-clunkers programs, Li & Wei (145) have demonstrated the inherent economic-climate trade-offs of vehicle scrappage programs, whereby rational consumers might purchase bigger and more luxurious vehicles than they otherwise would have. Such vehicles are often less fuel efficient.

Green policy archetypes: the menu of options available to policymakers for green spending (see **Table 1** for examples)

Apart from Batini et al. (71) and Hasna (142), quantitative studies do not attempt to compare the multiplier characteristics of green investments with traditional forms of spending. In response to COVID-19, Hepburn et al. (2) partially addressed this gap, using a survey of 231 participants from central banks, finance ministries, and academic institutions to indicatively categorize subjective perceptions of the relative long-run multipliers of 25 fiscal spending options. Green policies with comparatively high long-run perceived multipliers include clean energy infrastructure investment, clean R&D spending, and connectivity infrastructure.

One challenge to making robust progress on stimulatory green multipliers is that most studies (including those mentioned here) adopt at best a Bayesian approach with the assumption of constant parameters. By definition, however, an economic crisis brings significant and unanticipated shifts. In general, diffuse priors can distort outcomes, especially if outliers and shifts are not appropriately handled. A next step would be to derive results from other (non-Bayesian) modeling approaches that can handle distribution and parameter shifts (146, 147).

Despite useful initial works, there remain many gaps in the academic literature on green multipliers.

- First, all green policy archetypes identified in this review could benefit from further analysis, with particular consideration required for sustainable transport, natural capital investments, electric vehicles, energy efficiency programs, clean R&D, and green skill-building and retraining programs.
- Second, in the absence of long time-series data, which is often required for multiplier computation, unique methodologies in data collection and processing might be needed to reach empirical insights beyond Batini et al.'s (71). Artificial intelligence solutions could unlock particularly promising opportunities.
- Third, new (non-Bayesian) modeling approaches should be considered to appropriately tackle distributional and parameter shifts, which are inherent in times of economic crisis.
- Fourth, multiplier assessment terms need to be better defined and linked to other assessments of economic impact, for instance, labor market impact. To enable comparison across studies and national contexts, a consensus is needed on definitions for short- and long-term multipliers, as well as definitions for green policy archetypes.

5. CONCLUSION

The encouraging conclusion of this review is that although the field is nascent, the overall economic characteristics of green fiscal investment appear positive and are likely superior to dirty investment options. This is before essential cobenefits are considered, which range from improved health outcomes to reduced environmental degradation and a stabilized climate. The time to conduct higher quality research in this area is now—before levels of interest fall away and memories of the COVID-19 crisis fade. The results may not be needed for another decade, but when they are needed, they will be urgently needed.

In a sense, therefore, we hope that policymakers are not turning to the synthesis on green fiscal policy in this article for advice when subsequent crises hit. However, history suggests they may do

this, so we summarize the key recommendations for policymakers emerging from the literature at this stage:

- Green stimuluses can indeed be stimulating. The economic properties of recovery spending on the environment appear (on relatively weak evidence) to be relatively strong: Given that huge investments are required to achieve the world's climate and biodiversity goals, wise governments will seize the opportunity to progress two objectives with one intervention.
- Plan ahead; policy design is important. As with all recovery spending, the impact of green investment depends on the archetypes used, the national context, and specific design features. Among other factors, the financing, delivery mechanism, and target beneficiaries of a policy can significantly impact economic, social, and environmental returns. To get it right, policymakers must invest time in policy design—either by beginning as soon as a crisis hits or ideally preparing investment options in advance of a crisis. We prepare for rainy days with food banks and oil stockpiles—why not cache and refresh shovel-ready projects too?
- Invest in policy impact assessment. Policymakers often lack sufficient evidence to make the necessary design decisions for green investment. To build an evidence base to inform future decision making, policymakers should commit to policy impact assessments, with a portion of every fiscal investment reserved for ex post analysis. We did not learn sufficiently from GFC policy responses—we should not repeatedly make the same mistake.

Periods of economic crisis provide an opportunity for fiscal investment to reorient economic production and growth trajectories; the immense and growing risks of climate change require that this reorientation is toward green industries. It is imperative that we learn from the GFC and the COVID-19 pandemic so that during the next crisis we have a well-evidenced understanding of the benefits and trade-offs of green investments and can act to maximize shared prosperity.

SUMMARY POINTS

1. Green stimulus has a strong capacity to create jobs, to boost economic growth, and to do so in a timely manner.
2. Green investment for stimulus has grown with the resurgence of Keynesian narratives for public spending in economic recovery, seen in responses to the 2008–2009 Global Financial Crisis and the coronavirus disease 2019 (COVID-19) pandemic.
3. As of October 2021, green COVID-19 investment continues to lag behind spending in the Global Financial Crisis, despite a deeper recession and more advanced green technologies.
4. The research field of stimulatory green investment is nascent and contains many gaps. Gaps exist heterogeneously across archetypes, with greater existing coverage for energy efficiency and renewable energy policies; geographies, with greater existing coverage for Northern America and Europe; and methodologies.
5. Research critical of green stimulus policies focuses on the job creation aspects of green stimulus. It broadly fails to consider positive long-run spillovers and falling green technology costs.
6. Research patterns are unaligned to government spending patterns. Some poorly researched topics receive significant public investment, leaving policymakers to design policy without sufficient academic guidance.

7. In terms of methodology, for literature identification, we use a bespoke supervised machine learning algorithm based on the word2vec neural network model.
8. In terms of methodology, for literature synthesis, we use a structured qualitative review and several machine learning models, including Latent Dirichlet Allocation, t-Distributed Stochastic Neighbor Embedding, and collocation analysis.

FUTURE ISSUES

1. All green archetypes are understudied, with particularly low coverage of natural capital, green agriculture, sustainable transport, clean research and development (R&D), and green skill-building.
2. All fiscal recovery programs should designate funds to ex post impact assessment based on appropriate standards—these standards need to be designed and uniformly adopted.
3. A universal taxonomy for green investment archetypes should be used in ex post assessment and commentary. Recovery policy taxonomies need to be expanded.
4. Enhanced focus is needed for regions outside of Northern America and Western Europe.
5. Particular gaps for job creation should be addressed, including in induced job impacts, sufficiency and suitability of existing and future green skills, green business ecosystems capabilities and requirements, and appropriate absorptive capacity in R&D.
6. Particular gaps for timeliness should be addressed, including in quantitative analyses and trade-offs with other economic impacts.
7. Particular gaps for fiscal multipliers should be addressed, including in methods for acquiring adequate data, new (non-Bayesian) modeling approaches, and definitions of multiplier terminology.

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Will COVID-19 fiscal recovery packages accelerate or retard progress on climate change?

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4.1. Abstract

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4.2. Main paper

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Will COVID-19 fiscal recovery packages accelerate or retard progress on climate change?

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Abstract: The COVID-19 crisis is likely to have dramatic consequences for progress on climate change. Imminent fiscal recovery packages could entrench or partly displace the current fossil-fuel-intensive economic system. Here, we survey 231 central bank officials, finance ministry officials, and other economic experts from G20 countries on the relative performance of 25 major fiscal recovery archetypes across four dimensions: speed of implementation, economic multiplier, climate impact potential, and overall desirability. We identify five policies with high potential on both economic multiplier and climate impact metrics: clean physical infrastructure, building efficiency retrofits, investment in education and training, natural capital investment, and clean R&D. In lower- and middle-income countries (LMICs) rural support spending is of particular value while clean R&D is less important. These recommendations are contextualized through analysis of the short-run impacts of COVID-19 on greenhouse gas curtailment and plausible medium-run shifts in the habits and behaviours of humans and institutions.

Keywords: COVID-19, fiscal stimulus, climate change, green recovery

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I. Introduction

The COVID-19 crisis could mark a turning point in progress on climate change. This year, global greenhouse gas (GHG) emissions will fall by more than in any other year on record. The percentage declines likely in 2020, however, would need to be repeated, year after year, to reach net-zero emissions by 2050. Instead, emissions will rebound once mobility restrictions are lifted and economies recover, unless governments intervene. There are reasons to fear that we will leap from the COVID frying pan into the climate fire.

However, the crisis has also demonstrated that governments can intervene decisively once the scale of an emergency is clear and public support is present. COVID-19 has precipitated a major increase in the role of the state (Helm, 2020; Klenert *et al.*, 2020). Decisive intervention has begun to stabilize infection rates, prevent health systems being overwhelmed, and save lives.

The climate emergency is like the COVID-19 emergency, just in slow motion and much graver. Both involve market failures, externalities, international cooperation, complex science, questions of system resilience, political leadership, and action that hinges on public support. Decisive state interventions are also required to stabilize the climate, by tipping energy and industrial systems towards newer, cleaner, and ultimately cheaper modes of production that become impossible to outcompete (Acemoglu *et al.*, 2012; Grubb, 2014; Aghion *et al.*, 2014; Farmer *et al.*, 2019; Mealy and Teytelboym, 2020).

Will such action be forthcoming? Public support for action on climate change increased to a peak prior to the pandemic; government and corporate action was also gathering momentum. COVID-19 has clearly slowed this momentum, not least in delaying the international conference on climate (COP26) from 2020 to 2021. However, the momentum could find new strength if, humbled by the ability of 'natural' forces to shock the global economy, humans recalibrate our sense of omnipotence. Furthermore, opinion polls in many countries show that people are noticing the clean air, uncongested roads, the return of birdsong and wildlife, and are asking whether 'normal' was good enough; could we not 'build back better' (Ipsos, 2020)? The shape of COVID-19 fiscal recovery packages put in place in the coming months, once lockdowns are eased, will have a significant impact on whether globally agreed climate goals are met.

This paper identifies stimulus policies that are perceived to deliver large economic multipliers, reasonably quickly, and shift our emissions trajectory towards net zero. The recovery packages can either kill these two birds with one stone—setting the global

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economy on a pathway towards net-zero emissions—or lock us into a fossil system from which it will be nearly impossible to escape.[1]

In section II, we examine the recent effects of COVID-19 on emissions. In section III, we catalogue over 700 stimulus policies proposed or enacted during and since the Global Financial Crisis (GFC) and develop a set of 25 policy archetypes. We conduct a global survey of over 230 experts, including from financial ministries and central banks, to subjectively assess the economic and climate impact potential of these archetypes. We establish that respondents consider it feasible for policy action to stimulate economic activity and make progress towards net-zero emissions. In section IV, we briefly consider the broader impacts of COVID-19 on trends in individual and corporate behaviour, including towards less travel and more working from home, increased localization and self-sufficiency, and institutional trends towards scepticism of multilateralism and coordinated global action. We conclude that progress on climate change will depend significantly on policy choices in the coming 6 months; the right choices could drive a long-term downward trend in GHG emissions.

II. Early days: the economic slowdown and fiscal relief measures

(i) Decline in economic activity

All G20 nations have implemented restrictions on mobility (IMF, *2020a*) such as 'self-isolation' and 'social-distancing' (Wilder-Smith and Freedman, 2020). These restrictions have reduced the spread of the virus (Hou *et al.*, 2020; Koo *et al.*, 2020), but with severe economic consequences. On the supply side, an estimated 81 per cent of the global workforce has been hit by full or partial lockdown measures (del Rio-Chanona *et al.*, 2020; ILO, 2020), with unprecedented job losses and furloughs (ILO, 2020). On the demand side, consumer spending has fallen as it is no longer possible to travel, including to shop for discretionary items, go to restaurants, or to engage in experience-based activities (Chen *et al.*, 2020; Muellbauer 2020; Andersen *et al.*, 2020). Aviation volumes have collapsed, with international airlines projecting a reduction of 503–607m passengers and losses of US$112–135 billion in the first half of 2020 (UNICAO, 2020).

[1] Sustainable recovery packages from governments are *necessary* to address climate change. Without a sustainable recovery, emissions will rise, the private sector will not invest enough in clean technology in a depressed economy, and the Paris goals will be nearly impossible to meet. Given the scale of recovery packages, a sustainable recovery could also be nearly *sufficient* to address climate change. Once the macroeconomy has recovered and once the costs of clean technologies are low enough, the private sector would need limited further encouragement, although it is likely that government intervention will also be required to remove greenhouse gases from the atmosphere (Hepburn *et al.*, 2019). This blending of macroeconomic and microeconomic considerations is atypical of the approach to public economics involving a sequential focus on (i) stabilization of national income; (ii) economic efficiency; and (iii) fair distribution (Musgrave, 1959)—get the macro right before worrying about micro issues such as carbon prices. However, the macro and micro are inescapably interlinked here, due to the scale and timing of the climate challenge and the pandemic. We are grateful to David Vines for these observations.

Consumer confidence is falling (OECD, 2020) and job losses and furloughs simply exacerbate spending contractions as workers lose their incomes.

(ii) Decline in fossil fuel use and GHG emissions

These dramatic declines in economic activity have reduced energy demand and the use of fossil fuels, which supply 85 per cent of our energy demands (BP, 2019). The collapse in oil demand has exacerbated market imbalances (Oxford Analytica, 2020*a*; Oxford Analytica, 2020*b*), and contributed to Brent crude prices dipping to their lowest level in over two decades.[2]

The fall in fossil fuel use has reduced pollution of various kinds, including GHGs such as carbon dioxide (CO_2) and nitrous oxide (N_2O), as well as aerosols, short-lived gases (Jacobson, 2010; Myhre *et al.*, 2013), and harmful particulate matter. While it is currently impossible to accurately detect CO_2 emissions in the short term at a regional scale (Artuso *et al.*, 2009; Yang *et al.*, 2019), estimates can be pieced together using data on fuel use, and measurements of nitrogen dioxide (NO_2) concentrations (Konovalov *et al.*, 2016), which is emitted alongside CO_2 in industrial and automotive combustion.[3] For instance, it has been estimated that China's shutdown in February resulted in a 25 per cent decline in CO_2 emissions (200 $MtCO_2$) due to lower coal and oil consumption (Myllyvirta, 2020).

Globally, GHG emissions might fall by 8 per cent or 2.6 $GtCO_2$ in 2020 (IEA, 2020*a*), which is more in absolute terms than in any other year on record (Boden *et al.*, 2017; Le Quéré *et al.*, 2018). By comparison, annual CO_2 emissions fell by an average of 4 per cent during the Second World War (1939–45), 3 per cent during the 1991–92 recession, 1 per cent during the 1980–81 energy crisis, and 1 per cent during the 2009 Global Financial Crisis (Boden *et al.*, 2017). The declines in 2020 are significant relative to major historical wars and epidemics (Pongratz *et al.*, 2011; Boden *et al.*, 2017).

This decline in GHG emissions has been advanced as a 'silver lining' of the COVID-19 crisis (Bandyopadhyay, 2020; Isaifan, 2020; Teale, 2020), but the UN Environment Programme estimates that global GHG emissions must fall by 7.6 per cent *every year* from 2020 to 2030 to keep temperature increases to less than 1.5°C (UNEP, 2019). Further, every year that GHG emissions are above zero, atmospheric GHG concentrations continue to build, increasing the risk that even incremental increases could trigger feedback loops that result in outsized and permanent damage to the climate (Farmer *et al.*, 2019).

Without decisive government intervention, discussed in the next section, emissions will rebound once the lockdowns end.[4] However, the magnitude of the rebound will

[2] Demand for electricity (which is supplied by higher proportions of renewable energy) has been less affected than demand for transportation, which is predominantly supplied by liquid fossil fuels (IRU, 2020).

[3] While NO_2 is not itself a GHG, it also contributes to the formation of the potent GHG, ozone, in the atmosphere (Lerdau *et al.*, 2000; Ghazali *et al.*, 2009). As NO_2 has a short atmospheric lifespan (NOAA, 2020), it is a useful and measurable descriptor for period-specific economic activity (Cui *et al.*, 2019), for example in illustrating changes over the COVID-19 period at a local and regional scale (Worden *et al.*, 2020; EPA, 2020).

[4] Reductions in GHG emissions during other economic crises have been transitory. Global CO_2 emissions fell by 1 per cent during the GFC in 2009, but grew by 4.5 per cent in 2010, above the 5-year average increase of 2.4 per cent (Boden *et al.*, 2017). This rebound was attributable to high levels of government investment in fossil fuel dependent economic activities in order to stimulate domestic economies, coupled with low energy prices (Peters *et al.*, 2012).

depend on the speed of the economic recovery, the nature of rescue spending (keeping businesses and people alive) and recovery spending (reinvigorating the economy once mobility restrictions can be relaxed), the extent of a rebound in consumer demand, and the prescience of certain human and institutional trends discussed in section IV. Conceivably, in the event of a rapid rebound, pent-up demand could even bring a short-term increase in GHG emissions above the long-term average. A rebound in emissions can already be seen in China, where mobility restrictions are being relaxed and factories are reopening.

More important than the short-run impact on emissions are the impacts on investment in clean technologies such as renewable energy. Falling energy demand means sharp reductions in the growth of installed wind, solar, and battery capacity in 2020, with effects lingering into 2021; solar photovoltaic installations in particular are projected to fall by 48 per cent in Q2 2020, followed by a gradual recovery (Eckhouse and Martin, 2020). These challenges are further compounded by disruptions to global supply chains for key parts, as well as the collapse in oil prices (IEA, 2020*b*), which increases the allure of fossil-fuel-based consumption in the economic recovery phase, particularly in emerging economies (Fox-Penner, 2020).

(iii) The climate impact of existing rescue packages

Many G20 national governments have already proposed and/or implemented sizeable fiscal rescue measures. These emergency measures are hoped to protect balance sheets, reduce bankruptcies and address immediate human welfare concerns during lockdown periods, including through curtailing the spread of the virus and addressing incremental healthcare costs. In April 2020, all G20 nations (including most EU member states), had signed such fiscal measures into law, earmarking a total of over US$7.3 trillion in spending. We identified over 300 implemented policies of significant magnitude, detailed in full in the Supplementary Materials. Distinguishing between rescue and recovery measures (see section III) we find that the vast majority of these policies are of the rescue typology, including significant worker and business compensation schemes which defend livelihoods. Our subjective assessment is that 4 per cent of policies are 'green', with potential to reduce long-run GHG emissions, 4 per cent are 'brown' and likely to increase net GHG emissions beyond the base case, and 92 per cent are 'colourless', meaning that they maintain the *status quo*.

The priority of the rescue packages has naturally been to increase cash flows to individuals in financial distress and to support those who need to spend on food, shelter, health, electricity, and other basic goods. Multiple nations have already implemented policies hoped to have this effect. For instance, the 2020 United States *CARES Act*, signed into law on 27 March 2020, includes relief provisions to directly support citizens through cash-in-hand programmes (Courtney, 2020). Other countries have implemented schemes to similar effect. The UK's *Coronavirus Job Retention Scheme* (UK Coronavirus Act, 2020) allows firms to apply for government assistance to cover up to 80 per cent of furloughed workers' wages, capped at £2,500 monthly.

However, some rescue policies also cover emissions-intensive firms, such as airlines, that face bankruptcy or significantly reduced revenue as a result of COVID-19. Examples include Russian tax breaks for airlines (through the *Anti-crisis Fund*)

(Ostapets *et al.*, 2020), AU$715m of unconditional Australian airline relief (through the *Coronavirus Economic Response Package* (Commonwealth of Australia, 2020), and US$32 billion of bailouts (including grants and loans) for US airlines (through the *CARES Act*) (Courtney, 2020). Fossil fuel industries, facing extraordinarily low oil prices (Ngai *et al.*, 2020), are likely to request future tax breaks or bailouts. While there may be good reasons for such support, such bailouts should be conditional on these industries developing a measurable plan of action to transition towards a net-zero emissions future.

Overall, although COVID-19 has reduced GHG emissions in 2020, the overall impact will be driven by investment choices. The emergency rescue packages that are currently being implemented represent life and death decisions made by government officials about people alive today. The imminent recovery packages, soon to be designed and implemented, will reshape the economy for the longer-term, representing life and death decisions about future generations, including through their impact on the climate.

III. The climate impact of fiscal recovery packages

While most G20 governments have implemented rescue packages, as of April 2020 no government has fully exited lockdown and introduced significant recovery packages. These recovery packages could be 'brown', reinforcing the links between economic growth and fossil fuels and risking future stranded assets (Pfeiffer *et al.*, 2018), or 'green', decoupling emissions from economic activity.

Several factors are relevant to the design of economic recovery packages: the long-run economic multiplier, contributions to the productive asset base and national wealth, speed of implementation, affordability, simplicity, impact on inequality, and various political considerations. A key objective of any recovery package is to stabilize expectations, restore confidence, and to channel surplus desired saving into productive investment. However, 'business as usual' implies temperature increases over 3°C, implying great future uncertainty, instability, and climate damages. An alternative way to restore confidence is to steer investment towards a productive and balanced portfolio of sustainable physical capital, human capital, social capital, intangible capital, and natural capital assets (Zenghelis *et al*, 2020), consistent with global goals on climate change. Finally, any recovery package, including climate-friendly recovery, is unlikely to be implemented unless it also addresses existing societal and political concerns—such as poverty alleviation, inequality, and social inclusion—which vary from country to country.

(i) Assessing economic and climate impact potential

Studies of fiscal responses during the GFC suggest that the economic success of fiscal stimulus is strongly affected by two attributes: the speed at which the stimulus delivers real-world impact; and the short- and long-run economic multiplier, or return for every dollar of expenditure (Freedman *et al.*, 2009; Coenen *et al.*, 2012; Ramey, 2019). Compared to the GFC, the COVID-19 crisis has had a severe and broad impact; it is not focused on a particular sector (as distinct from 1973–5, 1981–2, 2001, and 2008–9). The rescue packages have had to be rapidly acting. Given the sudden need, limitations

on administrative capacities have affected the design of programmes and have been a binding constraint. Speed is important but less critical for the recovery packages, where there is greater scope for carefully directing resources towards investments in high productivity assets, with higher economic multipliers, to deliver a capital stock and a labour force suited to the challenges of the future (Hepburn *et al.*, 2020).

What determines the long-run multiplier? High-productivity economies of the future will be those that make the most of artificial intelligence and the technologies of the fourth industrial revolution (Schwab and Davis, 2018) while also protecting and enhancing natural capital, such as ecosystems, biodiverse habitats, clean air and water, productive soils, and a stable climate. Here, we focus on the climate impact. Co-benefits of climate policies (Karlsson *et al.*, 2020) often include reduced waste and inefficiency, pollution (Dong *et al.*, 2015; Bollen, 2015), congestion (Portugal-Pereira *et al.*, 2013), and food waste (Munesue *et al.*, 2015), and improved health outcomes (Chivian and Bernstein, 2008; Andersen, 2017; Quam *et al.*, 2017), biodiversity (Bryan *et al.*, 2016; Wüstemann *et al.*, 2017), and ecosystem sustainability (Palm *et al.*, 2014); these are vitally important but not the focus of this paper.

(ii) Lessons from previous crises

The COVID-19 crisis is different from the 2009 GFC, but there is nevertheless much to learn. Economic multipliers are near zero when the economy operates near capacity. In contrast, during crises such as the GFC, economic multipliers can be high. Uncertainty, reluctance to invest for the future, and concern about the affordability of spending prompts economic actors to take economically undesirable measures. Businesses may cut investment and shed workers, banks may rein in credit, and consumers may contain spending. Lack of confidence can thereby prove self-fulfilling in delivering a weaker economy through Keynesian 'multiplier' and 'accelerator' effects.

Expansionary policy in a slump can arrest the negative reinforcing feedback resulting from a shortfall in private activity and prevent negative hysteresis effects on future supply, whereby capital is scrapped and labour skills are lost due to underutilization (DeLong and Summers, 2012). Fiscal injections during such slowdowns have been found to generate multipliers as high as 1.5–2 (Auerbach and Gorodnichenko, 2012) or even as high as 2.5 (Blanchard and Leigh, 2013). Three models for the UK, applying estimates only to fiscal injections based on additional borrowing, find that the long-run multiplier lies in a narrow range of 2.5 to 3.0 (IMF, 2014; Abiad *et al.*, 2015; Mourougane *et al.*, 2016). In this case, depending on the nation and the sector, increased tax revenues can go a long way to financing any increases in expenditure.

Within the set of expansionary policies, government spending on investment appears preferable to tax reductions, delivering higher multipliers (Mahfouz *et al.*, 2002). Direct cash transfers to households have also performed well (Gechert and Rannenberg, 2018). So far, financial systems have remained functional and low real interest rates provide the opportunity for targeted investment in productive assets to deliver higher short- and long-run economic multipliers (Freedman *et al.*, 2009).

Of course, no crisis is the same. There are at least four reasons that COVID-19 spending might have smaller multipliers. First, if the uncertainty in the current crisis is deeper than in previous crises, individuals and firms could engage in more precautionary

behaviour, hoarding cash. Second, if fear of COVID-19 means that people choose not to engage in travel and social activities, efforts to stimulate economic activity will be less effective. Third, it may be difficult to target government injections to where there is a high marginal propensity to spend. Fourth, the impact on expectations may be shaped more by emerging health risks than by financial responses (Stiglitz, 2020).

Nevertheless, it is likely that there are lessons to heed from the past, including with respect to the impact of such measures on the climate. We therefore undertook a light-touch assessment of 196 stimulatory fiscal recovery policies implemented in response to the GFC, finding that 63 were green, 117 were colourless, and 16 brown. A lesson from the GFC is that green stimulus policies often have advantages over traditional fiscal stimulus. For instance, renewable energy investment is attractive in both the short and the long run. Renewable energy generates more jobs in the short run (higher jobs multiplier), when jobs are scarce in the middle of a recession, which boosts spending and increases short-run GDP multipliers (which are derived from expanding demand). In the long run, renewable energy conveniently requires less labour for operation and maintenance (Blyth *et al.*, 2014). This frees up labour as the economy returns to capacity. The more efficient use of labour and the savings on fuel means that renewables are also able to offer higher long-run multipliers (which are derived from expanding supply).

Green construction projects, such as insulation retrofits or clean energy infrastructure, can similarly deliver higher multipliers. These large construction projects are less susceptible to offshoring to imports (Jacobs, 2012). Clean energy infrastructure is also helpfully very labour intensive in the early stages—one model suggests that every $1m in spending generates 7.49 full-time jobs in renewables infrastructure, 7.72 in energy efficiency, but only 2.65 in fossil fuels (Garrett-Peltier, 2017). In the long run, these public investments offer high returns by driving down costs of the clean energy transition (Henbest, 2020). Harnessing more of these opportunities could result in 'kick starting the green innovation machine' (Acemoglu *et al.*, 2012) and driving an efficient, innovative, and productive economy, with higher spillovers that benefit the wider economy (Aghion *et al.*, 2014) and higher 'green complexity' (Mealy and Teytelboym, 2020).

Speed of implementation is critical for the rescue packages but also valuable for the longer-term recovery packages. Fast-acting climate-friendly policies include residential and commercial energy efficiency retrofits, as well as natural capital spending (afforestation, expanding parkland, enhancing rural ecosystems) (Bowen *et al.*, 2009; Houser *et al.*, 2009). When implemented through existing programmes (Houser *et al.*, 2009), energy efficiency retrofits can be the 'most obvious option for a shovel-ready, local green investment' (Kamal-Chaoui and Robert, 2009). Natural capital spending is fast-acting because worker training requirements are low, many projects have minimal planning and procurement requirements, and most facets of the work meet social distancing norms. Through their nationally determined contributions (NDCs), many countries have already prepared 'shovel-ready' projects, and in most lower- and middle-income countries (LMICs) these NDCs are heavily oriented towards infrastructure.

Investment could also be used for development and early-stage demonstration of key technologies that appear necessary to reach net-zero emissions. Greenhouse gas removal (GGR) technologies, including land-based biological processes and industrial carbon capture and storage (CCS), are one example. GGR technologies are necessary to meet the Paris goals, but barriers exist, and costs remain uncertain; more research, development, and deployment could be extremely beneficial (Hepburn *et al.*, 2019).

(iii) Global survey of fiscal recovery policies

In April 2020, we surveyed 231 finance ministry officials, central bank officials, and other economists, representing 53 countries including all G20 nations, to ascertain their perspectives on COVID-19 fiscal recovery packages. These perspectives are relevant to policy design. A set of 25 policy archetypes—6 rescue-type policies (A, C, D, I, K, O) and 19 recovery-type policies (Figure 1, details in Appendix 2)—were defined, following a wide cataloguing effort of over 700 significant G20 fiscal stimulus policies proposed or implemented over the period 2008–20. Respondents were systematically identified using a filtering procedure with associated methodology described in Appendix 3. Our 'target group' comprised senior central bank officials (226 contactable officials identified, 43 respondents), senior development bank officials (301 contactable officials identified, 41 respondents), senior members of finance/treasury ministries (147 officials identified, 23 respondents), expert academics (217 experts identified, 71 respondents), and think-tank commentators (128 experts identified, 21 respondents).

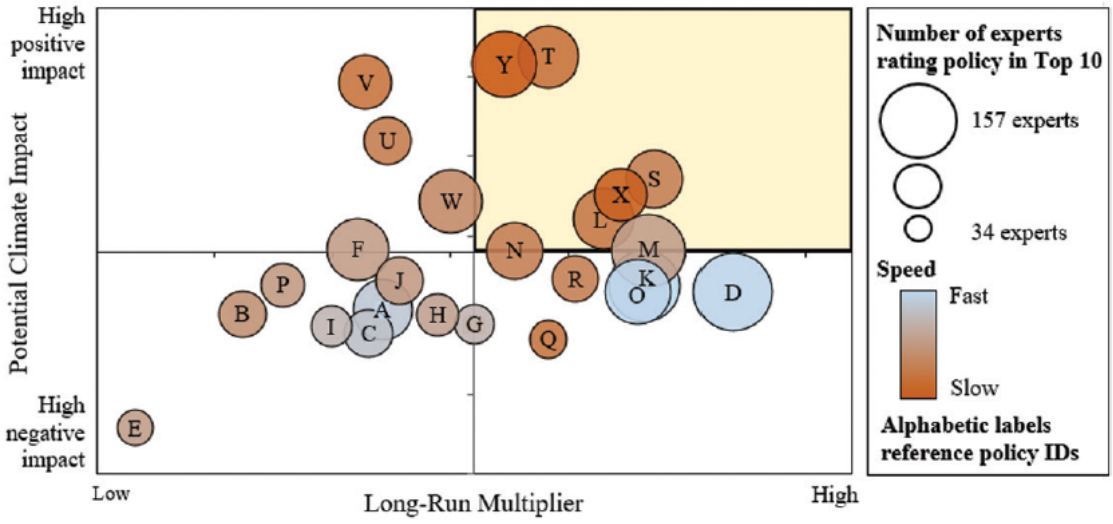
Respondents were asked to assess, in a relative and subjective manner using sliding responses, each policy archetype on three core metrics; 'speed of implementation' from the time of legislation (scaled from less than a month to more than 3 years), 'long-run economic multiplier' (low to high), and 'climate impact potential' (highly negative to highly positive). A fourth summative metric, 'overall desirability' (strongly opposed to strongly support) was also tested to account for relevant social, political, and personal factors not addressed by the climate and economic metrics. Respondents provided demographic data (6 questions) including country of focus, experience level, and educational training. Respondents were also encouraged to provide any additional comments in a free response question and had the option to leave their name for publication (see Appendix 1). In this way, each respondent answered 106–108 questions, giving a total of 24,703 data points for the survey. Each 'target group' expert received a controlled individual link for personal response as well as an unrestricted link for sharing with colleagues. Unrestricted respondents formed the 'supplementary group'. Details on sampling groups and survey design are included in Appendix 4.

Policies perceived to be in the desirable upper-right quadrant of Figure 1 (large long-run multiplier and strongly positive impact on climate) included connectivity infrastructure (S), general R&D spending (X), education investment (L), clean energy infrastructure (T), and clean energy R&D spending (Y). Each of these was also often identified as being in the top 10 desired recovery policies of respondents. Other notable policy options included healthcare investment (M) and worker retraining (N). Two archetypes scored highly on potential climate impact but were not recognized for high multiplier or speed of implementation: green spaces and natural infrastructure (V), and energy efficient buildings upgrades including retrofits (U).[5]

Many traditional 'relief type' measures, clumped to the centre right of the figure, including liquidity support for households, start-ups, and SMEs (D), direct provision of basic needs (K), and targeted direct cash transfers (O), predictably out-performed others in terms of speed of implementation and ranked among the highest for long-run multiplier. Non-conditional airline bailouts (E) recorded a markedly poor performance on all metrics and featured in fewer experts' top 10s than any other policy.

[5] We found this perception surprising: policies U and V have low worker training requirements and are potentially able to be rapidly deployed.

Figure 1: Target group mean survey results aggregated using relativity-adjusted scores



A	Temporary waiver of interest payments	N	Worker retraining
B	Assisted bankruptcy (super Chapter 11)	O	Targeted direct cash transfers or temporary wage increases
C	Liquidity support for large corporations	P	Rural support policies
D	Liquidity support for households, start-ups and SME's	Q	Traditional transport infrastructure investment
E	Airline bailouts	R	Project-based local infrastructure grants
F	Not for profits, education, research, health inst. bailouts	S	Connectivity infrastructure investment
G	Reduction in VAT and other goods and services taxes	T	Clean energy infrastructure investment
H	Income tax cuts	U	Buildings upgrades (energy efficiency)
I	Business tax deferrals	V	Green spaces and natural infrastructure investment
J	Business tax relief for strategic and structural adj.	W	Disaster preparedness, capacity building
K	Direct provision of basic needs	X	General R&D spending
L	Education investment	Y	Clean R&D spending
M	Healthcare investment		

The clean R&D archetype, when directly compared to general R&D, was perceived to be significantly more desirable overall, and to have greater positive climate impact potential. However, it received a lower ranking for both speed (25th vs 20th) and multiplier (12th vs 6th), suggesting target group respondents placed a relatively strong weighting on the importance of climate impact.

In the target group, the most desirable recovery-type policies (ordered by mean, starting with the best policy) were healthcare investment (M), disaster preparedness (W), clean R&D spending (Y), not for profit bailouts (F), and clean energy infrastructure investment (T). The worst-performing policies (ordered by mean, starting with the worst policy) were airline bailouts (E), traditional transport infrastructure (Q), income tax cuts (H), reduction in VAT and other goods and services taxes (G), and rural support policies (P).

Figure 2 illustrates notable response variation between sampling groups. After think tanks, finance and treasury ministry officials had the highest overall variation in responses from the target group mean (see Appendix 7). Finance officials reported comparatively low overall desirability for reduction in VAT (G), direct cash transfers (O) and direct provision of basic human needs (K). On climate, officials perceived that the negative climate impacts of unconditional airline bailouts (E) were not as severe as what others reported. Officials also indicated that the multiplier of business tax relief for strategic and structural adjustments (J) was much higher than the indications of other groups, while the speed of implementation of assisted bankruptcy (B) and VAT

reductions (G) were much lower. On an overall basis, opinion on the climate impact potential of policies across all groups was the least controversial (lowest variation) while speed of implementation was the most controversial (highest variation).

Under the hypothesis that national wealth influences optimal fiscal response strategy, all survey responses were categorically sorted into higher-income countries (HICs) (N = 168) and lower- and middle- income countries (LMICs) (N = 63) under the most recent OECD (2017) definition. As shown in Figure 2, variation in mean responses was sizeable, suggesting that local economic context is a significant driver of policy appropriateness. The greatest variations between HIC and LMIC expert opinion, those of 8 points or higher on the relativity-adjusted 100-point scale (see Appendix 7), were in rankings of overall desirability of targeted rural support policies (P: 13 point difference, LMICs higher than HICs) and clean R&D spending (Y: 8 point difference, HICs higher than LMICs). These policies manifest differently in LMICs to HICs. While rural support policy in a HIC may involve agricultural subsidies to support existing enterprise, in a LMIC it may involve direct creation of jobs through state-owned enterprises. While HIC clean R&D spending can represent investment to becoming a global leader in high-margin future industries, due to a deficit in local highly skilled labour, analogous LMIC spending is unlikely to bring the same multiplier.

Our results suggest that, in many cases, experts think that climate-positive policies also offer superior economic characteristics. However, there is the potential that these results are driven by participation and/or response bias related to any number of background factors. For instance, climate change beliefs of respondents could have influenced their responses to economic metrics in either direction. The survey was not framed as focused on climate change and the survey question on climate impact potential came after the questions on economic impact. However, the invitation for the survey was sent by the authors, who have a public track record of research on climate economics. We acknowledge the potential role of bias in our results and suggest that readers interpret them as uncorrected, subjective and relative perspectives.

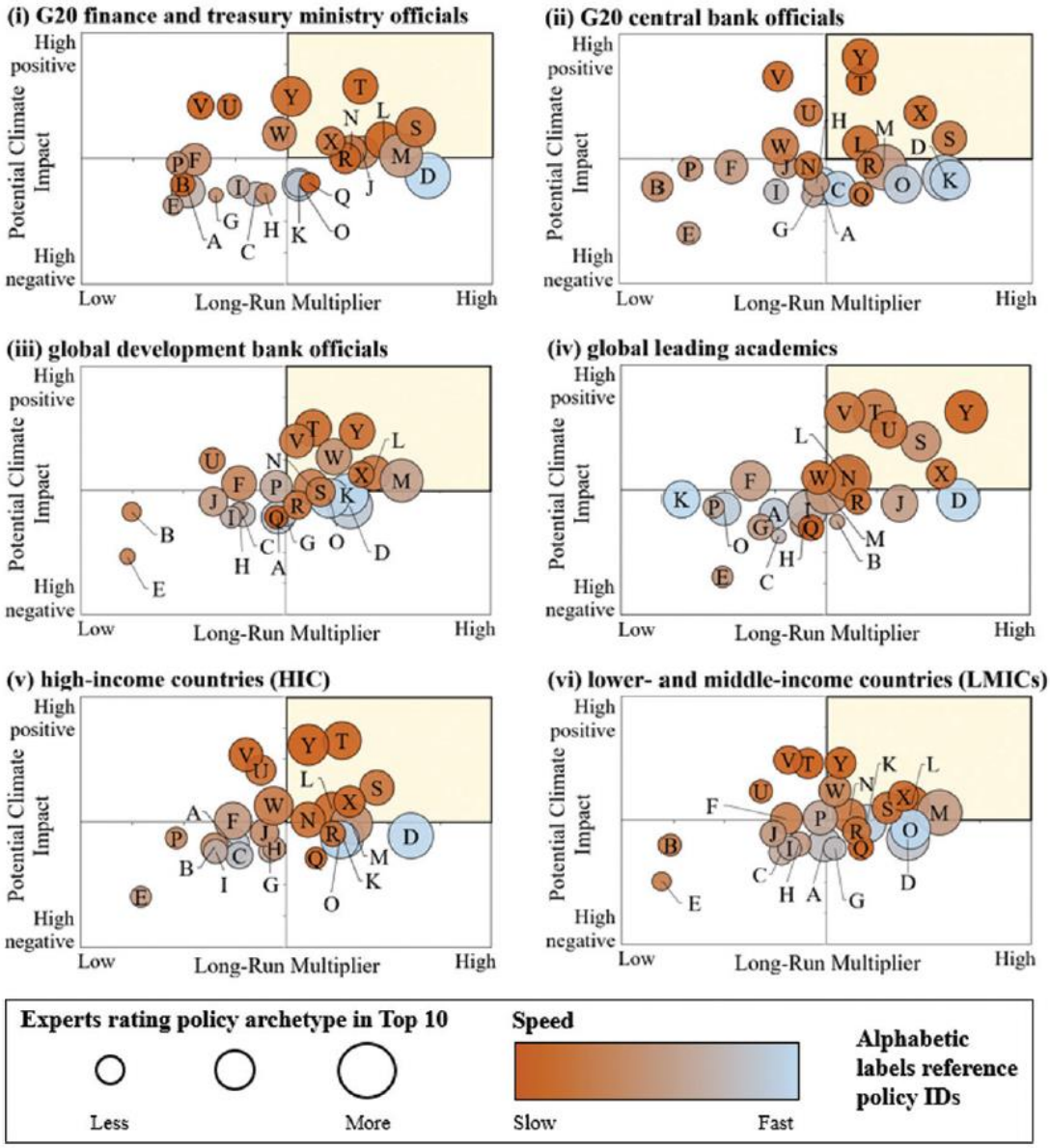
(iv) Guidelines for policy-makers

Based on our review of the literature, the survey results, and our own judgement, we suggest the following three key insights for policy-makers designing COVID-19 recovery packages.

1. **Recovery policies can deliver both economic and climate goals.** Following the 'colourless' emergency rescue packages, there are a set of fiscal recovery policy types which offer high economic multipliers and positive climate impact. Combining survey responses with evidence from the literature, five policy types stand apart from the rest:

   — clean physical infrastructure investment in the form of renewable energy assets, storage (including hydrogen), grid modernization, and CCS technology,
   — building efficiency spending for renovations and retrofits including improved insulation, heating, and domestic energy storage systems,
   — investment in education and training to address immediate unemployment from COVID-19 and structural shifts from decarbonization,

Figure 2: Mean policy response characteristics by sampling group (i to iv) and wealth of focus economy (v to vi)



— natural capital investment for ecosystem resilience and regeneration including restoration of carbon-rich habitats and climate-friendly agriculture, and
— clean R&D spending.

In many LMICs, clean R&D spending might be replaced with:

— rural support scheme spending, particularly that associated with sustainable agriculture, ecosystem regeneration, or accelerating clean energy installations.

While political and other circumstances related to the national interest may render some climate-negative policies unavoidable, even these policies can be designed to have long-term positive climate outcomes by attaching appropriate

conditions. For instance, conditional green bailouts for airlines could require achievement of net-zero emissions by 2050 with intermediate targets set at 5- or 10-year intervals (O'Callaghan and Hepburn, 2020). If airlines are unable to meet these targets, bailout funding could be converted to equity at today's very low stock market spot prices.

Finally, different countries have different starting points and national priorities. Mealy and Teytelboym (2020) show that it is possible to identify 'nearby' opportunity for expanding the green industrial base; policy-makers could use this framework to target stimulus towards industries adjacent to the newer clean industries of the future.

2. **Co-benefits can be captured.** As indicated by the survey results, there are non-economic, non-climate attributes of climate-positive policies which increase their overall desirability. For instance, electric vehicle incentives reduce local air pollution, which is especially valuable in dense urban areas. Support for energy efficiency retrofits could be directed towards lower-income households to decrease social and health inequality by shrinking real electricity costs and keeping homes warm in winter. In LMICs, new renewable energy can be used to increase rural electrification and provide support to citizens working to escape the poverty trap (Aklin *et al.*, 2018).

Policy-makers must proactively act to identify potential co-benefits during the policy design stage and shape implementation criteria to maximize impact. As national priorities and urgent social needs can differ manifestly between countries, the prioritization of relevant co-benefits is also likely to differ. Governments can shape policy to best meet the needs of their constituency.

3. **Policy design is important.** Poorly designed recovery policy is likely to be ineffective in delivering economic, climate, and social outcomes, regardless of theoretical potential. During the GFC, many governments needlessly wasted the opportunity for significant long-run economic benefits and climate impact.

Policy timeliness and flexibility will be important characteristics, since it is unclear how long the pandemic will last and whether there will be second or third waves. It also remains unclear whether the current recession will progress to a deeper depression with possible default cascades (Stiglitz, 2020).

Extreme urgency was appropriate in introducing rescue packages during the lockdown phase. There is probably more time to ensure that the recovery packages prioritize the types of investments that deliver productive assets for the future. This will be significantly more likely if policy design processes are fast but also consultative and evidence-based. Success will depend upon the specific social, political, environmental, and financial contexts of actors.

Finally, domestic climate-positive policy development should involve collaboration with and learning from the international community. A Sustainable Recovery Alliance, proposed in a UK government briefing prepared alongside this research paper (Allan *et al.*, 2020), could provide a forum for nations to avoid a race to the bottom, to learn from one another, and to coordinate their recovery packages for greater impact.

(v) Financial factors constraining and enabling government expenditure

The affordability of these potential interventions varies across countries. Government balance sheets and current financial conditions may limit significant expansionary policy in some LMICs. An internationally coordinated response with support from the IMF might address this (Cleevely *et al.*, 2020), or judicious and stronger use of unconventional monetary policy and other non-fiscal policies might be used to steer expectations and help restore confidence.

Concerns about repaying growing local currency public debt and limited 'fiscal space', though understandable, are overplayed in HICs, notwithstanding rapid increases in government borrowing following the pandemic. Real government bond rates in rich countries are near zero or negative, reflecting limited concerns at present about devaluation or default. The US Federal Reserve maintains a policy rate of 0 per cent (Federal Reserve, 2020), while the Bank of England maintains a rate of 0.1 per cent (Bank of England, 2020), and other central banks maintain similarly low rates.

Concerns about total global debt are also frequently raised. According to Tiftik *et al.* (2020), the ratio of global debt to GDP reached an all-time high of 322 per cent towards the end of 2019. More than two-thirds of the debt is in private hands, and dramatic declines in equity valuations and asset values has hit corporate balance sheets, increasing leverage ratios.

However, financial assets are not net wealth, and total global debt is only relevant in that it reflects underlying challenges, such as growing inequality, or in that it creates vulnerabilities from systemic financial interlinkages between entities. For every debtor there is a creditor, and what matters is whether borrowing is used to invest in sustainably productive assets. With rates low and the prospect that borrowing will boost nominal GDP with multipliers greater than one, the cost of servicing debt induced from a large fiscal stimulus is low and, in most cases, sustainable.

Nevertheless, avoiding a downward economic spiral will require careful management (Stiglitz, 2020). The global stock of non-financial corporate debt was at record levels of $74 trillion in Q3 2019 (Tiftik *et al.*, 2020). The quality of corporate bonds is also lower (OECD, 2020)—credit ratings are lower and maturities are longer—so the possibility of contagion to the banking system cannot be discounted. The UK Office for Budget Responsibility estimates that if lockdown remains in place for 3 months, UK output would plunge an unprecedented 35 per cent in 2020 Q2 (OBR, 2020). J. P. Morgan forecasts that the US economy will shrink by 9 per cent in the second quarter, relative to the previous quarter, on top of a 1.2 per cent contraction in the first quarter (Domm, 2020). In April, the IMF predicted that advanced economies' GDP will be 6.1 per cent lower than otherwise in 2021, even after a sharp recovery (IMF, 2020*a*). Such a recovery is far from guaranteed without efforts to restore private-sector confidence.

Recovery packages could exacerbate intergenerational inequities if they are focused on consumption, rather than productive investment delivering sustainable returns for future generations. Public borrowing for the recovery will necessarily be matched by corresponding private-sector net financial surpluses, implying greater claims on future taxpayers will be made by the private sector. The real value of the debt might also be eroded by inflation—if recovery plans do generate growth, inflation may well rise. Sensible responses would include progressive environmental and carbon taxes, in addition to conventional tightening monetary policy.

IV. Social and institutional shifts

COVID-19 has already triggered major shifts in individual behaviours, social practices, beliefs, the role of the government in the economy, and relationships between nations and international institutions. These shifts have occurred on remarkably rapid timescales. Which of these changes will have lasting consequences, and what are the climate implications?

(i) Behavioural change in work and transport practices

The COVID-19 crisis has encouraged a rapid shift to digital and remote working practices in many countries (WHO, 2020), and reduced aviation (UNICAO, 2020) and car transportation (IMF, 2020*b*). These 'adaptive behaviours' are common to large-scale disasters (Cohen, 2020). There has been rapid learning of how to manage remote work, improvements in technology, and an appreciation of some of the benefits.

As economies reopen, in some instances one may expect return to pre-crisis normal, but in others behaviour will change permanently. One (inevitably speculative) estimate is that up to one-third of the global workforce will sustain remote working practices part-time on a permanent basis (Global Workplace Analytics, 2020). Even the aviation industry anticipates a permanent shift in the nature of travel, with business travel projected to be permanently suppressed (Sorensen, 2020; Boone *et al.*, 2020) and with flight volumes that return to pre-crisis levels at a slower rate than in other recent pandemics (IATA, 2020).

The extent to which behavioural adaptations become embedded post-crisis is affected by policy choices during the recovery period, as well as the extent and severity of lockdown measures. Behavioural interventions have historically been more effective during times of transition (Geels, 2002; Reeves *et al.*, 2020). Post-crisis recovery spending offers an opportunity to embed climate-positive behaviours, by supporting teleworking, high-speed broadband connectivity, and residential energy efficiency.

(ii) Shifting dynamics of global institutions and leadership

COVID-19 has disrupted the global political and economic order, with potential long-term implications for multilateral institutions. The rapid spread of the virus has also led to calls for an 'unprecedented level' of global cooperation (Kokudo and Sugiyama, 2020), yet the pandemic has exposed weaknesses in international partnerships, particularly the World Health Organization (WHO), but impressive strengths in others. The IMF and United Nations Conference on Trade and Development (UNCTAD) have shown leadership in calling for funding to meet both the economic and health challenges, including a new issuance of Special Drawing Rights (SDRs), and for debt relief. But the multilateral institutions can only be successful if they receive the support of member countries, and with the current US government's weak support of multilateralism, cooperative effects are likely not to come up to what is needed. The WHO, which holds responsibility for coordinating the global health response to any pandemic, has faced criticism for failing to respond to the crisis with adequate speed and force (Mahase, 2020). International financial institutions such as the World

Bank and IMF have also faced criticism of their proposed economic relief programmes (IMF, 2020*c*; Malpass, 2020) for conditionalities and limited relief to countries where repayment obligations may undermine health funding (IMF, 2020*c*; Kentikelenis, 2020; Kickbusch *et al.*, 2020). The Joint Ministerial Committee of the Boards of Governors of the Bank and the Fund (the Development Committee) has, however, underscored the vital financial role of the IMF and the World Bank in responding to COVID-19 (World Bank, 2020). And forums such as the G20 have redoubled their commitment to international cooperation (G20, 2020).

These challenges to international institutions have ramifications for the climate crisis, posing risks and opportunities. With attention focused on COVID-19, climate change negotiations have been delayed. However, the lead up to the postponed COP26 to 2021, hopefully after the peak of COVID-19 crisis, offers an opportunity for countries to collaborate and share knowledge on climate-positive economic recovery packages. Global collaboration and strengthening the mandate and financing of global decision-making bodies is essential, not only to ensure an effective response to the virus, but also to facilitate ongoing collaboration in the climate domain (Steele *et al.*, 2014; Stavins *et al.*, 2014). With widespread international agreement concerning the importance of climate change, a new administration in Washington could also conceivably support an initiative for multilateral assistance for developing countries and emerging markets with climate-friendly policies as a central component.

V. Summary and conclusions

The COVID-19 crisis represents a dramatic shock to the global economy that will affect progress on climate change in multifaceted ways. The biggest driver of the long-term impact on climate is through fiscal recovery packages, along with possible shifts in power within and across national and international institutions. Green fiscal recovery packages can act to decouple economic growth from GHG emissions and reduce existing welfare inequalities that will be exacerbated by the pandemic in the short-term and climate change in the long-term. Short-term reductions in GHG emissions resulting from lockdowns will themselves have minor long-term effects, unless they facilitate deeper and longer-term human, business, and institutional changes. Urgent rescue packages have been necessarily 'colourless' and focused on preserving liquidity, solvency, and livelihoods, but their climate impact is also unlikely to be positive.

In this paper, a survey of officials from finance ministries, central banks, and other leading organizations is combined with a large-scale policy cataloguing effort and review of expansionary fiscal policy literature. We emerge with the recommendation of five policy items (plus one item specific to LMICs) that are well-placed to contribute to achieving economic and climate goals. These are:

— clean physical infrastructure investment,
— building efficiency retrofits,
— investment in education and training to address immediate unemployment from COVID-19 and structural unemployment from decarbonization,
— natural capital investment for ecosystem resilience and regeneration, and

— clean R&D investment.

For LMICs, rural support spending is another high-value policy item, with clean R&D investment less vital. National governments differ significantly in their economic, social, and environmental priorities, and recovery packages will reflect these priorities, with different consequences for the climate.

Several other insights emerged from the survey. Many climate-positive policies were perceived by survey respondents to have high overall desirability; most climate-negative policies had relatively low desirability. This was true even for climate-positive policies that took more time to implement. Long-run multipliers of climate-positive policies were found to be high, reflective of strong return on investment for government spending. Given the uncertainty in the future waves of the pandemic, flexibility and timeliness will also be important considerations. Finally, appropriate policies differ by national context.

As we move from the rescue to the recovery phase of the COVID-19 response, policymakers have an opportunity to invest in productive assets for the long-term. Such investments can make the most of shifts in human habits and behaviour already under way. In the lead up to COP26, recovery packages are likely to be examined on their climate impact and contributions to the Paris Agreement (UNFCCC, 2015). For many countries, this will be a matter of building on existing NDCs, already framed to facilitate fast-acting investment. Recovery packages that seek synergies between climate and economic goals have better prospects for increasing national wealth, enhancing productive human, social, physical, intangible, and natural capital.

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4.3. Additional unpublished text[49]

4.3.1. Summary

The purpose of this note is to report on ML analysis of the survey data collected in Paper B. Similarly to Paper C, ML is used here for validation (both of data and prior results) rather than for identifying new statistical relationships. Specifically, I use clustering techniques to investigate whether there are clear bundles in response patterns across demographic groups and ensemble learning methods to understand interrelationships in response patterns between questions (*i.e.*, does a particular response to one question or a group of questions predict responses to others?). To the first investigation, I find relatively weak clustering in responses and no obvious cluster definitions using demographic characteristics. The ensemble learning investigation confirms this, finding low explanatory power of demographic variables in predicting survey responses. Beyond that, the ensemble learning models indicate that other survey responses were only able to explain a relatively minor portion of the variation in question responses for most policy-impact pairs. Exceptions where moderate portions of response variation could be explained by responses to other questions were policies 20 and 25 (clean energy infrastructure and clean research and development), and to a lesser extent policies 12, 13, 22, and 24 (education investment, healthcare investment, green spaces and natural infrastructure, and general research and development). Questions on multipliers also seem

49 These additional unpublished materials are provided in addition to published supplementary materials, available on page 441. The published materials, released in May 2020, consider survey design and response statistics. These unpublished materials were developed in 2022 to further validate the survey response data and investigate potential bias using machine learning techniques.

to be more highly correlated to other responses, in some cases apparently driven more by responses on climate than by other responses. As an unintended but useful additional finding, the models revealed comparatively low explanatory power of any questions in predicting the overall attractiveness of policies—this supports the view detailed in this DPhil, Paper B, and Paper C that there are several factors beyond climate impacts, multiplier impacts, and speed that influence a policy's desirability.

4.3.2. Clustering with K-means++

Clustering has gained popularity as an approach for identifying groups in data when the potential cluster types are not known (unsupervised). In large part, this has been enabled by efficient ML algorithms which can iteratively do high-dimensionality calculations quickly. Although clustering methods were first investigated in a general sense in the 1930s for analysing cultural groupings (Driver and Kroeber, 1932), and the k-means method developed in the 1950s (Forgy, 1965; Lloyd, 1982; MacQueen, 1967), their widespread use has only come relatively recently as enormous data sets have become available and ML techniques have improved (Jain, 2010). In complexity theory, k-means clustering is classed as hard in nondeterministic polynomial time (NP-hard; see further description in section 2.3.2.2), but most approaches to solving clustering problems iteratively look for local optimum in a trade-off of complete accuracy for computational efficiency. The approach of Arthur and Vassilvitskii (2007), with k-means++ helps to identify intelligent initial locations for cluster centroids (seeds), thereby reducing sub-optimal clustering that might come in using heuristic algorithms rather than expectation-maximisation algorithms. The k-means

approach is an example of *hard* clustering, in which every data point has a binary cluster classification—it is either included in a cluster or not. The alternative to hard clustering is fuzzy clustering, in which all data points are considered a part of all clusters to some extent, with variance in how much it belongs. One method is not inherently superior to the other; both are useful tools for visualisation, although hard clustering is usually preferred for determining whether there are clear clusters in a dataset. K-means is, generally, a strict partitioning method, wherein every data point must belong to a cluster—in other words, there are no outliers. There are several alternatives to strict partitioning (subspace, overlapping, hierarchical, and more), but none are necessary for answering the first question of this subsection—are there any clear clusters in the dataset? If the answer to this question is *yes*, then other partitioning methods might be useful to considering finer arguments about which datapoints belong to each cluster.

K-means attempts to minimise the function J_m as in equation (14), where k is the number of data points, n the number of clusters considered, x_i the considered data point, and c_j the mid-point of the j^{th} cluster.

$$J_m = \sum_{i=i}^{k} \sum_{j=1}^{n} \overrightarrow{|x_\iota - c_J|}^2 \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (3)$$

Fuzzy c-means (built from Bezdeck, 1981) also attempts to minimise the function J_m (equation 15), where m (m>1) is the fuzzy partition matrix exponent (higher exponent brings borders between clusters with higher fuzziness) and u_{ij} is the degree to which x_i is a member of the j^{th} cluster. For any datapoint, the sum of membership to all clusters is one.

$$J_m = \sum_{i=i}^{k} \sum_{j=1}^{n} u_{ij}^{m} \overrightarrow{|x_i - c_J|}^{2} \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (5)$$

The specific heuristic contributed by the k-means++ algorithm to identify starting centroids first selects a random data point x in X as the first centroid c_1, next calculates the distance between each observation and the centroid $d(x_{obs},c_j)$ where j is one, then selects a second centroid, c_2, randomly with probability described by equation (16) and finds the distance from each observation and the new centroid $d(x_{obs}, c_j)$ where j is two. From here, each observation is assigned to its nearest centroid and the next centroid is selected, again by equation (15), repeating the process for each additional centroid until k centroids are selected. k is defined by the user. C_p denotes the set of observations that are closest to c_p. In essence, we are choosing starting centroids that are furthest from each other.

$$\frac{d^2(x_{obs},c_p)}{\sum_{h\,;\,x_h \in C_p} d^2(x_h,c_p)} \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (6)$$

In this note, I use k-means++ to consider whether there might be obvious clusters in the survey response data collected for Paper B. For k-means, I use the relevant Matlab function across a 231 x 100 dataset, representing 231 responses to the 100 questions in the survey (*i.e.*, 231 observations in 100 dimensions). I leave the responses untreated on their raw 100-point scale and replicate clusters at unique starting points using 50 replicates per run, selecting the best iteration. For the distance metric, I trialled several options (Figure 2), namely: squared Euclidean, Manhattan/cityblock (*i.e.*, sum of absolute distances), and the cosine method (*i.e.*, one minus the include angle cosine between a centroid and two points). Across trials, as one might expect, the Cosine method provides

relatively little visual value for distinguishing clusters—the method would be more closely considered if there were multiple responses from some individuals and not others, leading to some datapoints holding larger weights than others but not mean anything different. Of course, the survey was designed to ensure that this was not possible. It is difficult to designate either the Euclidean or cityblock method as superior as that clusters appear force-fit rather than natural in both. The Euclidean method does appear to give slightly higher separation between clusters and so is used as the default for further analysis. This follows other experimental and simulation results, which find the Euclidean method more useful, particularly for small sets of observational data like ours (Greche *et al.*, 2017; Mohibullah *et al.*, 2015).

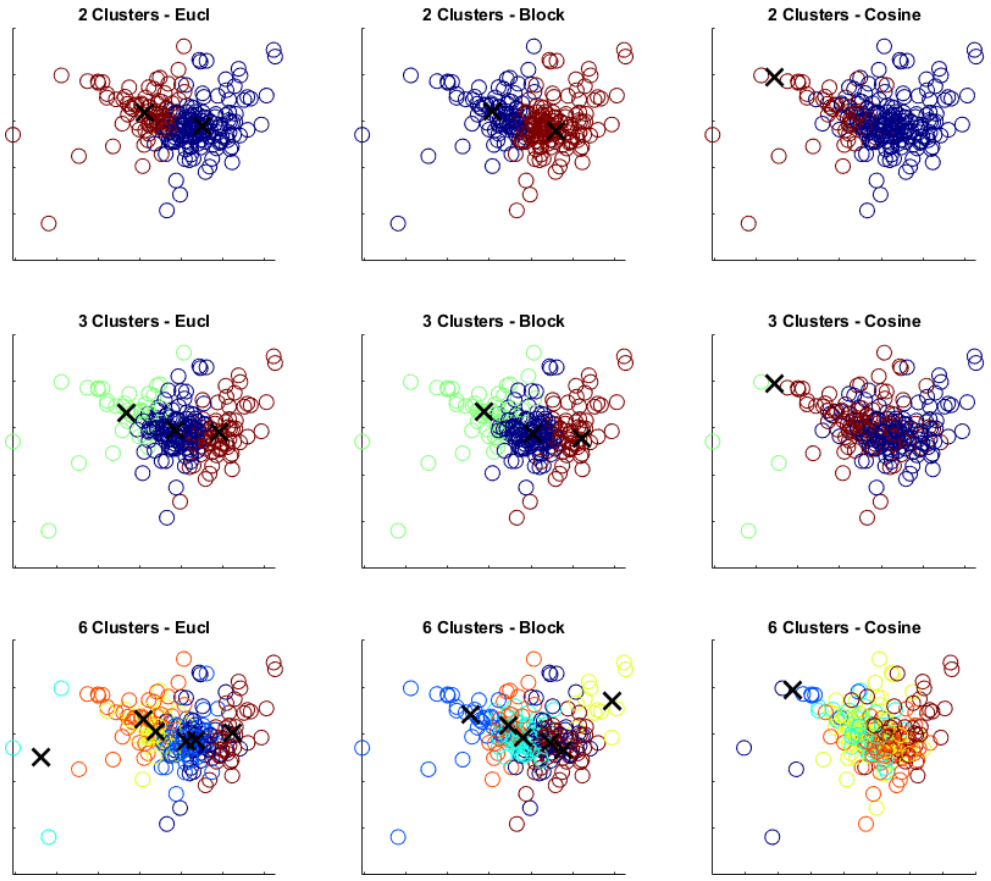


Figure 2. Comparison of distance measures for three different cluster sets applied to the full survey dataset (100-D). Circles are observations in the two most significant PCA dimensions, with different colours denoting different clusters.

Markings *X* are centroids. Apparent single centroids for the cosine method are in fact multiple almost-stacked centroids. Abbreviations: Eucl: Squared Euclidean method; Block: Cityblock (Manhattan) method; Cosine: Cosine method.

The high dimensionality of the dataset (*i.e.*, 100 dimensions, one per survey question) means that direct 2-D visualisation across any two dimensions is unlikely to be of much visual use (see Figure 3 as an example). Of course, for clustering across a subset of questions, a 2-D visualisation can be more helpful (see Figure 4). Many techniques are available for dimensionality reduction, including principal component analysis (PCA), t-distributed Stochastic Neighbor Embedding (t-SNE) (as used in Paper A), and ML techniques like autoencoding. t-SNE and ML approaches can be useful alternatives to PCA on efficiency grounds, however for such a small dataset, PCA is sufficient and straightforward. PCA finds the component axes to a dataset of infinite dimensionality that maximises variance between datapoints, with the first axis providing the greatest variance, the second providing the second most variance and so on. If prior knowledge of the cluster classes were known, linear discriminant analysis could have been a helpful alternative to clustering and PCA. As a supervised alternative to cluster analysis, linear discriminant analysis finds the component axes that maximise separation between classes (groups). However, without prior knowledge of these classes, the approach is of limited usefulness. With PCA dimensionality reduction, I analysed the clusters across policy types (*i.e.*, 4-D) and across questions (*i.e.*, 25-D), considering groups of 2, 3, and 5 clusters. Figures 5-7 provide output for all policies with figures 8-10 giving corresponding silhouette graphs. In most cases, clusters are relatively weak and, in all cases, definitions for clusters were elusive. This suggests that survey respondents were quite independent in their responses. That said,

while the dataset is small (231 observations per dimension) compared to most k-means analyses, there as many possible classes, and the dataset remains too large to effectively process trends by sight alone. Following the recommendations of Jain (2010), it might be worth considering semi-supervised clustering to better understand spreads in data, and it is likely only going to be worth doing so at the policy level (*i.e.*, looking at scoring for policy 1 across all questions) or the question level (*i.e.*, looking at the question on multiplier for all policies). Additionally, a more robust predictive analysis, such as an ensemble model, could provide additional perspective to this hypothesis. I consider this in the next section.

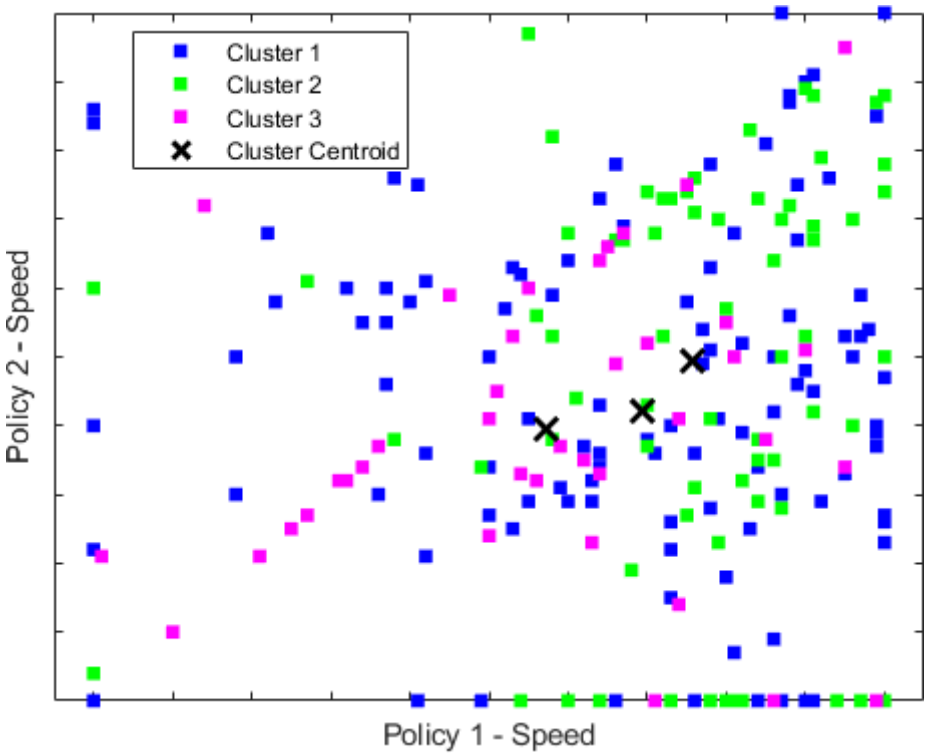


Figure 3. k-means clusters in full survey dataset (100-D), visualised in dimension of survey question 1 (policy 1 speed) and survey question 2 (policy 2 speed).

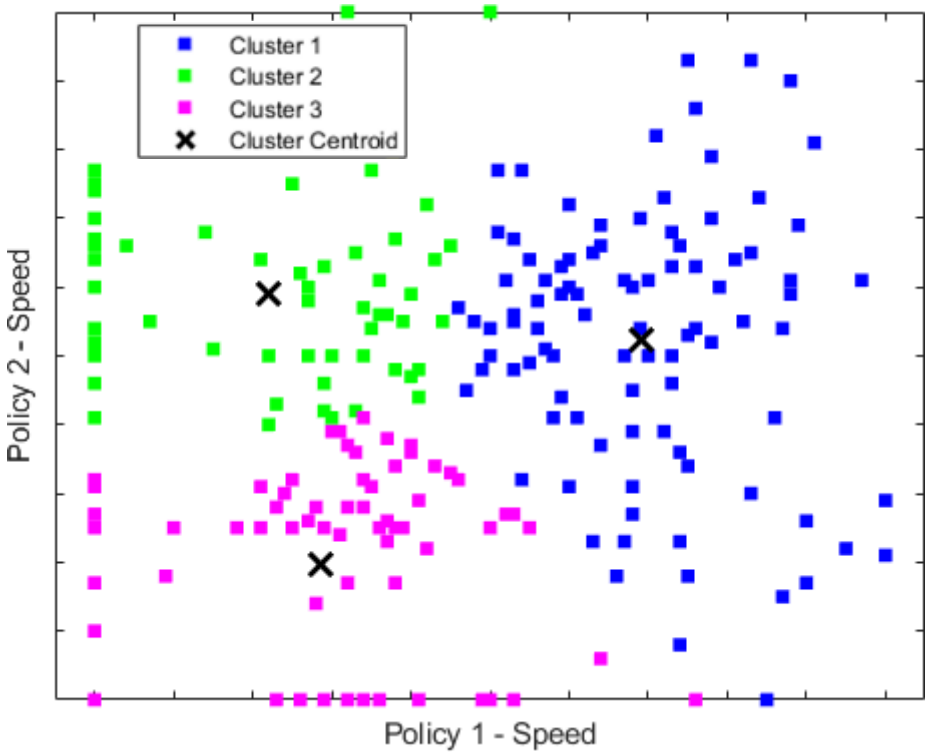


Figure 4. 3 k-means clusters identified in question 1 and 2 responses (2-D), visualised in the dimensions of the same questions.

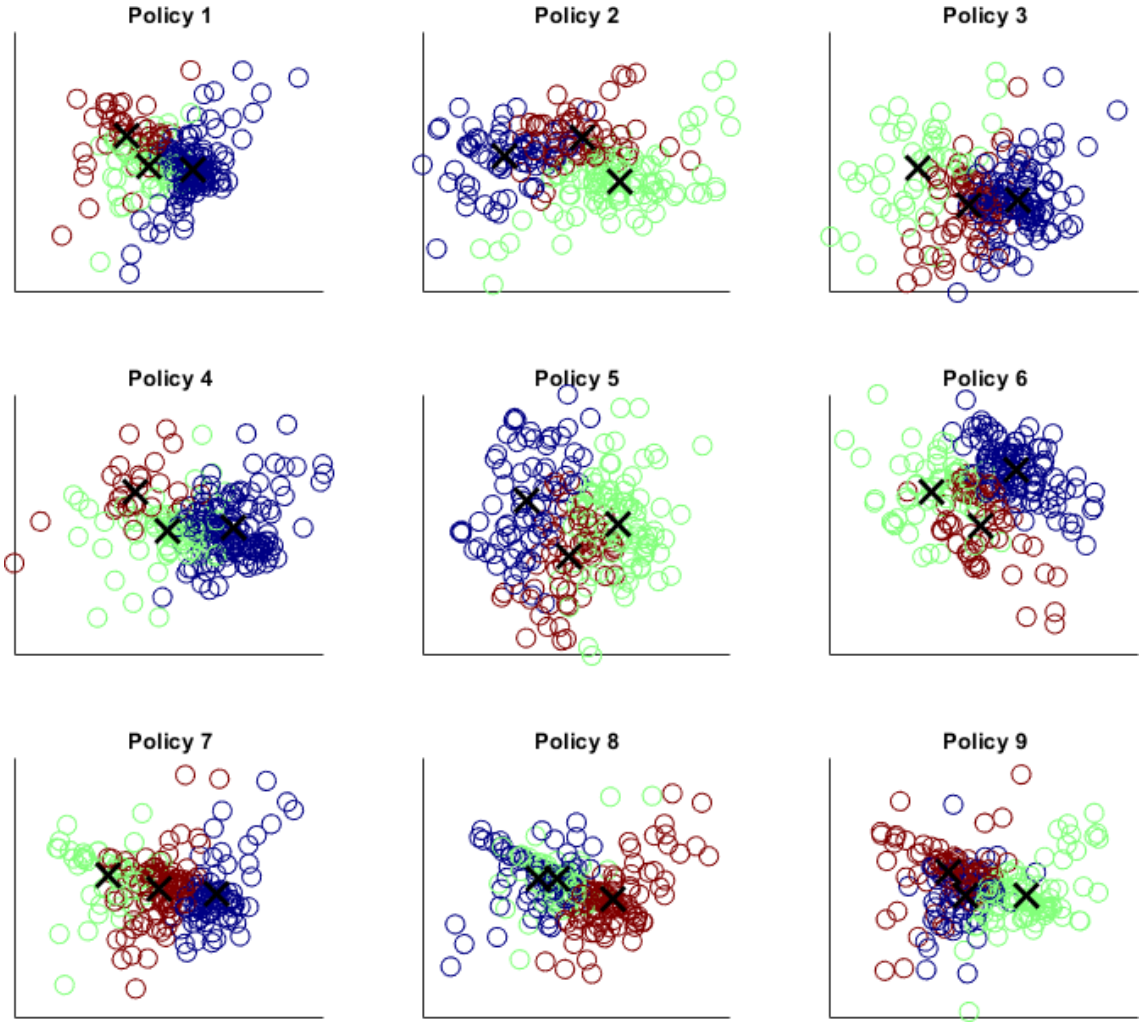


Figure 5. 3 k-means clusters identified for each of policies 1-9, using responses to the four survey questions (4-D). Visualised on the two principal axes of a PCA.

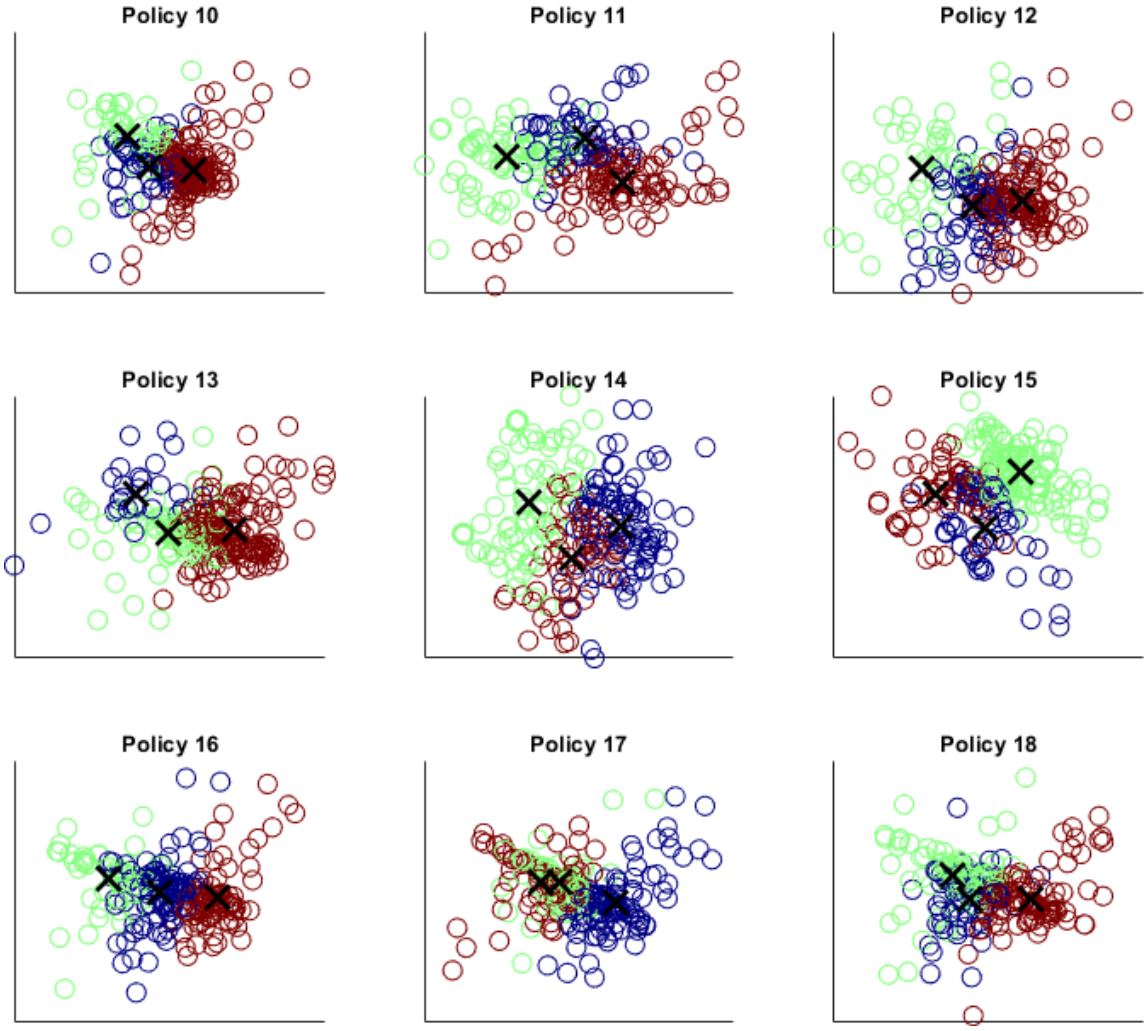


Figure 6. 3 k-means clusters identified for each of policies 10-18, using responses to the four survey questions (4-D). Visualised on the two principal axes of a PCA.

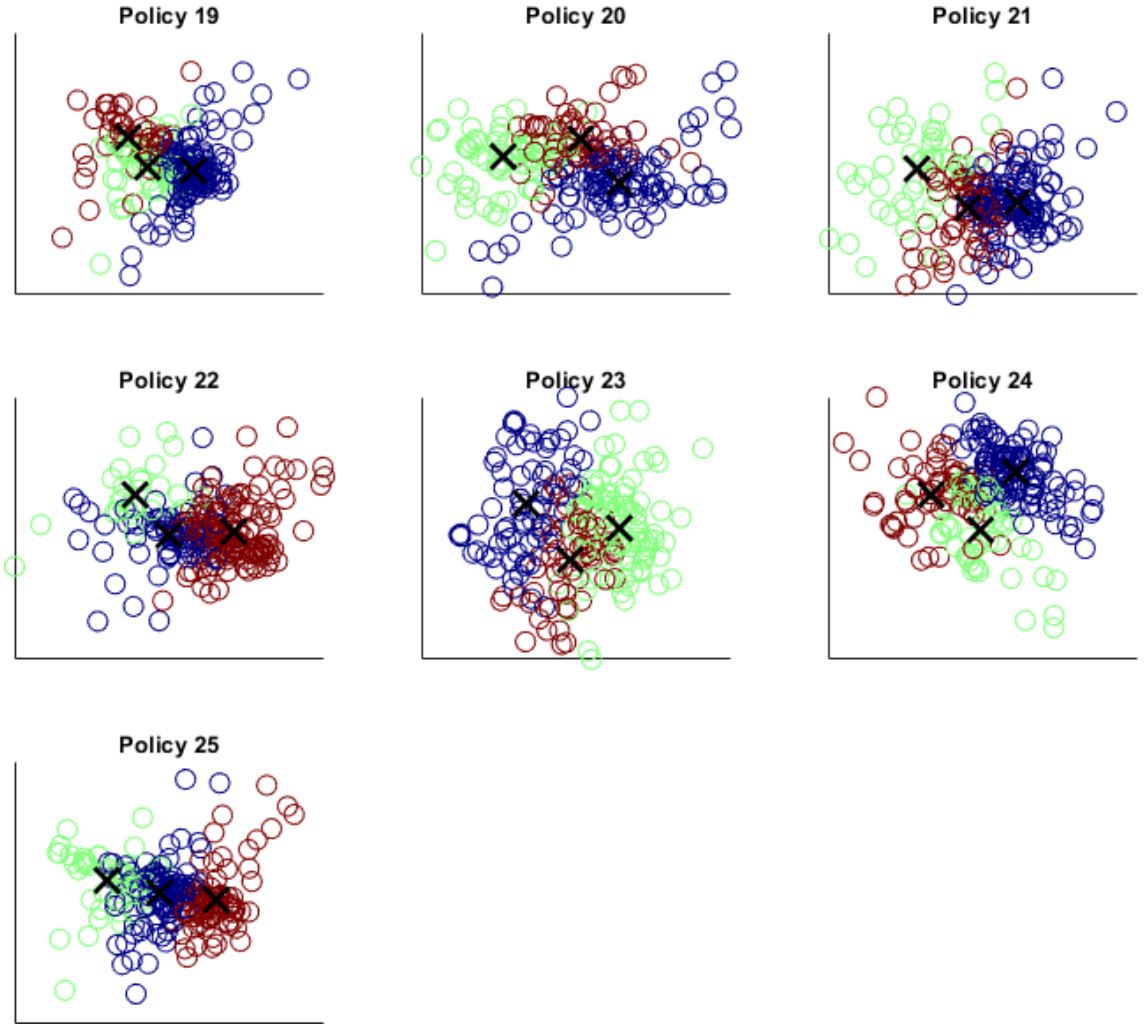


Figure 7. 3 k-means clusters identified for each of policies 19-25, using responses to the four survey questions (4-D). Visualised on the two principal axes of a PCA.

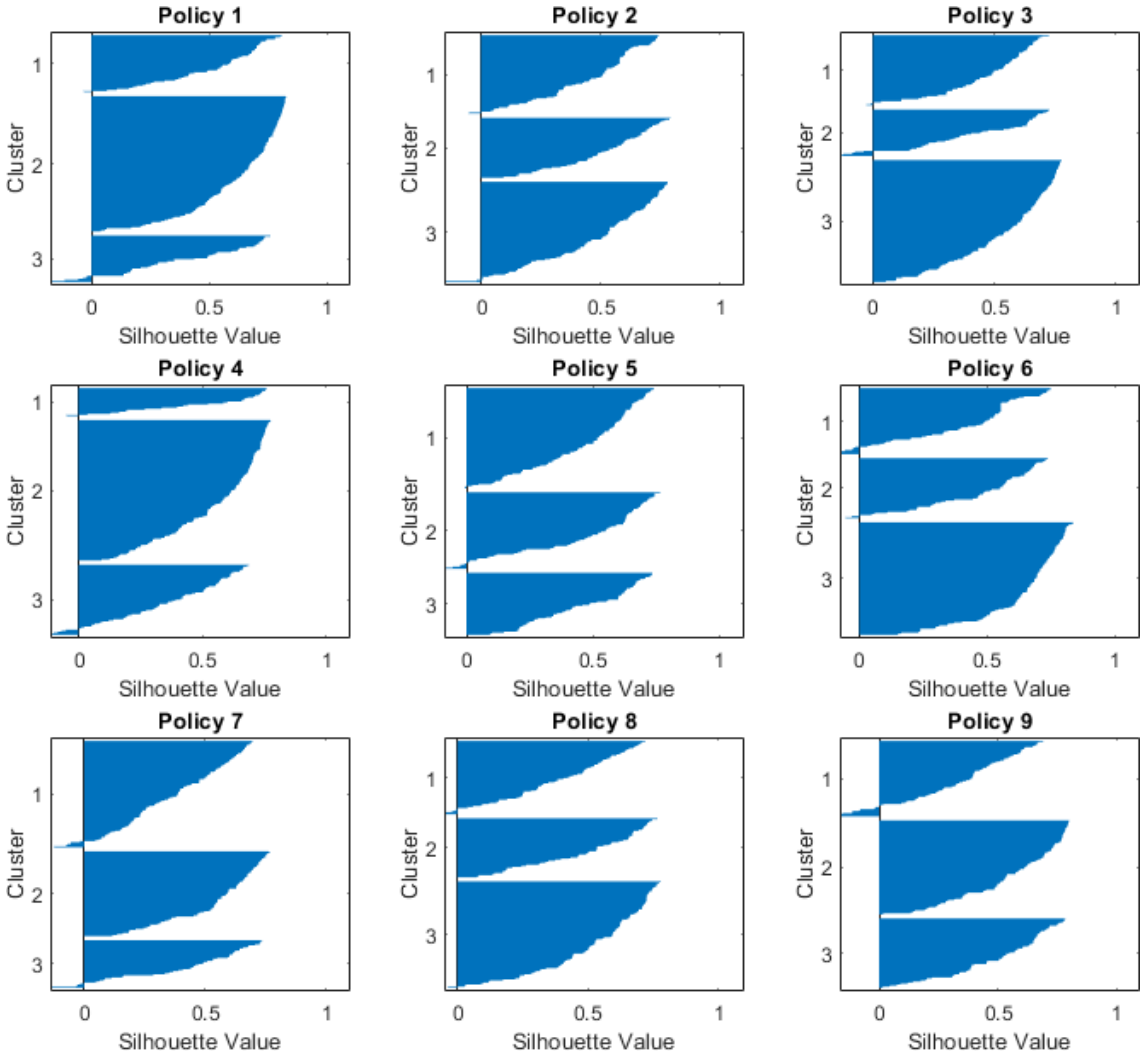


Figure 8. Silhouette diagrams for each of policies 1-9 in a 3 cluster PCA analysis using responses to the four survey questions (4-D). Clear clustering would be reflected by largely rectangular silhouettes (which appear largely absent in this figure). Negative silhouette values indicate datapoints that could be effectively grouped in other clusters.

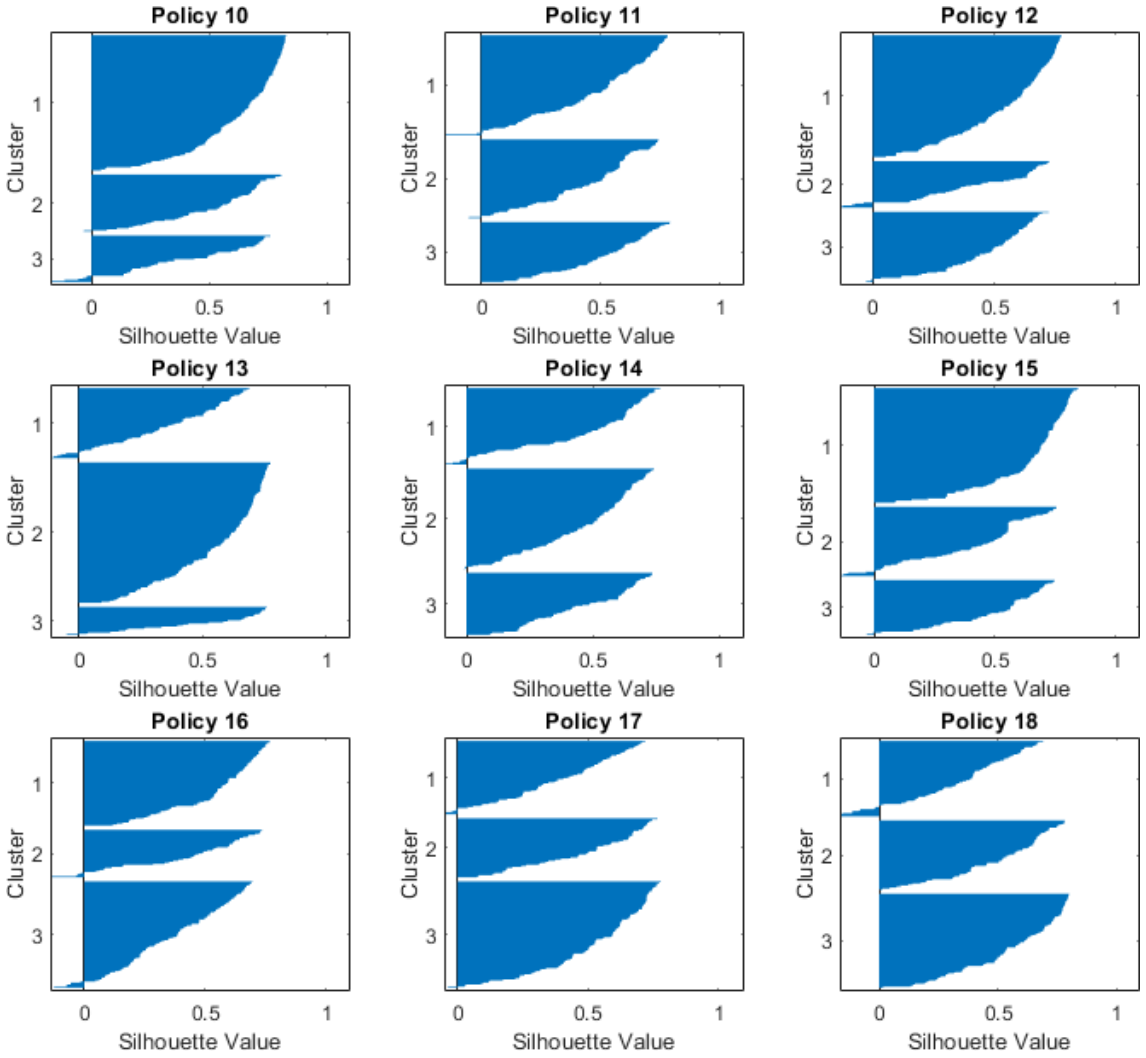


Figure 9. Silhouette diagrams for each of policies 10-18 in a 3 cluster PCA analysis using responses to the four survey questions (4-D). Clear clustering would be reflected by largely rectangular silhouettes (which appear largely absent in this figure). Negative silhouette values indicate datapoints that could be effectively grouped in other clusters.

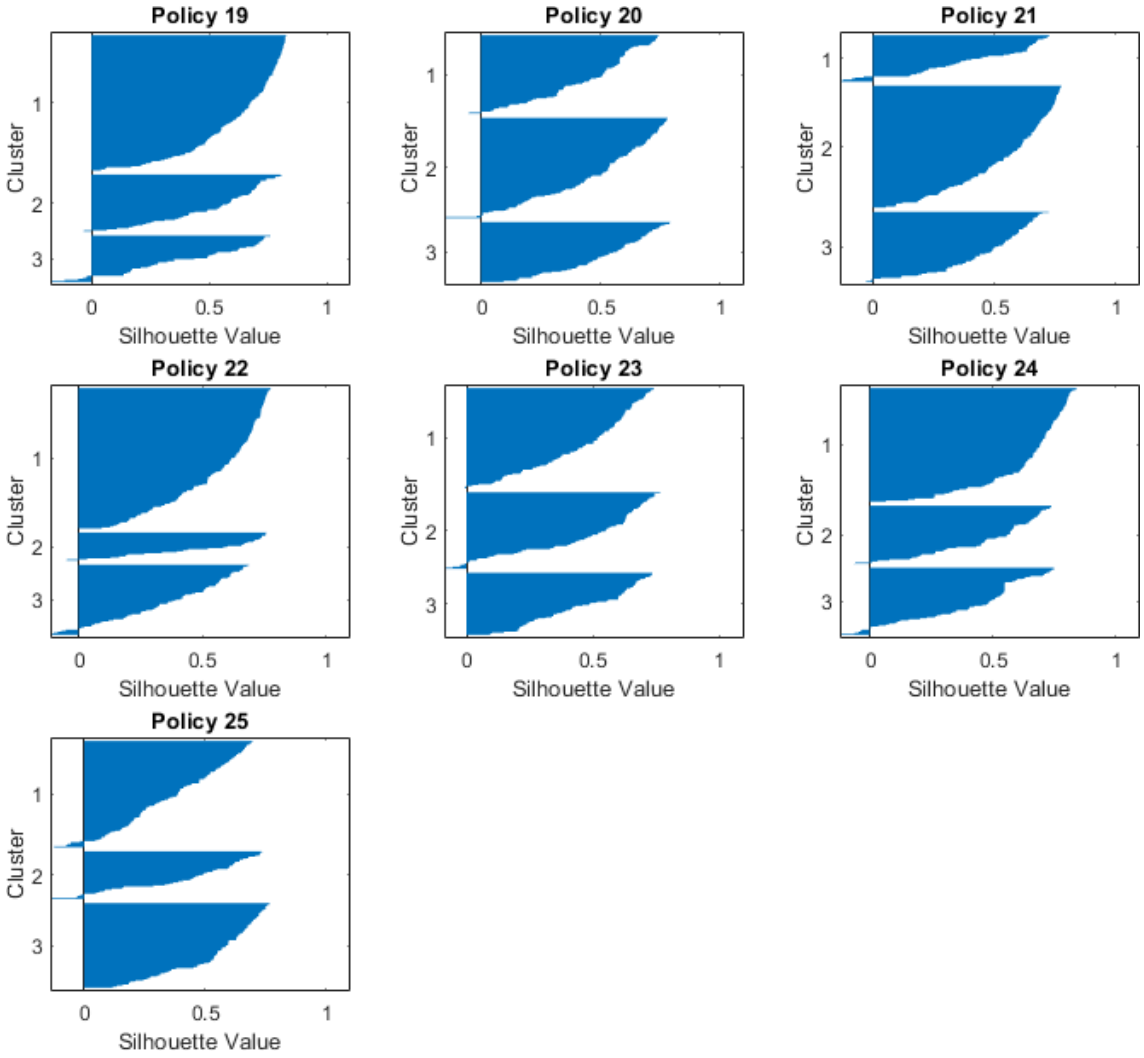


Figure 10. Silhouette diagrams for each of policies 19-25 in a 3 cluster PCA analysis using responses to the four survey questions (4-D). Clear clustering would be reflected by largely rectangular silhouettes (which appear largely absent in this figure, although the first cluster for policy 24 is approaching a rectangular shape). Negative silhouette values indicate datapoints that could be effectively grouped in other clusters.

4.3.3. Random forests

In the previous section, relatively weak clustering of survey responses suggested high independence of respondents. The findings did not, however, speak to potential demographic or other drivers of survey responses nor are they practically useful for considering interactions between pairs of responses (as there are too many dimensions for manual review).

Ensemble models are a form of data mining useful for understanding correlations in datasets and, particularly for surveys, determining whether there might be significant correlations between responses to different questions. Since their algorithms are definitionally black-box estimators, they are of limited usefulness for understanding relationships in data and only valuable for blind prediction of the future when the user is confident that the past predicts the future. Yet, they are more transparent (less black box) than alternative ML techniques like relevance vector machines, support vector machines, and multilayer perceptrons, which are often used for a similar purpose (Verikas *et al.*, 2011). While these alternative approaches can deliver high predictive power at high efficiency, they do not provide the relative performance of each predictor variable. Although these methods all clearly have their limitations, they might have some value to demonstrate independence in survey responses, either between respondents or across questions. Here I investigate this question with reference to the survey data of paper B.

Dong *et al.*, (2020) explain that at their core, ensemble learning methods take multiple learning algorithms and "fuse results with various voting mechanisms to achieve better performances than that obtained from

any constituent algorithm alone". What varies across supervised ensemble methods is which learning algorithms and classifiers are used, what method of bagging (if any) is applied, what voting mechanism is employed, and interactions between each of these features. As discussed, the most frequently used supervised ensemble methods over recent years have included random forest, random subspace, AdaBoost, and gradient boosting (Dong *et al.*, 2020). Which is best? Well, as is often the case, it depends. If you believe David Wolpert and William Macready, there is "no free lunch" in optimisation and certainly no optimisation methodology is going to be appropriate to every dataset (Wolpert and Macready, 1997). Here, informed by Kern *et al.*'s (2019) helpful paper on tree-based learning, and following examples from Best *et al.* (2022) and Cutler *et al.* (2007) amongst others, I apply random forests.

Random forests (Breiman, 2001) is an ensemble learning approach that builds from Ho's (1998) *Random Subspace Method for Constructing Decision Forests*. Kern *et al.* (2019) provide a helpful introduction to tree-based learning. Best *et al.* (2022) provide a useful example on how ensemble methods can be applied to survey data. Cutler *et al.* (2007) give an account of applying random forest models to a classification problem in ecology, along the way discussing the advantages and disadvantages of the method.

In this investigation, I use 106 fields from the survey (Figure 11), including all 100 slider responses on policy impact plus 6 demographic responses (focus country of work, highest level of education, employer type, number of years of experience as an economist, gender, advanced economy vs lower- and middle-income country focus, and G20 vs non G20 focus).

Since random forests work best with categorical data, for each of the 100 slider responses I apply five bucketing approaches to transform the continuous (non-demographic) data into Likert data. The five approaches are:

- 2 buckets (*i.e.*, data points 0-49 and 50-100)
- 5 buckets (0-19, 20-39, 40-59, 60-79, 80-100)
- 10 buckets (0-9, 10-19, …, 90-100)
- 20 buckets (0-4, 5-9, …, 96-100)
- 101 buckets (0, 1, 2, …, 100)

For each bucketed dataset, I train 100 random forest models, one for each survey policy response. Effectively, this process queries (i) to what degree each question response can be explained by other question responses and demographic variables (sample 1) and (ii) which question responses and demographic variables are most important for doing so. I repeat the process with only demographic independent variables (sample 2) and with only policy responses as independent variables (sample 3). For each model, I first use all predictors with a curvature test algorithm to build a decision tree learner (using Matlab's function built from Loh, 2002). This method minimises the p-value of chi-square independence tests to gain constant fit. For efficiency, I limit surrogate decision splits to a maximum of 10 per node. From here, I use Matlab's *fitrensemble* function to run the random forest ensemble with tree learners, 200 learning cycles to maximise fit, and otherwise default parameters. Figure 12 provides predictor importance

estimates for policy 1 in the 10 buckets scenario. In total, 1,500 such figures were created, with relatively high consistency between bucketing approaches. In most cases, removal of the demographic responses did little to influence the relative importance of any other dependent variable.

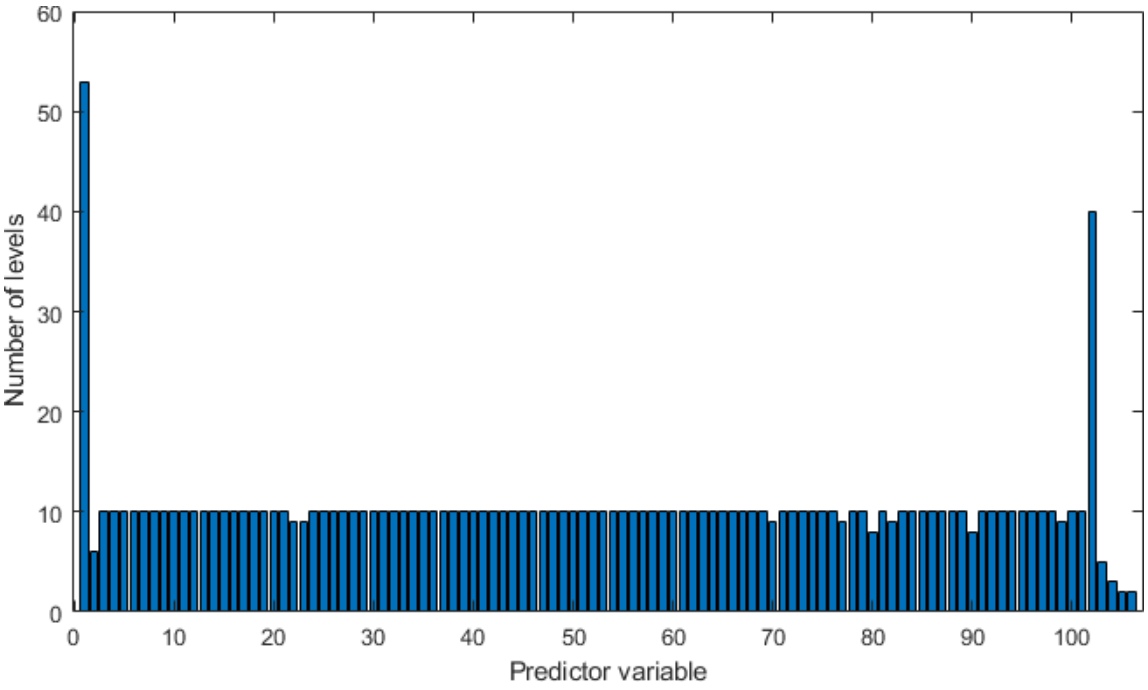


Figure 11. Number of categorical levels for each independent variable for the 10-category bucketing models.

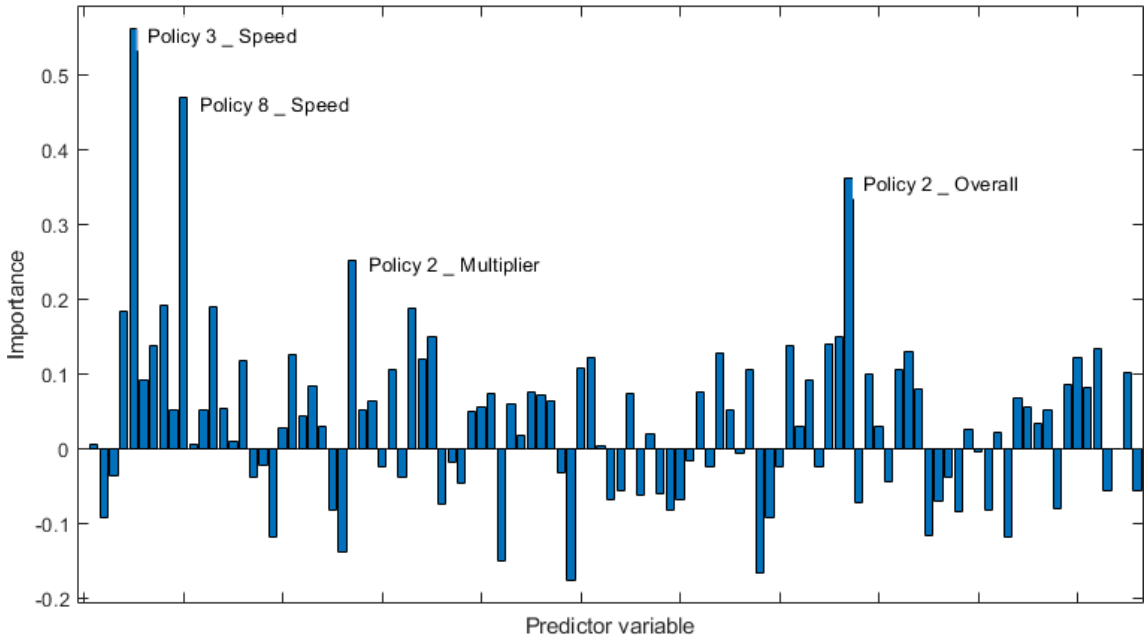


Figure 12. Relative importance of each independent variable for predicting responses to the survey question on speed for policy 1 (10-category bucketing).

Overall, the random forest models, were only able to explain a relatively minor portion of the variation in question responses for most policy-impact pairs (see averages across bucket groups in Figure 13 and examples for the 10-category bucket in figures Figure 13-Figure 16). The clear exceptions are policies 20 and 25 (clean energy infrastructure and clean research and development), and to a lesser extent policies 12, 13, 22, and 24 (education investment, healthcare investment, green spaces and natural infrastructure, and general research and development). Questions on multipliers also seem to be more highly correlated to other responses, in some cases apparently driven more by responses on climate than by other responses. This supports the findings of Paper B. Interestingly, responses on overall policy impact were also not highly correlated to other questions, suggesting that there might be several other factors not captured by the

survey that are nonetheless useful desirable for policymaking. Again, this supports the claims of Paper B and Paper C.

Demographic variables were of limited help in predicting variation of question responses (Figure 17). For many policies, the random tree model was sometimes unable to explain more than 1% or even 0.1% of the variation. This clarifies why it was so challenging to manually define clusters in the k-means++ and c-means exercises.

Across samples, using more categories led to higher R2 values (Figure 15), however this came at lower efficiency (*i.e.*, the algorithms were more computationally expensive to run). Around 10-20 categories seem to be optimal as the addition of more categories beyond this seems to have little benefit to R^2 but to increase processing time. It is also apparent that excluding the demographic variables improves computational efficiency without a loss in R^2, even bringing an increase in R^2 for smaller buckets.

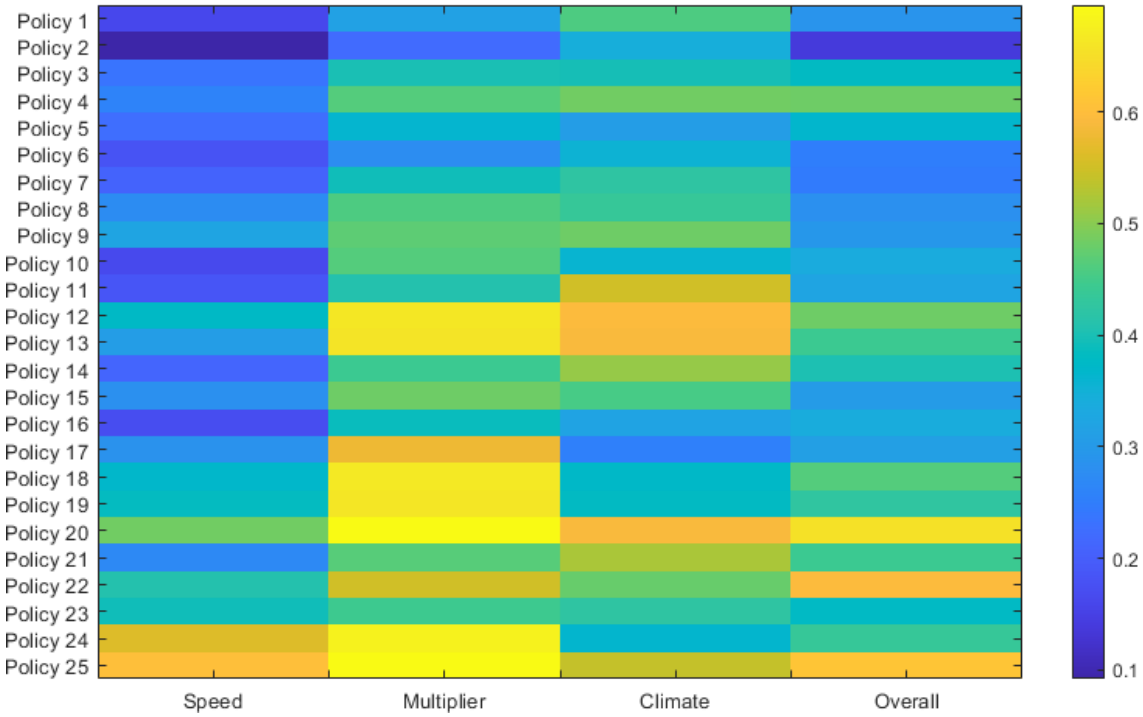


Figure 13. R^2 estimates for best-fit random forest models averaged across all bucket categories. Each cell represents the average of R^2 values in the different bucket categories for one survey question as a dependent variable and all others as independent variables (*i.e.*, sample 3). Demographic variables are included as additional dependent variables. Demographic variables are excluded. Colorbar ticks give R^2 values.

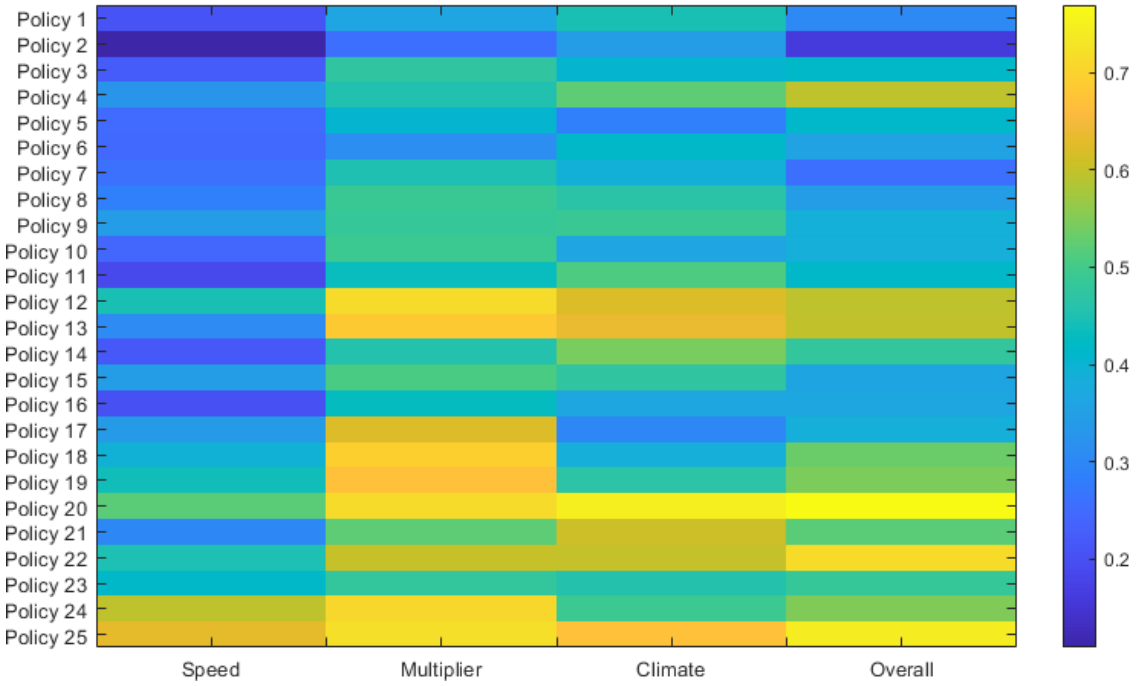


Figure 14. R^2 estimates for best-fit random forest models using 10-category bucketing. Each cell represents one survey question as a dependent variable and all others as independent variables (*i.e.*, sample 1). Demographic variables are excluded. Colorbar ticks give R^2 values.

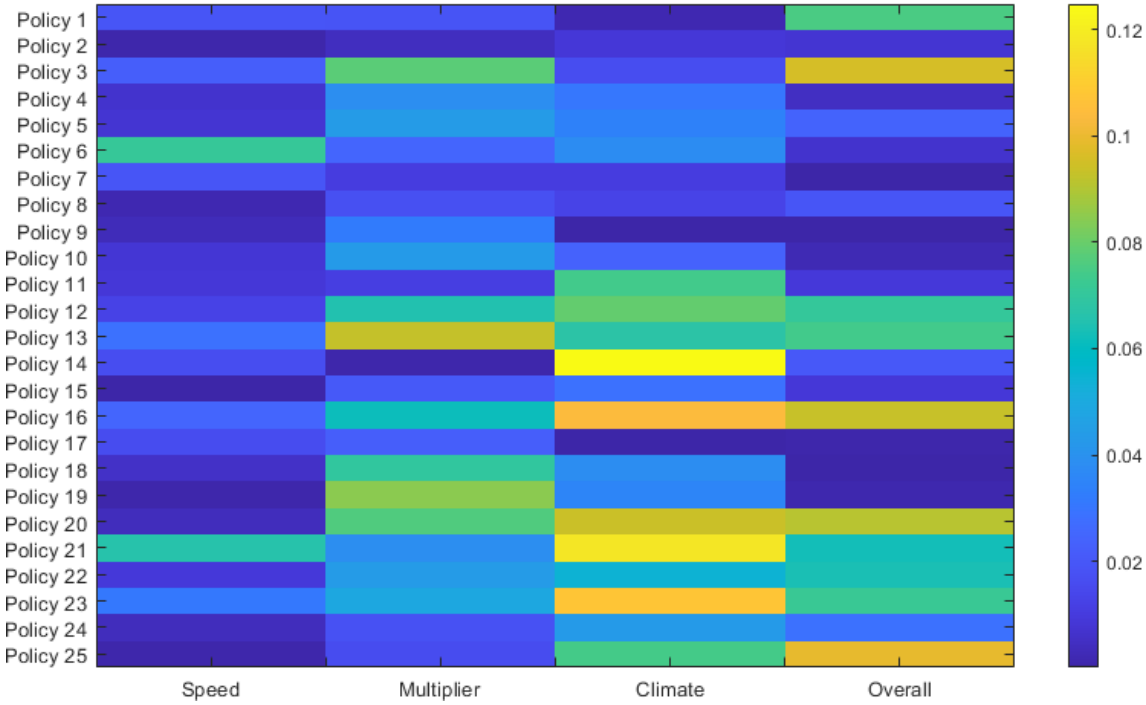


Figure 15. R^2 estimates for best-fit random forest models using 10-category bucketing. Each cell represents one survey question as a dependent variable and all demographic factors as independent variables (*i.e.*, sample 2). Other survey questions are excluded as variables. Colorbar ticks give R^2 values.

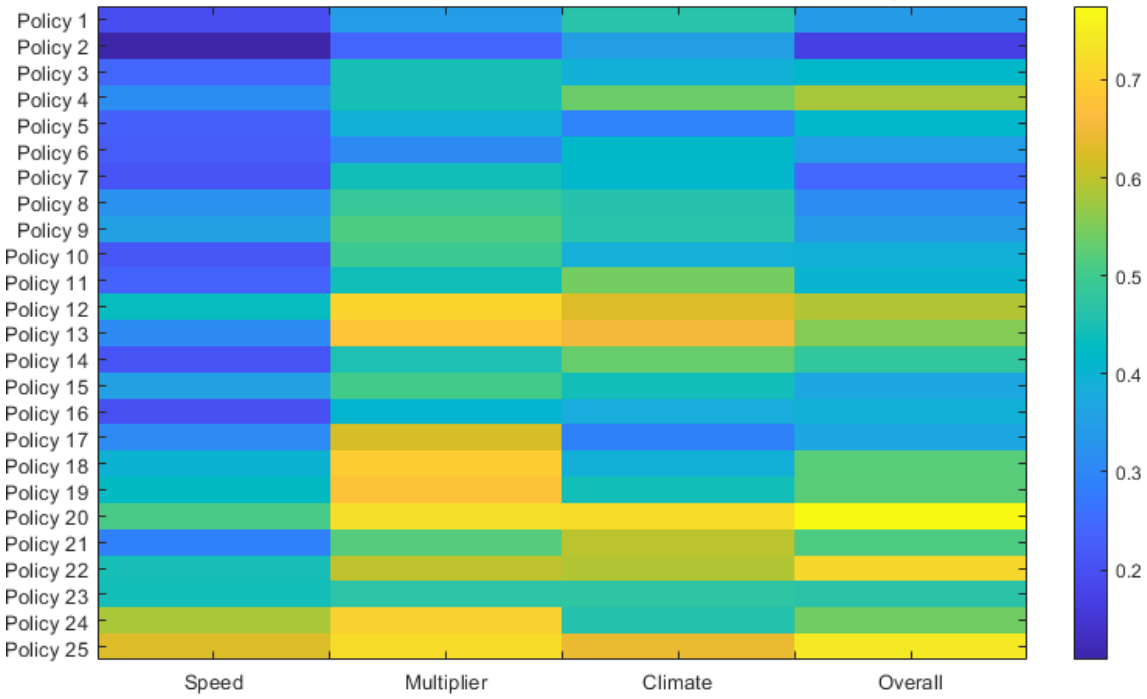


Figure 16. R^2 estimates for best-fit random forest models using 10-category bucketing. Each cell represents one survey question as a dependent variable and all others as independent variables (*i.e.*, sample 3). Demographic variables are included as additional dependent variables. Colorbar ticks give R^2 values.

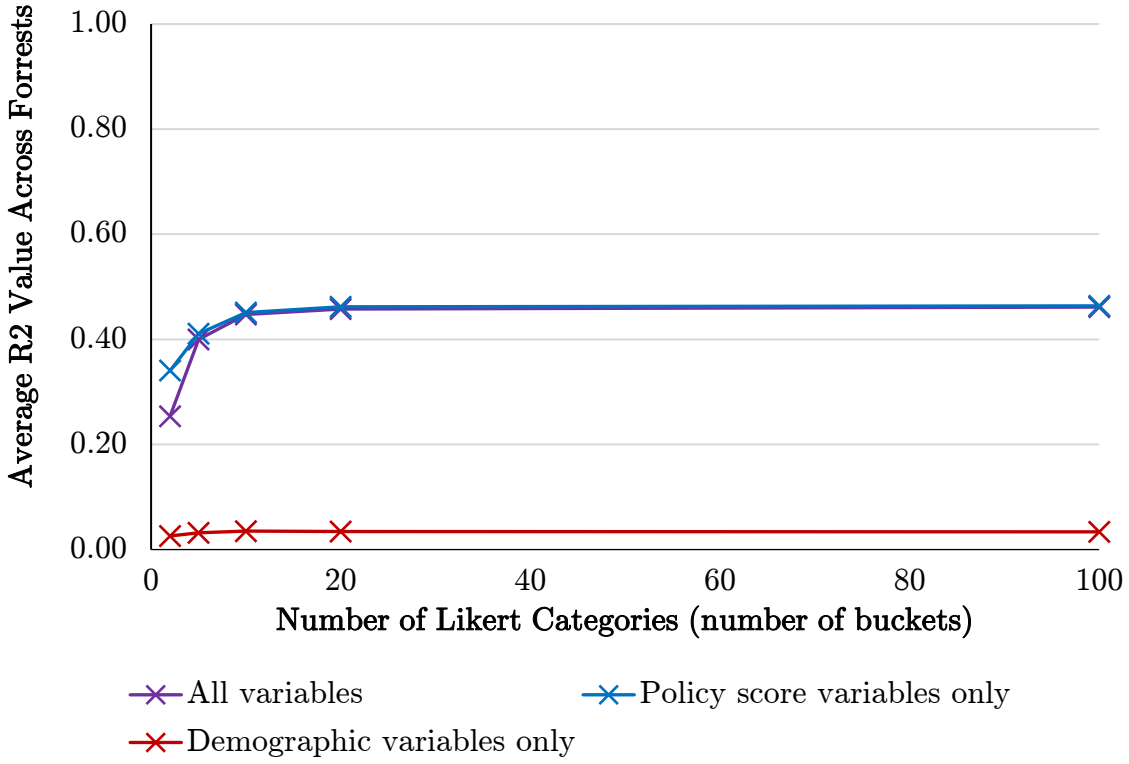


Figure 17. Average R^2 values for random forest model sets with different bucket-sample combinations. Each datapoint gives the average R^2 value across its respective 100 random forest models.

4.3.4. Conclusion

The validation exercises in this note provide results to strengthen the conclusions of Paper B as well as those of the overall DPhil. I find no evidence for demographic biases in response patterns using either clustering or ensemble modelling techniques. Based on very low clustering between respondents, I also find no evidence to suggest subgroup outliers (*i.e.,* collective anomalies). Together, these results suggest that the risks of significant bias in the Paper B dataset through known demographic and response factors are low. This further validates the Paper B dataset, strengthening the findings of that paper and hence the DPhil overall.

Supporting the DPhil, the note also comments on factors predicting strong economic characteristics of fiscal policy. To this end, the ensemble modelling suggests that responses to survey questions on multipliers are in some cases driven more by responses on climate (i.e., perceived positive climate impacts of the policy) than by any other factors in the independent variable set (demographic factors, perceptions of overall attractiveness, and perceptions of speed). While ensemble modelling is highly effective at identifying the presence of relationships in data, and the strength of these relationships, it is not adept at describing what these relationships are. This limitation is clear here and the nature of the relationship is left for Papers A and C.

Finally, the ensemble models in this note show comparatively low explanatory power of any questions (multiplier, speed, climate) in predicting the overall attractiveness of policies. This supports the view in this DPhil, explained through Paper B and Paper C, that there are several

factors beyond climate impacts, multiplier impacts, and speed that influence a policy's desirability. Political, social, non-climate environmental, and other factors are all relevant to the decision-making process. And, if policy makers consider 'growth' as only one, perhaps minor, component in fiscal decision making, then perhaps it is misguided to predominantly measure progress using growth-dominated metrics like GDP. In totality the findings of this note then support the broader message of paper B and the DPhil on whole: deficit spending on climate measures compared to traditional measures appears justifiable on economic metrics, yet the promise and relevance of climate measures are much more than economic.

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5

Reviewing the COVID-19 "Green Recovery": rhetoric or reality?

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See Appendix C for supplementary materials (481)

5.1. Abstract

COVID-19 forced an unprecedented discontinuity in patterns of public investment; more was spent on the pandemic in real terms than on any other sudden-onset crisis in history. In the early stages, economists suggested that policy makers might use climate-friendly investments to accelerate economic recovery—decoupling growth from environmental degradation.[1] To test the rhetoric and the reality, this paper introduces the world's largest database on recessionary fiscal investment, covering 8,001 policies in 88 countries.[2] Using a new fiscal taxonomy, we find that US$ 978 billion of total COVID-19 spending (5.4% of total spending) and US$ 945 billion of recovery spending (31.1% of recovery spending) might reduce long-term greenhouse gas emissions, but 9.1% of total spending might increase emissions and opportunities for pricing reform were missed. Gold-standard recurrent neural networks provide validation of the categorised dataset, classifying with high accuracy. International differences in green recovery are explored with general-to-specific econometric model selection, suggesting nations that invested proportionally more on climate were those that had higher human capital, already supported higher renewable energy generation, had more arable land, and were working against higher rates of unemployment. Having established the reality, green investment is mapped to green political rhetoric using a new dataset of 3,817 pandemic-era English political speeches,[3] finding that investment did not meet rhetoric for most countries. The methods and datasets introduced here could be used to incorporate the greenhouse gas impacts of announced fiscal policy into climate modelling and better inform policymaking.

5.2. Main paper

In economic crisis, effective governments can use public funds as economic stimulus to support employment, boost productivity, spawn new industries, and strengthen domestic economic resilience.[4–7] For policy makers interested to build additional long-term human wellbeing, it is possible to "green" stimulus such that it both meets immediate economic needs and addresses systemic environmental problems, of which climate change is one of the most urgent.[1,6,8,9]

It follows that understanding the magnitude and direction of current fiscal expenditures could provide a lens on future economic, social, and environmental change. For researchers, a better understanding of present policy can guide research priorities towards the most immediately relevant topics; for civil society, it can provide a quantitative basis for holding governments accountable; for businesses, it can inform decisions on where and how to allocate resources and production; for investors, it can guide capital allocation towards growth; and for policy makers, it can measure progress towards their own policy goals.

Perhaps over 100 trillion dollars in climate-friendly spending will be required to limit global temperature rise to 1.5-2 degrees Celsius and avert the worst consequences of climate change.[10] While most spending will come from the private sector, government can accelerate these funds through regulation, pricing reforms, and with their own spending or taxation incentives (i.e., green fiscal stimulus).[11] In the COVID-19 pandemic response, green stimulus measures have garnered the strongest policy and research attention. The most comprehensive definitions for "green" include consideration of biodiversity, pollution, climate, and more, however in this study, only the greenhouse gas (GHG) impacts of policy are considered. Here, green policies are those that might reduce net-GHG emissions in the long term compared to a scenario in which they are not implemented.

A recent review of the stimulatory characteristics of green spending, beginning with ancient Egypt and ending in 2021, found evidence for higher job creation and long-run economic multipliers compared to traditional policies.[6] A global survey of leading economists at the outset of the pandemic suggested that the same positive characteristics apply to COVID-19 fiscal response.[1] The present study builds on these works, focusing on the implications of 8,001 announced fiscal measures on greenhouse gases (GHGs) over the short-term (policy implementation) and the long-term (after policy implementation). It uses a purpose-built policy taxonomy, validated with international peer review and machine learning processes, to move beyond early directional commentaries that considered a similar question for sub-periods of the pandemic.[12–15] It uses econometric model selection to understand correlation of economic, social, and environmental factors to responses across countries. It uses natural language processing to understand whether spending patterns met the rhetoric of heads of state. An article map is presented as extended data figure 1.

BUILDING THE GLOBAL RECOVERY OBSERVATORY

The Global Recovery Observatory (GRO), introduced in its complete form by this paper (see supplementary data), tracks legislated government spending in response to the COVID-19 pandemic in 88 countries. The dataset is the world's largest and most detailed recessionary fiscal policy dataset, containing 8,001 policies from 2020-2021, each catalogued with country name, policy name, policy description, policy value (in local currency and USD), date of confirmation, official document references, and sources, providing 58,704 datapoints. The dataset is unique in (i) the number of countries it covers, (ii) that it records initiatives at the policy level rather than the package level, and (iii) that it covers all sectors for both announced taxation and expenditure measures. The dataset delineates between two subcategories of what has traditionally been called fiscal stimulus—rescue-type policies and recovery-type policies. Rescue spending is that designed to foremostly protect businesses and people from

the immediate impacts of the crisis—for instance, vaccine spending, food stamps, unemployment support, or business liquidity measures. Recovery spending is that used primarily to stimulate demand, address supply shocks, or otherwise reinvigorate an economy—for instance, new infrastructure investment, incentives to purchase priority goods or services, or cash payments with explicit intent to stimulate economic activity. The dataset shows that US$ 18.2 trillion was announced in COVID-19 fiscal spending— in real terms, more than that spent in response to any modern war or financial crisis. Of this, US$ 12.6 trillion (69.6%) was rescue type, US$ 3.0 trillion (16.7%) recovery type, and the remainder unclear. Driven, presumably, by social and economic needs, the composition of new spending shifted from predominantly rescue over Jan 2020—Mar 2021 to predominantly recovery from Apr 2021 onwards (figure 1; extended data table 1). For recovery spending, transportation received more spending than any other named sector (19% of total), with other industrials (12%), energy and water (9%), education and training (6%), health care (4%), consumer including tourism and agriculture (4%), and materials including forestry and nature (3.2%) trailing behind. Variation between nations was high, e.g., transportation received over 50% of recovery spending in nine countries but 0% of recovery spending in thirty-one countries.

Advanced economies (AEs) spent on average US$ 13,575 per capita compared to US$ 746 for emerging markets and developing economies (EMDEs) (US$ 464 excluding China). As demonstrated with econometric modelling in a later section, this difference seems to have been partially driven by low access to affordable capital (higher expected default on borrowing). With EMDE governments unable to adequately service their immediate fiscal needs, it is possible that recent increases in poverty will not reverse quickly and international inequality will expand.[15,16] This finding supports calls for enhanced support of EMDEs by AEs, perhaps using green financial instruments.[17,18]

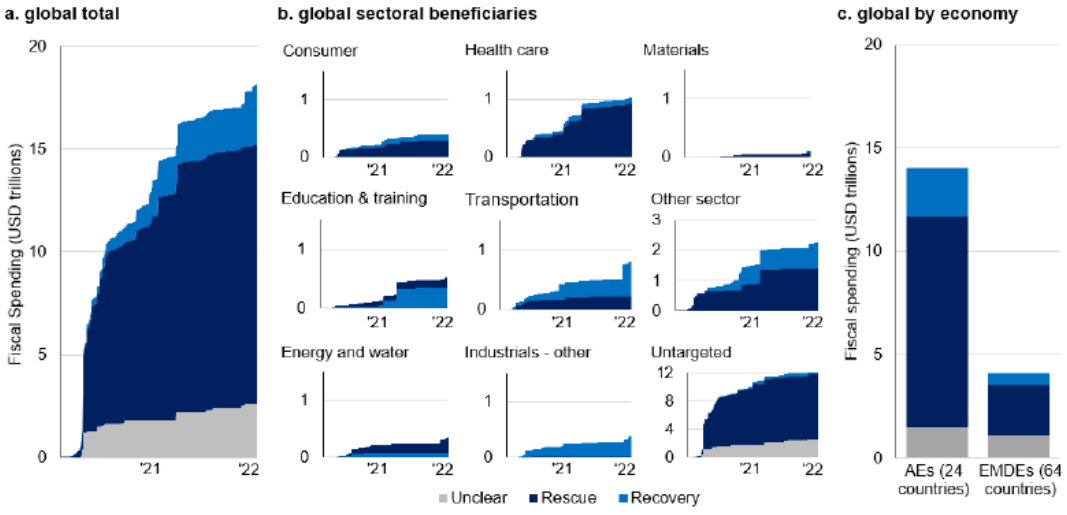


Fig. 1: Cumulative COVID-19 spending patterns over 2020-2021. **a** shows total rescue, recovery, and unclear spending over time; **b** shows the same spending by sector over time; **c** shows total spending in AEs and EMDEs. Consumer spending includes tourism and agriculture spending; materials includes forestry and nature.

FISCAL TAXONOMY FOR ENVIRONMENT AND ECONOMY

The granular data of GRO allows for a bottom-up investigation of the potential environmental impacts of COVID-19 fiscal spending. To conduct such an investigation, this paper introduces perhaps the first comprehensive fiscal taxonomy for recessionary spending (see extended

data table 2). This taxonomy expands indirectly from the 3-category (7-subcategory)taxonomy of Robins et al.,[19] and directly from the incomplete 25-archetype taxonomy featured in previous work.[1] It incorporates perspectives on the impacts of spending in the Global Financial Crisis (GFC).[20–22] The taxonomy, refined through peer-review from over 20 international collaborators, categorises fiscal measures on the grounds of both economic impact and environmental impact. It contains 42 policy archetypes and 221 subarchetypes, all independently assessed for greenhouse gas (GHG) impacts over both the immediate- and long-term (see extended data table 2 for a list and supplementary methods for definitions and details).[a] A five-point Likert scale is used for ex-ante assessment of potential policy impact, with scores based on literature review and expert input through a global survey of leading economists.[1] All spending was assessed for its impact on a given sector compared to a situation in which it were not announced and no substitute policy were announced. For example, the counterfactual to spending on electric vehicle charging stations is not additional "road construction" (archetype $\gamma 1$) but is rather "no further transport investment". For all archetypes, a general case was used, acknowledging that the impacts of some investments will deviate significantly around the mean, but presuming that deviations would be in both directions such that the general case remained appropriate. While all assessments are detailed in the supplementary methods, some immediate clarifications might be helpful: productive natural infrastructure initiatives (e.g., funds for the "sustainable management of forests, including indigenous forests" in South Africa) can, if appropriately designed,[23] support greater carbon sequestration and/or reduce the likelihood that existing carbon sinks are weakened;[24,25] R&D in digitalisation, health, and science are assumed to be moderately helpful in reducing emissions by generally leading to more efficient processes (e.g., 5G communications appear to lead to lower carbon impact than 4G communications)[26] and in some cases directly assisting climate science – for this archetype, researcher discretion was used on a case by case basis; liquidity support with green conditions is a relatively new concept, demonstrated by agricultural loans explicitly supporting lower-carbon modes of production and the French bailout of Air France-KLM with conditions including a halving of Air France's overall carbon dioxide emissions per passenger-kilometre by 2030—we assume that on whole, the incentives in these measures might reduce carbon intensity; expansion of rail infrastructure, particularly electric rail, theoretically incentivises consumers to use lower-carbon rail transport over higher carbon road and/or air transport,[27] however the induced demand effect can result in a net increase in carbon emissions in some, particularly developing, contexts[28]—driven by these conflicting factors, the archetype is assessed to have only a moderately positive impact; finally, investments in green market creation, which is a broad category often acting as an 'other' bucket for low-carbon initiatives, are thought to generally incentivise more efficient industry—examples include "Building an industrial cluster for green technology" and "promoting low-carbon manufacturing", both in South Korea. Nation-specific adjustments were made for nine subarchetypes based on the carbon profile of the respective national energy mix (see supplementary methods).

The taxonomy was applied to the GRO dataset, highlighting potential immediate- and long-term GHG impacts for 7,838 of the 8,001 policies (98.0%). The remaining policies were insufficiently described in government documentation to make an archetype assessment and labelled "unclear". Validation of the taxonomy and its application to GRO data was completed with international peer review, blind side-by-side human review, and with a unique application

[a] By way of example, archetypes include communications infrastructure, traditional transport infrastructure, and clean transport infrastructure. For the clean transport archetype, there are seven subarchetypes, including: new public transport systems or line expansions, existing public transport capacity expansions, EV charging infrastructure, cycling and walking infrastructure, and improvement of efficiency in dirty transport.

of recurrent neural network (RNN) models, described in the methods (see accuracy reported in extended data table 3 and extended data figure 4). Having been trained on a rich dataset, the same RNNs could now be used to automatically categorise future public spending, particularly in the event of future global disruptions, and the deep learning method replicated for other applications in tracking economic policy.

DISTRIBUTION OF GREEN RECOVERY SPENDING

Over the period 2020-2021, US$ 978 billion was invested in initiatives with low long-term GHG profiles, reflecting 5.3% of total spending. Of this, US$ 945 billion was both long-term green and recovery-type, reflecting 31.1% of total recovery spending. This share is higher than the GFC, where 16% of recovery spending was classified as "green",[6,19] yet there were still trillions of dollars in lost opportunities to add green criteria to traditional spending. Potentially green spending came in every sector, with the most richly served archetypes in clean transport infrastructure (US$ 214 billion), green market creation ($176 billion), and clean energy infrastructure (US$ 161 billion) (figure 2), all of which hold high potential for economic growth.[15] <<insert about different spend why green>>. The United States' *Infrastructure Investment and Jobs Act*[29] accounted for 27% of all global climate-positive spending. In totality, global spending in response to the pandemic was the largest ever public spending in climate change mitigation. As during the GFC, this new climate-positive spending could directly accelerate climate mitigation and indirectly accelerate technological learning rates for green technologies,[30] which also supports mitigation efforts.

However, spending was heterogenous across countries with only 17 of the 88 tracked nations who spent above 1% of GDP on recovery giving more than 30% of those funds to low GHG measures (figure 3). Many opportunities to further decouple growth from emissions were missed, implying that underinvesting nations have reinforced domestic transition risks and global physical risks from climate change. With over US$ 100 trillion still required to meet net zero,[10] and fiscal space shrinking as monetary policy tightens, many countries need to better prioritise initiatives that counter climate change in their fiscal allocations. This is not to say that nations should spend more in total, but rather that if nations are to spend, it should be greener.

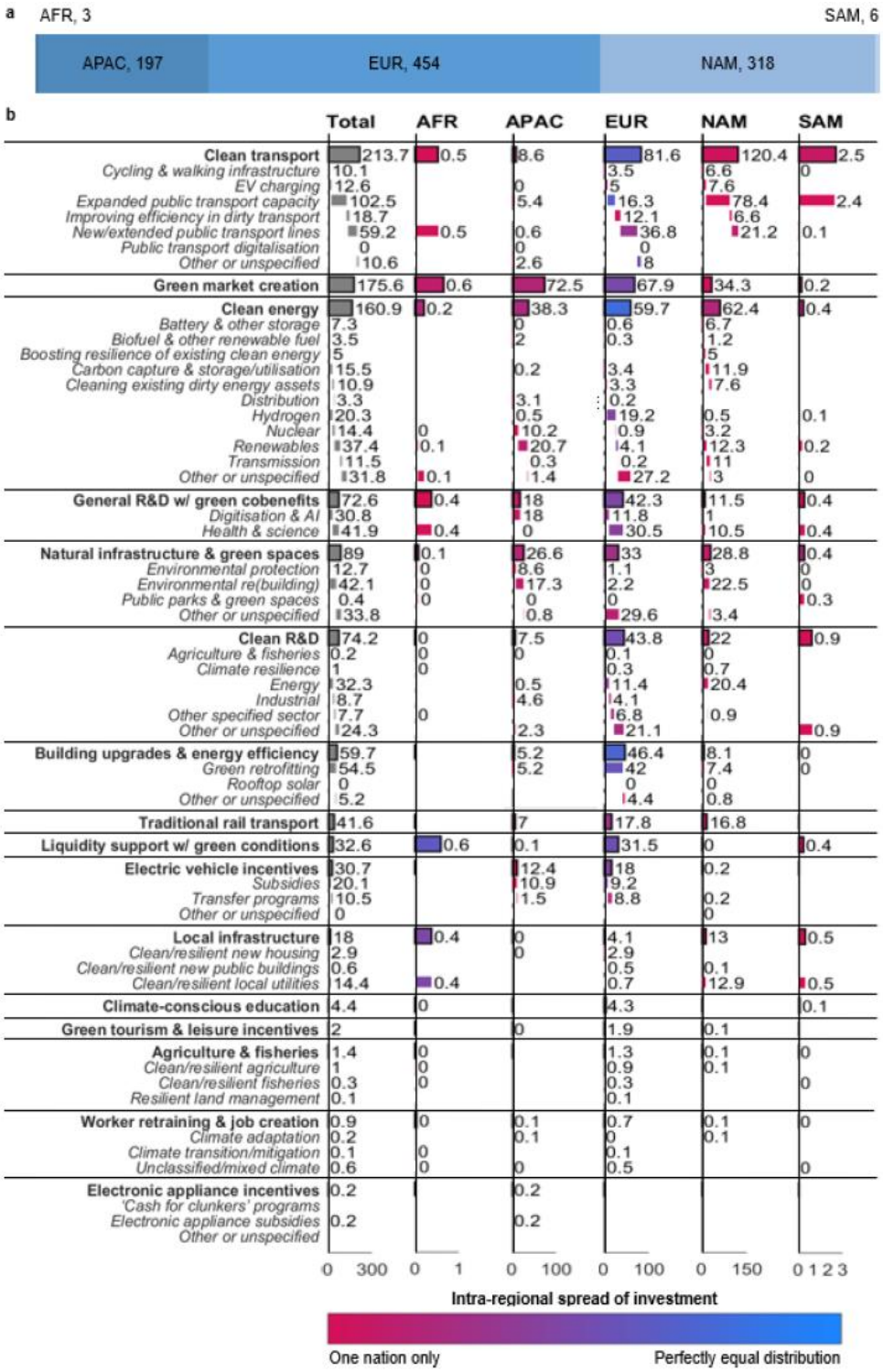


Fig. 2: COVID-19 spending with low long-term GHG emissions profiles, totalling US$ 978 billion. This spending accounts for 863 out of 8,001 policies in GRO. 806 of these (US$ 945 billion) are also recovery policies. **A**, total low emissions spending in each region. **B**, total spending by low emissions subarchetype in each region. Zero values reflect a total spending of less than US$ 50 million while blank values suggest no spending for the

subarchetype. Business tax cuts with green conditions are excluded from the figure as no relevant policies were recorded for this subarchetype. Calculations for intra-regional spread of spending are included in the supplementary materials. AFR: Africa (11 countries); APAC: Asia and the Pacific (23 countries); EUR: Europe (19 countries); NAM: North America (23 countries); SAM: South America (12 countries).

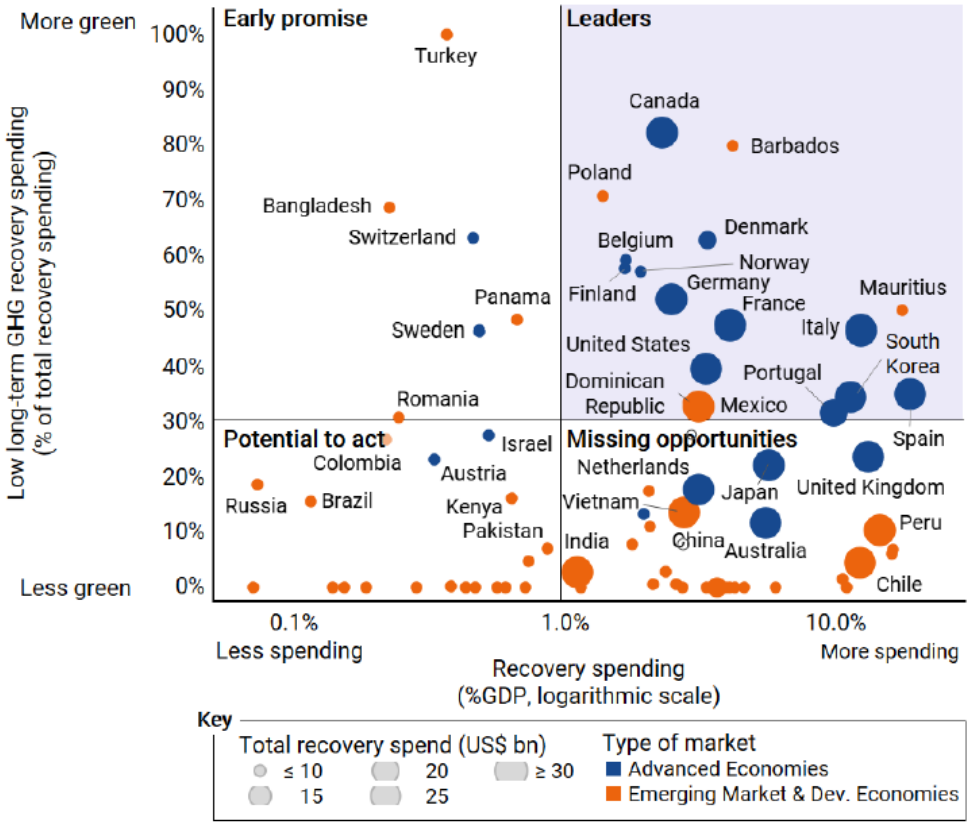


Fig. 3: Global spread of COVID-19 recovery spending that is likely to reduce long-term GHG emissions. Nations spending less than 1% of GDP on recovery tend to have very few policies in GRO; in these cases, indications of GHG spending are driven by very limited data. For instance, Turkey only has one recovery policy. See analysis on per-capita terms and for total spending in extended data figures 2 and 3, respectively.

STATISTICAL PATTERNS IN GREEN SPENDING

Using the aggregated GRO data, automated general-to-specific (GETS) econometric model selection was used to investigate what factors correlate best with variation in spending across countries. GETS selection takes a base general model, that incorporates the core features of the underlying dataset, and applies the theory of reduction to eliminate statistically insignificant variables and determine those factors most important for predicting outcomes.[31,32] It finds the *most appropriate* model that fits the data by trading off the number of selected regressors with the model's explanatory power. GRO policies were aggregated by country over the full period 2020-21 and analysed log-log as cross-sectional data using PcGive in the OxMetrics package.[33,34] This used the Schwarz information criterion for relating regressors to explanatory power. Depending on the sample, between 47 and 91 explanatory variables were considered (see extended data table 4).

Cross-sectional models were built for four dependent variables (figure 4): total spending (US $), total recovery spending (US $), low-GHG recovery spending (US $), and low-GHG recovery spending as a percentage of total recovery spending. Each dependent variable was

modelled with four country samples: (A) 84 economies, (B) 81 economies, (C) 50 economies, and (D) 47 economies. The 84 economies sample included all nations in the GRO dataset, except four nations with insufficient statistics to build regressor datasets (Cuba, Taiwan, Uruguay, and Venezuela). The 81 economies sample excluded the three nations without contested elections (China, Saudi Arabia, and Vietnam), so that election data might be tested as a potential regressor. The 50 economies sample was limited to the largest 50 economies and the 47 economies sample to the same, excluding nations without contested elections. The smaller samples (C and D) allowed additional potential regressors to be tested where data availability prohibited their consideration in samples A and B. For instance, S&P default rates and indices on the stringency of government policy responses to COVID-19.[35,36] The 16 final models passed diagnostic tests for normality, heteroscedasticity (with and without cross products), and regressor specification (see extended data table 5). The selected regressors were all retained at the 0.05 level, and almost all at the 0.005 level. In a few cases, alternative models with very similar Schwarz criterion emerged; the preferred model was selected based on congruence to models identified for other samples.

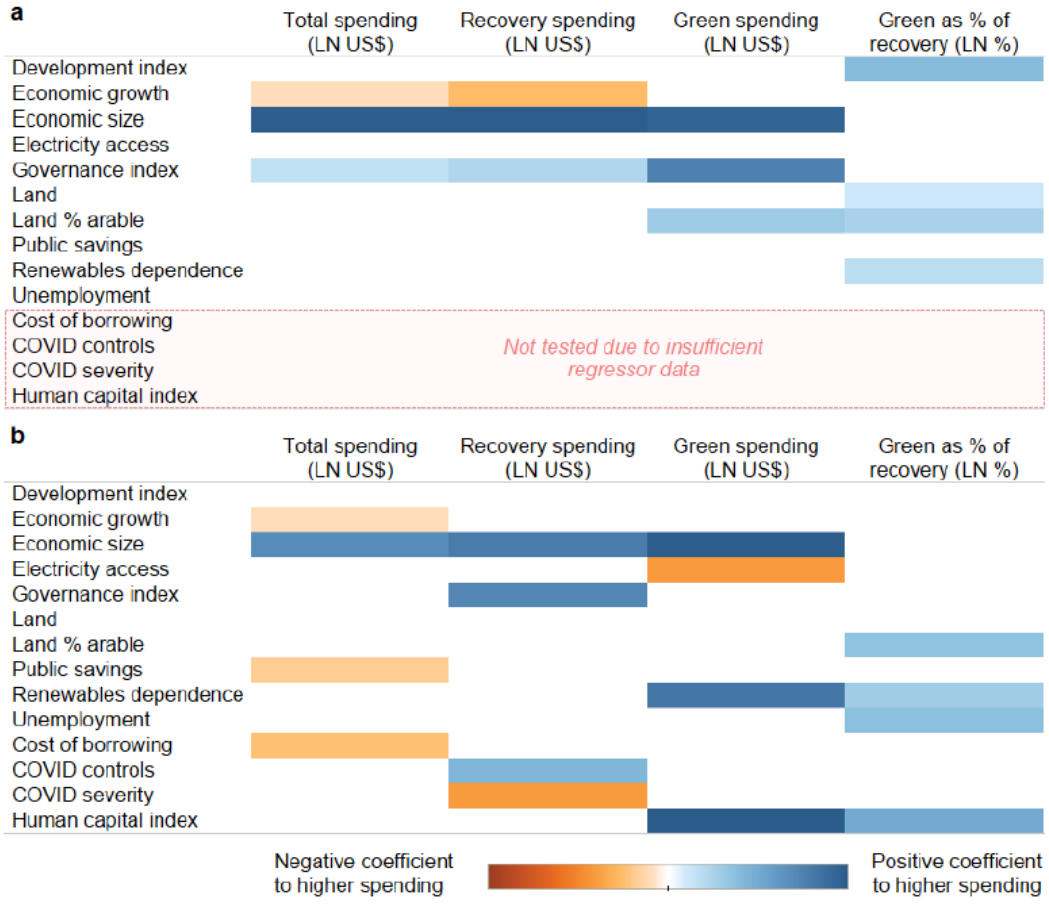


Fig. 4: Selected predictors of COVID-19 spending from GETS model selection. **a**, 84 economies sample (A) with models selected from 51 potential regressors. **b**, 50 economies sample (B) with models selected from 91 potential regressors. The colorbar indicates the magnitude of standardised regression coefficients. Variables are as follows: for development index, the United Nations' Human Development Index; for economy size, Gross Domestic Product in current US$; for economic growth, annual growth in Gross Domestic Product; for electricity access, % of population with access to electricity; for land, surface area in km²; for land % arable, arable land as % of total surface area; for public savings, gross domestic savings as % of GDP; for renewables dependence, renewable energy consumption as % of total energy consumption; for unemployment, ILO estimates are used as % of total

labour force; for regulatory strength index, either the World Bank's Rule of Law Index or Voice and Accountability Index; for cost of borrowing, the 24-month cumulative average default rate associated with S&P credit rating; for COVID-19 controls index, the OxCGRT Stringency Index as of 31/12/2020; for COVID-19 severity, reported COVID-19 cases per capita as of 31/12/2020; for human capital index, and the World Bank reported index scores. All variables except HDI, COVID-19 metrics, and cost of borrowing are three-year (2018-2020) average figures.

The GETS output for the most appropriate models highlights that total COVID-19 spending and recovery spending were both crucially correlated with factors of economic size (larger economies spent more) and economic growth (lower growth rates predicted higher spending). For total low-GHG spending, economic size is similarly important, but economic growth is not highlighted. The first of these correlations is unsurprising; ceteris paribus, larger economies have the capacity to spend more in absolute terms. The second correlation is less clear. Once economy size is controlled for, if following a Keynesian doctrine, nations with worse economic performance might have a greater incentive to spend on stimulating demand and thereby reinvigorating their economy. However, this might be counterbalanced by the reality that higher forecast growth rates increase the national carrying capacity for debt and hence, countries with higher forecast growth rates should be willing to spend more on an absolute basis. Perhaps then what we observe is a situation in which many nations were not operating at their debt limit, and/or perhaps this is an instance of political economy spill over where public outcry correlates negatively to growth rates and policy maker action correlates positively with public outcry. For green spending, an absence of literature on green fiscal multipliers might have impacted policy responses—there was little evidence to prompt lower growth economies to spend greener than others. Although, the findings of recent works might change this dynamic in future crises.[6,37,38] For low-GHG spending as a proportion of total spending, neither economic size nor economic growth emerged in the most appropriate model.

Another important factor for total spending was, for samples A, B, and C, strength of governance (countries with higher strength spent more). Higher fiscal capacity has been shown to lead to stronger governance, in both AEs and EMDEs, and a similar relationship might be at play here.[39,40] For sample B, where election factors were included in the set of test explanatory variables, days until next election was a selected variable (countries with longer until a federal election spent more). Election factors were not prominent in any other model. While public perception is often that massive fiscal policy decisions are used as a tool to sway voter sentiment in favour of the incumbent, Klomp and de Haan (2013) and Payne (1991) find little evidence in the data to support that hypothesis.[41,42] While new spending might be raised around elections, the volume of spending can be very small compared to the budget on whole—a US$10 million policy might appear enormous to the public but is insignificant in the context of a multibillion (or multitrillion) dollar budget. The trend towards higher spending away from elections might be explained by a hesitance to over index on rescue measures for fear of accusations of fiscal irresponsibility—in other words higher spending immediately before an election might be perceived as a vote loser. For the smaller samples (C), the introduction of additional regressors replaces the leading role of strength of governance with S&P credit rating 24-month default rates, as a proxy for sovereign borrowing costs (countries with higher implied default risk spent less), and gross domestic savings (countries with lower consumer savings spent more). The inverse relationship between cost of capital and level of spending is theoretically obvious, with empirical studies demonstrating that EMDEs tend to employ procyclical fiscal policies during recession, while AEs have the fiscal space to deliver countercyclical responses.[43,44]

Models for recovery spending for the larger samples (A and B) were similar to total spending models, although with varied coefficient magnitudes. For the smaller samples, where additional trial regressors were available, recovery spending was correlated with economic size and governance, but also with COVID-19 cases (countries with more cases per capita

spent less on recovery) and the severity of government policy responses to the pandemic (countries with stricter responses spent more) as reported by the Oxford COVID-19 Government Response Tracker (OxCGRT) on 31/12/2020.[36] From OxCGRT data, we already know that more stringent policy tends to correlate with higher fiscal responses, so it is comforting to see this reflected in the preferred model. The negative correlation to COVID-19 cases is perplexing. It might be explained by the fact that rescue spending correlates far more strongly with case numbers than does recovery spending, implying that higher COVID-19 caseloads precipitated higher need for rescue spending, leaving less appetite for additional recovery spending among those nations. There might be more complex timing and interaction effects at play that would be better investigated with time-series modelling, or perhaps the relationship is spurious.

Spending on low-GHG initiatives in all samples tended to be positively correlated with economic size. Additionally, in the larger samples, it was related to strength of governance (countries with higher strength spent more on low-GHG measures) and arable land area as a percentage of total area (countries with more arable land spent more). The positive relationship of arable land to green spending is difficult to interpret without further analysis. It might speak to a greater economic dependence on agricultural product and social dependence on agricultural livelihoods, both of which are particularly vulnerable to climate change and must be protected.[45,46] Agriculture is "arguably the sector most affected by climate change" and "there is ample reason to be concerned", although, "assessments differ" and it is difficult to understand comparative risk between countries in global models.[47,48] Alternatively, it might relate to stronger opportunities for direct investments in agriculture. Analysing the GRO data, there is a moderate-strong correlation (0.41) between spending on low-carbon agriculture (ω2) and total low-carbon spending ex. low-carbon agriculture. However, total spending on low-carbon agriculture was very small and land-based spending is therefore unlikely to be the driver of the correlation. With additional trial regressors in the smaller samples (C and D), three different, perhaps more revealing, selections emerged: electricity access (countries with lower existing electricity access spent more), existing renewable energy consumption (countries with higher existing dependence on renewables spent more), and human capital index (countries with higher human capital spent more). Public spending on renewable energy tends to support energy access, particularly in developing nations.[49] Human capital tends to be correlated with lower GHG emissions and is a pre-requisite for successful implementation of environmental policies including green innovation.[50-52]

Finally, low-GHG recovery spending as a percentage of total recovery spending was most crucially related, in the 50 and 47 economy samples (C and D), to a nation's:

- Existing dependence on renewable energy (countries with higher renewables use spent greener), reflecting a tendency for countries to reinforce their economic status quo;
- human capital (countries with higher human capital spent greener), which is a key enabler of green policy implementation and innovation;
- arable land as a percentage of total land area (countries with more arable land spent greener), which could be explained by several factors, as described above;
- and unemployment (countries with higher unemployment spent greener), which might suggest that policymakers perceive a higher jobs benefit from green recovery spending compared to other forms of recovery spending. This perception is empirically supported by a wide range of existing literature.[6]

In the larger 84 and 81 economy samples (A and B), which are limited by the number of tested regressors, selected regressors include renewables dependence and arable land, as well as

Human Development Index (instead of Human Capital Index, which was not available in the set of potential regressors) and total surface area. When total surface area is considered alongside arable land as a percentage of total area, the two variables function in concert to describe total arable land.

These findings should not be interpreted as causal, but on whole, they provide at least three essential reminders: (1) more is required to decouple spending from high-GHG industries, particularly in nations with low existing dependence on renewable energy, (2) boosting human capital should remain a key priority as an enabler of green policy implementation and innovation, and (3) more should be done to free capital in nations with high sovereign debt risk, as these nations are already tending to spend greener than others on a relative basis.

DID SPENDING MATCH POLITICAL RHETORIC?

Having established an analysis of the reality, we move to a discussion of the rhetoric which surrounded pandemic response. In 2020, "build back better" and "green recovery" became global rallying cries. To understand whether green statements from political leaders were matched by climate-positive spending, a green rhetoric index was created from a novel dataset of 3,817 political speeches from 43 countries. The analysis presented in figure 5 suggests that both speech and spending patterns varied significantly across nations, with several prominent countries failing to match comparative rhetoric with action.

The speech dataset (*Global COVID-19 Speech Database*) comprises a full corpus of official transcripts from heads of government and select heads of state over the period 2020-2021, compiled using standard web scrapping techniques (dataset available in supplementary materials). The corpus was preprocessed and subsequently analysed using a dictionary of 247 green terms (356 including plural and hyphenated forms) in 10 green categories. The dictionary was extended from O'Callaghan et al. (2022) using the dictionary-building algorithm introduced by those authors, but trained on the new speech corpus.[6] The algorithm self-identified terms like 'zero_carbon' and 'conserve_nature' that were absent from the starting dictionary. The green rhetoric score was defined by the relative frequency of green terms occurring compared to other terms in the text for any country. Ten rhetoric sub-analyses were conducted for each of the ten green categories observed in the speeches (see extended data table 6). The nations were analysed in three groups based on number of published speeches; this loosely controlled for the type of speeches given by heads of state (i.e., only formal addresses vs all discourse, including regular press briefings).

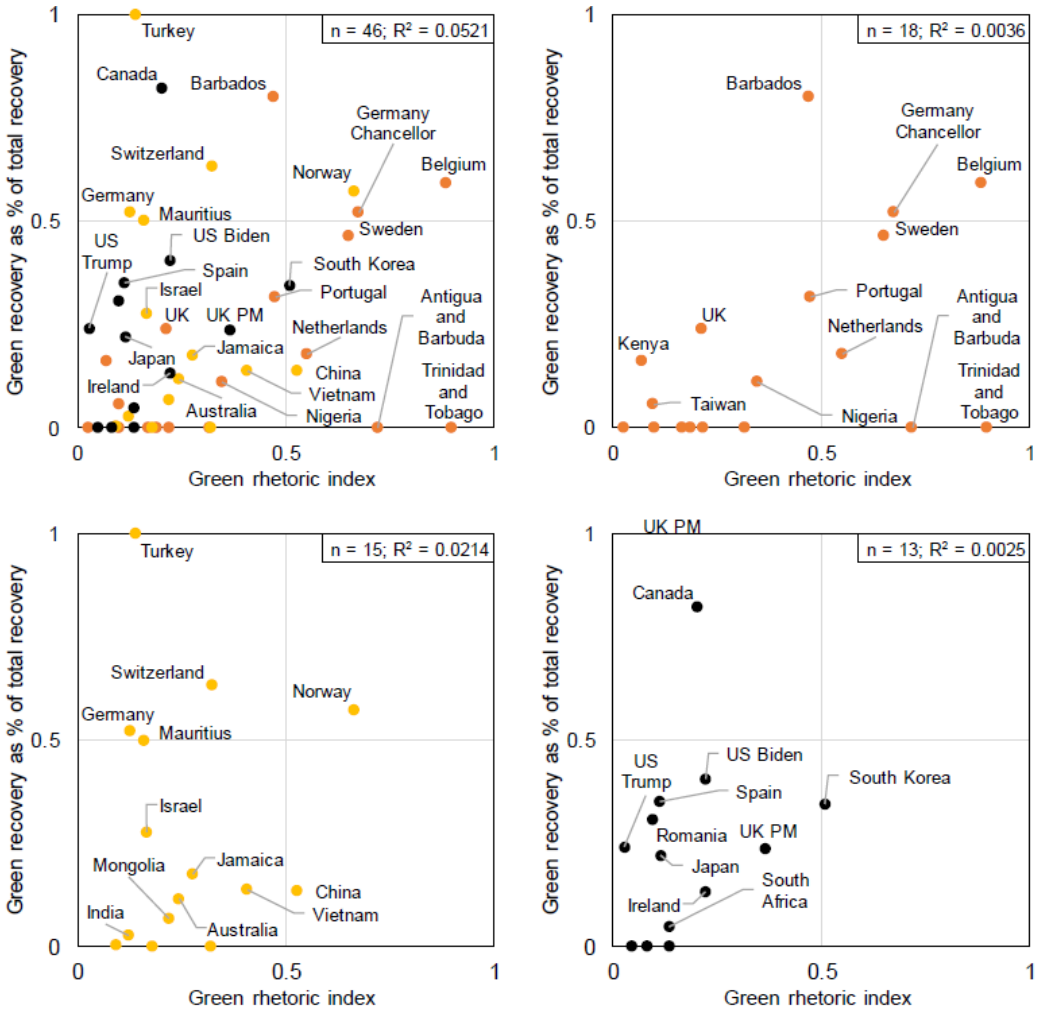


Fig. 5: Green rhetoric compared to climate-positive recovery spending in 43 countries. For some countries, where there is significant variation between rhetoric of heads of government and/or a head of state, multiple speakers are presented for reader interest. **a**, all 43 nations analysed. **b**, nations with fewer than or equal to 20 transcribed English speeches. **c**, nations with between 20 and 100 transcribed English speeches. **d**, nations with more than 100 transcribed English speeches.

While the results in figure 5 do suggest some relationship between green political rhetoric and climate-positive reality, it is also clear that the trend is weak (linear R^2 = 5.21% when considering only one data point per country). The gap between rhetoric and reality in many countries could lead to their promises being reasonably described as "*blah blah blah*".[53] Despite similar levels of green rhetoric, nations including China, the Netherlands, and Vietnam tended to direct significantly lower portions of their recovery spending to low-GHG initiatives than counterparts including Canada, Barbados, and Switzerland. Significant variation within countries—between heads of state, as in Trump-Biden, and between head of state and head of government, as in the UK and in Germany—show the highly political nature of climate change and compel closer attention from civil society organisations (CSOs) and researchers. CSOs could use this analysis to better hold governments accountable and interpret ambition communicated in government announcements compared to past and present global efforts. Future work might incorporate advanced linguistic comparisons to understand and, if

necessary, correct for natural variation in speech patterns between different speakers. Future work might also extend the analysis to languages other than English, test the political rhetoric scores in the GETS model selection process, and use topic modelling, sentiment analysis, or other advanced natural language processing (NLP) method to better understand rhetoric.

CONCLUSION

The COVID-19 recovery provided the largest ever investment in the climate (US$978 billion), with these funds likely to accelerate low-carbon shifts in many sectors. Yet, this spending followed decades of under-investment and cumulative spending remains wholly incommensurate with the scale of climate change. Additionally, significant funds totalling 9.1% of recovery investment, were directed to initiatives likely to increase long-term GHGs—this might counteract the positive impacts of the low-carbon investments. This is not to mention the dearth of appropriate fossil fuel pricing reforms needed to support low-carbon investment. Considering the short-term, spending outcomes are likely to be lopsided, with perhaps as much as 71.5% of spending leading to increased emissions (driven by embedded carbon in physical infrastructure, as well as existing energy and resource inefficiencies in most sectors). Aligned with the findings of prior studies,[13-15,54] I suggest that all in all, the COVID-19 fiscal recovery delivered only a fraction of the low-carbon investment required by scenarios for a 1.5-degree aligned green recovery and failed altogether to increase fossil fuel divestment required by the same scenario.[8] Future fiscal investments must be paired with complementary pricing reforms, which could also help continually fund the measures. Other useful supporting policies to accelerate a low-carbon transition include upholding environmental regulation, supporting technology-push policies like financial and non-financial R&D incentives, and situating all of these measures with respect to a long-term climate strategy.

The GRO and pandemic speech datasets together affirm that which is already widely presumed—governments do not necessarily act in accordance with their rhetoric, especially on climate change. New automated policy impact assessment could follow the neural network models demonstrated in this paper to support researchers, businesses, and civil society in holding governments accountable to their words. Policy makers have herein been put on notice: there is no time for duplicity on climate, we are watching every fiscal action.

There are several limitations to this paper, relating to both data compilation and analysis. First, the GRO policy dataset, while the most detailed and expansive of its kind, considers only policies publicly announced by government—it is hence possible that some fiscal measures are not included in GRO, although testing against fiscal data reported by countries to the IMF and OECD suggests that this is infrequently the case. Second, and perhaps a greater issue, 22% of policies do not include a quantified fiscal impact, meaning that figures reported in this paper are likely underestimates of true value. Third, the categorisation of policies to the new fiscal taxonomy is based on descriptions provided by policymakers—it is likely that these articulations are the most positive interpretations of policy coverage and based on this, categorisation of GRO policies might overstate climate relevance. Fourth, the potential directional GHG impact assessments provided by the taxonomy are ex-ante in nature, meaning that they are much more useful on an aggregate basis where variations between policies can, on average, be cancelled out (see details in supplementary materials). Fifth, all analysis in this paper concerns announced spending rather than actual spending—many announced initiatives will be implemented over many years. Actual spending does not always match announced spending and the discrepancy between the two could only be deduced once all COVID-19 measures have concluded, around 2030. Small variations in actual spending could significantly impact, for example, results of the GETS analysis, which is very sensitive to its inputs.

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METHODS

This paper combines several methods to provide a multi-dimensional analysis of COVID-19 recovery spending. Policy making in the face of climate change is complex and approaches are diverse; appropriately interpreting trends requires multiple perspectives. Two new data sets are created, one providing granular COVID-19 fiscal policy in 88 countries (8,001 policies, 58,704 data fields) and another providing COVID-19 era speeches of heads of state in 43 countries (3,817 speeches). Data categorisation is conducted with a novel fiscal policy taxonomy, which is in turn validated with blind side-by-side human review and neural network models. Data is analysed in three dimensions: (i) using descriptive statistics, (ii) using general to specific econometric modelling, and (iii) using machine learning techniques in natural language processing.

OBSERVATORY DATA

The Global Recovery Observatory, which covers 88 countries and 8,001 COVID-19 fiscal expenditure policies, was manually compiled over two years, with >3,000 hours of input from Oxford University research assistants. Extreme heterogeneity in how and where countries report fiscal expenditure, as well as an absence of reliable test data, made efforts for automated data collection processes impossible. To guide data collection, research assistants received a written set of instructions and standards, a verbal introduction to the task, and a sample of 500 recorded policies from the GFC and 500 from the first weeks of the pandemic. Weekly meetings with research assistants helped resolve outstanding questions and validate data for regular public updates through the Observatory website (https://recovery.smithschool.ox.ac.uk/tracking/). ~20 correction suggestions were received from the public and government entities over eighteen months of live data releases, with four dataset reviews conducted by government representatives, and 60,000 views. Only five of the suggestions were implemented, with the balance rejected as inaccurate or unsubstantiated.

Policies were included in the Observatory only if publicly announced by a government entity, tagged by the entity as related to COVID-19, and legislated or otherwise confirmed for implementation by a delegated decision-making body (e.g., national cabinet). This introduces a limitation in that governments might make fiscal changes without public announcement; however, consultation of IMF and OECD databases (which include non-public country submissions) suggests that this was infrequently done in response to the pandemic. Policies were recorded at the highest granularity that was possible given government descriptions. Recorded data fields are *policy name*, *policy description*, *official document reference*, *financial value*, *date*, and *source*. Later, policies were categorised by *archetype*, *subarchetype*, and *sector.* For grouped policies, where a single cumulative financial value was provided for a set of named investments, the value was assumed to be equally spread across policies (this is noted in the dataset where applicable). Future machine learning efforts might use the source materials identified alongside each policy as test data for automating future data collection.

The GRO is unique amongst other fiscal policy trackers in its granularity, global coverage, and breadth of policy attention across sectors. Initiatives like the IMF Fiscal Policy Tracker (~850 fiscal packages) and Nahm et al. (366 fiscal packages) track at the package level (less granular).[14,46] Energy Policy Tracker, Nahm et al., and Vivid Economics have limited country coverage.[14,47,48] Energy Policy Tracker, IEA, OECD, and Nahm et al. track only initiatives likely to have an impact on GHGs rather than the full breadth of policies.[12,14,47,49] The Yale *COVID-19 Response Tracker* is perhaps the closest in coverage, with ~45% as many measures as GRO, but no taxonomy for classifying policies and no assessment of GHG or other environmental impact.[50] The supplementary methods (table S1) contain a detailed comparison of fiscal policy trackers.

TAXONOMY DESIGN AND VALIDATION

Taxonomy-based approaches to impact assessment group policies based on similarities in function, use, or some other unifying characteristic. They assume that heterogeneities between policies within a category are distributed around a mean with somewhat predictable impact characteristics. The approach is hence more useful for understanding groups of policies than individual policies.

A custom-designed taxonomy was necessary to group fiscal recovery policies based on both economic and environmental similarities. In total, 42 archetypes and 221 subarchetypes were established. At creation, no previous recovery taxonomy had incorporated more than 7 categories.[19] Generalised fiscal taxonomies (i.e., those not explicitly designed for recessionary fiscal policy) either do not distinguish environmental policies by sector[51–53] or only cover environmentally-relevant categories.[54] No prior taxonomy distinguishes between policy types based on both economic and environmental characteristics.

Archetypes and subarchetypes in the GRO taxonomy were designed to:

- group policies based on both economic and environmental similarity;
- be sufficiently granular to reflect the policy detail provided by governments;
- be of similar granularity at each level (i.e., archetype and subarchetype);
- be mutually exclusive; and
- be collectively exhaustive.

Whereas other taxonomy approaches employ two-point scale assessments of climate impact, every policy subarchetype in the GRO was assessed on a five-point Likert scale for potential short- and long-term impact on greenhouse gas emissions compared to a scenario in which the archetypal policy was not implemented. Likert categories were, *large increase in GHG emissions (-2), moderate increase (-1), minor or no impact (0), medium decrease (+1), and large decrease (+2)*. Impact assessment was based on a comprehensive literature review (see supplementary methods, with some guidance from O'Callaghan et al., 2022),[6] survey input from leading global economists,[1] and a one-year peer review involving over 20 professionals and academics. A correction factor was applied for the nine archetypes where GHG impact varies approximately linearly with the carbon intensity of a national electricity mix.

DATASET VALIDATION WITH HUMANS AND DEEP LEARNING

Validation of the taxonomy was established with three methods, two by humans and one with deep learning. The first method was international peer review, as described above. The second method was a controlled side-by-side test in which two research assistants, trained on the taxonomy, completed a blind side-by-side archetyping exercise of the same set of 2,406 policies (30.1% of the final dataset). The researchers converged on assigned archetypes for 92.6% of policies and after discussion, 98.6% of policies. Given the necessarily broad descriptions of some policies, this convergence is considered high.

The third validation method was to train RNNs using categorised GRO data with an 80:20 (train:validate) split. The models learnt how policy names and descriptions were labelled in the training set and applied the learned model of classification to the validation set. If the taxonomy were perfect and perfectly applied, the RNNs would learn how to categorise any policy from the training data with 100% accuracy. For the GRO dataset, the RNNs were up to 92.8% accurate in classifying a policy by whether it might have a positive, neutral, or negative impact on a national GHG trajectory. Compared to other model dataset pairs in short-text classification, this result is high,[55] suggesting potentially well-described and aptly-categorised data. On a five-point scale—differentiating between strong positive, positive, neutral, negative,

and strong negative impacts—they were up to 91.5% accurate. On two-point scales—for instance, positive impact versus other impact—they were up to 95.9% accurate. For policy function—differentiating between rescue and recovery policy types—they were up to 87.1% accurate. The RNNs sort policies into the 42 archetypes with up to 55.9% accuracy.

To the specifics of the RNN application, the long short-term memory (LSTM) approach was used instead of transformer methods like BERT given LSTM's strength in analysing small corpuses.[56–58] Similar approaches have been applied to, amongst other things, diagnose cancer,[59] detect anomalies in aircraft data,[60] and identify hate speech on Twitter.[61] While discussed often, RNNs have been used relatively infrequently in climate policy and so far as I am aware, never in fiscal policy studies.[62,63]

The models in the present work use the Adaptive Moment Estimation (Adam) optimiser,[64] a sequence input layer of size 1, a green spending embedding layer of dimension 100 (domain-specific layer adopted from O'Callaghan et al., 2022),[6] a fully connected layer, a softmax layer, a classification layer, and an 80:20 training:validation set. Alternative optimisers and embedding layers were trialled, with varying success. Other optimisers including Stochastic Gradient Descent with momentum (SGDM) and Root Mean Squared Propagation (RMSProp) failed to outperform the Adam optimiser. Some alternative word embeddings, like FastText, were comparable to the green spending embedding, sometimes delivering better results and sometimes not. Five independent models were optimised, using two sets of input data (policy description; concatenated policy name + policy description). The models used preprocessed policy information as input to determine (i) policy archetype, (ii) policy function (rescue or recovery), (iii) likely GHG impact on a two-point scale, (iv) likely GHG impact on a three-point scale, and (iv) likely GHG impact on a five-point scale. The model accuracy optimisation process created and compared thousands of models by varying learning rate (0.00025-1), mini-batch size (8-512), various momentum scenarios for SGDM, and preprocessing word exclusions (see extended data figure 4). The target accuracy metric was "best validation loss", i.e., validation accuracy at the lowest validation loss. Standard preprocessing techniques, including lemmatisation, were used to prepare the input data. Sequence length was limited to 50 words to exclude the long tails in policy description associated with a small minority of policies. There remains significant opportunity to further improve the models developed in the present study, particularly through trials of advanced solvers and more targeted preprocessing. Yet, even in their current state, the models are useful for auto-assessment of fiscal policy announcements and among other applications could be used in future national budgeting processes, business decision making, and to provide objective fiscal policy inputs to climate modelling.

GENERAL-TO-SPECIFIC AUTOMATIC SELECTION

General-to-specific (GETS) model selection is used to select useful empirical models from general input sets.[25,26] For applications in fiscal economics, these methods recognise that economies are inherently complex, nonlinear, simultaneous, high-dimensional, and constantly evolving. They implicitly acknowledge that deriving complete theoretical models to define, for instance, why governments spend as they do, is an impossible task. To arrive at useful empirical models, GETS relies on the theory of reduction, which explains that empirical models describe the reduced form of the actual mechanisms that demonstrate economic outcomes.[65]

To meet their objectives, these methods take a long list of possible explanatory variables, test all feasible reduction paths and eliminate variables with coefficients that are statistically insignificant until only relevant variables remain. The leading and most widely studied GETS computer automated program, and that employed in the present study, is PcGive.[66,67] There is considerable literature on the virtues and potential deficiencies of PcGive, summarised in

part by Campos et al. (2005).[26] For the present study, which uses cross-sectional data only and relies on reported rather than measured data, the method is considered more than sufficient.

To address incomplete data availability across countries for some potential regressor variables, four separate country samples were established for analysis: (A) 84 economies, (B) 82 economies, (C) 50 economies, and (D) 47 economies (see extended data table 1). Samples B and D exclude nations without contested elections (China, Saudi Arabia, and Vietnam) so that additional regressors are tested (*time until next election* and *percentage of government term remaining*).

Each sample was tested with between 47-91 potential regressors, four times, once for each dependent variable (extended data table 2). These potential regressors were selected from a preliminary set of 1,386 variables, identified from ten sources, intending to meaningfully represent the universe of plausible independent variables. The list was first reduced by eliminating all incomplete variable sets, i.e., those that did not at least fully cover the smallest sample (D). It was further reduced by eliminating duplicate variables, variables clearly unrelated to the dependent variables, and variables that were highly granular subsidiary terms of other variables (see section 6.1 in the supplementary methods). Interpolation for missing data was avoided in all situations except for providing an expected 12-month and 24-month default rate for the Islamic Republic of Iran. Other default rate expectations were based on S&P cumulative average default rate tables.[68]

Model runs on PcGive software used automatic model selection (size = small) for standard ordinary least squares (OLS) estimation with Impulse Indicator Saturation (IIS) for outlier detection. The software automatically checked for normality with χ^2 tests for normality (two-sided) and White tests for heteroscedasticity (both with and without cross products); any models which failed these tests were discarded. Full statistical results for each of these tests is included in extended data table 2. As prompted by normality observations and RESET tests for misspecification, all models were considered in transformed log-log form.

NLP FOR POLITICAL SPEECHES

Having established an understanding of the reality of COVID-19 response, natural language processing (NLP) is used to consider the surrounding rhetoric. NLP uses artificial intelligence to efficiently interpret and analyse large text corpuses. For climate change topics, NLP techniques have been applied to understand ESG reporting in public financial reports,[69] misinformation in US philanthropy,[70] news reporting,[71] population sentiment,[72,73] green academic literature,[6] and more. Although NLP has been used for processing smaller corpuses of head of state speeches in the past,[74–79] so far as I am aware, it has not yet been used to analyse the environmental content of head of state speeches. A Non-negative Factorization (NMF) model in conference proceedings of Gautrais et al. (2017) showed the progression of climate change as one of fifteen core topics in Trump-Clinton speeches, however this was not by design, not the focus of the paper, and it was limited to only one country.[80] Willis (2017) provides a corpus-based analysis of political speeches related to the 2008 Climate Change Bill in the United Kingdom, but without focus on the head of state.[81]

The speech database introduced in this paper includes 3,817 archived head of state speeches (available in supplementary materials) identified from official government websites and in some cases, the personal websites of former leaders. For nations where the head of state was different from the head of government, speeches were compiled for the less ceremonial and more political post. The speeches were extracted and compiled for analysis using basic web-scrapping algorithms. The analysis corpus included only English speeches or speeches

published with official English translation. The corpus was preprocessed using standard techniques, including tokenisation, removal of stop words (to reduce variation in word counts based on speaker style), and lower casing. Lemmatization and other forms of word normalisation were avoided to ensure that nuances in textual meaning were effectively captured. The preprocessed corpus contained 3,817 speeches and 2,106,933 word tokens; a 52% size reduction compared to 4,391,891 word tokens in the starting corpus.

The corpus was analysed using simple term frequency and topic identification techniques. For frequency analysis, a bespoke green dictionary was developed using a supervised machine learning algorithm trained on the corpus. This process used the ending dictionary in O'Callaghan et al. (2022) as its starting dictionary and the method described in that paper for expanding the dictionary.[6] Green terms were considered in ten categories: general environmental, energy efficiency, carbon capture and storage, electric vehicles, green energy, green liquidity, green research and development, green skills, natural capital, and sustainable transport. The new green policy dictionary extends the O'Callaghan et al. dictionary to include 247 green terms (356 including plural and hyphenated forms), with most new terms unique to modern policy discourse. A green rhetoric index was constructed to reflect the proportion of words that a politician uses to refer to green topics compared to other topics. The index was transformed to a 0-1 scale.

Alongside the rhetoric index, topic identification using Latent Dirichlet Allocation (LDA) was used to understand broad characteristics of the texts across nations, but not to search for patterns. LDA is a popular form of unsupervised topic modelling that identifies topics in any given corpus (see for instance Gautrais et al., 2017[80]). Alternative semantic models were also considered, however, due to very low frequency of anti-green rhetoric in head of state speeches, the simpler term frequency model was considered superior.

The dataset released alongside this paper includes speeches in languages other than English with the invitation for researchers to expand the rhetoric models to include other languages. Any such analysis should consider and appropriately adjust for inter-language variations in what defines a word,[82] information density,[83] and other factors. Indeed, variations should also be considered on an intra-language basis,[84] as natural differences in modes of speech between speakers could skew the results of a comparative analysis. Future work should consider how individual correction factors could reduce uncontrolled bias in the results.

Among its other contributions, this paper demonstrates the immense scope for NLP techniques to be used to hold political leaders accountable to their commitments. Data scientists already have a powerful arsenal of advanced NLP techniques that could significantly improve the proof-of-concept model introduced in this paper.

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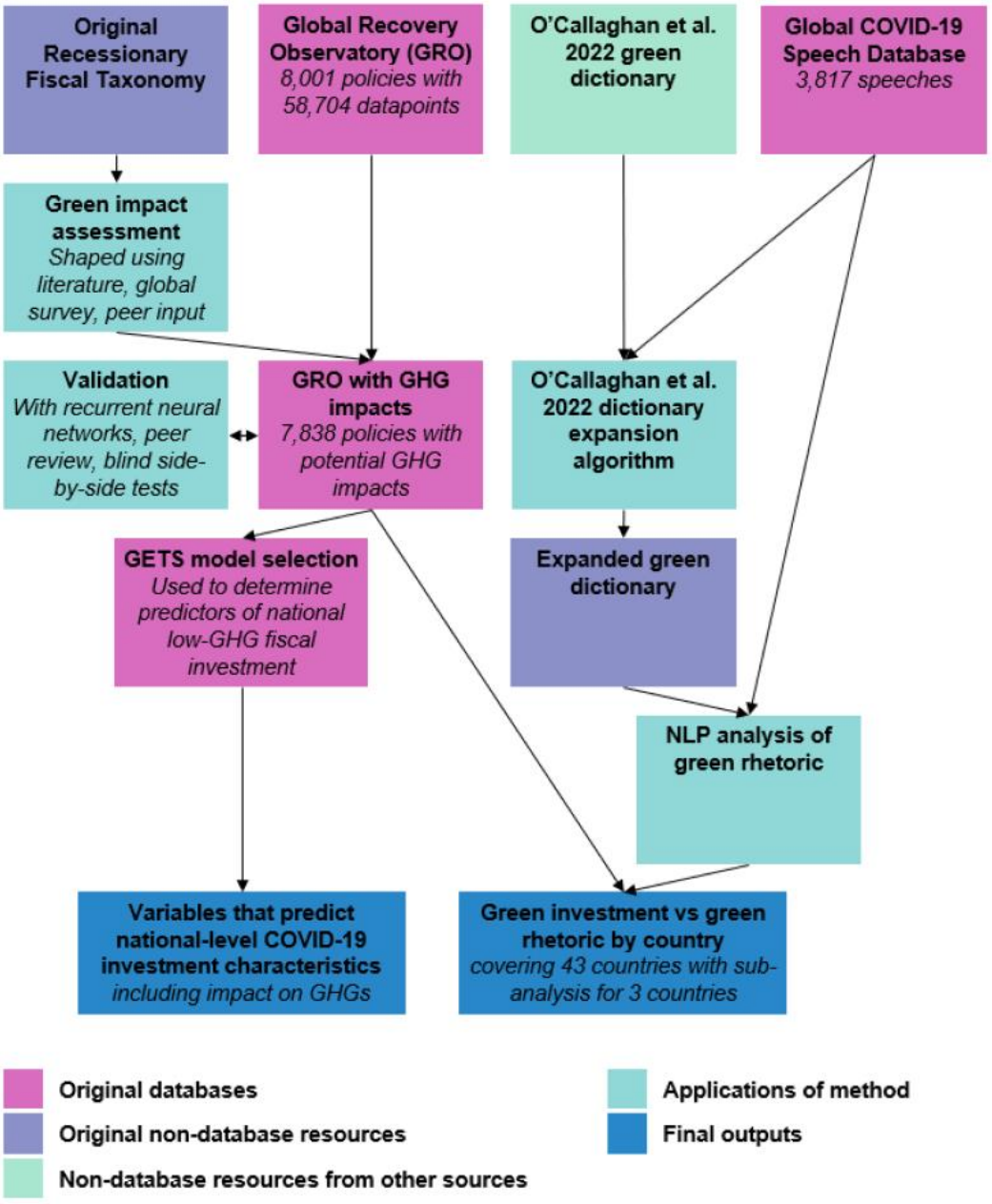
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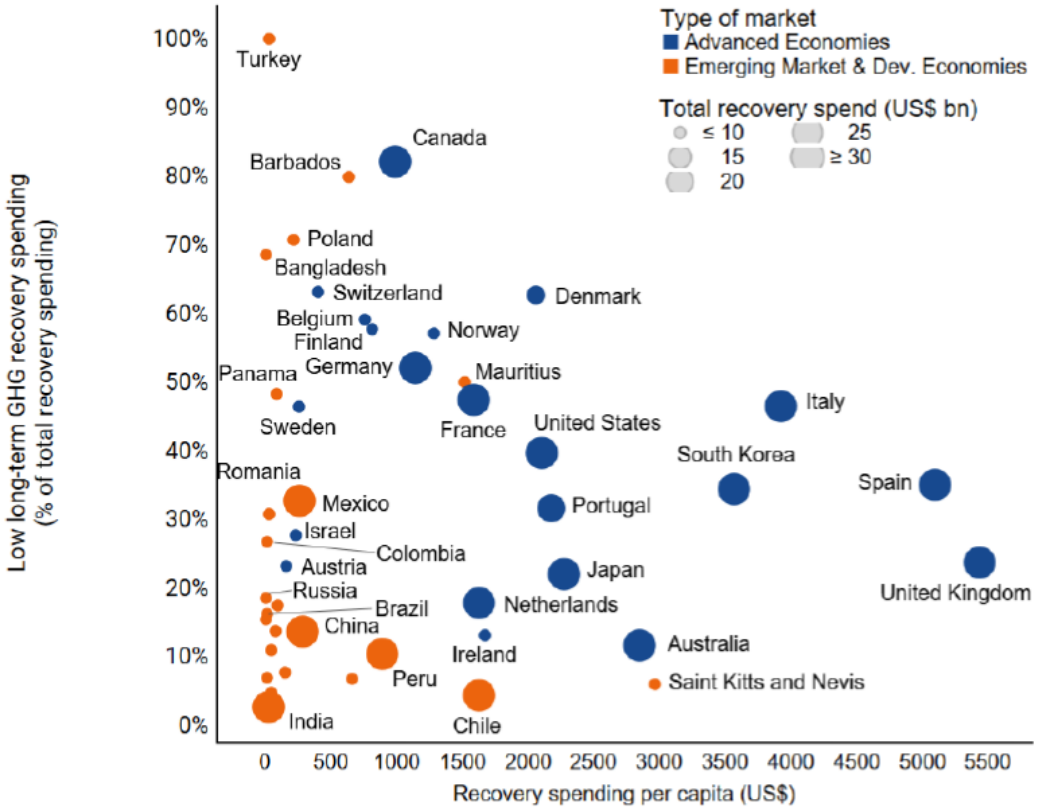
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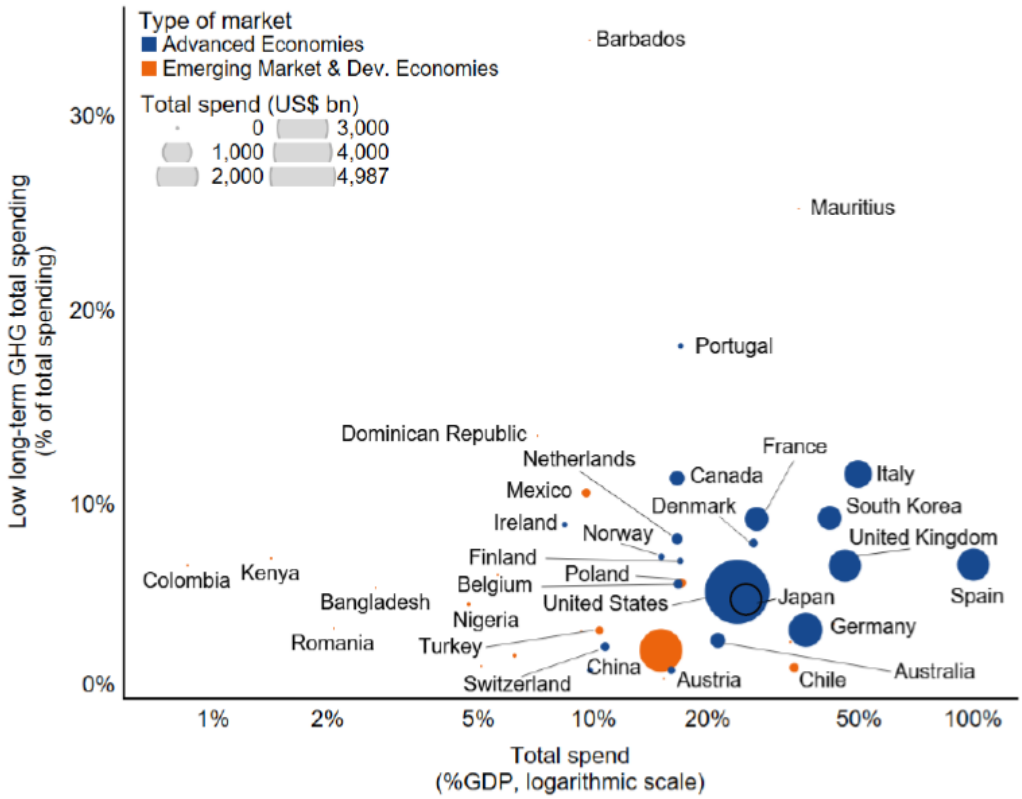
Extended data figure 1. Article map illustrating interactions between employed methods and datasets.



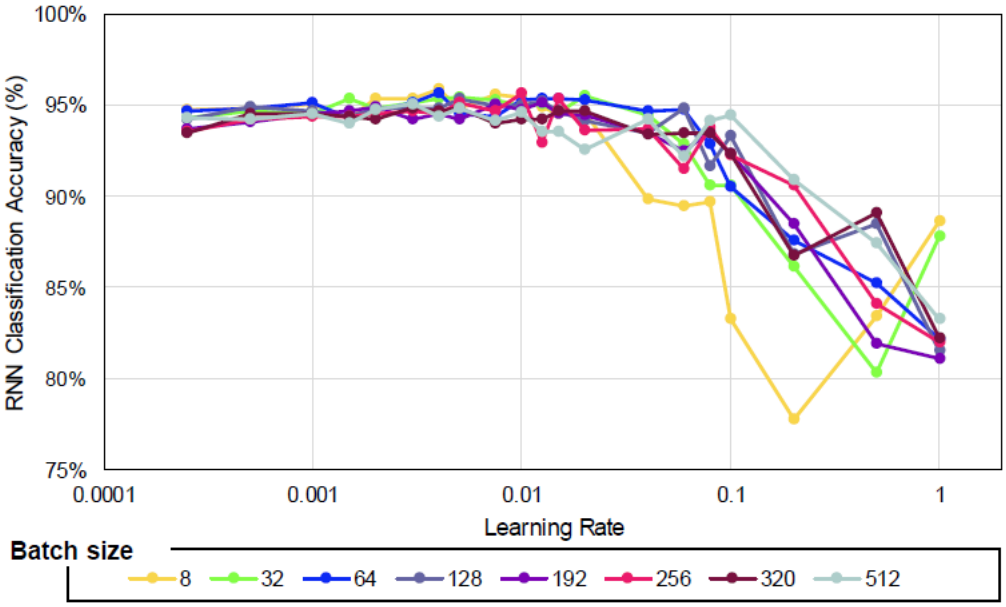
Extended data figure 2. Per capita global spread of COVID-19 recovery spending that is likely to reduce long-term GHG emissions. Nations with less than 1% of recovery spending directed to low long-term GHG initiatives are excluded.



Extended data figure 3. Global spread of total COVID-19 spending that is likely to reduce long-term GHG emissions. Nations with less than 1% of recovery spending directed to low long-term GHG initiatives are excluded.



Extended data figure 4. RNN accuracy for long-term GHG impact classification trials using a 2-point (positive-other) scale. Each circle shows the average of five RNN models at a given batch size and learning rate.



Extended data table 1. Aggregate quarterly COVID-19 fiscal spending for all 88 countries in GRO (all figures in US$ billions).

	Q1 2020	Q2 2020	Q3 2020	Q4 2020	Q1 2021	Q2 2021	Q3 2021	Q4 2021	Total
Antigua and Barbuda	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1
Argentina	8.9	8.1	1.1	1.0	1.8	2.2	0.5	0.6	24.2
Australia	60.2	65.1	16.1	80.7	7.5	50.8	0.2	2.1	282.7
Austria	59.5	8.8	0.0	0.6	0.4	0.1	0.0	0.0	69.5
Bahamas	0.0	0.5	0.0	0.2	0.0	0.4	0.0	0.0	1.1
Bangladesh	0.1	3.5	0.0	3.6	0.3	0.7	0.4	0.0	8.7
Barbados	0.0	0.2	0.1	0.0	0.1	0.1	0.0	0.0	0.4
Belgium	58.4	16.0	0.4	0.0	3.3	8.5	0.4	0.3	87.3
Belize	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
Bolivia	0.2	3.2	0.3	0.7	0.0	0.3	0.2	0.3	5.3
Brazil	71.1	76.6	26.0	5.9	9.7	11.1	5.6	1.3	207.3
Burkina Faso	0.0	0.3	0.0	0.0	0.1	0.0	0.0	0.0	0.4
Canada	39.3	119.7	44.7	24.2	11.6	10.2	2.8	20.6	272.9
Chile	11.2	15.7	1.6	2.7	6.9	0.4	0.0	47.0	85.6
China	283.2	1047.6	48.7	228.2	461.1	3.1	0.0	142.2	2214.2
Colombia	0.0	0.0	0.2	0.3	1.2	0.3	0.3	0.0	2.3
Costa Rica	1.8	0.6	0.0	0.0	0.1	0.1	0.0	0.0	2.5
Cuba	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.7	0.7
Czech Republic	15.3	8.7	0.8	1.3	0.4	0.0	0.0	0.0	26.6
Democratic Republic of the Congo	0.0	6.8	0.1	0.4	0.0	0.2	0.0	0.0	7.5
Denmark	22.0	43.3	4.2	4.6	16.5	2.9	0.2	0.2	93.9
Dominica	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1
Dominican Republic	0.0	1.1	0.1	0.8	0.1	0.4	1.1	2.2	5.6
Ecuador	0.0	1.7	0.4	0.0	0.0	0.0	0.0	0.0	2.1
Egypt	7.3	2.3	0.0	1.7	0.0	22.2	0.0	0.0	33.6
El Salvador	0.1	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.3
Finland	20.3	21.2	0.2	3.1	0.8	0.2	0.0	0.0	45.8
France	381.5	96.5	85.8	25.6	89.4	2.2	13.5	13.3	707.8
Germany	1077.4	280.2	0.0	0.0	0.2	38.7	0.0	0.0	1396.4
Ghana	0.3	0.3	0.1	0.9	0.1	0.1	1.7	0.1	3.5
Grenada	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
Guatemala	0.0	1.5	0.0	0.0	0.0	0.0	0.0	0.0	1.6
Guyana	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.2
Haiti	0.0	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.3
Honduras	0.0	0.3	0.1	0.0	0.3	0.1	0.0	0.0	0.8
India	21.5	297.1	0.0	45.4	4.8	92.2	17.4	0.0	478.3
Indonesia	14.3	57.4	7.8	0.0	4.8	0.0	0.0	0.0	84.3
Iran	0.0	0.0	11.6	0.0	0.0	0.0	0.0	0.0	11.6
Iraq	0.0	0.3	0.0	5.5	0.2	0.3	0.0	0.0	6.3
Ireland	3.4	7.9	6.3	2.0	10.0	3.2	1.6	1.4	35.8
Israel	20.7	3.5	6.2	3.0	1.3	4.7	0.6	0.0	39.9
Italy	27.9	608.4	31.4	14.3	10.2	1.0	14.6	234.4	942.3
Jamaica	0.1	0.0	0.0	0.0	0.4	0.0	0.2	0.0	0.8
Japan	4.3	739.3	0.0	548.1	0.0	0.0	0.0	0.0	1291.8
Kazakhstan	0.0	2.9	0.0	2.8	0.0	0.0	0.0	0.0	5.7
Kenya	0.1	0.4	0.0	0.0	0.0	0.7	0.0	0.2	1.4
Kyrgyz Republic	0.0	0.7	0.2	0.0	0.0	0.0	0.0	0.0	0.9
Malaysia	55.8	10.5	0.7	0.0	0.0	9.7	0.0	0.0	76.7
Mauritius	0.1	1.4	0.0	0.0	0.0	2.3	0.0	0.0	3.8
Mexico	0.7	21.1	0.0	12.6	0.0	0.0	29.7	39.0	103.1
Mongolia	1.8	0.5	0.0	0.2	3.0	0.0	0.0	0.2	5.7
Morocco	1.0	1.5	5.5	0.0	0.0	0.0	0.0	0.0	8.1
Netherlands	1.9	46.9	23.0	12.0	37.9	24.2	5.8	0.6	152.3
Nicaragua	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.3
Nigeria	7.7	5.9	6.5	0.0	0.2	0.0	0.0	0.0	20.3
Norway	23.3	28.4	2.4	0.6	0.0	0.0	0.0	0.0	54.7
Pakistan	13.8	3.0	0.2	0.0	0.2	0.8	9.8	0.0	27.8
Panama	0.0	0.0	3.5	1.1	0.2	0.1	0.0	0.0	5.0
Paraguay	0.0	1.1	0.4	0.0	0.0	0.0	0.0	0.0	1.6
Peru	0.0	3.3	0.7	3.3	11.2	2.0	1.3	23.4	45.2
Philippines	4.5	30.7	120.6	0.0	0.0	0.0	0.0	0.0	155.8
Poland	33.3	24.5	9.9	2.1	16.0	14.4	1.9	0.0	102.1
Portugal	3.4	11.0	1.2	0.0	0.1	19.8	1.1	2.4	38.9
Romania	1.3	0.5	0.5	0.0	0.4	0.2	0.0	2.3	5.2
Russia	30.2	9.2	1.4	0.0	0.0	0.3	0.0	0.8	41.9
Rwanda	0.0	0.1	0.0	0.0	0.3	0.3	0.0	0.0	0.6
St. Kitts and Nevis	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.3
St. Lucia	0.0	0.1	0.2	0.0	0.0	0.0	0.0	0.0	0.3
St. Vincent & the Grenadines	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
Saudi Arabia	33.3	19.1	7.1	0.0	21.9	19.2	0.0	0.0	100.5
Senegal	0.0	1.8	0.0	0.0	1.0	0.6	0.0	0.0	3.4
Singapore	0.8	5.8	6.1	0.1	18.2	1.7	9.9	0.0	42.5
South Africa	0.1	29.2	2.9	0.0	9.6	0.1	0.0	5.7	47.6
South Korea	90.6	396.1	144.3	8.1	13.4	0.2	32.7	0.0	685.4
Spain	278.1	226.9	63.8	640.5	40.2	0.5	1.2	34.0	1285.1
Suriname	0.0	0.3	0.0	0.0	0.1	0.2	0.0	0.0	0.5
Sweden	94.8	9.0	2.8	0.5	6.2	7.5	1.8	0.0	122.5
Switzerland	31.4	22.4	3.4	8.7	14.9	0.0	0.0	0.0	80.8
Taiwan	2.0	12.1	0.1	0.0	0.0	9.4	0.0	0.0	23.6
Thailand	0.0	3.8	0.0	5.1	10.4	5.2	0.5	0.1	25.2
Trinidad and Tobago	1.0	0.1	0.0	0.2	0.0	0.0	0.0	0.0	1.4

Turkey	22.9	5.7	42.4	3.3	0.2	0.0	0.0	0.0	74.5
UAE	21.7	0.3	2.4	0.1	1.7	0.0	0.0	0.0	26.2
United Kingdom	606.3	34.1	111.1	335.0	71.6	24.2	86.8	0.0	1269.1
United States	1968.7	484.2	53.5	932.0	977.8	0.3	0.0	570.6	4987.1
Uruguay	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Venezuela	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Vietnam	0.0	27.2	0.0	0.0	0.0	0.0	0.0	12.2	39.4
Total	5540.7	5025.4	911.8	2973.7	1900.5	400.5	243.9	1158.6	18154.9

Extended data table 2. Recessionary fiscal taxonomy with potential directionally GHG impact scores.[b]

Archetype	Short-term impact score	Long-term impact score
A Liquidity support for subnational public entities		
• A1	-1	0
• A2	-1	0
• A Unclear	-1	0
B Liquidity support for large businesses		
• B1	-1	0
• B2	-1	1
• B3	-2	0
• B4	-2	1
• B5	-2	-1
• B6	-2	1
• B7	-1	0
• B8	-1	1
• B9	-1	0
• B10	-1	1
• B11	-1	0
• B12	-1	1
• B13	-1	0
• B Unclear	-1	0
C Liquidity support for start-ups and SMEs		
• C1	-1	0
• C2	-2	0
• C3	-1	0
• C4	-1	0
• C5	-1	0
• C6	-1	0
• C Unclear	-1	0
D Liquidity support for not for profit organisations		
• D1	0	0
• D2	0	0
• D3	0	0
• D4	0	0
• D5	0	0
• D Unclear	0	0
E Temporary waiver of interest payments for businesses		
• E1	-1	0
• E2	-1	0
• E3	-1	0
• E4	-1	0
• E5	-1	0
• E6	-1	0
• E Unclear	-1	0
F Direct provision of basic needs		
• F1	0	0
• F2	0	0
• F3	0	0
• F4	0	0
• F5	0	0
• F Unclear	0	0
G Targeted welfare cash transfers		
• G1	-1	0
• G2	-1	0
• G3	-1	0
• G4	-1	0
• G Unclear	-1	0
H Job continuation support		
• H1	-1	0
• H2	-1	0
• H Unclear	-1	0
I Temporary waiver of interest payments for individuals		
• I1	-1	0
• I2	-1	0
• I3	-1	0

[b] Archetype and subarchetype definitions included alongside examples in supplementary materials.

• I4	-1	0
• I Unclear	-1	0
J Healthcare services support		
• J1	-1	0
• J2	0	0
• J3	0	0
• J4	0	0
• J5	-1	0
• J Unclear	-1	0
K Emergency services (disaster management) support		
• K1	0	0
• K2	-1	0
• K Unclear	-1	0
L Income tax cuts		
• L1	-1	0
• L2	-1	0
• L3	-1	0
• L4	-1	0
• L Unclear	-1	0
M VAT and other goods and services tax cuts		
• M1	-1	0
• M2	-1	0
• M3	-1	0
• M4	-1	0
• M Unclear	-1	0
N Business tax cuts		
• N1	-1	0
• N2	-1	0
• N3	0	1
• N4	-1	0
• N Unclear	-1	0
O Business tax deferrals		
• O1	-2	0
• O2	-1	0
• O Unclear	-1	0
P Reduced prices for centrally-controlled products and services		
• P1	0	0
• P2	-2	0
• P3	0	0
• P Unclear	0	0
Q Other tax cuts and deferrals		
• Q1	-1	0
• Q Unclear	-1	0
R Targeted recovery cash transfers		
• R1	-1	0
• R2	-1	0
• R3	-1	0
• R4	-1	0
• R Unclear	-1	0
S Tourism and leisure industry incentives		
• S1	-2	-1
• S2	0	1
• S3	-2	-1
• S4	0	0
• S5	-1	0
• S Unclear	0	0
T Electric vehicle incentives		
• T1	-1	1
• T2	-1	1
• T Unclear	-1	1
U Electronic appliance incentives		
• U1	-1	1
• U2	-1	1
• U Unclear	-1	1
V Green market creation		
• V1	0	2
• V2	0	2
• V3	0	2
• V4	0	2
• V Unclear	0	2
W Other incentive measures		

• W1	0	0
• W Unclear	0	0
X Worker retraining and job creation		
• X1	0	2
• X2	0	1
• X3	0	1
• X4	0	0
• X Unclear	0	0
Y Education investment		
• Y1	-1	0
• Y2	0	0
• Y3	0	0
• Y4	-2	0
• Y5	0	1
• Y Unclear	0	0
Z Healthcare investment (non-infrastructure)		
• Z1	-1	0
• Z2	-1	0
• Z3	-1	0
• Z4	-1	0
• Z5	-2	0
• Z Unclear	-1	0
α Social and cultural investment (non-infrastructure)		
• α1	0	0
• α2	0	0
• α3	0	0
• α Unclear	0	0
β Communications infrastructure investment		
• β1	-2	0
• β2	-1	0
• β3	0	0
• β4	0	0
• β5	0	0
• β Unclear	-2	0
γ Traditional transport infrastructure investment		
• γ1	-2	0
• γ2	-2	-2
• γ3	-2	-2
• γ4	-2	-1
• γ5	-2	1
• γ Unclear	-2	-1
δ Clean transport infrastructure investment		
• δ1	-2	2
• δ2	-2	2
• δ3	-2	2
• δ4	0	2
• δ5	-2	2
• δ6	-2	2
• δ7	-1	0
• δ Unclear	-2	2
ε Traditional energy infrastructure investment		
• ε1	-2	-2
• ε2	-2	-2
• ε3	-2	-2
• ε4	-2	-2
• ε5	-1	-1
• ε Unclear	-2	-2
η Clean energy infrastructure investment		
• η1	-2	2
• η2	-2	2
• η3	-2	2
• η4	-2	2
• η5	-2	2
• η6	-2	2
• η7	-2	2
• η8	-2	2
• η9	-2	2
• η10	-1	1
• η Unclear	-2	2
θ Local (project-based) infrastructure investment		
• θ1	-2	0

• $\theta 2$	-2	0
• $\theta 3$	-2	1
• $\theta 4$	-2	0
• $\theta 5$	-2	1
• $\theta 6$	-2	0
• $\theta 7$	-2	1
• θ Unclear	-2	0
λ Buildings upgrades and energy efficiency infrastructure investment		
• $\lambda 1$	-2	2
• $\lambda 2$	-2	2
• $\lambda 3$	-2	0
• λ Unclear	-2	2
μ Natural infrastructure and green spaces investment		
• $\mu 1$	1	1
• $\mu 2$	1	2
• $\mu 3$	1	2
• μ Unclear	1	2
ω Agriculture and Fisheries		
• ω1	0	0
• ω2	1	2
• ω3	-1	-1
• ω4	1	1
• ω5	0	1
• ω Unclear	0	0
π Other large-scale infrastructure investments		
• $\pi 1$	-2	0
• $\pi 2$	-2	0
• $\pi 3$	-2	0
• $\pi 4$	-2	0
• $\pi 5$	-2	-1
• π Unclear	-2	0
σ Armed forces investment		
• $\sigma 1$	-2	-2
• $\sigma 2$	-1	-2
• σ Unclear	-2	-2
τ Disaster preparedness and capacity building investment		
• τ1	-1	0
• τ2	0	0
• τ3	-1	0
• τ4	0	0
• τ5	-1	0
• τ6	0	0
τ Unclear	-1	0
φ General research and development investment		
• $\varphi 1$	0	1
• $\varphi 2$	0	1
• $\varphi 3$	0	-1
• $\varphi 4$	0	0
• φ Unclear	0	0
ψ Clean research and development investment		
• $\psi 1$	0	2
• $\psi 2$	0	2
• $\psi 3$	0	2
• $\psi 4$	0	2
• $\psi 5$	0	1
• ψ Unclear	0	2
Unclear	0	0

Extended data table 3. Maximum RNN model accuracy for each policy classification target.

Policy classification	Rescue policies (train n = 4425, test n = 1106)	Recovery policies (train n = 2146, test n = 536)	All policies (train n = 6598, test n = 1649)
Long-term GHG impact, 2-point scale (positive, not positive)	98.82%	87.69%	95.88%
Long-term GHG impact, 3-point scale (positive, neutral, negative)	98.85%	81.34%	92.79%
Long-term GHG impact, 5-point scale (very positive, positive, neutral, negative, very negative)	98.65%	75.63%	91.47%
Policy function (rescue or recovery)	NA	NA	87.08%
Archetype (60 categories)	65.10%	57.72%	55.85%

Extended data table 4. Regressors tested in model selection by sample.

Potential regressor	Date	Source	Category	Is regressor tested? Sample A (84 economies)	Sample B (81 economies)	Sample C (50 economies)	Sample D (47 economies)
LN(Access to electricity (% of population))	2018-2020	World Bank WDI	Development	1	1	1	1
LN(Adjusted savings: consumption of fixed capital (% of GNI))	2018-2020	World Bank WDI	Resource use	1	1	1	1
LN(Agricultural land (% of land area))	2018-2020	World Bank WDI	Physical	1	1	1	1
LN(Arable land (% of land area))	2018-2020	World Bank WDI	Physical	1	1	1	1
LN(Birth rate, crude (per 1,000 people))	2018-2020	World Bank WDI	Development	0	0	1	1
LN(C6_Stay at home requirements_2020)	01/03/20-31/12/20	Oxford CGRT	COVID-19	0	0	1	1
LN(C6_Stay at home requirements_2021)	01/03/20-31/12/21	Oxford CGRT	COVID-19	0	0	1	1
LN(C8_International travel controls_2020)	01/03/20-31/12/20	Oxford CGRT	COVID-19	0	0	1	1
LN(C8_International travel controls_2021)	01/03/20-31/12/21	Oxford CGRT	COVID-19	0	0	1	1
LN(Capacity-weighted fair share)	2021	CERF	Environmental	1	1	1	1
LN(Central Bank Rate)	2022	Compiled	Economic	0	0	1	1
LN(CO2 emissions (kg per 2015 US$ of GDP))	2018-2020	World Bank WDI	Environmental	1	1	1	1
LN(Coal rents (% of GDP))	2018-2020	World Bank WDI	Resource use	1	1	1	1
LN(ConfirmedCases per capita people_2021)	31/12/2021	Oxford CGRT	COVID-19	0	0	1	1
LN(ConfirmedCases per capita_2020)	31/12/2020	Oxford CGRT	COVID-19	0	0	1	1
LN(ContainmentHealthIndex_2020)	01/03/20-31/12/20	Oxford CGRT	COVID-19	0	0	1	1
LN(ContainmentHealthIndex_2021)	01/03/20-31/12/21	Oxford CGRT	COVID-19	0	0	1	1
LN(Control of Corruption: Estimate)	2020	World Bank WGI	Enabling environment	1	1	1	1
LN(Cost of business start-up procedures (% of GNI per capita))	2018-2020	World Bank WDI	Enabling environment	1	1	1	1
LN(Current health expenditure (% of GDP))	2018-2020	World Bank WDI	Economic	1	1	1	1
LN(Days until next election_2020)	2020	Manual	Electoral	0	1	0	1
LN(Days until next election_2021)	2021	Manual	Electoral	0	1	0	1
LN(Death rate, crude (per 1,000 people))	2018-2020	World Bank WDI	Development	0	0	1	1
LN(Domestic private health expenditure (% of current health expenditure))	2018-2020	World Bank WDI	Economic	1	1	1	1
LN(Ease of doing business score)	2018-2020	World Bank WDI	Enabling environment	1	1	1	1
LN(Employment in agriculture (% of total employment) (modeled ILO estimate))	2018-2020	World Bank WDI	Employment	0	0	1	1
LN(Employment in industry (% of total employment) (modeled ILO estimate))	2018-2020	World Bank WDI	Employment	0	0	1	1
LN(Employment in services (% of total employment) (modeled ILO estimate))	2018-2020	World Bank WDI	Employment	0	0	1	1
LN(Exports of goods and services (% of GDP))	2018-2020	World Bank WDI	Economic	0	0	1	1
LN(External balance on goods and services (% of GDP))	2018-2020	World Bank WDI	Economic	0	0	1	1
LN(Final consumption expenditure (% of GDP))	2018-2020	World Bank WDI	Economic	0	0	1	1
LN(Fixed telephone subscriptions (per 100 people))	2018-2020	World Bank WDI	Development	0	0	1	1
LN(Foreign direct investment, net inflows (% of GDP))	2018-2020	World Bank WDI	Economic	1	1	1	1
LN(Foreign direct investment, net outflows (% of GDP))	2018-2020	World Bank WDI	Economic	1	1	1	1
LN(Forest area (% of land area))	2018-2020	World Bank WDI	Physical	1	1	1	1
LN(Forest rents (% of GDP))	2018-2020	World Bank WDI	Resource use	1	1	1	1
LN(GDP (current US$))	2018-2020	World Bank WDI	Economic	1	1	1	1
LN(GDP deflator)	2018-2020	World Bank WDI	Economic	1	1	1	1
LN(GDP growth (annual %))	2018-2020	World Bank WDI	Economic	1	1	1	1
LN(General government final consumption expenditure (% of GDP))	2018-2020	World Bank WDI	Economic	0	0	1	1
LN(Government Effectiveness: Estimate)	2020	World Bank WGI	Enabling environment	1	1	1	1
LN(GovernmentResponseIndex_2020)	01/03/20-31/12/20	Oxford CGRT	COVID-19	0	0	1	1
LN(GovernmentResponseIndex_2021)	01/03/20-31/12/21	Oxford CGRT	COVID-19	0	0	1	1
LN(Gross capital formation (% of GDP))	2018-2020	World Bank WDI	Economic	0	0	1	1
LN(Gross domestic savings (% of GDP))	2018-2020	World Bank WDI	Economic	0	0	1	1
LN(Gross national expenditure (% of GDP))	2018-2020	World Bank WDI	Economic	0	0	1	1
LN(H2_Testing policy_2020)	01/03/20-31/12/20	Oxford CGRT	COVID-19	0	0	1	1
LN(H2_Testing policy_2021)	01/03/20-31/12/21	Oxford CGRT	COVID-19	0	0	1	1
LN(H7_Vaccination policy_2020)	01/03/20-31/12/20	Oxford CGRT	COVID-19	0	0	1	1
LN(H7_Vaccination policy_2021)	01/03/20-31/12/21	Oxford CGRT	COVID-19	0	0	1	1
LN(Human Development Index)	2020	UNDP	Development	1	1	1	1
LN(Human capital index (HCI) (scale 0-1))	2018-2020	World Bank HCI	Development	0	0	1	1
LN(Imports of goods and services (% of GDP))	2018-2020	World Bank WDI	Economic	0	0	1	1
LN(Labor force participation rate, total (% of total population ages 15+) (modeled ILO estimate))	2018-2020	World Bank WDI	Employment	0	0	1	1
LN(Life expectancy at birth, total (years))	2018-2020	World Bank WDI	Development	0	0	1	1
LN(Mineral rents (% of GDP))	2018-2020	World Bank WDI	Resource use	1	1	1	1
LN(Mobile cellular subscriptions (per 100 people))	2018-2020	World Bank WDI	Development	0	0	1	1
LN(Mortality rate, infant (per 1,000 live births))	2018-2020	World Bank WDI	Development	1	1	1	1
LN(Natural gas rents (% of GDP))	2018-2020	World Bank WDI	Resource use	1	1	1	1
LN(Oil rents (% of GDP))	2018-2020	World Bank WDI	Resource use	1	1	1	1

LN(Percentage through maximum election term_2020)	2020	Manual	Electoral	0	1	0	1
LN(Percentage through maximum election term_2021)	2021	Manual	Electoral	0	1	0	1
LN(Permanent cropland (% of land area))	2018-2020	World Bank WDI	Physical	1	1	1	1
Political Stability and Absence of LN(Violence/Terrorism: Estimate)	2020	World Bank WGI	Enabling environment	1	1	1	1
LN(Population ages 65 and above (% of total population))	2018-2020	World Bank WDI	Demographic	0	0	1	1
LN(Population density (people per sq. km of land area))	2018-2020	World Bank WDI	Demographic	1	1	1	1
LN(Population growth (annual %))	2018-2020	World Bank WDI	Demographic	1	1	1	1
LN(Population, total)	2018-2020	World Bank WDI	Demographic	1	1	1	1
LN(PPP conversion factor, GDP (LCU per international $))	2018-2020	World Bank WDI	Economic	1	1	1	1
LN(Profit tax (% of commercial profits))	2018-2020	World Bank WDI	Economic	1	1	1	1
LN(Proportion of seats held by women in national parliaments (%))	2018-2020	World Bank WDI	Development	1	1	1	1
LN(Regulatory Quality: Estimate)	2020	World Bank WGI	Enabling environment	1	1	1	1
LN(Renewable energy consumption (% of total final energy consumption))	2018-2020	World Bank WDI	Resource use	1	1	1	1
LN(Rule of Law: Estimate)	2020	World Bank WGI	Enabling environment	1	1	1	1
LN(Rural population (% of total population))	2018-2020	World Bank WDI	Demographic	1	1	1	1
LN(Rural population growth (annual %))	2018-2020	World Bank WDI	Demographic	1	1	1	1
LN(S&P 12-month cumm avg default rate)	2021	S&P	Economic	0	0	1	1
LN(S&P 24-month cumm avg default rate)	2021	S&P	Economic	0	0	1	1
LN(Secure Internet servers (per 1 million people))	2018-2020	World Bank WDI	Development	1	1	1	1
LN(Strength of legal rights index (0=weak to 12=strong))	2018-2020	World Bank WDI	Enabling environment	1	1	1	1
LN(StringencyIndex_2020)	01/03/20-31/12/20	Oxford CGRT	COVID-19	0	0	1	1
LN(StringencyIndex_2021)	01/03/20-31/12/21	Oxford CGRT	COVID-19	0	0	1	1
LN(Surface area (sq. km))	2018-2020	World Bank WDI	Physical	1	1	1	1
LN(Terrestrial protected areas (% of total land area))	2018-2020	World Bank WDI	Physical	1	1	1	1
LN(Time required to start a business (days))	2018-2020	World Bank WDI	Enabling environment	1	1	1	1
LN(Total natural resources rents (% of GDP))	2018-2020	World Bank WDI	Resource use	1	1	1	1
LN(UHC service coverage index)	2018-2020	World Bank WDI	Development	1	1	1	1
LN(Unemployment, total (% of total labor force) (modeled ILO estimate))	2018-2020	World Bank WDI	Employment	0	0	1	1
LN(Urban population (% of total population))	2018-2020	World Bank WDI	Demographic	1	1	1	1
LN(Voice and Accountability: Estimate)	2020	World Bank WGI	Enabling environment	1	1	1	1
LN(Vulnerable employment, total (% of total employment) (modeled ILO estimate))	2018-2020	World Bank WDI	Employment	0	0	1	1

Extended data table 5. Statistical output for models selected using GETS.

Find a visual representation in the supplementary methods, figure S5. Alongside coefficients, the figure include residual histograms and predicted log values (x) versus actual log values (y).

Sample A.1 (n = 84)
Dependent variable = Total COVID-19 spending ($US)
R^2 = 0.9332; log-likelihood = -90.8268
χ2 = 1.3428, P = 0.5110; White heteroscedasticity 1.3265, P = 0.2558; White heteroscedasticityX = 1.4222, P = 0.1946

Selected regressors	Coefficient	Standardised coefficient	p-value	Standard error
Intercept	-206.2346		0.0000	42.5696
LN(GDP (current US$))	1.0908	2.5708	0.0000	0.0385
LN(GDP growth (annual %))	-3.3553	-0.2610	0.0032	1.1021
LN(Rule of Law: Estimate)	44.0756	0.4207	0.0000	9.0944
IIS outlier: Colombia	-2.2714	-0.2478	0.0031	0.7450

Sample A.2 (n = 84)
Dependent variable = Recovery COVID-19 spending ($US)
R^2 = 0.7580; log-likelihood = -159.480
χ2 = 3.879, P = 0.1446; White heteroscedasticity = 2.1939, P = 0.0531; White heteroscedasticityX = 1.8479, P = 0.0747

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
Intercept	-284.0368		0.0067	101.9334
LN(GDP (current US$))	1.0888	2.5662	0.0000	0.0848
LN(GDP growth (annual %))	-8.7515	-0.6808	0.0014	2.6460
LN(Voice and Accountability: Estimate)	65.8012	0.6028	0.0030	21.4337
IIS outlier: Burkina Faso	-4.1135	-0.4488	0.0203	1.7359
IIS outlier: Indonesia	-4.0468	-0.4415	0.0211	1.7178
IIS outlier: Iran	-5.7649	-0.6290	0.0015	1.7554
IIS outlier: Paraguay	-5.2355	-0.5712	0.0032	1.7211

Sample A.3 (n = 84)
Dependent variable = Green recovery COVID-19 spending ($US)
R^2 = .7178; log-likelihood = -184.752
χ2 = 1.3779, P = 0.5021; White heteroscedasticity = 1.900, P = 0.0918; White heteroscedasticityX = 1.7805, P = 0.0869

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
Intercept	-1014.4091		0.0000	129.1792
LN(Arable land (% of land area))	0.7091	0.7834	0.0032	0.2328
LN(GDP (current US$))	1.0386	2.4480	0.0000	0.1114
LN(Voice and Accountability: Estimate)	214.9619	1.9692	0.0000	28.0709
IIS outlier: China	5.6754	0.6192	0.0209	2.4080
IIS outlier: Czech Republic	-7.3268	-0.7994	0.0021	2.3026

Sample A.4 (n = 78)
Dependent variable = Green recovery as % of total recovery (%)
R^2 = 0.5617; log-likelihood = -120.157
χ2 = 0.53542, P = 0.7651; White heteroscedasticity = 1.8066, P = 0.0909; White heteroscedasticityX = 1.4992, P = 0.1382

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
LN(Arable land (% of land area))	0.6010	0.6704	0.0000	0.1210
LN(HDI)	6.2438	1.0167	0.0000	0.8432
LN(Renewable energy consumption (% of total final energy consumption))	0.3228	0.4731	0.0028	0.1045
LN(Surface area (sq. km))	0.1157	0.3100	0.0000	0.0267
IIS outlier: Czech Republic	-3.6009	-0.4077	0.0035	1.1920

Sample B.1 (n = 81)
Dependent variable = Total COVID-19 spending ($US)
R^2 = 0.9486; log-likelihood = -76.2986
χ2 = 2.7714, P = 0.2501; White heteroscedasticity = 1.1775, P = 0.3253; White heteroscedasticityX = 1.2278, P = 0.2787

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
Intercept	-198.0880		0.0000	38.3200
LN(GDP (current US$))	1.1235	2.6200	0.0000	0.0364
LN(GDP growth (annual %))	-4.1695	-0.3257	0.0001	1.0036
LN(Days until next election_2020)	0.2504	0.2470	0.0019	0.0778

LN(Rule of Law: Estimate)	42.5761	0.4134	0.0000	8.1992
IIS outlier: Colombia	-2.2131	-0.2459	0.0013	0.6628
IIS outlier: Mongolia	2.3217	0.2596	0.0009	0.6734
IIS outlier: Romania	-1.8279	-0.2057	0.0072	0.6610

Sample B.2 (n = 81)

Dependent variable = Recovery COVID-19 spending ($US)

R^2 = 0.7300; log-likelihood = -157.801

χ2 = 3.4573, P = 0.1775; White heteroscedasticity = 1.3704, P = 0.2244; White heteroscedasticityX = 1.2099, P = 0.2902

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
Intercept	-648.9983		0.0000	135.6520
LN(Current health expenditure (% of GDP))	-1.6464	-0.6533	0.0124	0.6429
LN(GDP (current US$))	1.1156	2.6015	0.0000	0.0937
LN(GDP growth (annual %))	-10.6556	-0.8324	0.0002	2.7250
LN(Voice and Accountability: Estimate)	147.3336	1.2692	0.0000	28.9531
IIS outlier: Paraguay	-4.5717	-0.5080	0.0127	1.7899

Sample B.3 (n = 81)

Dependent variable = Green recovery COVID-19 spending ($US)

R^2 = 0.7217; log-likelihood = --177.018

χ2 = 1.3712, P = 0.5038; White heteroscedasticity = 2.0285, P = 0.0726; White heteroscedasticityX = 1.6350, P = 0.1222

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
Intercept	-1068.2867		0.0000	133.9135
LN(Arable land (% of land area))	0.6575	0.7249	0.0064	0.2343
LN(GDP (current US$))	1.0340	2.4111	0.0000	0.1107
LN(Voice and Accountability: Estimate)	226.6938	1.9529	0.0000	29.1164
IIS outlier: Czech Republic	-7.2890	-0.8099	0.0019	2.2598

Sample B.4 (n = 75)

Dependent variable = Green recovery as % of total recovery (%)

R^2 = 0.5565; log-likelihood = -116.813

χ2 = 0.35607, P = 0.8369; White heteroscedasticity = 2.0177, P = 0.0579; White heteroscedasticityX = 1.6531, P = 0.0915

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
LN(Arable land (% of land area))	0.5973	0.6652	0.0000	0.1235
LN(HDI)	6.2994	1.0414	0.0000	0.8664
LN(Renewable energy consumption (% of total final energy consumption))	0.3493	0.4462	0.0076	0.1271
LN(Surface area (sq. km))	0.1106	0.2954	0.0005	0.0305
IIS outlier: Czech Republic	-3.5960	-0.4152	0.0042	1.2146

Sample C.1 (n = 50)

Dependent variable = Total COVID-19 spending ($US)

R^2 = 0.9041; log-likelihood = -38.0825

χ2 = 0.70039, P = 0.7046; White heteroscedasticity = 0.92962, P = 0.5033; White heteroscedasticityX = 0.74363, P = 0.7172

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
LN(GDP (current US$))	1.1470	1.2577	0.0000	0.0761
LN(GDP growth (annual %))	-3.9580	-0.1796	0.0000	0.4838
LN(Gross domestic savings (% of GDP))	-0.7456	-0.3233	0.0007	0.2051
LN(S&P 24-month cumm avg default rate)	-0.0541	-0.4383	0.0000	0.0114
IIS outlier: Colombia	-2.9032	-0.4106	0.0000	0.5761
IIS outlier: Romania	-1.5293	-0.2185	0.0098	0.5662

Sample C.2 (n = 50)

Dependent variable = Recovery COVID-19 spending ($US)

R^2 = 0.7909; log-likelihood = -79.0414

χ2 = 1.1527, P = 0.5620; White heteroscedasticity = 1.7867, P = 0.1094; White heteroscedasticityX = 1.2545, P = 0.2859

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
Intercept	-622.1501		0.0000	111.8754
LN(ConfirmedCases per capita (31/12/2020))	-0.4014	-0.7435	0.0022	0.1234
LN(GDP (current US$))	1.2956	1.4207	0.0000	0.1715
LN(Voice and Accountability: Estimate)	124.3781	1.3065	0.0000	23.8504
LN(StringencyIndex_2020)	5.0167	0.7821	0.0004	1.2951
IIS outlier: Indonesia	-4.6753	-0.6612	0.0008	1.2896

IIS outlier: Iran	-4.5099	-0.6378	0.0023	1.3889

Sample C.3 (n = 50)
Dependent variable = Green recovery COVID-19 spending ($US)
R^2 = 0.8274; log-likelihood = -95.9261
χ2 = 2.3396, P = 0.3104; White heteroscedasticity = 1.5631, P = 0.1696; White heteroscedasticityX = 1.2213, P = 0.3097

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
LN(Access to electricity (% of population))	-7.9695	-0.7516	0.0000	1.3606
LN(GDP (current US$))	1.6412	1.7997	0.0000	0.2304
LN(Human capital index (HCI) (scale 0-1))	8.7161	1.8219	0.0000	1.2394
LN(Renewable energy consumption (% of total final energy consumption))	0.9666	1.4927	0.0000	0.1740
IIS outlier: Czech Republic	-6.4592	-0.9135	0.0011	1.8488
IIS outlier: Indonesia	-6.4259	-0.9088	0.0011	1.8364
IIS outlier: Singapore	-5.4456	-0.7701	0.0070	1.9185
IIS outlier: Thailand	-6.2713	-0.8869	0.0014	1.8295

Sample C.4 (n = 49)
Dependent variable = Green recovery as % of total recovery (%)
R^2 = 0.6319; log-likelihood = -67.7550
χ2 = 2.5075, P = 0.2854; White heteroscedasticity = 0.79646, P = 0.6090; White heteroscedasticityX = 0.66163, P = 0.7936

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
LN(Arable land (% of land area))	0.5721	0.6386	0.0001	0.1350
LN(Human capital index (HCI) (scale 0-1))	4.3375	0.9142	0.0000	0.7344
LN(Renewable energy consumption (% of total final energy consumption))	0.3473	0.5285	0.0023	0.1077
LN(Unemployment, total (% of total labor force) (modeled ILO estimate))	1.1781	0.6697	0.0000	0.1870

Sample D.1 (n = 47)
Dependent variable = Total COVID-19 spending ($US)
R^2 = 0.9154; log-likelihood = -31.9806
χ2 = 0.79834, P = 0.6709; White heteroscedasticity = 1.0285, P = 0.4224; White heteroscedasticityX = 0.73550, P = 0.6739

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
Intercept	-232.7369		0.0000	38.1576
LN(GDP (current US$))	1.1488	1.1787	0.0000	0.0806
LN(Voice and Accountability: Estimate)	46.5344	0.4496	0.0000	8.4343
LN(Gross domestic savings (% of GDP))	-0.5029	-0.2203	0.0086	0.1819
Colombia	-2.8568	-0.4167	0.0000	0.5444
Romania	-1.9208	-0.2802	0.0009	0.5327

Sample D.2 (n = 47)
Dependent variable = Recovery COVID-19 spending ($US)
R^2 = 0.7877; log-likelihood = -74.7904
χ2 = 1.6016, P = 0.4490; White heteroscedasticity = 1.6354, P = 0.1492; White heteroscedasticityX = 1.2600, P = 0.2873

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
Intercept	-666.5451		0.0000	122.2982
LN(ConfirmedCases per capita (31/12/2020))	-0.4076	-0.5908	0.0129	0.1566
LN(GDP (current US$))	1.2999	1.3336	0.0000	0.1970
LN(Voice and Accountability: Estimate)	133.8572	1.2932	0.0000	26.1966
LN(StringencyIndex_2020)	5.1417	0.8186	0.0004	1.3431
IIS outlier: Indonesia	-4.6138	-0.6730	0.0012	1.3240
IIS outlier: Iran	-4.2699	-0.6228	0.0047	1.4254

Sample D.3 (n = 47)
Dependent variable = Green recovery COVID-19 spending ($US)
R^2 = 0.7807; log-likelihood = -94.9987
χ2 = 1.9933, P = 0.3691; White heteroscedasticity = 0.99811, P = 0.4548; White heteroscedasticityX = 1.7963, P = 0.0891

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
LN(Access to electricity (% of population))	-8.5526	-0.8303	0.0000	1.6338
LN(GDP (current US$))	1.7040	1.7483	0.0000	0.2795
LN(Human capital index (HCI) (scale 0-1))	8.1613	1.7532	0.0000	1.3476

LN(Renewable energy consumption (% of total final energy consumption))	1.2092	1.5245	0.0000	0.2392
IIS outlier: Czech Republic	-6.2325	-0.9091	0.0040	2.0391
IIS outlier: Indonesia	-6.5683	-0.9581	0.0024	2.0229
IIS outlier: Thailand	-6.3233	-0.9223	0.0032	2.0171

Sample D.4 (n = 46)

Dependent variable = Green recovery as % of total recovery (%)

R^2 = 0.6010; log-likelihood = -63.9665

χ2 = 2.3992, P = 0.3013; White heteroscedasticity = 1.1446, P = 0.3578; White heteroscedasticityX = 0.87050, P = 0.5950

Selected regressors	Coefficient	Standardised coefficients	p-value	Standard error
LN(Arable land (% of land area))	0.5363	0.5951	0.0004	0.1389
LN(Human capital index (HCI) (scale 0-1))	4.4800	0.9710	0.0000	0.7491
LN(Renewable energy consumption (% of total final energy consumption))	0.4444	0.5415	0.0018	0.1336
LN(Unemployment, total (% of total labor force) (modeled ILO estimate))	1.1116	0.6278	0.0000	0.2013

Extended data table 6. Green rhetoric with raw green counts by country.

Nation	Number of words in speeches (pre-processed)	Green rhetoric index	Occurrence of green terms (raw counts)										
			Category: General environmental	Category: Energy efficiency	Category: Carbon capture and storage	Category: Electric vehicles	Category: Green energy	Category: Green liquidity	Category: Green R&D	Category: Green skills	Category: Natural capital	Category: Sustainable transport	Term: " green recovery"
Antigua and Barbuda	5079	0.72	65	0	0	0	3	0	0	0	0	1	2
Australia	80789	0.24	303	1	0	2	50	0	0	0	3	13	0
Bahamas	92381	0.08	88	0	0	0	27	0	0	0	8	21	1
Barbados	5516	0.47	46	0	0	0	2	0	0	0	0	1	0
Belgium	3054	0.89	32	2	0	0	14	0	0	0	2	1	0
Canada	113853	0.20	326	10	0	11	11	0	0	0	25	52	1
China	35105	0.53	303	1	0	0	7	0	0	0	35	3	3
Dominica	1905	0.03	1	0	0	0	0	0	0	0	0	0	0
Germany	32459	0.13	62	0	0	1	7	0	0	0	1	7	0
Germany_Chancellor	13811	0.68	149	1	0	1	9	0	0	0	15	1	0
Ghana	18514	0.09	25	0	0	0	0	0	0	0	2	6	0
Guyana	31847	0.32	132	3	0	1	23	0	0	0	26	7	0
India	39083	0.12	41	1	0	0	15	0	0	0	9	24	0
Indonesia	162755	0.14	233	2	0	20	54	0	0	0	38	71	1
Iraq	7253	0.22	26	0	0	0	0	0	0	0	0	4	0
Ireland	90119	0.22	278	3	0	2	2	0	0	0	73	19	0
Israel	4792	0.17	12	0	0	0	0	0	0	0	0	3	0
Jamaica	15884	0.28	51	0	0	0	13	0	0	0	14	5	0
Japan	78739	0.11	115	1	0	2	29	0	0	0	1	22	0
Kazakhstan	2128	0.10	4	0	0	0	0	0	0	0	0	0	0
Kenya	16335	0.07	8	1	0	0	0	0	0	0	0	13	0
Mauritius	11651	0.16	25	0	0	1	2	0	0	0	5	2	0
Mongolia	9205	0.22	25	0	0	0	5	0	0	0	7	1	0
Morocco	5966	0.17	18	0	0	0	0	0	0	0	0	1	0
Netherlands	4518	0.55	32	0	0	0	1	0	0	0	7	7	0
Nigeria	5046	0.35	19	1	0	0	6	0	0	0	2	5	0
Norway	18719	0.66	191	0	0	0	21	0	0	0	11	11	0
Philippines	205687	0.05	69	0	0	1	2	0	0	0	19	90	1
Portugal	7580	0.48	55	2	0	0	1	0	0	0	0	10	0
Romania	73480	0.10	83	1	0	9	6	0	0	0	0	35	0
Saint Lucia	15980	0.19	51	0	0	0	4	0	0	0	0	2	0
Singapore	52509	0.18	127	0	0	4	28	0	0	0	1	20	0
South Africa	119583	0.13	171	2	0	6	34	0	0	0	28	63	3
South Korea	204265	0.51	1342	4	0	67	425	0	0	0	16	105	15
Spain	65168	0.11	103	0	0	1	10	0	0	0	7	18	1
Sweden	9862	0.65	103	4	0	1	2	0	0	0	5	6	0
Switzerland	11795	0.32	45	3	0	2	3	0	0	0	10	9	0
Taiwan	12319	0.10	15	0	0	0	6	0	0	0	0	2	0
Thailand	6693	0.32	10	0	0	3	2	0	0	0	25	0	0
Trinidad and Tobago	6247	0.90	36	18	0	4	41	0	0	0	3	4	0
Turkey	7191	0.14	14	0	0	0	1	0	0	0	4	0	0
United Kingdom	101477	0.37	484	2	0	8	52	0	0	0	11	142	0
United Kingdom_Queen	2474	0.21	9	0	0	0	0	0	0	0	1	0	0
United States_Biden	91430	0.22	262	1	0	38	16	0	0	0	4	63	1
United States_Trump	195316	0.03	74	1	0	0	2	0	0	0	8	16	0
Vietnam	11431	0.41	77	0	0	0	3	0	0	0	8	0	2

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The two unique datasets generated and analysed during the current study are available on figshare with the identifiers http://dx.doi.org/10.6084/m9.figshare.20338395 and http://dx.doi.org/10.6084/m9.figshare.2033853 (O'Callaghan et al., 2020; O'Callaghan, 2022).

6

Paper synthesis

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This chapter briefly summarises the three DPhil papers in dot point form, reiterating their motivation, methodology, and findings. Next, methodological and content interdependencies are identified and discussed. The three papers are then considered for similarities and differences in their findings, allowing a set of collective outcomes to be established. Finally, based on these overall findings, policy recommendations are provided alongside an agenda for future work.

6.1. Summary of papers and their findings

6.1.1. Paper A: How Stimulating Is a Green Stimulus? The Economic Attributes of Green Fiscal Spending

Paper A synthesises existing literature on the economic characteristics of green investment, supported by new and established techniques in NLP. Table 3 provides an overview of publication details. The remainder of this section provides brief dot points to summarise the motivation, methodology, and findings of the paper.

Table 3. Publication details of Paper A.

Co-authors	Cameron Hepburn (University of Oxford) and Nigel Yau (University of Oxford)
Journal	Annual Review of Environment and Resources, Volume 47
Status	Published as a Review in Advance (available here: https://doi.org/10.1146/annurev-environ-112420-020640)
Length of main body	11,000 words excluding references
Length of supplementary materials	4,000 words

6.1.1.1. Motivation

- As expressed in the paper, “When deep recessions hit, some governments spend to rescue and recover their economies”. In

response to COVID-19, it was proposed that governments could use recovery spending to simultaneously pursue lasting social and environmental objectives.

- Up to US$20 trillion was injected in response to the pandemic, but policy makers remained relatively ill-informed on the economic benefits of green investment. While past green spending programs have been significant, existing literature on recessionary green spending is limited, disparately located, and not conveniently summarised.
- Knowledge was lacking on the relative alignment of research patterns to spending patterns.

6.1.1.2. Methodology

- Used desktop research to provide a historical lens on green fiscal stimulus in response to crisis (beginning with Ancient Egypt and ending with the GFC).
- Created a novel iterative ML algorithm to identify and classify existing studies on the economic impacts of green fiscal investment.
- Collated a new inventory of literature focused on green investment, including 908 papers.
- Conducted qualitative literature analysis to synthesise findings on job creation, timeliness, and long-run multiplier across green policy archetypes.

- In a unique application of existing method, used NLP techniques to quantify the relative focus of existing literature across economic and environmental domains.
- Compared quantitative data on literature coverage with GRO fiscal spending data, identifying misalignments and research priorities.

6.1.1.3. Findings

- Existing literature suggests that green stimulus measures have a capacity to, on a timely basis, create jobs and boost economic performance.
- Research critical of green stimulus policies has often focused on the job creation characteristics of such measures. This research broadly fails to consider positive long-run spillovers and falling green technology costs.
- The research field of stimulatory green investment is nascent and contains many gaps. Gaps exist heterogeneously across: (i) archetypes, with greater existing coverage for energy efficiency and renewable energy policies, (ii) geographies, with greater existing coverage for Northern America and Europe, and (iii) methodologies.
- Research patterns are misaligned to government spending patterns. Some poorly researched topics receive significant public investment, leaving policymakers to design policy with little academic guidance.
- ML methods can be effectively used to identify and survey literature; they provide a valuable approach for quantitatively understanding disparate research and its gaps.

6.1.2. Paper B: Will COVID-19 Fiscal Recovery Packages Accelerate or Retard Progress on Climate Change?

Paper B uses a digital survey to elicit the perspectives of leading economists on the environmental characteristics of traditional and green fiscal investments. The survey results are analysed with traditional statistical techniques as well as, in an extra unpublished note, ML tools like clustering and ensemble methods. Table 4 provides an overview of publication details. The remainder of this section provides brief dot points to summarise the motivation, methodology, and findings of the paper.

Table 4. Publication details of Paper B.

Co-authors	Cameron Hepburn (University of Oxford), Nicholas Stern (London School of Economics), Joseph Stiglitz (Columbia University), and Dimitri Zenghelis (Cambridge University)
Journal	Oxford Review of Economic Policy, Volume 36, Issue Supplement-1
Status	Published on 8th May 2020 at https://doi.org/10.1093/oxrep/graa015
Citation count	221 (Scopus)
Altmetric score	1400 (top 5% of all outputs)
Length of main body	8,000 words excluding references
Length of supplementary materials	7,000 words excluding tables (1,000 words) and references
Length of additional note	3,500 words

6.1.2.1. Motivation

- At the beginning of the crisis, it was unclear what impact COVID-19 might have on climate change and how policy makers should respond.
- There was an understanding that green investment might hold economic promise as stimulus, but the relative characteristics of green investment to traditional investment were unclear.

- Findings of prior works seemed inappropriate to the unique characteristics of the COVID-19 crisis—namely the state-mandated mobility restrictions that precipitated simultaneous demand- and supply-side shocks

6.1.2.2. Methodology

- Synthesised academic and grey literature on declining economic activity to postulate short-term GHG impacts of the crisis.
- Built a database of fiscal policies announced in response to the GFC and categorised these by GHG impact to suggest green opportunities for the present crisis.
- As described in the text, "Surveyed 231 central bank officials, finance ministry officials, and other economic experts from G20 countries on the relative performance of 25 major fiscal recovery archetypes across four dimensions: speed of implementation, economic multiplier, climate impact potential, and overall desirability".
- Analysed survey data using statistical techniques.
- Relied on observed trends to hypothesise long-term social and institutional shifts likely to result from the crisis and their impact on GHG emissions.
- Additional note: Applied k-means++ and fuzzy c-means algorithms to visualise whether and how survey respondents were clustered.
- Additional note: Used ensemble methods in random forests to understand how responses and demographic factors were interrelated.

6.1.2.3. Findings

- The biggest impacts on climate from COVID-19 are likely to come from fiscal recovery packages and perhaps in long-term changes to power dynamics within and between national and international institutions.
- As expressed in the text, "Green fiscal recovery packages can decouple economic growth from GHG emissions and reduce existing welfare inequalities that will be exacerbated by the pandemic in the short-term and climate change in the long-term".
- Surveyed experts believe that five policy areas are particularly helpful for simultaneously advancing economic and climate objectives: clean physical infrastructure investment, investment in education and training, building efficiency retrofits, natural capital investment for ecosystem resilience and regeneration, and clean R&D investment. Rural support spending is also perceived to have high potential in lower- and middle-income countries, but the attractiveness of R&D is greatly discounted.
- ML analysis suggests that there are no definable clusters of respondents that remain consistent across the survey data. Respondents appear independent and responses to questions largely do not predict responses to other questions. This is also true for responses to the question of 'overall impact' for each policy type; they are mostly not predictable from prior responses, suggesting that there are important factors beyond policy speed, multipliers, and climate impact that are important to policy selection.

6.1.3. Summary of Paper C: Reviewing the COVID-19 "Green Recovery": rhetoric or reality?

Paper C uses results from the first two papers, with two new datasets and methods in deep learning and econometric model selection, to understand sectoral and global variation in government COVID-19 fiscal investment and its drivers. Table 5 provides an overview of publication details. The remainder of this section provides brief dot points to summarise the motivation, methodology, and findings of the paper.

Table 5. Publication details of Paper C.

Co-authors	None (sole author paper)
Journal	Targeting *Nature Climate Change* or *Nature Sustainability*
Status	Submitted
Length of main body	7,500 words excluding tables and references
Length of supplementary materials	14,500 words excluding tables (an additional 11,300 words) and references

6.1.3.1. Motivation

- At the time of writing, fiscal programs responding to the COVID-19 pandemic had mostly been announced yet the impact of recovery packages on climate change remained unclear. To this end, it was uncertain whether policy makers had been convinced by of the economic rationale for green spending.
- Significant government rhetoric in support of green investment appeared misaligned to actual spending patterns, but this was difficult to substantiate and compare across nations.

- It would be helpful to understand what drove differences in COVID-19 related green spending between nations to better inform future efforts to integrate climate priorities into fiscal policy.

6.1.3.2. Methodology

- Built the world's largest database on recessionary fiscal policy, the Global Recovery Observatory, using manual data scraping.
- Developed a novel fiscal taxonomy for recessionary investment, categorising all policies in the Observatory based on both economic and environmental characteristics.
- Conducted a peer-reviewed literature review of long-term GHG emissions impact for each policy subarchetype in the taxonomy. This enabled reporting on the global and sectoral spread of low-carbon COVID-19 investment using policies in the Global Recovery Observatory.
- Built a series of LSTM RNNs to validate the internal consistency of the taxonomy dataset. This RNN application is perhaps the first to categorise fiscal policy and one of the first to predict climate impact from policy descriptions, in large part due to a previous lack of adequate training datasets.
- Used automated GETS econometric model selection in a unique application to investigate factors correlated with inter-country variation in COVID-19 recovery investment.

- Built the world's largest database of head of state speeches, which was subsequently analysed for green rhetoric using a unique application of NLP and compared to low-carbon spending profiles.

6.1.3.3. Findings

- RNNs are a powerful tool for validating policy datasets. In this case, they predicted the long-term emissions characteristics of fiscal policies in the Global Recovery Observatory dataset with up to 96% accuracy.
- US$967 billion (32% of recovery investment) might reduce long-term greenhouse gas emissions, supporting the hypothesis that policy makers perceive strong gains to be available from green investments. Green fiscal policies were present in every sector.
- However, cumulative low-carbon spending remains wholly incommensurate with the scale of climate change, significant funds totalling 9.1% of recovery investment, were directed to initiatives likely to increase long-term GHGs, and there was a dearth of much needed fossil fuel pricing reforms.
- GETS model selection suggests nations that invested proportionally more on climate were those that had higher human capital, already supported higher renewable energy generation, had more arable land, and were working against higher rates of unemployment. The presence of unemployment as a critical factor means we cannot reject that policy makers might have prioritised green investment to address unemployment.

- Natural language processing of speeches suggests climate investment did not match political rhetoric—the gap between rhetoric and reality could reasonably be described as a function of political "blah blah blah" (Thunberg, 2021).

6.2. Paper interdependencies

The three papers are interdependent, each building from ideas, methodologies, and findings introduced by the others.[50] These interdependencies include purpose-built tools like the green fiscal taxonomy and related terminologies, methods for assessing potential climate impacts, and, perhaps most importantly, my academic perspectives and those of my fellow authors.

The base fiscal taxonomy introduced in Paper B was significantly expanded in Paper A and Paper C. This expansion was supported by a major process of peer input and peer review, before validation with a series of RNNs in Paper C. In both Paper A and Paper B, the taxonomy is used mostly as a categorisation tool, whereas in Paper C it serves both as a categorisation tool and as a basis for defining the climate mitigation impacts of fiscal policy options. In paper B, the taxonomy naturally included far fewer and far broader categories since the objective was to be collectively exhaustive of the universe of recessionary fiscal policy with a limit of 25 categories. The freeform responses to the survey reinforced our perspective that this approach came with challenges and so the taxonomy was

[50] Paper B was authored first (March-April 2020), Paper A followed second (June 2020—February 2022), and Paper C was the final contribution (June 2020—August 2022). Paper B and Paper C were written mostly in parallel to each other.

dramatically expanded in subsequent works. In retrospect, the Paper B survey would have been even more effective if constrained to a subset of policies from Paper C's taxonomy—this would have also enabled direct pairing of survey results with tracking of spending.

The taxonomy rests on unique descriptive terminology, which was also updated between papers. Paper B was the first academic work to define two distinct phases of economic response as "rescue" and "recovery"; Paper A built on this foundation to introduce a third phase of response, "reinforcement", although this term entered the public domain before publication of Paper A in O'Callaghan *et al.* 2021a and O'Callaghan *et al.* 2021b (both supplementary papers to this DPhil).

The methods for assessing the potential climate impacts of policy options are another source of interdependency across papers. As the most recent and most informed work of the three, Paper C uses the survey results of Paper A plus the sources identified with an iterative ML model in Paper B as core inputs to its assessment of subarchetype climate mitigation scores. Additionally, the iterative ML algorithm introduced in Paper A was used in Paper C to define an expanded dictionary of green terms. Yet, Paper A relies on an earlier version of the subarchetype scores used in Paper C as the basis for its initial definition of "green". Paper B also relies on a (much) earlier version of the scores, but this was only for weak validation of survey results. It was then possible to observe how identification of green spending progressed over the course of the crisis. For spending to April 2020, Paper B identified no recovery spending, Paper A identified US$63 billion in green recovery spending, and Paper C identified US$69 billion. For spending to

October 2020, Paper A identified US$423 billion in green recovery spending while Paper C found US$511 billion in green recovery spending. A large portion of these discrepancies can be explained by incomplete data collection due to slow government releases, but a significant portion was also thanks to a more refined assessment approach in Paper C, relying on progress made in both Paper A and Paper B.

Perhaps the most important class of interdependencies across the three papers relate to the ideas and perspectives of the authors. Certainly, some core assumptions and beliefs remain constant throughout the papers, but some perspectives also evolve from paper to paper. Regarding the constancy of most core assumptions, this is both a strength and a significant limitation. It is a strength in that it enables a shared foundation for comparison of results between papers. It is a limitation in that it naturally constrained the field of view and perhaps led to important perspectives and framings being missed. For instance, all five of my DPhil paper co-authors appear aligned to hopeful perspectives on the potential for green growth (based on their own publications). Collaborating with members of the degrowth community might have changed how each paper was designed. More foundationally, all five co-authors generally appear amenable to heterodox economic interpretations. If I were to have included only the most orthodox of economists as co-authors, the content and methods of the papers would have likely been quite different.

On the other hand, my understanding of the economic factors at play in fiscal policy decisions evidently increased between each of the papers and the supplementary works. For instance, in the first paper by date published,

Paper B, core economic factors for fiscal decision making were limited to just two,

Studies of fiscal responses during the GFC suggest that the economic success of green fiscal stimulus is strongly affected by two attributes: the speed at which the stimulus delivers real-world impact; and the short- and long-run economic multiplier, or return for every dollar of expenditure (Coenen et al., 2012; Freedman et al., 2009; Ramey, 2019),

whereas eighteen months later in Paper A,

The characteristics of green fiscal spending could be evaluated across at least eight important dimensions, namely (a) boosting employment and doing so in areas of greatest need, (b) optimizing the time of action, (c) maximizing the economic multiplier, (d) ensuring fiscal affordability, (e) reducing inequality and meeting other social prerogatives, (f) supporting the natural environment, (g) achieving simplicity for implementation, and (h) political considerations.

Knowing what I know now, if working without time or capacity constraints, it might have been most useful to complete Paper A first, to ensure a comprehensive understanding of the existing literature and have a more strategic lens on how to design the survey. To this end, I would have likely included an additional question on the job creation potential of each policy type, slightly rejigged which 25 policies were included in the survey, and expanded the list of experts in three or four case study countries to better understand how policy attractiveness might vary between economies. Ideally, I would have finalised the Paper C taxonomy before conducting the survey so that the survey results could be directly paired to the Paper C tracking effort.

As another example of interdependency, guided more by practicality than anything else, my recount of the COVID-19 fiscal response shifted from Paper B at the beginning of the crisis to Paper C at the end of the crisis. In Paper B we note,

While most G20 governments have implemented rescue packages, as of April 2020 no government has fully exited lockdown and introduced significant recovery packages

while in Paper C,

The COVID-19 fiscal response has been complex, discontinuous, temporally and cross-nationally heterogeneous, and at times without clear explanation.

Similarly, perspectives on the potential climate impact of government spending only grew stronger over the crisis as the evidence became clearer. In the abstract of paper (B), released May 2020 my co-authors and I explain that

Imminent fiscal recovery packages could entrench or partly displace the current fossil-fuel-intensive economic system.

In the abstract of paper (A), completed February 2022, we explain that for

countercyclical spending … governments can also use this spending to achieve long-term social and environmental goals.

And in the introduction of paper (C), completed in August 2022,

"Wise investment would also address systemic social and environmental problems, of which climate change is one of the most urgent (Hepburn et al., 2020; IPCC, 2022; O'Callaghan et al., 2022)".

Not only does each paper explicitly reference those that precede it, but the ideas contained within each are also dependent on those evidenced before.

6.3. Triangulation of outcomes

The three papers approach questions of climate-friendly fiscal investments in response to recession from three different perspectives. The first paper systematically assesses existing literature aided with ML, the second undertakes a digital survey with additional ML results analysis in appendix,

and the third collates and analyses spending data with ML and econometric methods.

Triangulating collective outcomes across three papers with distinct methods helps mitigate the influence of limitations from any single paper. The main limitations are:

- In paper A, that some texts in the literature appraisal could be biased positively to support climate measures. That said, perspectives from all sides are included in the paper, including those deriding the prospects of green investments.
- In Paper B, that the surveyed experts could be insufficiently informed to comment. However, experts were selected based on the most robust (and intensive) form of expert identification available. Also in Paper B, unidentified biases could have influenced the survey results, but a ML analysis (Chapter 4.3) suggests that the risks of significant bias through known demographic and response factors are low.
- In Paper C, that the ML modelling and econometric data analysis could have limited validity due to unknown gaps in the database of the Global Recovery Observatory. However, this database has been extensively verified by countries and with ML techniques; continuing gaps are likely to be minor.

These limitations are all discussed with mitigating notes and comparison to alternative methodologies in the literature review (Chapter 2.3-2.4) and, in abbreviated form, in each paper (Chapters 3-5 and supplementary materials in Appendices A-C0). By using all three papers to answer the same set of

questions, the continuing limitations of any single paper have reduced effect on the ultimate findings.

6.3.1. Question 1: Do climate measures make economic sense?

Each of the three papers consider distinct stakeholder perspectives, methodologies, and timings to respond to the first major question of the DPhil: *if a government were to care only about conventional economic indicators, would it make sense to invest in climate mitigation solutions over traditional initiatives?* The conclusion is: *yes, in many cases it would.*

Regarding stakeholder perspectives, in paper A the question was considered based on current green economic literature, asking *what do past studies suggest?* In paper B, the same question was considered with a survey of leading economists, asking *what do economists think?* Finally, in Paper C, the question was posed with respect to what we might learn from the actions of policymakers, asking *how do policy makers act and what might this reveal about their own perspectives and decision making?*

Each paper was methodologically distinct in its response to the first question, mainly to enable analysis of different stakeholder perspectives.[51]

[51] It is worth clarifying that selection of the elicitation approach for Paper B was also influenced by practical constraints associated with data availability and timing. One of the core targets for the investigation was to discover how green fiscal multipliers might differ from traditional multipliers. However, there is a paucity of granular time series data to support direct empirical work. Batini *et al.*'s 2022 study demonstrates this—it is forced to compute and compare multipliers across very different sets of countries and different time periods for the different policy types. The validity of its comparative results is therefore reduced. Even if appropriate data were available, methodological limitations lead to most studies adopting at best a Bayesian approach with the assumption of constant parameters (which is clearly inappropriate). Developing a non-Bayesian approach would have taken significant time, which was not available to respond to the immediate policy need. Time and data constraints are a valid reason for judicious use of the elicitation approach; the literature review (Chapter 2.4.1) explains that it "can be particularly useful for scenarios in which requisite data is not available for a direct empirical study or otherwise such a study is not possible due to time constraints (*e.g.*, to answer an urgent policy question)".

To sufficiently identify and analyse the existing literature, Paper A relied on a systematic review—identification of relevant papers was supported by an iterative ML approach and NLP analysis. To understand perspectives of leading economists, Paper B used a digital survey analysed with basic statistical techniques. To understand policy maker actions, Paper C used manual and automated techniques to build relevant datasets and then analysed this data with statistical, econometric, and NLP methods. Areas of methodological overlap across the papers are included in a discussion on interdependencies (Chapter 6.2).

The time dimension was consistent across studies at the macro level in that all three papers consider the COVID-19 economic response. However, it was varied at the micro level wherein Paper B considered perspectives at the very beginning of the pandemic (April 2020) while Paper A integrated some perspectives built during the mid-stage of the pandemic, and Paper C summarised actions over the entire duration of the pandemic to date. While these differences in timing are relatively minor (between a few months and two and a half years), they are known to be important; time series analysis in Paper C suggested that the recovery spending profiles of nations became greener over time.

Despite their unique perspectives, methods, and timelines, the three papers are ultimately aligned in their response to the first DPhil question: *yes, climate mitigation solutions can make sense on conventional economic grounds in many contexts*. Paper A summarises, based on existing literature, that "although the field is nascent, the overall economic characteristics of green fiscal investment appear positive and are likely

superior to dirty investment options". For a subset of policy types that have been well-studied (especially energy investment), the literature suggests "that green investments can indeed create more jobs and deliver higher fiscal multipliers than non-green investments". Paper B analyses its survey results to find that "in many cases, experts think that climate-positive policies also offer superior economic characteristics" and elsewhere "long-run multipliers of climate-positive policies were found to be high, reflective of strong return on investment for government spending".[52] Paper C finds "that US$ 945 billion of recovery investment (31.1%) might reduce long-term greenhouse gas emissions", suggesting that policy makers perhaps perceive that some green investments have strong economic attributes compared to alternative non-green investments. This posit rests on two core assumptions: (i) that a primary objective (but not necessarily the sole or leading objective) of public spending in a recession is to bolster conventional economic indicators (e.g., jobs and growth) and (ii) that policy makers believe that fiscal policy, at least partially, achieves its economic objectives. To the first, recessionary economic conditions are often associated with job losses and reduced social outcomes of many kinds (Di Tella et al., 2003; Kentikelenis, 2011), which can reduce aggregate demand through several mechanisms and become reinforcing (Challe et al., 2017). Governments are concerned with alleviating these stresses and stabilising the economy—a historically practical mechanism for doing so is boosting economic outcomes

[52] These trends were particularly pronounced for clean physical infrastructure (including renewable energy), building efficiency with renovations and retrofits, green skills development and training, natural capital investment, clean R&D spending in advanced economies and rural support schemes in emerging market and developing economies.

and this is the stated prerogative of many governments (for example, see Council of Economic Advisers, 2022, p. 29-32; Elmendorf and Furman, 2008; The Commonwealth of Australia, 2020). For (ii), regarding the effectiveness of fiscal policy on economic criteria during a recession, a deep literature supports the notion that fiscal stimulus boosts fiscal multipliers (see prior discussion in Chapter 2.2.1 citing Barnichon *et al.*, 2022 ; Caggiano *et al.,* 2015; Candelon and Lieb, 2013; Gechert, 2015; Ilzetki *et al.,* 2013; Leduc and Wislon, 2012; and Qazizada and Stockhammer, 2014) and it is elementary that stimulatory fiscal policy can create jobs in the loose labour markets that often coincide with economic recession, at least in the short run (see amongst many others, Fatás and Mihov, 2001; Moszoro 2021). The ultimate suggestion that policy makers were led to spend on some green initiatives by economic objectives in response to COVID-19 is further supported by a notable result from the GETS analysis of Paper C: "nations that invested proportionally more on climate were those that… [amongst other things] were working against higher rates of unemployment". While this result certainly does not prove causality, the high strength of the relationship suggests that there was likely some degree of conscious or unconscious prioritisation that led countries with higher unemployment to spend greener.[53] Furthermore, the additional ML analysis of Paper B's survey shows that high scores for economic factors like fiscal multiplier and speed of implementation were significant positive predictors of the overall attractiveness of green policies, including clean energy

[53] By "strength" I mainly refer to the presence of the factor in the "most appropriate" model for predicting low-GHG recovery spending as a percentage of total recovery, as selected by the GETS methodology.

infrastructure, clean research and development, and natural infrastructure. In other words, green investments could have been perceived as desirable based in part on their strong economic characteristics.

While it is not the objective of this DPhil to determine the non-economic advantages of investment in climate mitigation, it is worth noting that all three papers make strong related comments, and these comments are strongly supported by the literature (see introduction of 2.1). The papers explain that the economic conceptions and analyses that they rely on have mostly not incorporated the economic advantages of non-economic co-benefits. In Paper A my co-authors and I explain,

in most cases, factoring in the nongrowth benefits of green investments would significantly improve their policy appeal compared to other investments—examining only the impacts on GDP understates benefits of green investment spanning health (Carleton et al., 2022; Scovronick et al., 2019; Watts et al., 2017), the environment (IPCC, 2014; Nemet et al., 2010), economic stability (Kahn et al., 2019; Lamperti et al., 2019; Stern 2006), among others (see Karlsson et al., 2020).

We conclude by reiterating that the broad economic appeal of the policies come

before essential cobenefits are considered, which range from improved health outcomes to reduced environmental degradation and a stabilized climate.

Paper B includes a recount of the literature on co-benefits despite its secondary relevance to the aims of the paper. It explains,

Co-benefits of climate policies (Karlsson et al., 2020) often include reduced waste and inefficiency, pollution (Bollen, 2015; Dong et al., 2015), congestion (Portugal-Pereira et al., 2013), and food waste (Munesue et al., 2015), and improved health outcomes (Andersen, 2017; Chivian and Bernstein, 2008; Quam et al., 2017), biodiversity (Bryan et al., 2016; Wüstemann et al., 2017), and ecosystem sustainability (Palm et al., 2014); these are vitally important but not the focus of this paper.

Paper B concludes by explaining,

recovery packages that seek synergies between climate and economic goals have better prospects for increasing national wealth, enhancing productive human, social, physical, intangible, and natural capital.

The fiscal archetypes and subarchetypes introduced in Paper C are assessed for their potential climate impacts in Paper C and for a host of additional co-benefits in subsequent work.[54]

6.3.2. Question 2: Are some solutions better than others?

In the broadest sense, all three papers align on the question, *Are some climate mitigation solutions better than others on conventional economic indicators?* The answer is: *yes, but which solutions are most attractive depend on policy design and other factors*. Each paper identifies some set of policy types that appear to be more attractive for investment than others. However, the papers are not aligned on which policies are best. To some degree, this is explained by a common observation, expressed most completely in Paper A,

policy design is important. As with all recovery spending, the impact of green investment depends on the archetypes used, the national context, and specific design features. Among other factors, the financing, delivery mechanism, and target beneficiaries of a policy can significantly impact economic, social, and environmental returns.

Paper B concludes, based on survey opinion, that five policy types might hold particularly strong potential: (1) clean physical infrastructure in the form of renewable energy assets, storage, grid modernization, and CCS technology, (2) building efficiency spending for renovations and

[54] See *Introducing the Sustainable Budgeting Approach* in Appendix E. Archetypes are all assessed for impact characteristic on climate, natural capital, air pollution, quality of life, income inequality, and rural-urban inequality.

retrofits, (3), investment in decarbonisation education and training, (4) natural capital investment, and (5) clean R&D spending. Paper B also specifies that in low- and middle-income countries, spending on rural support schemes have high potential. The specificity of results is perhaps to be expected for Paper B. The elicitation exercise required participants to provide slider-scale responses which naturally rank individual policies compared to each other, providing false precision. Furthermore, the results are presented foremostly as a global aggregation, but as was made clear in Paper A and Paper C (which both came after Paper B), country-level variation in economic characteristics can be significant. If the survey were to be run again with significantly more participants, in perhaps only a few focus countries, we could compile enough data for country-to-country comparisons and understand whether the aggregated results reflected some majority of countries or was simply the median in a significant range. To some degree, based on the comparison of results in advanced economies to emerging market and developing economies, we can already hypothesise that perspectives on some archetypes might be relatively consistent between countries, but vary widely on others. For instance, the discussion in Paper B (as well as comments in Chapter 6.3.3; see Table 6) note that R&D was favoured significantly more and rural support less in advanced economies compared to emerging market and developing economies.

Paper A and Paper C do not have as clear results as those expressed in Paper B's headline findings. Paper A identifies evidence to support clean energy investment and energy efficiency retrofits as having stronger economic characteristics than alternative traditional measures. For other

policy types, it finds that there is insufficient evidence to come to a firm conclusion. One might then question how economists in Paper B were able to hold informed opinions on these topics without sufficient academic evidence: were they informed by lived experience, non-public research, or were there other factors at play? Perhaps respondents were informed by their understanding of other, well-researched, policy items with similar economic characteristics? Or perhaps they were simply inadequately knowledgeable and therefore the survey itself lacked academic credibility (see limitations of the elicitation approach in Chapter 2.4.1). From prior academic studies, we know that policy makers (which formed a significant portion of survey respondents) lean heavily on experiential learning (see Dolowitz and Marsh, 2002) and that economists frequently make inferences from one policy to another—these features alone make it challenging to entirely discount the survey results. A nuanced view of the survey findings of Paper B considering the literature review of Paper A might suggest that the survey results be considered a temporary placeholder until further empirical work can be done to understand which green policies drive greater economic value in different economic contexts.

Paper C adds complexity to this perspective. As previously discussed, if we assume that policy makers are acting purely with orthodox economic rationality in response to the COVID-19 recession, the spending patterns analysed in Paper C should reveal which policies are viewed by policy makers to have strong economic characteristics. To this end, Paper C finds that clean transport infrastructure (US$214 billion), green market creation ($176 billion), and clean energy infrastructure (US$161 billion) together

received the majority of green investment. Other major green spending categories included general R&D with green co-benefits (US$73 billion), natural infrastructure and green spaces (US$89 billion), clean R&D (US$74 billion), building upgrades and energy efficiency (U$S59 billion), traditional rail transport (US$42 billion), electric vehicles (US$31 billion), liquidity support with green conditions (US$33 billion), and clean local infrastructure including new housing and local utilities (US$18 billion). There are differences in size order amongst sub-samples—for instance, clean transport solutions are of pronounced focus in North America as well as Latin America and the Caribbean while green market creation finds high relative focus in Africa and Asia Pacific. Asides from the greater focus on clean transport, the patterns of Paper C largely align with the findings of Paper B and can be taken to reflect policy maker perspectives on the comparative strength of green policies during the COVID-19 period. However, as before, since Paper A suggests that there is insufficient evidence in the literature to make absolute claims on comparative value, policy maker perspectives should not be conflated with conceptions of truth. Instead, they should serve as placeholder perspectives until further evidence can be compiled.

Recent works, including some of the supplementary works to this DPhil, have begun to fill some of these evidence gaps. For instance, new global empirical insights include Batini *et al.* (2022). Batini *et al.* consider biodiversity conservation to have more attractive multipliers than clean energy. Input-output modelling in four supplementary works consider green investment for four national economies: O'Callaghan *et al.* (2021c) in South Africa, O'Callaghan *et al.* (2021d) in the Democratic Republic of the Congo,

O'Callaghan *et al.* (2021e) in Egypt, and O'Callaghan *et al.* (2021f) in Kenya. These works join a broader group of recent input-output analysis from Vivid Economics (2022) in ten countries and Kiss-Dobronyi *et al.* (2021) in South Africa. The four supplementary works align with the Vivid Economics pieces to suggest that the highest spending multipliers (measured by Gross Value Added) tend to vary significantly between country—that said, on average, natural capital investment options and low-carbon transport programs deliver slightly higher GVA. On whole then, the views of economists, expressed in Paper B, seem aligned to known and emerging evidence—the biggest gap in stated findings is for clean transport, which was not included in the top five recommendations of Paper B. However, this gap is almost certainly an artefact of broad archetype definitions used in Paper B—Paper B did not include "low-carbon transportation" as a response variable, instead using "connectivity investment" as a catch-all that included both public transportation and broadband-type investments. Connectivity investment was the second-highest performing archetype on long-run multiplier in Paper B, only excluded from the recommended policy list as it was not originally perceived to fall in the same "low-carbon" group as other policy options. If the survey were to be repeated, policy makers should be asked to consider public transport, other low-carbon transport, and broadband-type investments independently. Of course, all the input-output findings are only indicative and should be complemented by many future empirical case studies to better understand the dynamics of the investments. To repeat, policy design

can have as much, or even greater, impact on policy outcomes as investment type. As summarised by Paper A,

Policy design is important… Among other factors, the financing, delivery mechanism, and target beneficiaries of a policy can significantly impact economic, social, and environmental returns.

6.3.3. Question 3: Does the answer change between economies?

All three papers in this DPhil adopt a global lens in their analyses. Paper A is agnostic to region in its selection of green investment literature and discusses differences in findings across regions where they emerge. Paper B solicits perspectives from expert economists representing all regions (44 countries); more than that, the Paper B survey was specifically designed to seek and gain representation of all regions. Paper C tracks COVID-19 related spending in 88 countries, covering every major region. In this way, Paper C relies on national heterogeneities across economies to analyse potential drivers of difference in fiscal policy responses. Holding a global perspective across all three papers enables collective analysis of the question: *does the relative strength of climate mitigation investments over traditional investments vary between economies?* The clear conclusion is that climate investments hold promise in all economies, although the most attractive set of climate archetypes are likely to vary from economy to economy, based on factors including level of development, human capital, present unemployment, and existing structure of the economy and its key sectors.

In Paper A, the economic history of green Keynesianism is discussed by region. The United States, Canada, Australia, Europe (to a lesser degree), and certain economies in Asia (in particular, China, Japan, and

South Korea), have the strongest documented history of green fiscal investments in response to economic downturn.[55] It is unsurprising then that the economic analyses reviewed in Paper A focus largely on these regions. Unfortunately, even for this subset of nations, while estimates for fiscal multiplier and job creation can be easily found, they vary significantly in magnitude based on methodological differences and policy nuance. Indirect comparisons across papers are hence largely impossible. This leaves analyses that include economic impact metrics for multiple nations, of which there are only a few. On whole, these works suggest that economic multipliers vary more "between countries than… between green policy types". As discussed in the prior section, four of the supplementary works to this DPhil are input-output analyses conducted with Vivid Economics, each of which focus on a different nation.[56] After those reports, Vivid Economics (2022) produced six more. Surveying all ten pieces, it is clear that (a) some green investments can outperform traditional alternatives in every nation but (b) the relative strength of any one green archetype compared to the others varies significantly. For instance, the models suggest that more jobs can be created per dollar of investment in developing and emerging market economies than in advanced economies. While there are few empirical comparisons in the literature, the theoretical basis for these differences is widely discussed. As described in Paper A and the literature

[55] As discussed in Paper A and in the literature review, this is mostly driven by fiscal actions during the GFC, but also includes once-off measures in the preceding century (for instance, Roosevelt's Civilian Conservation Corps (Executive Order No. 6101, Starting The Civilian Conservation Corps, 1933).

[56] O'Callaghan *et al.* (2021c) in South Africa, O'Callaghan *et al.* (2021d) in the Democratic Republic of the Congo, O'Callaghan *et al.* (2021e) in Egypt, and O'Callaghan *et al.* (2021f) in Kenya.

cited therein, green job creation and green economic multipliers might be influenced by a nation's trade position (imports in particular), the initial public stock of capital, unemployment rate, savings rate, cost of capital, existing and future skill base, existing and future absorptive capacity in R&D, existing green business ecosystems and contractor capabilities.[57] Each of these factors vary significantly from country to country and so even without empirical comparisons, it is safe to assume that the relative economic strength of any particular investment will vary from nation to nation. While the strength of green energy investments for job creation seemed constant in Paper A regardless of national income level, there is "insufficient evidence to definitively comment" on other archetypes. The Paper notes that in terms of further research needs, "Across each archetype, particular focus is required in emerging markets and developing economies".

The process of expert selection in Paper B's survey was designed to include expert economists with local knowledge of every major region. Responses were received from experts focusing on 44 countries in total, representing all regions.[58] The baseline statistical analysis in the paper considers the world in aggregate as well as subset aggregations for high-income countries and low- and middle-income countries. Figure 18 indicates

[57] There are many additional perspectives in the literature which support the notion that existing economic structures determine the most valuable areas of policy attention, but these are not directly investigated by papers in this DPhil (although some are explored in Appendix E). For example, Fankhauser et al. (2013) suggest that nations might look to existing areas of competitive strength for successful greening and that every nation has "niches of green competitiveness". Mealy and Teytelboym (2020) show that existing green industrial capabilities and other production capabilities, in "skills, infrastructure and know-how", influence which green diversification opportunities are most appropriate. The Green Adjacent Possible (GAP) maps the *simplest* pathways for an economy to gain economic advantage through a green transition.

[58] Figure B1. highlights the "country of focus" submitted by all experts in the survey.

some variability in perceptions of climate impact, long-run multiplier, speed, and overall perspective based on the respondent's country of focus.[59] However, the rank order of the average response for each policy is similar across both country groups on most metrics. The high (close to 1) Spearman coefficients for policy speed and climate impact in Table 6 suggest that the overall trends in responses were similar across policies. The slightly lower, but still quite high, coefficients for long-run multiplier and overall perspective suggest that there might be greater economic variability than climate variability in policy impact across nations. In identifying the most attractive investment archetypes, Paper B explains that compared to high income nations,

In many low- and middle-income countries, clean R&D spending might be replaced with rural support scheme spending, particularly that associated with sustainable agriculture, ecosystem regeneration, or accelerating clean energy installations.

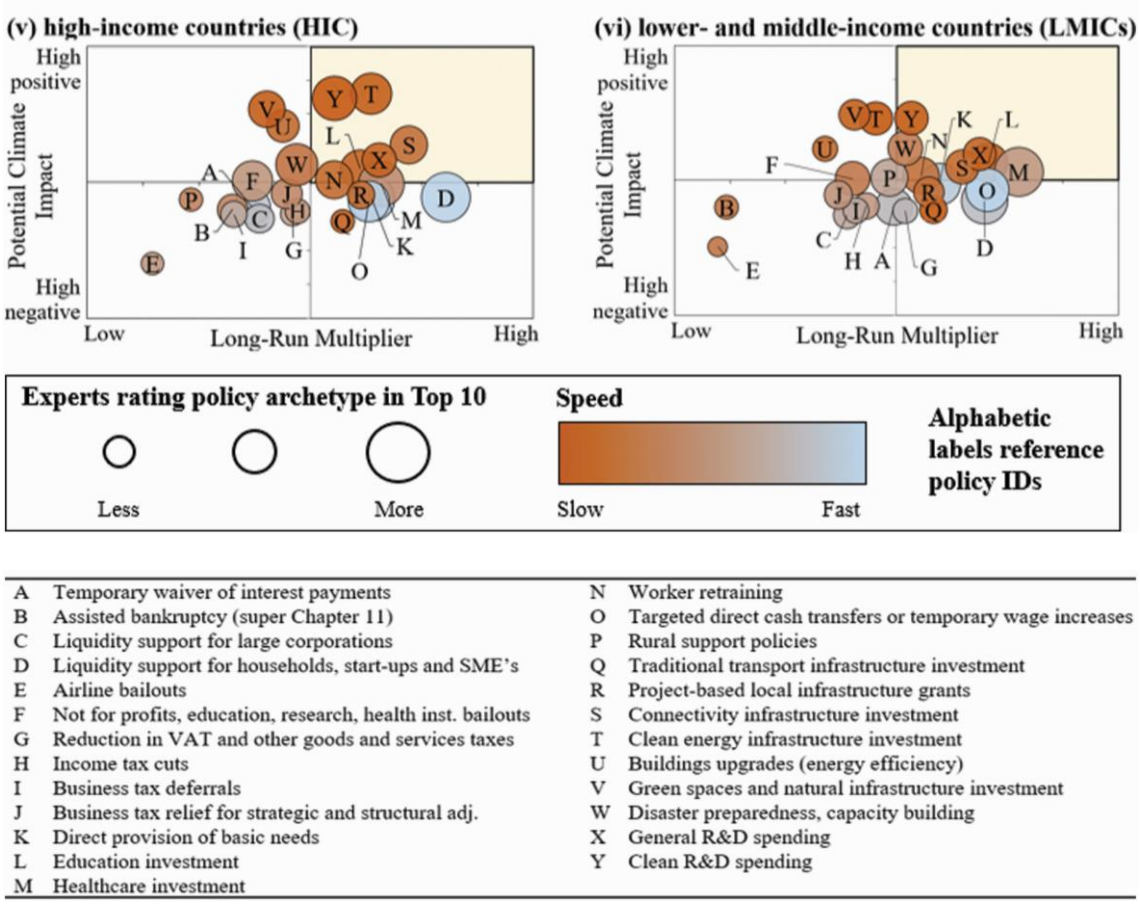
The higher perceived economic value for rural support schemes is likely due to a higher reliance of low- and middle-income nations on rural economies to sustain lives, provide employment, and provide economic product. The paper explains the varied attractiveness of clean R&D spending,

while HIC clean R&D spending can represent investment to becoming a global leader in high-margin future industries, due to a deficit in local highly skilled labour, analogous LMIC spending is unlikely to bring the same multiplier.

An interesting additional note from Table 6 is that despite being the only archetype with a strong empirical evidence basis for economic strength across regions in Paper A, clean energy investment was undervalued by

[59] Respondents were requested to complete the survey with respect to their "country of focus".

policy makers and other experts in low- and middle-income countries in Paper B. The reasons for this are unclear. The additional energy access benefits from renewable energy in low-income nations should increase its attractiveness in those contexts, however, perhaps a high reliance on imports for these investments reduces perceptions of economic strength.



A	Temporary waiver of interest payments	N	Worker retraining
B	Assisted bankruptcy (super Chapter 11)	O	Targeted direct cash transfers or temporary wage increases
C	Liquidity support for large corporations	P	Rural support policies
D	Liquidity support for households, start-ups and SME's	Q	Traditional transport infrastructure investment
E	Airline bailouts	R	Project-based local infrastructure grants
F	Not for profits, education, research, health inst. bailouts	S	Connectivity infrastructure investment
G	Reduction in VAT and other goods and services taxes	T	Clean energy infrastructure investment
H	Income tax cuts	U	Buildings upgrades (energy efficiency)
I	Business tax deferrals	V	Green spaces and natural infrastructure investment
J	Business tax relief for strategic and structural adj.	W	Disaster preparedness, capacity building
K	Direct provision of basic needs	X	General R&D spending
L	Education investment	Y	Clean R&D spending
M	Healthcare investment		

Figure 18. Mean policy response characteristics by focus economy in Paper B survey. Reprinted from Paper B with adaptions.

Table 6. Similarity of rank order responses between the high-income and low- and middle-income country groups. Major (minor) drivers of difference are those policies with a difference in ranking of 7 or more (5-6) places between country groups. The extreme driver of difference for the overall perspective had a rank order difference of 16 places. Green drivers scored higher in low- and middle-income nations. Red drivers scored higher in high-income nations.

Metric	Spearman Coefficient	Drivers of difference
Speed	0.913	Major: rural support policies Minor: reductions in VAT, project-based local infrastructure
Long-run multiplier	0.831	Major: clean energy, clean R&D Minor: temporary waiver of interest payments, education, healthcare, direct cash transfers, buildings upgrades
Climate Impact	0.940	Major: None Minor: Connectivity infrastructure
Overall perspective	0.760	Major: rural support policies (extreme), buildings upgrades, clean R&D Minor: temporary waiver of interest payments, assisted bankruptcy, clean energy

Paper C highlights extreme variation in actual COVID-19 fiscal spending patterns across nations. Nations varied in how much they spent overall (*e.g.*, as a proportion of GDP), what portion of their spending was green, and what kinds of green initiatives they focused on. High variation was present between nations as well as both inter- and intra-regionally. Figure 2 in Paper C contains a profile of investments likely to have low long-term GHG emissions by region and by archetype. The colour of each bar indicates intra-regional spread of investment; it is apparent that in many regions, intra-regional variation is quite higher. Emerging market and developing economies tended spent a significantly higher proportion of green investment on natural infrastructure and green market creation compared to advanced economies. They spent a lower proportion on clean transport and clean R&D. The paper's GETS model selection demonstrates

that national variation in total and proportional green spending was most critically correlated with economic factors, development factors, governance factors, fundamental factors, and factors related to the COVID-19 health burden. The most critical variables for the group of the largest fifty nations includes human capital score, existing dependence on renewable energy (i.e., existing economic structures in the energy sector), arable land (i.e., existing economic structures in the agricultural sector), and unemployment. The implications of these findings are practical and differentiated across countries,

(1) more is required to decouple economic investment from high-GHG industries, particularly in nations with low existing dependence on renewable energy, (2) boosting human capital should remain a key priority as an enabler of green policy implementation and innovation, and (3) more should be done to free capital in nations with high sovereign debt risk, as these nations are already tending to spend greener than others on a relative basis.

In sum, while Paper A and Paper B summarise theoretical perspectives on how spending priorities might vary between nations, Paper C demonstrates, based on real spending data, that variation is present and significant.

One of the most worrying discrepancies is that levels of green spending from major emerging market emitters like China, India, and Russia was significantly less than that from advanced economies. Partially, this is explainable by lower fiscal space for deficit spending, but particularly in China, fiscal space cannot explain all the variation. According to Robins *et al.* (2009), China announced US$303.5 billion in green spending in response to the GFC.[60] This is approximately 5.5x higher than that announced by China in response to COVID-19. It is possible that there was

[60] US$221.3 billion in 2009 adjusted for inflation to 2022.

higher transparency on fiscal policy in 2009, but unfortunately, we have little reason to suspect that actual COVID-19 green investment was significantly higher than reported in public statements. Considering a wider set of countries, GETS analysis in Paper C suggested that nations with higher existing rates of renewable energy tended to spend more on low-carbon measures—in other words, there appears to be a general stickiness in emissions intensity pathways. The implication of this is that we are unlikely to see significant fiscal-policy-induced "greening" in many of the emerging market economies currently expanding their carbon footprint. A similar implication could be drawn for economies that offset their positive low-carbon spending with support of high-carbon measures (fiscal or otherwise). Both these trends suggest that while global public spending on low-carbon measures was unprecedented in its volume, variation in spending patterns across economies (both low and high carbon) means that the net impact of spending in many economies will likely not be a meaningful reduction in emissions.

6.3.4. What about green growth and COVID-19?

The literature review of this DPhil suggests that the raison d'être of green growth is to challenge low growth assumptions that mainstream economics has traditionally associated with environmental measures. The three papers consider the challenge in the context of the COVID-19 recession. As discussed in Chapter 6.3.1, the papers each demonstrate that green investment can, in some cases, deliver equivalent or higher economic multipliers and job creation than traditional measures. Paper C notes, with the support of an extensive green fiscal taxonomy, that green investments

sometimes bring embedded GHG emissions in the short term (*e.g.*, through the construction phase) but these emissions tend to be displaced by a reduction in system-wide emissions in the long term. Taken together, the high multiplier and low emissions characteristics of these investment types supports the possibility of green growth. Furthermore, Paper C suggests that some countries may have recognised this and acted partially in accordance with that knowledge (see Chapter 6.3.1).

The three papers also speak to decoupling growth and GHG emissions, particularly in the context of economic recovery. Paper B, written very early in the pandemic, suggests that the severity of the COVID-19 economic slowdown would require massive economic reinvigoration and that this represented somewhat of an opportunity. It concludes based on its survey results,

Green fiscal recovery packages can act to decouple economic growth from GHG emissions and reduce existing welfare inequalities that will be exacerbated by the pandemic in the short-term and climate change in the long-term. Short-term reductions in GHG emissions resulting from lockdowns will themselves have minor long-term effects, unless they facilitate deeper and longer-term human, business, and institutional changes.

Paper A furthers this discussion with respect to standard economic metrics explaining,

Even with a narrow, orthodox lens, the response to the COVID-19 pandemic arguably represented the single biggest opportunity to date to decouple fossil emissions from economic growth and keep within Paris climate targets (Hepburn et al., 2020).

Finally, Paper C reflects on the crisis noting that

Many opportunities to further decouple growth from emissions were missed, implying that underinvesting nations have reinforced domestic transition risks and global physical risks from climate change.

Following GETS model selection, which suggested that economies more reliant on fossil fuels tended to spend less green, the Paper suggests

more is required to decouple economic investment from high-GHG industries, particularly in nations with low existing dependence on renewable energy.

In finding that deficit spending can support low-carbon growth when directed to appropriate investments, emerges a question of how financially sustainable such a program might be over the long term. Could repeated deficit spending, on the scale of the COVID-19 response, be repeated globally year on year over the long term? Here, it is helpful to reflect on the Keynesian purpose of deficit spending—that is, to reinvigorate economic growth during a downturn. If that is the primary purpose, and environmental benefits are secondary, then in the words of Henry Morgenthau Jr, "In a depression it is inevitable that there will be deficits… the sequel should be surpluses during years of prosperity" (76 Cong. Rec. 84-13, 1939).61 However, as some argue Franklin D. Roosevelt learnt in his 1937 reversal of New Deal expansionary policy, there is crucial importance in not shifting gears too early. A group of Harvard and Tufts economists reflected in 1938, "The New Deal has not failed. Rather its weakness has been a wavering adherence to its own principles" (Gilbert et al., 1938). But are environmental benefits secondary? Perhaps the non-economic benefits of low-carbon deficit spending are even more important than the economic ones. Based on the ML-assisted literature review of Paper B, and recent

61 Henry Morgenthau Jr was Secretary of the Treasury of the United States through most of the Franklin D. Roosevelt administration, overseeing, and sometimes arguing against, *New Deal* spending.

works like Way et al.'s (2022) study on experience curves for green energy technologies, it is apparent that targeted investment, in R&D but also in green assets, can accelerate climate objectives in many ways, for instance by accelerating technological advances and establishing markets for nascent green products. If governments were to maintain their rates of COVID-19 green spending (US$ 978 billion) while ceasing the non-green COVID-19 spending items (US$ 17.2 trillion), the program would be 5% of the cost and a less than 5% increase to annual budgets. Half of the increase could be offset by ceasing to subsidise fossil fuels, which tally US$ 470 billion per year (Parry *et al.*, 2021). The rest could be easily met by better taxing the negative externalities of fossil fuel use, which currently receives implicit subsidies in excess of $US5.4 trillion per year (Parry *et al.*, 2021). Combining these perspectives, a reframing of the question "are high rates of low-carbon deficit spending sustainable" might be "are high rates of global warming more sustainable than minor increases in deficit spending, which can themselves be funded with better taxing of fossil fuels". And to that question, the answer is "no".

However, spending is not the only policy option available to governments on climate. Although this DPhil focuses on greening fiscal stimulus in times of recession, it does not in any way suggest that this is the only or necessarily the optimal path to achieving low-carbon growth. As explored in the literature review, pricing reforms and a raft of other policy measures interventions can support efforts towards emissions-growth decoupling (Chapter 2.1.3.2). Subsequent works to this DPhil, such as *Introducing the Sustainable Budgeting Approach* (see Appendix E) and a

landmark report of The Coalition of Finance Ministers for Climate Action (2022), *Strengthening the Role of Ministries of Finance in Driving Climate Action*, explore greening fiscal policy in periods outside of recession, listing benefits that could come from systematically changing how budgetary decisions are made.

Beyond questions of growth, all papers in this DPhil support the notion that GDP is an inadequate measure for wellbeing.[62] For one, all papers are clearly motivated by a motivation to address the challenges of climate change for the benefit of humanity. Beyond the value of climate action, Paper A's literature review suggests,

More broadly, human wellbeing is not only driven by innovation, good jobs, and growth but also by our relationship with nature itself, its ecosystems, landscapes, and nonhuman species.

In its review of existing literature, it notes that

factoring in the nongrowth benefits of green investments would significantly improve their policy appeal compared to other investments—examining only the impacts on GDP understates benefits of green investment spanning health (Carleton et al., 2020; Scovronick et al., 2019; Watts et al., 2017), the environment (IPCC, 2014; Nemet et al., 2010), economic stability (Kahn et al., 2019; Lamperti et al., 2019; Stern, 2006), among others (see Karlsson et al., 2020).

In Paper B, the inclusion of a question on overall policy desirability allowed for the relevance of factors not related to economic multiplier, speed, or climate to be considered. Ranked overall desirability across policies had the lowest Spearman Coefficient to other ranked question responses, indicating that

[62] Contrary to common conception, this is a view widely held of the green growth literature.

there are non-economic, non-climate attributes of climate-positive policies which increase their overall desirability.

Paper B goes on to provide several examples of relevant co-benefits. Paper C introduces fiscal archetypes and subarchetypes to immediately assess potential climate impacts (which emerge as significant) and provide a platform for discussion of associated co-benefits in subsequent work.[63]

Further, on moving beyond traditional growth measures, papers A and B note that many existing methods for economic analysis are inadequate for considering the economic characteristics of green investment, particularly in recessionary environments. Investment in any new industries is likely to bring induced positive and negative impacts to other industries—for instance, cheaper electricity generation through renewable energy is an enabler of electric vehicles. However, the induced effects of policy are notoriously difficult to capture. In review of existing literature on green investment, Paper A explains,

Particular gaps for job creation should be addressed, including in induced job impacts.

On the other side, support for inefficient fossil industries is likely to bring negative externalities, like health burdens through air pollution, which are often unpriced.

6.4. Policy recommendations

Several policy recommendations naturally emerge from the findings of the three papers. The recommendations are organised based on those relevant

[63] See *Introducing the Sustainable Budgeting Approach* in Appendix E. Archetypes are all assessed for impact characteristic on climate, natural capital, air pollution, quality of life, income inequality, and rural-urban inequality.

(a) to all economies, (b) specifically to advanced economies, (c) specifically to emerging market and developing economies, and (d) to policy makers hopeful to support further research on this topic. In the below text, *strong* recommendations are those with clear support from one or more DPhil papers, while *weak* recommendations have only indirect or inferred support.

6.4.1. Recommendations for all economies

6.4.1.1. Prioritise green investment (strong recommendation)

All three papers support the proposition that green public investments can outperform traditional alternatives on orthodox economic metrics including job creation and fiscal multiplier in some cases. Paper A demonstrates that this notion is supported by the literature. Paper B shows that it is supported by expert economists. Paper C demonstrates that some policy makers are already acting on this basis. As discussed in papers A and B, prior literature also demonstrates that investment in climate mitigation can serve health, security, social, environmental, and other priorities. Policy makers can learn from over 850 COVID-19 green spending measures recorded in Paper C's Global Recovery Observatory, with examples in almost every sector.

6.4.1.2. Invest time in policy design (strong recommendation)

The success or failure of a fiscal policy depends on its design characteristics. As detailed in Paper A, these characteristics include, among other aspects, the target beneficiaries, delivery mechanism, social marketing, supervisory controls, and financing. Each factor can significantly impact the policy's economic, social, and environmental impact. Based on literature reviewed across all three papers, even when there is scope to adjust a policy during

implementation, investing time early in collaborative policy design seems to deliver dividends.

However, there are conflicting priorities during periods of economic crisis. As discussed in Papers A and B, when effective fiscal response is most critical, the imperative for fast action can conflict with the imperative for well-designed policy. To combat this, policy makers could build up caches of well-designed and shovel-ready fiscal policies—a green backlog.

6.4.1.3. Ensure that political rhetoric is matched by action because tracking demands accountability (strong recommendation)

As demonstrated by Paper C, developments in ML threaten to remove the shroud of mystery that has long shielded fiscal policy from greater public criticism than it already attracts.[64] New tracking initiatives like GRO (the fiscal policy dataset of Paper C) and others like it, facilitate better understanding of the magnitude of public spending relative to other domestic and international measures. Civil society is already using these comparisons to demand changes in spending patterns and hold government accountable to their rhetoric—indeed, that is one of the supplementary outcomes of this thesis. For policy makers, the recommendation is then to align fiscal actions with their positive rhetoric and use trackers like GRO to benchmark against other nations.

[64] Anecdotally, it seems like policy makers often rely on the publics' unfamiliarity with big numbers to disguise the relative size of their investments. For instance, a US$500 million investment in green hydrogen might receive just as much, or more, government communications focus as a US$50 billion investment in defence—while US$500 million and US$50 billion are two orders of magnitude apart, to the public both are very large numbers and the difference in size is lost without side-by-side comparison.

6.4.1.4. Don't forget about green enablers (strong recommendation)

Many large-scale green investments are only plausible with access to key enabling resources and capabilities. Paper A explains from the literature that these include access to sufficient and suitable green-skilled labour, a green business ecosystem with sufficient material supplies, skilled contractors, and the administrative capacity to handle regulatory procedures and approvals efficiently, and absorptive capacity for R&D. Any long-term and large-scale policy intervention should be accompanied by appropriate investment in these enablers to ensure timely and high-quality delivery. Skilling and reskilling programs can be particularly important since access to skills can be a prerequisite for boosting other enablers.

6.4.1.5. Look for triple wins (strong recommendation)

While not a focus of this thesis, an adjacent message of two of the papers (A and B) was that green investment could be turned from a double win on climate and economy into a triple win by integrating social and/or security priorities. These additional priorities could be met through targeting of beneficiaries—for instance, by directing subsidies for home efficiency retrofits to lower income households, thereby improving efficiency and lowering gas bills. Additional priorities might also be achieved through supervisory controls—for instance, to reduce human rights violations in upstream supply chains, government might mandate sustainable procurement and provide enforcement with a new oversight body.

6.4.1.6. Invest in machine learning for policy design and measurement (strong recommendation)

As businesses expand their ML capabilities to gain a competitive edge in commerce, so too can governments use ML to guide their economies to trade strength, natural environments to healing, and social systems to justice. Papers A and C demonstrate that applications of ML in fiscal policy can support traditional fields of inquiry to provide new insights—it is imagined that similar applications can support all kinds of non-fiscal policy too. Governments should invest internally in ML capabilities, empowering staff to apply these techniques to all kinds of problems. In so doing, policy makers should prioritise integrating ML-equipped staff into policy teams, rather than using such staff prescriptively as a part of external teams. It is imperative that policy makers begin investing in these skillsets upstream in the education pipeline—and there is no reason that it cannot begin as early as primary school (Druga *et al.*, 2019; Shamir and Levin, 2021; Shamir and Levin, 2022; Volpe *et al.*, 2005). Partly this is about investing in teacher capacity (Mason and Rich, 2019; Rich *et al.*, 2019) and partly it is about addressing stereotypes associated with computer scientists (Gretter *et al.*, 2019), particularly for women (Cheryan *et al.*, 2015; Vitores and Gil-Juárez, 2016). Fundamentally, ML is a tool to supplement human intelligence (Domingos, 2015) and the societies that best embrace it are likely to most benefit from it.

6.4.1.7. For long-term growth, prioritise industries in which you have natural advantage (weak recommendation)

Often fiscal measures might be only one part of a broader industrial policy to establish or expand long-term domestic production. In these cases, policy

makers are rightly concerned with which green initiatives hold the greatest potential for their economy—opportunities including solar panel manufacturing, electric vehicle assembly, electrolyser development, lithium processing, and carbon capture all hold high-growth potential but are not equally suited to every economy. As Paper A indicates, and supported by the literature review, policy makers should consider their own sources of natural comparative advantage—which might come from an existing skills mix, natural resource endowment, geographic proximity to key demand, or any other characteristic—and then consider which green sectors are the most closely related. If appropriately executed, early movement with comparative advantage could lead to long-term competitive advantage, particularly in energy sectors.

6.4.1.8. Integrate sustainable budgeting into general fiscal planning (weak recommendation)

As shown in the literature review, in many nations, budgeting processes are not supported by comparisons of quantified forecasts of policy impact, and where they are, orthodox economic metrics tend to be disproportionately favoured. Policy makers should at least partially systematise policy decision making by relying on forecast economic, environmental, and social impact—and economic impact should consider both orthodox and heterodox indicators. The taxonomy of Paper C provides a skeleton on which these analyses could be added, and this has been partially complete in a supplementary paper to this DPhil, *Introducing the Sustainable Budgeting Approach*.

6.4.2. Recommendations for advanced economies

6.4.2.1. R&D investments should be prioritised for their high long-run economic and innovation returns (strong recommendation)

As noted in Paper A, R&D opportunities for low-carbon technologies are available in every economic sector. Provided that there is sufficient domestic absorptive capacity, investments in R&D are often reported in the literature to have some of the highest economic multipliers. Paper B found strong policy maker support in high-income countries for that perspective and Paper C revealed significant related spending in response to COVID-19. When supported by complimentary commercialisation initiatives, successful R&D can conceivably spawn new industries, create jobs and unlock additional later opportunities for technological innovation. Additionally, most pathways to a sustainable carbon future rely on technologies yet to be invented or commercialised—without R&D, either publicly- or privately-funded, a zero-carbon future is implausible. As highlighted in Paper A, Advanced economies generally hold advantage over developing countries in R&D domains due to better access to skilled innovators and higher absorptive capacity, amongst other factors.

6.4.2.2. Provide better support to vulnerable nations in their carbon transitions (strong recommendation)

Paper C identified a significant gap in COVID-19 recovery investment in emerging markets and developing economies compared to advanced economies. It explains, “Advanced economies (AEs) spent on average US$ 13,575 per capita compared to US$ 746 for emerging markets and developing economies (EMDEs) (US$ 464 excluding China)”. With GETS model selection, this gap appears to be partially driven by differences in

fiscal space and cost of debt. Economies are highly interdependent through globalisation such that vulnerability in any one country detracts from the resilience of others. As such, hamstrung economic recovery in many vulnerable nations puts global economic stability at risk—not to mention supply chains, health, food security, migration, and the climate. Advanced economies can support vulnerable nations with finance, technology, and technical assistance, already pledged under numerous UNFCCC agreements. Advanced economies can act in their own interests by moving beyond pre-existing agreements and ensuring future agreements are significantly more collaborative and constructive—for instance by prioritising long-term partnership as well as securing more finance, technology, and technical assistance. Delays in support will directly increase long-term climate risk and economic risk, with potentially disastrous consequences.

6.4.3. Recommendations for emerging market and developing economies

6.4.3.1. Take particular care in designing policy as fiscal space is limited (strong recommendation)

The role for sustainable budgeting is particularly pronounced in EMDEs where dollars for spending are often very limited. Paper C uses GETS model selection to show that the relatively low spending in developed is critically correlated to differences in the cost of debt. It goes on to explain, "The inverse relationship between cost of capital and level of spending is theoretically obvious, with empirical studies demonstrating that EMDEs tend to employ procyclical fiscal policies during recession, while AEs have the fiscal space to deliver countercyclical responses". Policy makers must

look for fiscal double- or triple-wins as a default, being sure to understand the likely relative economic, social, and environmental consequences of any policy before proceeding. Nations must fill, with priority, any known gaps in the processes and staffing of their budgetary planning functions, or further risk low-growth cycles and/or inefficient natural capital use. Tools like that described in *Introduction to the Sustainable Budgeting Approach* might assist in filling these gaps.

6.4.3.2. Renewable energy, low-carbon mobility, and natural capital seem to be particularly attractive (weak recommendation)

Across the DPhil papers and the supporting materials, three categories of green investment tend to emerge as high priority for EMDEs: renewable energy particularly with wind electricity, solar electricity, sometimes hydroelectricity, and transmission; low-carbon mobility, mainly through public transport and/or electric vehicles; and natural capital through any number of interventions, depending on the economy in question. These received the highest level of financial support from EMDEs in Paper C's COVID-19 spending analysis. An additional measure receiving high support from surveyed EMDE experts in Paper B was "rural support". This is not necessarily green but can be. For instance, sustainable agriculture or well-planned natural capital solutions. Each solution area can deliver high direct economic returns on traditional economic criteria while also contributing indirect economic benefits. Renewable energy can boost electrification, which in turn increases health outcomes through electrified hospitals, employment outcomes by enabling new industrial development, and education outcomes by simplifying household tasks, amongst other things.

Low-carbon mobility can increase productivity and access to labour markets by making transportation more widely affordable. Investments in nature can protect natural capital, safeguarding resources for the public, while unlocking new opportunities for tourism, international carbon trade, and more.

6.4.4. Recommendations for research funding

6.4.4.1. Invest in policy impact assessment for COVID-19 investments to learn for the future (strong recommendation)

Paper B uses ML to confidently identify many gaps in understanding across the green growth literature, suggesting that policymakers often lack the evidence needed to make informed fiscal decisions. However, nearly US$1 trillion in green spending through over 850 fiscal investments provides an immediate opportunity to fill these gaps and prepare for the future. Compared to the GFC, spending is more widely distributed across sectors and geographies, providing a broad opportunity for meaningful ex-post analysis. Paper A and B both indicate that we did not learn sufficiently from GFC investments—it is imperative that policy makers do not repeat this mistake following from COVID-19. Practically, policy makers could prescribe that a small portion of each policy's fiscal allocation is used for controlled trials and other academically-rigorous approaches for measuring impact. Global standards could be set for such reviews to ensure comparability of results across nations and provide confidence in their validity. These standards might be set by a council of academic experts with politically-salient stipulations for release—for instance, there might be

a five-year publication ban on results to do away with the threat of misaligned political incentives.

6.4.4.2. Fund fiscal accountability projects, particularly with ML (strong recommendation)

Fiscal accountability can help to restore trust in government. As the custodian of public funds, it is appropriate for government to give the public full information on how funds are used in both absolute and relative terms. Some of this information is already provided through budgetary documents, but these are often insufficiently granular, and do not put spending in the context of other global actions. For effective governments, there is a strong incentive to demonstrate how domestic actions might exceed the performance of global peers—successfully doing so could bring electoral dividends. Developments in ML could facilitate a live and automatically updated data platform on global fiscal actions and their impacts. Such a platform could easily feed into other policy modelling, demonstrating how certain policy changes might, for example, influence future carbon emissions. Global climate models do not currently account for fiscal investments and rely instead on targets and/or trailing indicators like measured GHG emissions (or perhaps this is unnecessary).

6.5. Future work

The fields of green growth and green Keynesianism have, if anything, risen in prominence over the course of the COVID-19 pandemic. However, as demonstrated by Paper A, current research is insufficient to fully guide government policy interest on these topics. Significant additional work is needed to better understand the economic characteristics of green

investment. Broadly, suggestions forthcoming from the literature review and papers of this DPhil might be grouped as follows below.

6.5.1.1. Ex-post study of green investments, particularly those announced in response to COVID-19

Paper A concludes that gaps in understanding of green investment characteristics continue in every sector, in every geography, and for every economic indicator. Empirical assessment of COVID-19 policies could provide significant new evidence in support of future policy making. By archetype, renewable energy and energy efficiency policies tend to be more widely studied. By geography, North America and Europe are more widely studied. By indicator, job creation is more widely studied. The positive long-run spillovers of green investment and falling long-term costs in green technology, tend to be ignored. Similarly, the different characteristics of spending at different points in the economic cycle tend to be ignored.

6.5.1.2. Machine learning in fiscal policy

There is significant scope to expand the use of ML for tracking, understanding, and making fiscal policy decisions (as well as many other kinds of policy decisions). These opportunities span all investment types (green, dirty, other). Papers A and C, as well as the extra note to Paper B, demonstrate how ML techniques including NLP, clustering, ensemble methods, and RNNs might aid fiscal policy decision making and evaluation. The literature review describes how forthcoming opportunities with ever-improving tools are even stronger. As discussed in the literature review, there are few examples of ML supporting fiscal decision making, despite these processes being some of the most consequential in public policy.

As one direct application from this DPhil, RNN, transformer, or other methods could be used to categorise fiscal policies as they are announced by governments and feed these policies into a live global database akin to GRO. With new training data, already being compiled through sustainable budgeting initiatives, other ML methods could be used to analyse all kinds of characteristics of spending within and across economies. Entirely new models with not-yet-created data could be applied to learn from empirical analyses to learn from the past and create better policies in the future.

6.5.1.3. Development of new methods to study economic multipliers in the absence of long time-series data

Without long time-series data, analysing economic multipliers can require creativity. In some cases, entirely new modelling methods might be necessary. Papers like Batini *et al.* (2022) and Hasna (2021) provide some empirical insights to green multipliers, but significantly more is required, and in a wider set of geographies. Even these promising papers struggle due to data limitations (particularly Batini *et al.*). Generally speaking, non-Bayesian modelling approaches are required to deal with non-linearities, including distribution and parameter shifts, which are inherent to analysing an economic shock. Beyond modelling method, the future work recommendations in Paper A suggest that it would also be helpful for the field to standardise definitions of multiplier terminology and set a universal taxonomy for the analysis of green investment archetypes. This taxonomy may build from that included in Paper C.

6.5.1.4. Pronounced attention to emerging market and developing economies

Responding to tedious fiscal positions, EMDE governments seem particularly captivated by high-carbon investments that bring short-term payoffs with potentially long-term economic drag (*e.g.*, new oil and gas drilling).[65] Further work is required to demonstrate the economic risks of such action and accompanying multi-faceted benefits of alternative green investments. To this end, further research is needed on the economic characteristics of all green investment archetypes across all nations.

When it comes to finance, Paper C notes that EMDEs operate with constrained fiscal space, and this has limited the magnitude of their fiscal response to COVID-19. Research is needed to develop new access pathways to alternative finance. This might include developing alternative financing models and particularly models that allow country-specific risk to be carried by willing partners to private capital. It might also include support of ongoing multilateral negotiations on the topic, including the UNFCCC Article 9 negotiations for the New Collective Quantified Goal on climate finance.

[65] This is not to say that advanced economies cannot or do not suffer the same plight. At the time of writing, many such economies, including the United States of America, continue to expand oil and gas production.

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7

Conclusion

This DPhil presents new evidence and discussion in support of fiscal policy measures that spur green growth during periods of economic contraction. In so doing, it contributes to the understanding of environmental policy in a recessionary context. Using a literature review and three papers, it investigates conventional economic metrics for green investments. It contributes new data (original expert elicitation survey, database of COVID-19 fiscal policy, database of COVID-19 head of state speeches), adapted methods (several forms of machine learning, survey-based elicitation, general-to-specific econometric model selection), and analysis to a new instructive event (COVID-19). The first paper (Chapter 3) uses new and existing techniques in natural language processing to synthesise the existing literature on the economic characteristics of green investment. The second paper (Chapter 4) surveys leading economists to understand the perceived characteristics of green and other investments amongst policymakers. The final paper (Chapter 5) uses the results of the first two papers, with a new dataset and multiple methods in deep learning and econometric model selection, to understand sectoral and global variation in actual spending habits and their drivers in response to the COVID-19 crisis.

The core contributions of the thesis can be grouped into six categories: new datasets, unique application of existing methods, new methods and structures, new evidence in support of theories on green growth, evidenced policy recommendations, and suggestions for future research.

To the questions posed in the introduction of this DPhil, I provide preliminary responses:

Q. If a government were to care only about conventional economic indicators, would it make sense to invest in climate mitigation solutions over traditional initiatives?

A. Yes, in many cases it would. In this DPhil, a ML-enhanced review of existing literature (Paper A, see Chapter 3.2) and a new survey of expert economists (Paper B, see Chapter 4.2) both suggest that well-designed green investments can deliver fiscal multipliers and job creation equivalent to or higher than traditional alternatives in some sectors. Based on the fiscal response to COVID-19 (Paper C, see Chapter 5.2), this DPhil finds that some governments prioritised green investment more than others and that this prioritisation might have been based partially on economic criteria. To this end, GETS model selection (Paper C, see Chapter 5) revealed that higher unemployment rates were a critical predictor of green spending (as a proportion of total spending) and additional ML analysis of the expert survey (Paper B, see Chapter 4.3.1) showed that high scores for economic factors predicted high scores for the overall desirability of several green policy archetypes. Further discussion in Chapter 6.3.1.

Q. Are some climate mitigation solutions better than others on conventional economic indicators?

A. Yes, but the most attractive measures tend to vary between economies and depend on the specifics of policy design. This DPhil shows that COVID-19 investment was directed to green initiatives in every sector (Paper C, see Chapter 5), suggesting that perhaps conventional economic priorities could be met with well-designed climate mitigation investments in all sectors. That said, the opinions of economists in the elicitation survey (Paper B, see Chapter 4.2), when globally averaged, indicated that some low-carbon solutions might be considered more attractive based on their economic multiplier than others. Yet, regional analysis of survey responses shows that the relative magnitude of green fiscal multipliers and the overall desirability of any green policy varied between countries (see next question). Further discussion in Chapter 6.3.2.

Q. Does the relative strength of climate mitigation investments over traditional investments vary between economies?

A. Climate investments appear promising in all geographies, but the most attractive measures vary between economies. This DPhil identifies that economic development, human capital, existing economic structures, and present unemployment are all important factors for determining the economic outcomes of fiscal policies during economic contraction. In the expert elicitation survey (Paper B, see Chapter 4.2), preferred investments were different

for respondents of high-income nations to those of low- and middle-income nations. In the latter group, rural-support measures were highly preferred while R&D measures were discounted for both economic and overall attractiveness. In Paper C (Chapter 5), spending patterns varied significantly between nations at both the global and regional level, with emerging market and developing economies spending a significantly higher proportion of green investment on natural infrastructure and green market creation compared to advanced economies, but a lower proportion on clean transport and clean R&D. Asides from differences in GDP, GETS model selection suggests that national variation in total and proportional green spending for the largest fifty nations was most critically correlated with human capital, economic structures (e.g., existing dependence on renewable energy, arable land), and unemployment. This implies that policy selection might have been influenced by similar factors. Paper A (Chapter 3.2) finds support for these findings in the literature, suggesting that green job creation and green economic multipliers can be influenced by a nation's trade position, the initial public stock of capital, unemployment rate, savings rate, cost of capital, existing and future skill base, existing and future absorptive capacity in R&D, existing green business ecosystems, contractor capabilities, and more. Further discussion in Chapter 6.3.3.

To the broader theme of green growth, I demonstrate that certain kinds of investments can possess both strong economic and environmental

attributes. On this basis, I provide additional theoretical and empirical (survey) evidence in support of absolute decoupling of GDP growth and greenhouse gas emissions. The evidence speaks specifically to decoupling as a feature of economic recovery from a recession, where pronounced fiscal multipliers deliver higher growth returns for public investment. Further discussion in Chapter 6.3.4.

Regarding the likely overall impacts of the COVID-19 fiscal response on GHG emissions, this DPhil provides a sobering assessment: an unprecedented US$18.2 trillion in deficit spending provided opportunity to meaningfully shift the carbon intensity of our economic systems, but this opportunity appears to have been mostly missed. While US$978 billion in new spending might reduce long-term GHG emissions, this was a relatively minor portion of total spending (5.4%) and incommensurate with the scale of the investment needed to facilitate a low-carbon transition. Furthermore, US$278 billion was directed to initiatives likely to increase long-term GHGs, counteracting some of the positive impacts of the low-carbon investments. Many measures supportive to deficit spending, like fossil fuel pricing reforms, were altogether absent from the policy mix, further suggesting that the overall impact of the COVID-19 policy response on emissions fell well short of its potential.

Alongside evidence to assure policy makers of the strong growth characteristics of green investments, this DPhil also questions reliance on traditional economic metrics like GDP growth as measures of wellbeing. Joining much of the existing green growth literature, the literature review of this DPhil suggests that human wellbeing is often associated with growth,

high-quality jobs, and innovation, but also with social and environmental factors like our relationship with nature, its ecosystems, landscapes, and nonhuman species (Chapter 2.1). Beyond this, it notes that traditional economic measures frequently fail to capture even the full economic benefits of initiatives which preserve and build wealth through natural capital and other often ignored forms of capital. Relying on traditional economic measures is shown to be sufficient for prioritising some green investments but generally insufficient for directing fiscal policy on whole. In other words, green investments can emerge as attractive even when their strong social and environmental characteristics are ignored.

The data and analysis in this DPhil focus on the single instructive event of the COVID-19 economic contraction and recovery. However, its results could be relevant to other future crises and perhaps also to intermediate periods of the business cycle. There were extreme idiosyncrasies in the COVID-19 economic crisis compared to previous crises, for instance, simultaneous demand- and supply-side shocks, restricted mobility leading to restricted recovery options, and very low costs of debt. However, the core conclusion, that green investments can have strong economic characteristics compared to traditional alternatives, even on conventional metrics, is likely to be relevant in many scenarios. Rather than speaking to *how much should governments spend* or *when to spend*, this DPhil considers, *what to spend on*. In that way, its findings, data, and taxonomies might be relevant even to *typical* budgetary cycles outside of economic contraction.

This DPhil provides several policy recommendations:

- Prioritise green investment (Chapter 6.4.1.1),
- Invest time in policy design (Chapter 6.4.1.2),
- Ensure that political rhetoric is matched by action because tracking demands accountability (Chapter 6.4.1.3),
- Don't forget about green enablers (Chapter 6.4.1.4),
- Look for triple wins (Chapter 6.4.1.5),
- Invest in machine learning for policy design and measurement (Chapter 6.4.1.6),
- For advanced economies: R&D investments should be prioritised for their high long-run economic and innovation returns (Chapter 6.4.2.1),
- For advanced economies: provide better support to vulnerable nations in their carbon transitions (Chapter 6.4.2.2),
- For emerging market and developing economies: take particular care in designing policy as fiscal space is limited (Chapter 6.4.3.1),
- For research funding: invest in policy impact assessment for COVID-19 investments to learn for the future (Chapter 6.4.4.1), and
- For research funding: fund fiscal accountability projects, particularly with ML (Chapter 6.4.4.2).

The DPhil proposes a research agenda to further advance understanding of green fiscal policy. The core pillars of this agenda are:

- Ex-post study of green investments, particularly those announced in response to COVID-19 (Chapter 6.5.1.1),
- Machine learning in fiscal policy (Chapter 6.5.1.2),
- Development of new methods to study economic multipliers in the absence of long time-series data (Chapter 6.5.1.3), and
- Pronounced attention to emerging market and developing economies (Chapter 6.5.1.4).

Appendices

Please note that portions of the text in the Appendices have appeared in various forms in my academic and non-academic publications. Accordingly, this statement serves as proper attribution to those prior works.

A

Supplementary Materials for

How Stimulating Is a Green Stimulus? The Economic Attributes of Green Fiscal Spending

O'Callaghan, B., Yau, N., & Hepburn, C.

A.1. Literature Categories

We established three mutually exclusive categories of literature for targeted analysis: premier journals, secondary journals, and grey literature. The premier and secondary journal categories were exhaustive across their categories, while the grey literature category reflected a sample of the field. The premier journal group totalled one-hundred-and-fifty sources and included the top one-hundred "economics" journals, top one-hundred "environmental science" and "environmental studies" journals (combined for analysis), and top fifty journals "overall", all measured by journal impact factor (JIF) scores in the 2020 edition of the Journal Citation Reports from Clarivate Analytics (Clarivate Analytics, 2020).

The "overall" category was important for capturing broad science journals like *Nature* and *Science*. Alternative approaches for defining journal impact involve using composite indexes, such as that of Combes and Linnemer (2010) for the economics field, however, a similarly comprehensive index is not readily available for environmental science literature. Stricter definitions for 'premier journal', for instance limiting to the top fifty journals in the economic and environmental science categories, led to insufficient paper sample sizes. Constraining the sample to the top one-hundred journals in each field mirrors the approaches of Drupp *et al.* (2018), Howard and Sylvan (2015), and Hepburn *et al.* (2020). The full list of relevant journals is included in table A1. The secondary journal group included all peer-reviewed academic journals not in the premier category. The grey literature group was limited to proceedings papers, book chapters, book reviews, news items, meeting abstracts, news items, and notes in the

Web of Science data collection. Further work could consider a broader sample of grey literature, however, given the breadth and heterogeneity of grey literature types and sources (Paez, 2017), it will be difficult to cover all literature. As such, if attempting to systematically cover a full literature domain, researchers will likely remain constrained to grey literature databases and digital repositories rather than the open web (Adams *et al.*, 2016; Corlett, 2010).

Table A1. Print ISSNs of premier journals used in literature analysis.

Top 50 "Overall" journals	Top 100 "Environmental Science" & "Environmental Studies" journals		Top 100 "Economics" journals	
0007-9235	1754-5692	2049-1948	0033-5533	1475-1461
1471-0072	1758-678X	1680-7316	0013-0095	1354-8166
0028-4793	2398-9629	1086-0266	0002-8282	0889-3365
1474-1776	2542-5196	2325-1026	0022-3808	2083-1277
0140-6736	1064-3389	1750-6816	0022-0515	0304-3932
1759-4774	0043-1354	2095-6339	1752-1378	0950-0804
2058-8437	1540-9295	0006-3207	0921-898X	1043-951X
2058-7546	1543-5938	N/A (eISSN - 1476-069X)	0895-3309	1042-4431
1474-175X	0261-5177	2190-4707	1559-7431	1941-1383
1740-1526	1354-1013	2212-0955	0022-1082	0734-306X
0009-2665	0304-3894	0926-860X	1945-7782	2040-5790
1545-8636	0964-4733	0886-6236	0140-9883	0002-9092
1538-3598	0921-3449	0305-9006	0304-405X	1566-0141
1545-8601	0034-4257	2405-8807	1366-5545	0021-9886
1546-1696	2210-4224	0301-4207	0009-2303	2029-4913
1460-4744	0160-4120	1462-9011	0735-0015	0266-903X
1539-0756	2214-1588	0167-8809	0034-6535	1572-3097
1546-170X	0959-3780	1001-0742	0034-6527	0167-6296

1471-0064	2059-7037	1559-0631	0301-4215	0304-3878
1474-1741	0959-6526	0025-326X	1750-6816	0165-1587
2056-676X	0091-6765	0098-8472	0012-9682	0169-2070
1476-4687	0013-936X	1361-9209	0893-9454	0022-1090
2051-5545	1610-3653	2212-0416	0165-4101	1572-3089
1095-9203	1535-3958	0264-8377	1098-3015	1618-7598
1759-5053	2051-8153	0921-8009	0191-2615	1389-9341
1527-7755	0269-7491	0197-3975	0965-8564	0094-1190
1474-4465	1569-1705	0198-9715	0022-166X	0021-857X
1476-4660	0048-9697	2452-0748	0921-8009	0954-349X
1759-5037	2328-8930	1364-8152	1945-7731	0022-0507
1759-4766	0179-5953	1726-2135	0305-750X	1309-4297
2520-1158	N/A (eISSN - 2328-4277)	2352-1864	1941-1340	2333-5955
1097-4172	1757-7780	0043-1397	0950-0170	1366-2716
1474-5488	0956-053X	1208-6053	0257-3032	1080-8620
2542-4351	0045-6535	0272-4944	2444-8834	0022-1996
1433-8351	1877-3435	1080-7039	0966-6923	2214-8450
1756-1833	1088-1980	1110-9823	1170-7690	1479-8409
1873-2208	2214-6296	1941-1340	0038-0121	0939-3625
2159-8290	1748-9326	0044-7447	1468-2702	0013-0133
1748-3395	0301-4797	1469-3062	1381-4338	0264-9993
1749-4893	0964-4016	2352-5509	1945-7707	0047-2727
1754-5706	0263-7758	2468-2039	1804-171X	1755-5345
1546-1718	0888-8892	1085-3278	0276-8739	0960-6491
1539-6053	0013-9351	1470-160X	1356-3467	0016-3287
1522-1210	1093-7404	N/A (eISSN - 2047-2382)	0967-070X	0378-4266
1879-212X	2198-6592	1010-6049	0034-3404	1057-9230
1471-0048	1862-4065	1382-6689	0969-2290	1024-5294

2397-3358	0147-6513	N/A (eISSN - 2072-4292)	0095-0696	1331-677X
2520-1131	0013-9165	0168-2563	1542-4766	1060-586X
1569-8041	0169-2046	1352-2310	1368-4221	0266-4658
1759-5010	0301-4215	0165-0009	0306-9192	1941-1367

A.2. Literature Identification

As described in the main text, the process of literature identification involved a six-step iterative method (figure 2 from main text reprinted here as figure A1). The starting dictionary was developed by collating relevant terms identified independently by two domain experts (the authors). The initial set contained 13 words, and 141 bigrams, totalling 154 terms. By comparison, Fisch-Romito *et al.* (2021), who recently completed a systematic review of carbon lock-in of long-lived capital, adopted a starting inclusion list of 41 terms and an exclusion list of 3 terms. Notably the terms in Fisch-Romito *et al.* were significantly less targeted than ours (for instance "fossil", "retirement", and "scenario") leading to a search query yielding 34,002 publications (compared to the 766 in our first query).

The Web of Science (WoS) full database was searched for relevant English literature—both in the first search iteration where only the preliminary user-defined dictionary was used, and in subsequent iterations with expanded dictionaries. WoS is both widely available to scholars and highly appropriate for systematic reviews and meta-analyses (Gusenbauer and Haddaway, 2019; Levay *et al.*, 2015). While WoS can have limitations in retrieving older literature (*i.e.*, pre-1990) (Liu, 2021), given the relatively recent growth of green investment in the 21st century (Eyraud *et al.*, 2013),

this caveat was of lesser relevance to our analysis. Our analysis was, however, limited. Like Fisch-Romito *et al.*, our search focused only on English publications due to difficulties in accurately and consistently translating pdf documents and a lack of domain-specific term awareness in foreign languages (*e.g.*, "fiscal stimulus" is a technical term likely to be inadequately translated using only online tools). We were also limited to only using WoS due to limited query sizes in other databases and note that there are likely to be valuable papers that were missed as a result.

To query the database, dictionary terms were sorted into those of economic relevance (n terms) and those of environmental relevance (m terms). The search query was then built by combining each economic term with each environmental term, giving the following generic structure: "ts=((<economic term 1> AND <economic term 1>) OR (<economic term 2> AND <economic term 1>) OR (<economic term 1> AND <economic term 2>) OR … OR (<economic term n> AND <economic term m>). In the instance that multiple sub-terms were relevant to each economic or environmental term, more complex term comparators were used, for instance, (<economic term Y> AND <economic term X—subterm 1> AND <economic term X—subterm 2>).

The full query for the economic term, "economic stimulus", is printed below. This query format was repeated for each economic term, *i.e.*, substituting "fiscal stimulus" for each of the other economic terms.

ts=(("fiscal stimulus" AND "ghg emissions") OR ("fiscal stimulus" AND "fishstock management") OR ("fiscal stimulus" AND "forests

restoration") OR ("fiscal stimulus" AND "forests managed") OR ("fiscal stimulus" AND "sustainable hydrogen") OR ("fiscal stimulus" AND "renewable farm") OR ("fiscal stimulus" AND "renewable grid") OR ("fiscal stimulus" AND "efficiency sustainability") OR ("fiscal stimulus" AND "carbon protection") OR ("fiscal stimulus" AND "efficient environmental") OR ("fiscal stimulus" AND "efficiency environmental") OR ("fiscal stimulus" AND "environmental efficacy") OR ("fiscal stimulus" AND "saving environmental") OR ("fiscal stimulus" AND "efficient fuel") OR ("fiscal stimulus" AND "energy-efficient retrofit") OR ("fiscal stimulus" AND "efficiency insulation") OR ("fiscal stimulus" AND "insulation buildings") OR ("fiscal stimulus" AND "efficiency buildings") OR ("fiscal stimulus" AND "energy-efficient buildings") OR ("fiscal stimulus" AND "conservation natural") OR ("fiscal stimulus" AND "forests natural") OR ("fiscal stimulus" AND "restoration natural") OR ("fiscal stimulus" AND "forests management") OR ("fiscal stimulus" AND "management natural") OR ("fiscal stimulus" AND "management forests") OR ("fiscal stimulus" AND "capital green") OR ("fiscal stimulus" AND "green capital") OR ("fiscal stimulus" AND "conservation agricultural") OR ("fiscal stimulus" AND "resource conservation") OR ("fiscal stimulus" AND "conservation water") OR ("fiscal stimulus" AND "natural rehabilitation") OR ("fiscal stimulus" AND "green resources") OR ("fiscal stimulus" AND "natural forests") OR ("fiscal stimulus" AND "natural evergreen") OR ("fiscal

stimulus" AND "natural reserve") OR ("fiscal stimulus" AND "green electricity") OR ("fiscal stimulus" AND "hybrid electricity") OR ("fiscal stimulus" AND "electric charging") OR ("fiscal stimulus" AND "electric infrastructure") OR ("fiscal stimulus" AND "green infra") OR ("fiscal stimulus" AND "green infrastructure") OR ("fiscal stimulus" AND "vehicle charging") OR ("fiscal stimulus" AND "green transition") OR ("fiscal stimulus" AND "sunpower solar") OR ("fiscal stimulus" AND "hydrogen solar") OR ("fiscal stimulus" AND "green wind") OR ("fiscal stimulus" AND "hydrogen power") OR ("fiscal stimulus" AND "green generation") OR ("fiscal stimulus" AND "clean power") OR ("fiscal stimulus" AND "green generation") OR ("fiscal stimulus" AND "clean power") OR ("fiscal stimulus" AND "smart energy") OR ("fiscal stimulus" AND "renewable power") OR ("fiscal stimulus" AND "offshore renewable") OR ("fiscal stimulus" AND "wind tower") OR ("fiscal stimulus" AND "communications infrastructure") OR ("fiscal stimulus" AND "green") OR ("fiscal stimulus" AND "clean") OR ("fiscal stimulus" AND "environmental sustainab") OR ("fiscal stimulus" AND "environmental protection") OR ("fiscal stimulus" AND "environmental resilience") OR ("fiscal stimulus" AND "environmental conservation") OR ("fiscal stimulus" AND "carbon reduction") OR ("fiscal stimulus" AND "carbon removal") OR ("fiscal stimulus" AND "fuel efficien*") OR ("fiscal stimulus" AND "fuel saving") OR ("fiscal stimulus" AND "insulation retrofits") OR ("fiscal stimulus" AND "efficiency retrofits")*

OR ("fiscal stimulus" AND "green retrofits") OR ("fiscal stimulus" AND "insulation retrofits") OR ("fiscal stimulus" AND "energy efficien") OR ("fiscal stimulus" AND "building upgrades") OR ("fiscal stimulus" AND "buildings upgrades") OR ("fiscal stimulus" AND "insulation" AND "emissions") OR ("fiscal stimulus" AND "insulation" AND "climate") OR ("fiscal stimulus" AND "insulation" AND "efficien*") OR ("fiscal stimulus" AND "appliance efficiency") OR ("fiscal stimulus" AND "appliance incentive*") OR ("fiscal stimulus" AND "daylighting") OR ("fiscal stimulus" AND "electrification") OR ("fiscal stimulus" AND "natural capital") OR ("fiscal stimulus" AND "natural resource") OR ("fiscal stimulus" AND "natural sustainability") OR ("fiscal stimulus" AND "natural environment protection") OR ("fiscal stimulus" AND "nature based solutions") OR ("fiscal stimulus" AND "nbs") OR ("fiscal stimulus" AND "natural assets") OR ("fiscal stimulus" AND "environmental assets") OR ("fiscal stimulus" AND "climate friendly farming") OR ("fiscal stimulus" AND "climate resilient farming") OR ("fiscal stimulus" AND "biodiversity") OR ("fiscal stimulus" AND "conservation agriculture") OR ("fiscal stimulus" AND "regenerative agriculture") OR ("fiscal stimulus" AND "soil conservation") OR ("fiscal stimulus" AND "water conservation") OR ("fiscal stimulus" AND "nature conservation") OR ("fiscal stimulus" AND "fish*" AND "green") OR ("fiscal stimulus" AND "fish*" AND "clean") OR ("fiscal stimulus" AND "forest rehabilitation") OR ("fiscal stimulus" AND "forest restoration") OR*

("fiscal stimulus" AND "forest management") OR ("fiscal stimulus" AND "green space") OR ("fiscal stimulus" AND "nature reserve") OR ("fiscal stimulus" AND "tree planting") OR ("fiscal stimulus" AND "waterway protection") OR ("fiscal stimulus" AND "waterway enhancement") OR ("fiscal stimulus" AND "ecological conservation") OR ("fiscal stimulus" AND "electric automobile") OR ("fiscal stimulus" AND "electric car*") OR ("fiscal stimulus" AND "electric vehicle*") OR ("fiscal stimulus" AND "green automobile*") OR ("fiscal stimulus" AND "green car*") OR ("fiscal stimulus" AND "green vehicle*") OR ("fiscal stimulus" AND "hybrid automobile*") OR ("fiscal stimulus" AND "hybrid car*") OR ("fiscal stimulus" AND "hybrid vehicle*") OR ("fiscal stimulus" AND "EV") OR ("fiscal stimulus" AND "EVs") OR ("fiscal stimulus" AND "cash for clunker*") OR ("fiscal stimulus" AND "charging infra*") OR ("fiscal stimulus" AND "charging station*") OR ("fiscal stimulus" AND "green retraining") OR ("fiscal stimulus" AND "green skills") OR ("fiscal stimulus" AND "green jobs") OR ("fiscal stimulus" AND "green education") OR ("fiscal stimulus" AND "green training") OR ("fiscal stimulus" AND "future industries retraining") OR ("fiscal stimulus" AND "future industries skills") OR ("fiscal stimulus" AND "future industries jobs") OR ("fiscal stimulus" AND "future industries education") OR ("fiscal stimulus" AND "future industries training") OR ("fiscal stimulus" AND "just transition") OR ("fiscal stimulus" AND "conditional bailout") OR ("fiscal stimulus" AND "green bailout") OR*

("fiscal stimulus" AND "clean bailout") OR ("fiscal stimulus" AND "climate bailout") OR ("fiscal stimulus" AND "conditional loan") OR ("fiscal stimulus" AND "green loan") OR ("fiscal stimulus" AND "clean loan") OR ("fiscal stimulus" AND "climate loan") OR ("fiscal stimulus" AND "green R&D") OR ("fiscal stimulus" AND "green research") OR ("fiscal stimulus" AND "green innovation") OR ("fiscal stimulus" AND "clean R&D") OR ("fiscal stimulus" AND "clean research") OR ("fiscal stimulus" AND "clean innovation") OR ("fiscal stimulus" AND "CCS") OR ("fiscal stimulus" AND "carbon capture") OR ("fiscal stimulus" AND "carbon storage") OR ("fiscal stimulus" AND "carbon sequestration") OR ("fiscal stimulus" AND "green hydrogen") OR ("fiscal stimulus" AND "green electrolysis") OR ("fiscal stimulus" AND "ghg removal") OR ("fiscal stimulus" AND "greenhouse gas removal") OR ("fiscal stimulus" AND "green digitalisation") OR ("fiscal stimulus" AND "low-carbon manufact") OR ("fiscal stimulus" AND "green energy") OR ("fiscal stimulus" AND "clean energy") OR ("fiscal stimulus" AND "renewable energy") OR ("fiscal stimulus" AND "sustainable energy") OR ("fiscal stimulus" AND "solar power") OR ("fiscal stimulus" AND "solar generation") OR ("fiscal stimulus" AND "solar panel*") OR ("fiscal stimulus" AND "solar farm") OR ("fiscal stimulus" AND "solar energy") OR ("fiscal stimulus" AND "wind turbine*") OR ("fiscal stimulus" AND "wind farm") OR ("fiscal stimulus" AND "wind power") OR ("fiscal stimulus" AND "wind energy") OR ("fiscal stimulus" AND "geothermal power") OR ("fiscal*

stimulus" AND "geothermal generation") OR ("fiscal stimulus" AND "geothermal plant") OR ("fiscal stimulus" AND "geothermal energy") OR ("fiscal stimulus" AND "WWS") OR ("fiscal stimulus" AND "hydroelectric") OR ("fiscal stimulus" AND "wave power") OR ("fiscal stimulus" AND "wave energy") OR ("fiscal stimulus" AND "offshore wind") OR ("fiscal stimulus" AND "smart grid") OR ("fiscal stimulus" AND "battery infrastructure") OR ("fiscal stimulus" AND "battery storage infrastructure") OR ("fiscal stimulus" AND "communication infrastructure") OR ("fiscal stimulus" AND "connectivity infrastructure") OR ("fiscal stimulus" AND "broadcasting infrastructure") OR ("fiscal stimulus" AND "telecommunications infrastructure") OR ("fiscal stimulus" AND "3g infrastructure") OR ("fiscal stimulus" AND "4g infrastructure") OR ("fiscal stimulus" AND "5g infrastructure") OR ("fiscal stimulus" AND "public transport") OR ("fiscal stimulus" AND "clean transport") OR ("fiscal stimulus" AND "train infrastructure") OR ("fiscal stimulus" AND "bus infrastructure") OR ("fiscal stimulus" AND "tram infrastructure") OR ("fiscal stimulus" AND "metro infrastructure") OR ("fiscal stimulus" AND "cycling infrastructure") OR ("fiscal stimulus" AND "walking infrastructure") OR ("fiscal stimulus" AND "bike infrastructure") OR ("fiscal stimulus" AND "bike share infrastructure") OR ("fiscal stimulus" AND "ferry infrastructure") OR ("fiscal stimulus" AND "micromobility") OR*

("fiscal stimulus" AND "electric bus") OR ("fiscal stimulus" AND "hydrogen bus*") OR ("fiscal stimulus" AND "bike lane*"))*

As indicated in the above search extract, we used the *Topic Search* (TS) function for querying the WoS database. TS is the widest search function available and considers titles, abstracts, keyword fields, and keyword plus fields. According to WoS documentation (Clarivate Analytics, 2018), "the keyword plus field is an algorithm that provides expanded terms stemming from the record's cited references or bibliography".

In the post-processing step, we removed papers from journals in clearly unrelated research areas, namely: oncology, pathology, physiology, religion, reproductive biology, toxicology, nutrition dietetics, psychology, women studies, genetics heredity, history, virology, veterinary sciences, and demography. Articles from journals in these fields were manually double-checked for relevance, however no relevant articles were found in these fields and hence all were excluded. Post-processing also included removal of duplicates and a light-touch manual review to exclude irrelevant papers. This review gave particular attention to (i) papers published before 2008, as green investment analysis before this date was scarce, (ii) abstracts that included acronyms like "gva" and "ghg" as we discovered that these terms sometimes had alternatives meanings and appeared in contexts unrelated to our analysis, and (iii) papers that returned blank abstracts from the database.

Once all relevant texts were identified, they were sorted into the three literature categories, downloaded in pdf format, and stored for processing in Matlab.

The machine learning algorithm, built in Matlab script, first read and tokenized all pdfs, creating a document set, a bag-of-words model, and several bag-of-Ngrams models (bigrams, trigrams, and quadrigrams). Pre-processing included lowering the case of all text, removing all non a-z characters from the text, removing short words (length less than or equal to two), removing infrequent words (those occurring less than ten times), erasing URLs, and erasing pdf tags. This process was repeated for separate bag-of-word and bag-of-Ngram models with lemmatisation to support later LDA and t-SNE analyses.

The processed corpus was then used to train word embedding models of dimension 100 (using words and bigrams occurring at least three times in the corpus) and vectorised using the word2vec neural network algorithm (Mikolov *et al.*, 2013).

Alternative approaches to understanding the domain-specific similarity of words were also considered. Earlier natural language processing (NLP) methods, including N-gram models, present "atomic" representations (Mikolov *et al.*, 2013), which are essentially sophisticated means of counting words and co-occurrences (see Brown *et al.*, 1992; Ullmann, 1977). These might be useful for the simplest analyses but are of limited use in building advanced models suitable for our purposes. More recent alternatives have included models trained based on distributed word representations (Bengio *et al.*, 2003; Schwenk, 2006), however these might struggle to run efficiently

and successfully with higher vector dimensionality (Mikolov *et al.*, 2013), leading to potentially lower quality output. The word2vec model has been used to improve countless NLP applications (Acosta *et al.*, 2017; Chung *et al.*, 2016; Li et al 2019; Ma and Zhang, 2015; Sivakumar *et al.*, 2020). Newer alternatives to word2vec include both other context-independent embeddings like Glove (Pennington *et al.*, 2014) and context-dependent embeddings which capture the positions of words in sentences like ELMo (Peters *et al.*, 2018) and BERT (Devlin *et al.*, 2018). These could be considered in future work.

Once the corpus was used to train the word embedding model, we used a simple function to expand the initial dictionary set:

1. The vectorised position of all n initial dictionary terms, $i_1 \rightarrow i_n$, was recorded.

2. A loop calculated the vector midpoint between the n x n pairings of the dictionary terms, *e.g.*, for the first two terms,

$$pairing\ midpoint, i_1, i_2 = \frac{\overrightarrow{i_1} + \overrightarrow{i_2}}{2}$$

3. For each nxn pairing midpoint, the algorithm identified the most closely located word vector from the corpus and tested if this word vector was already some i_x in the domain dictionary. If the word vector was new, it was recorded as i_{n+1} and step 4 was taken. If the word vector was not new (*i.e.*, some i_x), no action was taken and the loop in step 2 resumed.

4. Steps 2 and 3 were repeated using i_{n+1} consecutively as a replacement for i_1 and then for i_2. This continued until no new word vector was discovered and the loop set in step 2 could resume.

The new domain-specific similar dictionary terms (of number x) were finally added to the original dictionary, expanding the total number of terms to n + x. With these expanded search terms, all steps, from literature identification to text processing to dictionary expansion, were repeated until no further terms were identified. See descriptive characteristics of process in table A2 (table 2 from main text reprinted here as table A2).

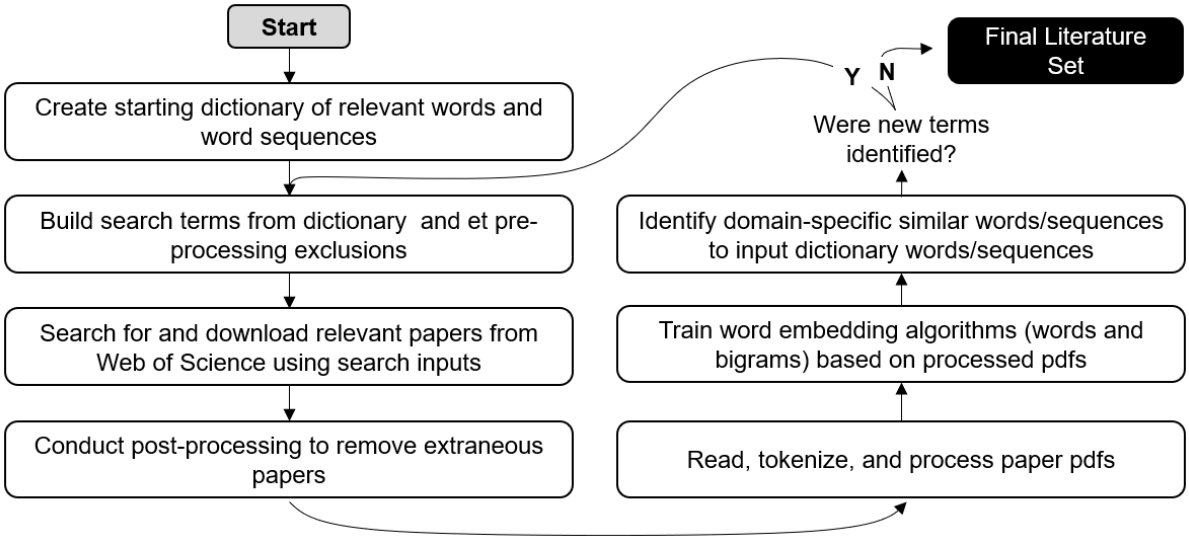


Figure A1. Approach to identifying relevant literature (reprinted from main text).

Table A2. Descriptive characteristics of literature identified by application of bespoke neural network model based on word2vec (reprinted from main text).

Iteration number	**Terms added to dictionary set *(words, bigrams)***	**Papers added to review set**				**New unique words in review set, post-processing *(lemmatised)***	**Total words in review set, pre-processing, millions**	**Total words in review set, post-processing, millions**
		(1)	(2)	(3)	Total			
Initial	154 *(13, 141)*	158	434	174	766	20,898 *(16,950)*	6.42 M	3.48 M
1st review iteration	70 *(4, 66)*	29	75	28	138	3,584 *(2,981)*	1.85 M	1.03 M
2nd review iteration	9 *(1, 8)*	3	5	2	10	157 *(137)*	0.09 M	0.05 M
3rd review iteration	1 *(0, 1)*	0	0	0	0	0 *(0)*	0	0
Total	**234**	**190**	**514**	**204**	**908**	**24,639 (*20,068*)**	**8.36 M**	**4.54 M**

A.3. Literature Analysis

As expounded in the main text, for quantitative literature analysis, we experimented with some of the most common natural language processing techniques including Latent Dirichlet Allocation (LDA), t-Distributed Stochastic Neighbour Embedding, and collocation analysis (for a helpful introduction, see figure 1 in Grimmer and Stewart, 2013). For collocation, since our dictionary set was defined by specific terms, we used a non-lemmatised corpus. For LDA and t-SNE, while we trialled both normal and lemmatised corpuses, we considered lemmatised text to be the most appropriate as clustering was preferred based on term meaning rather than specific word use. The outputs of these analyses are included in figures A2-A22. Images from these analyses are more easily and usefully explored natively in the MATLAB environment. MATLAB files are available for

download here: https://recovery.smithschool.ox.ac.uk/ARER-ocallaghan-yau-hepburn/

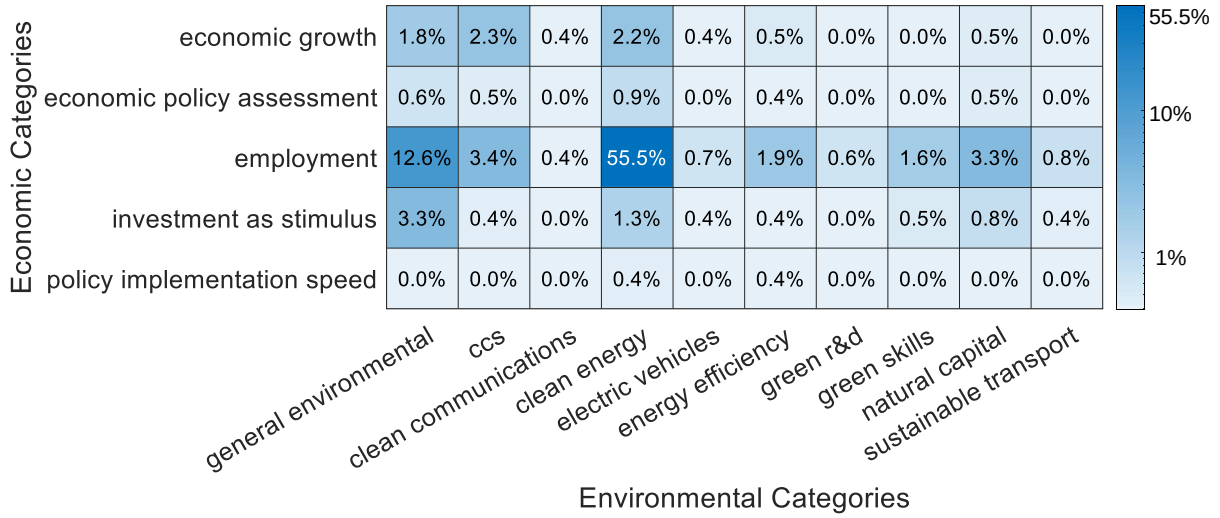


Figure A2. Collocation category output—overall (reprint of figure 4 in main text).

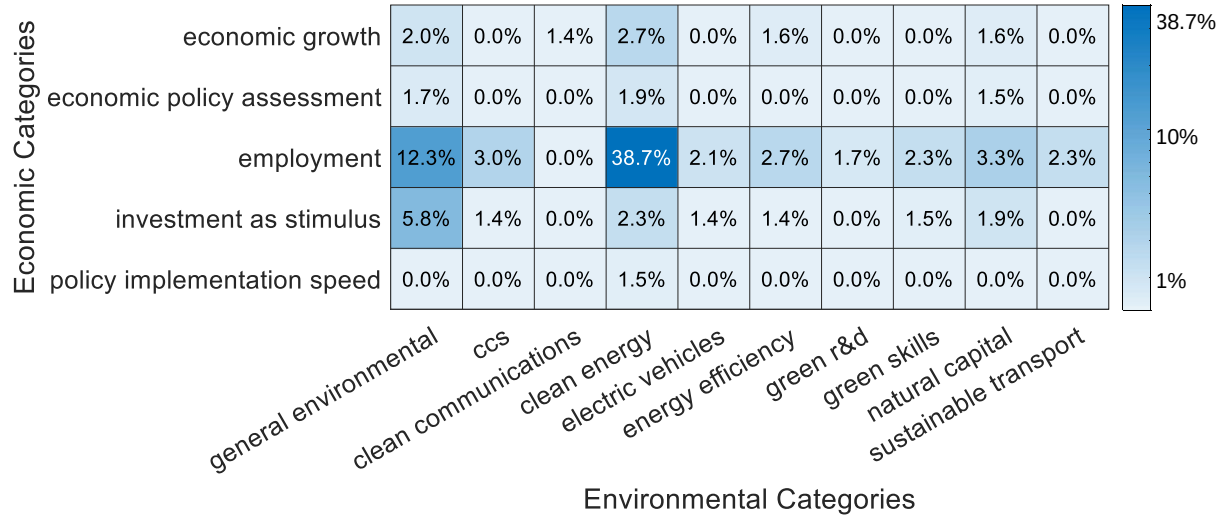


Figure A3. Collocation category output—premier journals.



Figure A4. LDA topic word cloud—overall—lemmatized.

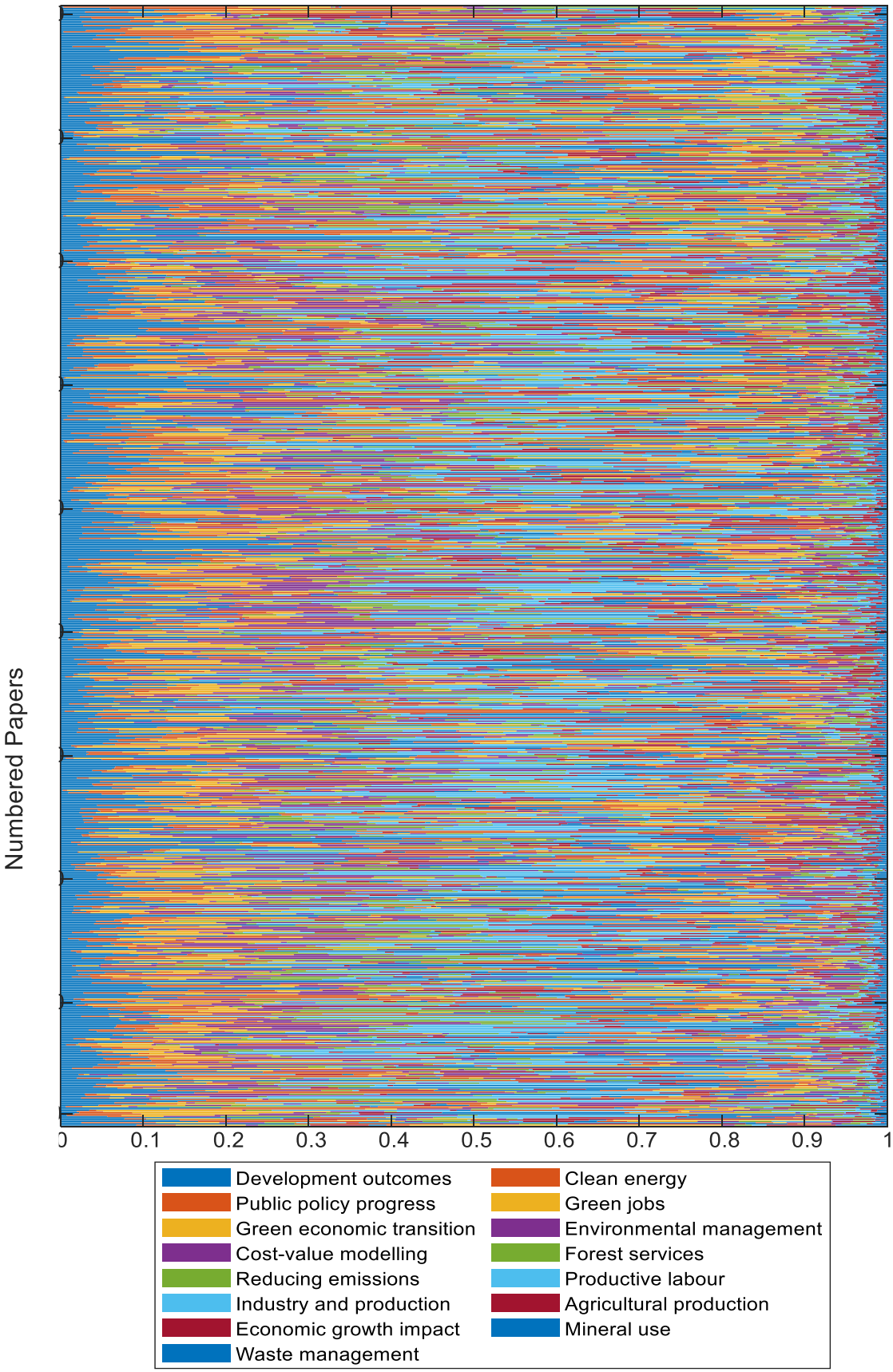


Figure A5. LDA topic mixture—overall—lemmatized.

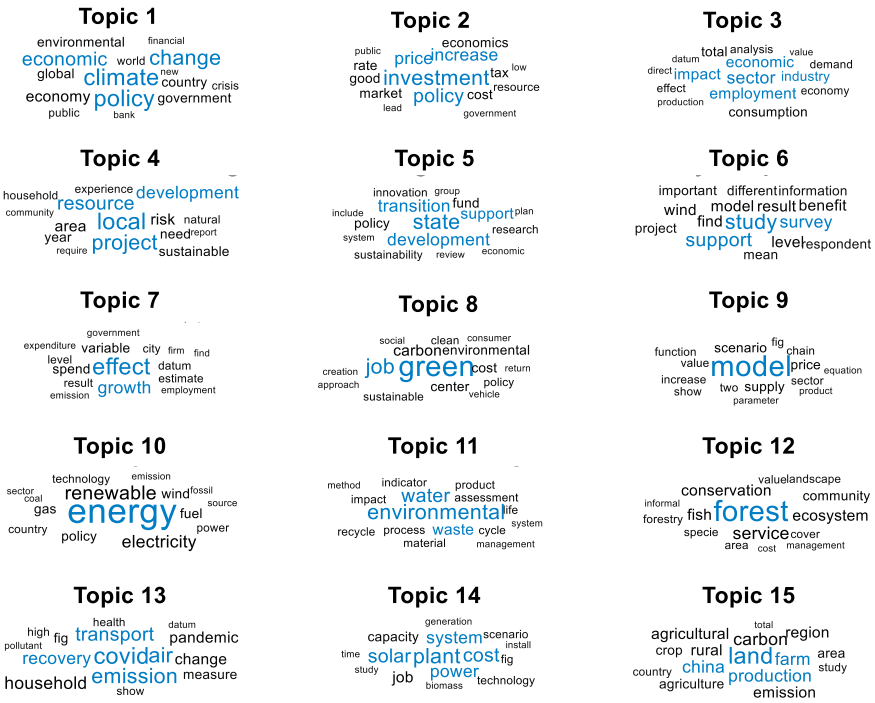


Figure A6. LDA topic word cloud—premier journals—lemmatized.

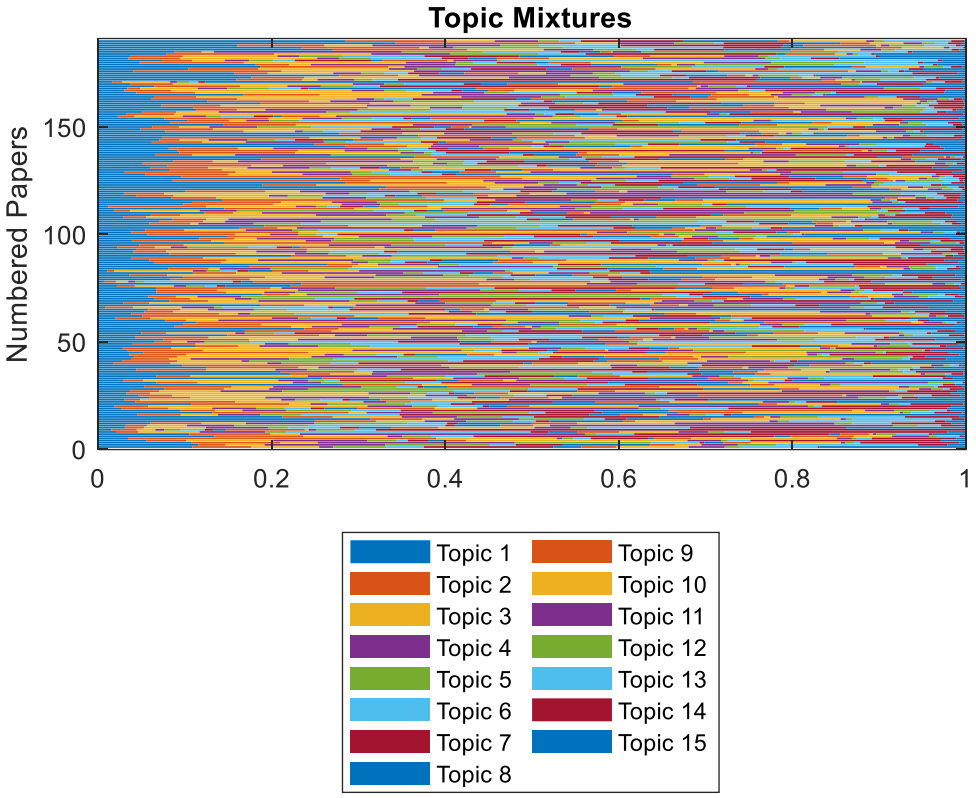


Figure A7. LDA topic mixture—premier journals—lemmatized.



Figure A8. LDA topic word cloud—secondary journals—lemmatized.

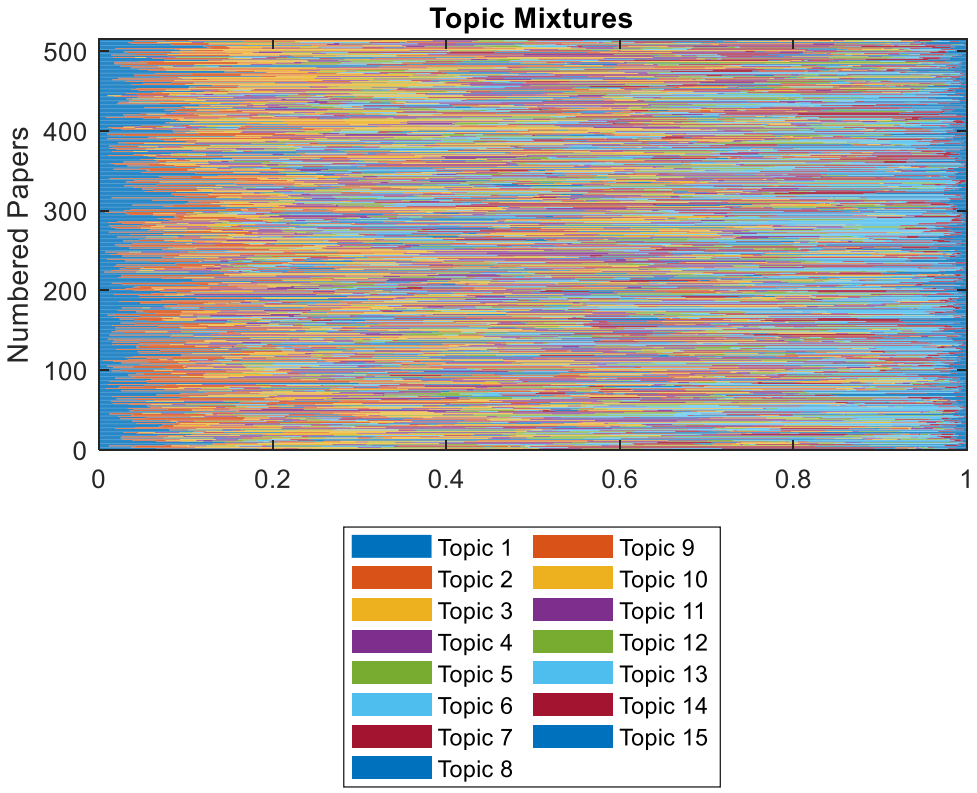


Figure A9. LDA topic mixture—secondary journals—lemmatized.



Figure A10. LDA topic word cloud—grey literature—lemmatized.

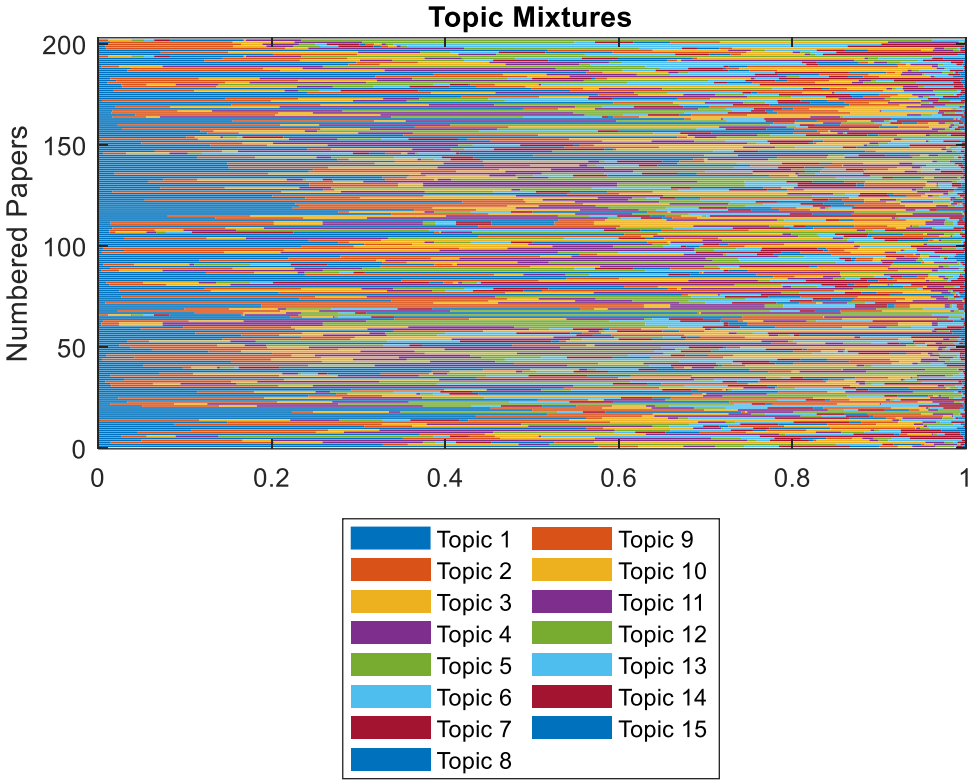


Figure A11. LDA topic mixture—grey literature—lemmatized.



Figure A12. LDA topic word cloud—overall—not lemmatized.

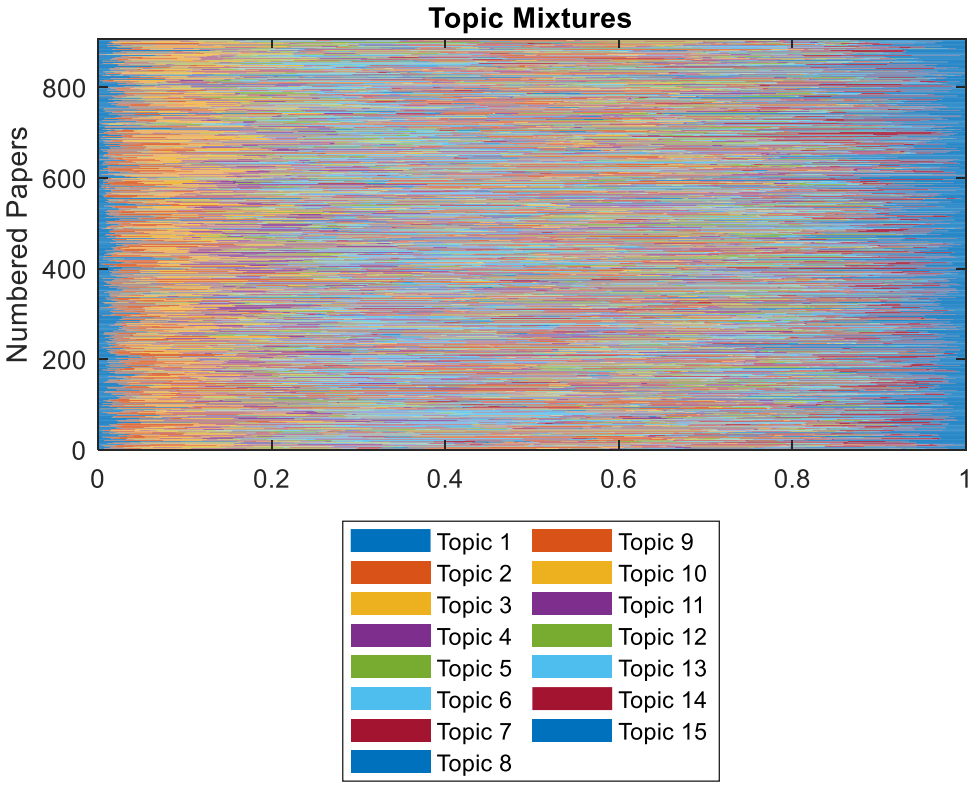


Figure A13. LDA topic mixture—overall—not lemmatized.



Figure A14. LDA topic word cloud—premier journals—not lemmatized.

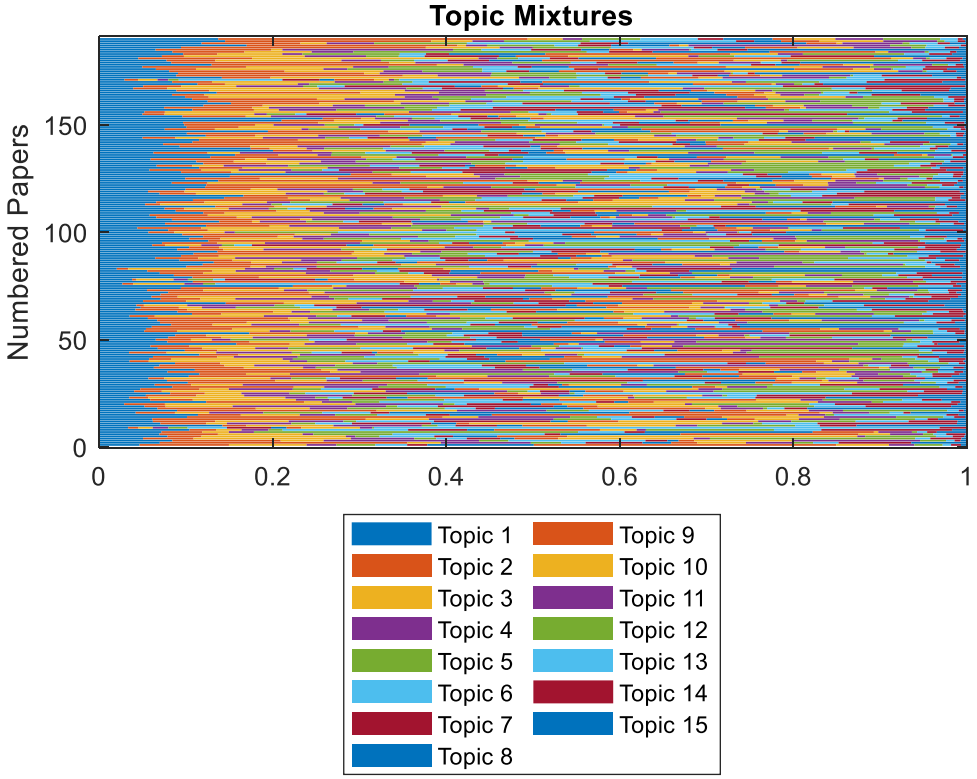


Figure A15. LDA topic mixture—premier journals—not lemmatized.



Figure A16. LDA topic word cloud—secondary journals—not lemmatized.

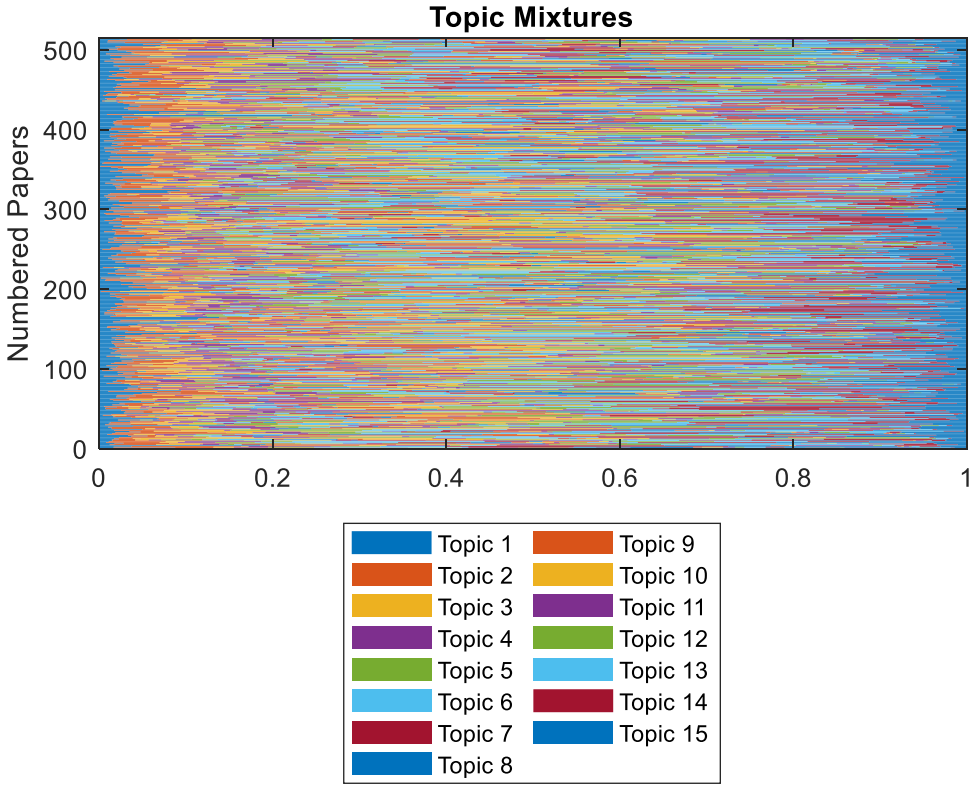


Figure A17. LDA topic mixture—secondary journals—not lemmatized.

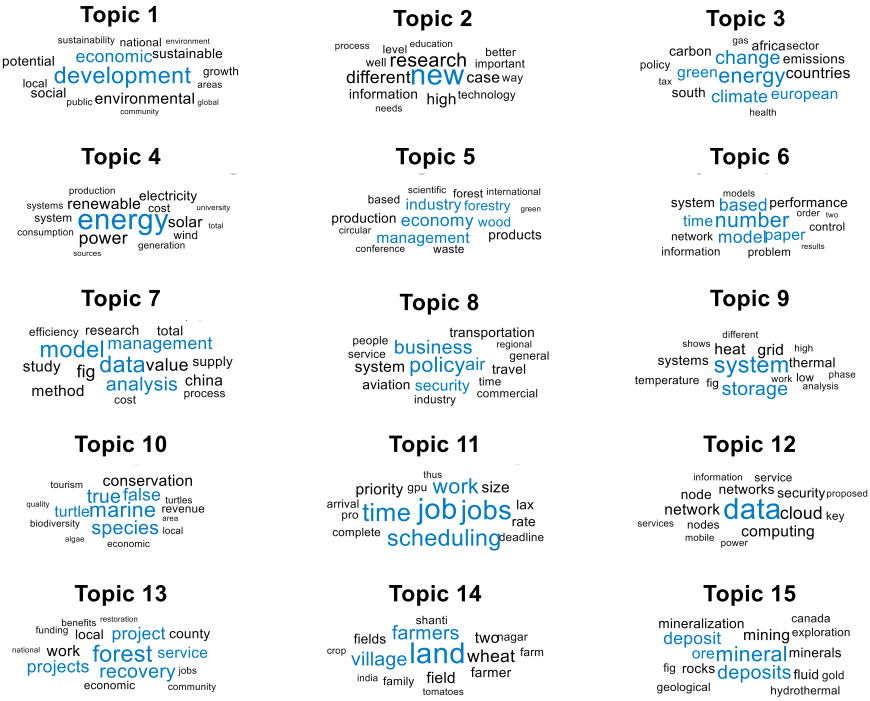


Figure A18. LDA topic word cloud—grey literature—not lemmatized.

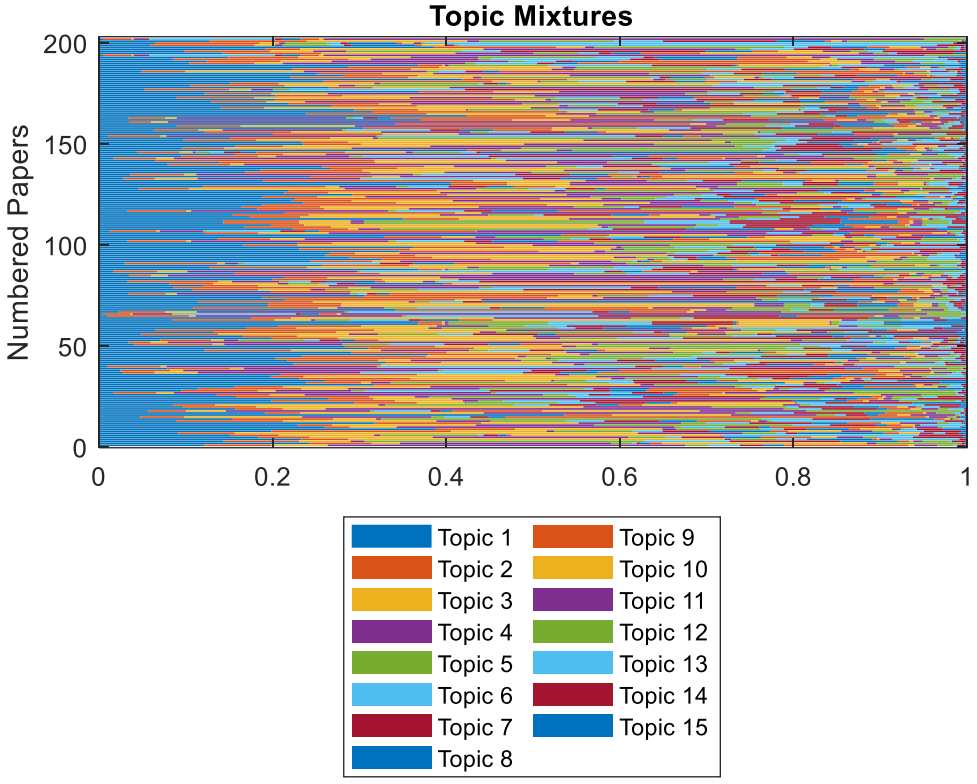


Figure A19. LDA topic mixture—grey literature—not lemmatized.

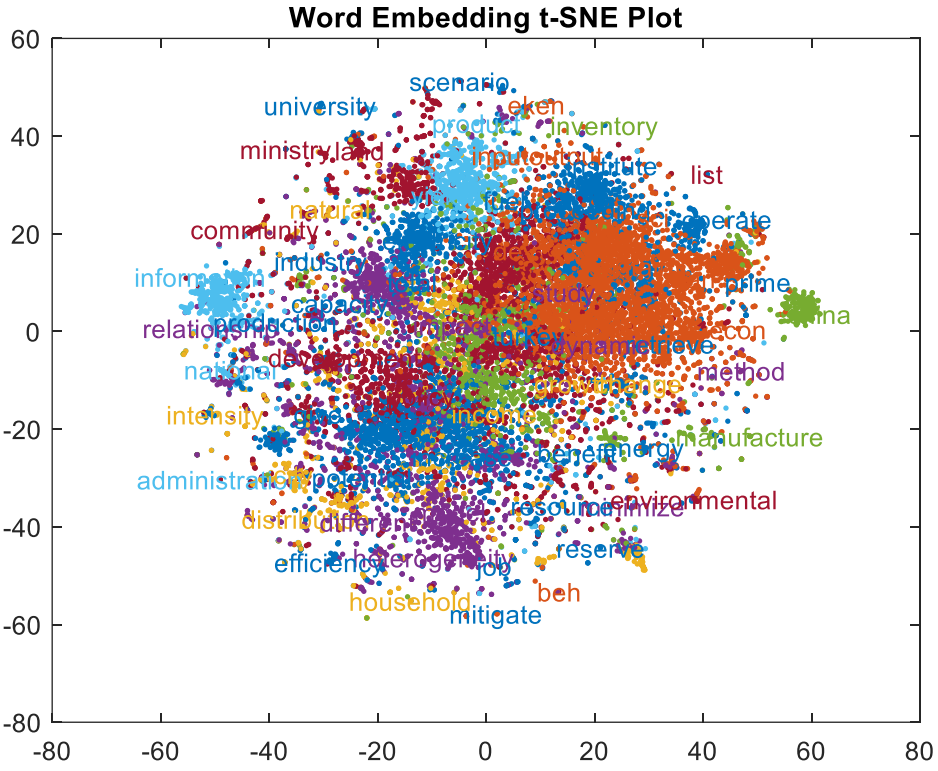


Figure A20. t-SNE output—premier journals—lemmatized.

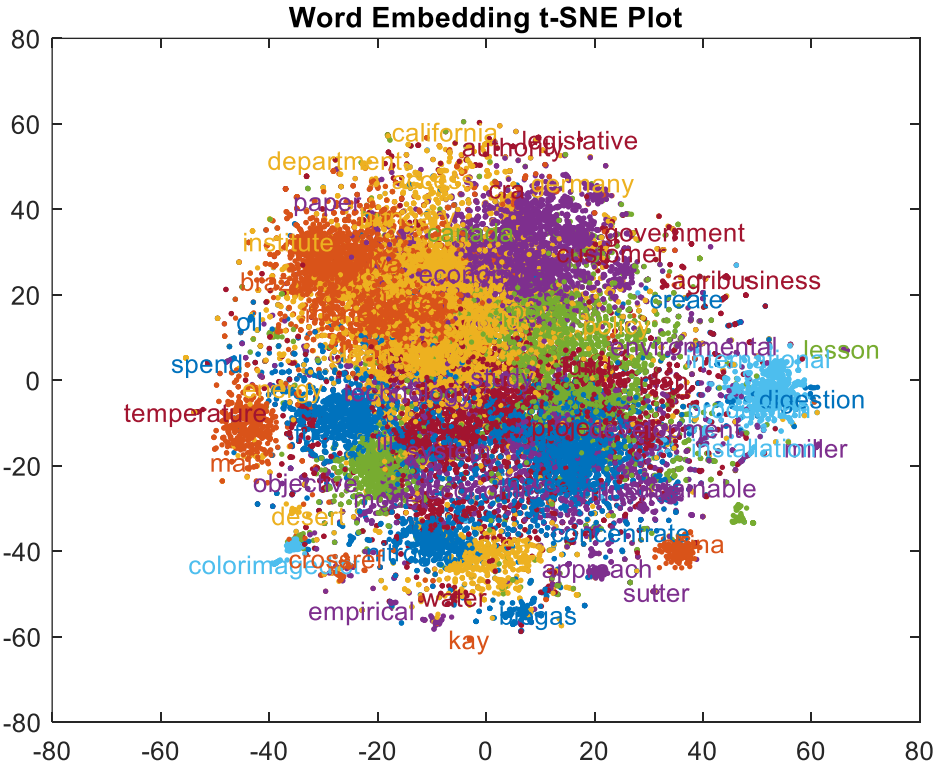


Figure A21. t-SNE output—secondary journals—lemmatized.

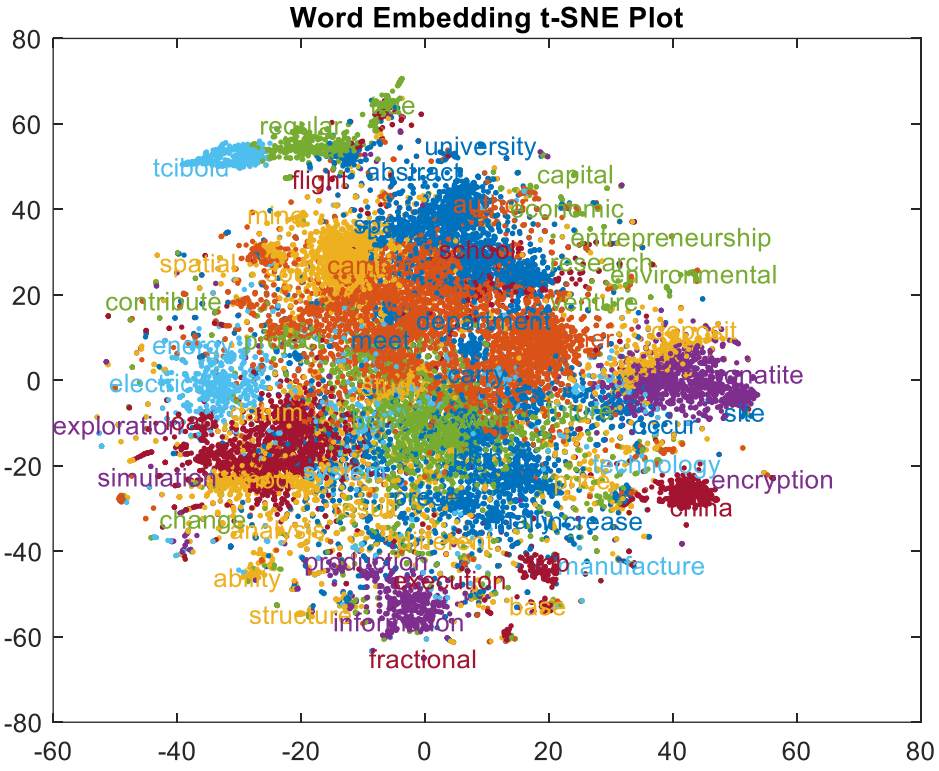


Figure A22. t-SNE output—grey literature—lemmatized.

B

Supplementary Materials for

Will COVID-19 fiscal recovery packages accelerate or retard progress on climate change?

Hepburn, C., O'Callaghan, B., Stern, N., Stiglitz, J., & Zenghelis, D.

B.1. List Of Experts

The following alphabetised list includes respondents who provided permission for their names to be reproduced in this publication. The list represents 63% (146/231) of total respondents.

Abiad, Abdul

Acconcia, Antonio

Alexander, Sir Danny

Armstrong, Angus

Bardt, Hubertus

Barrow, Lamin

Bartzokas, Anthony

Basile, Raffaella

Bauducco, Sofia

Berger, David

Best, Michael

Bianchi, Francesco

Bjørnskov, Christian

Bobiash, Donald

Boehm, Christoph

Boone, Laurence

Bordo, Michael

Boussaid, Mohamed

Brazys, Samuel

Ibrahim, Musa Jega

Ilzetzki, Ethan

Imai, Katsushi

Jaramillo, Serafin M.

Jayne, Thomas

Kabagambe, Anne

Kahanec, Martin

Kalinowski, Thomas

Kaplan, Ethan

Kavaš, Damjan

Kganyago, Lesetja

Kollmann, Robert

Kreivi, Eila

Kremer, Manfred

Kurlyandskaya, Galina

Landau, Bettina

Lee, Keun

Leiser, Stephanie

Levine, Paul

Özatay, Fatih

Ozkan, Gulcin

Pacini, Henrique

Parigi, Guseppe

Pasha, Farooq

Pastor, Manuel

Pereira, Luis Melim

Petersen, Luba

Piantini, Marco

Pippin, Sonja

Repett, Luca

Revoltella, Debora

Rickman, Dan

Romani, Mattia

Ruggiero, Gian Paolo

Saraceno, Francesco

Sawada, Yasuyuki

Semmler, Willi

Sishi, Edgar

Buti, Marco	Levy, Joaquim	Sorensen, Bent
Camacho, Edna	Li, Minqi	Sousa, Ricardo
Cespedes, Luis Felipe	Li, Rong	Stein, Betina
Chika, Urama Kevin	Liebreich, Michael	Subramaniam, Ramesh
Colombo, Emilio	Liepach, Werner	Tambakis, Demosthenes
Dave, Nanda	Lim, Jamus	Taylor, Mark
de Lemos, Samuel	Llewellyn, John	Temiz, Taskin
de Oliveira Segundo, Francisco O.	Lucas, Deborah	Terkper, Seth

B.2. Policy Archetypes Included in Global Expert Survey

25 policy archetypes were developed based on a rigorous cataloguing of over 700 G20 proposed and implemented fiscal stimulus policies covering both the GFC and the COVID-19 response. The policy archetypes were developed from the catalogue solving for the following criteria:

- Archetypes must be relevant to the current COVID-19 fiscal recovery policy landscape
- Archetypes must collectively reflect *a priori*tisation of fiscal recovery policies over fiscal relief policies (see section B3)
- Archetypes must be relevant to multiple geographies (*e.g.* early superannuation funds release is excluded as a uniquely Australian measure)
- Archetypes must be mutually exclusive
- Archetypes must drive towards being collectively exhaustive

- Merging of policies into a single archetype is permissible when the perceived multiplier-implementation-green potential is highly similar (*e.g.* investment in road infrastructure and investment in airport infrastructure)

Table B1. Full description of policy archetypes as included in survey.

A	**Temporary waiver of interest payments** Holidays on interest payments or other relief on mortgages or commercial loans.	H	**Income tax cuts** Reduction in marginal income tax rates, increase in tax-free thresholds or expanded deductions.
B	**Assisted bankruptcy (super Chapter 11)** Government consolidates troubled businesses and resolves all of them in a common procedure, which may involve swapping debt for shares across the board.	I	**Business tax deferrals** Deferral of payment of corporate taxes (strengthened carry-back provisions in ta loss offsets.
C	**Liquidity support for large corporations** Government support for banks to rapidly provide liquidity to large corporations on terms favourable to the government.	J	**Business tax relief for strategic and structural adj.** Tax credits for specific business investments in future-oriented capabilities, swaps to electric vehicle fleets, green R&D, energy efficiency measures, investments in artificial intelligence and robotics.
D	**Liquidity support for households, startups, SMEs** Government support for banks to rapidly provide liquidity to households as well as startups and small/medium sized businesses on terms favourable to the government.	K	**Direct provision of basic needs** Direct funds to the immediate local production and distribution of essential goods such as food, health and transport, irrespective of whether these are part of the formal or informal economies.
E	**Airline bailouts** Support for airlines suffering financial stress.	L	**Education investment** Injections to fund improved teacher training, in-classroom and digital materials and other education capital for pre-primary, primary & secondary, increased support for tertiary students in high-productivity sectors.
F	**Not for profits, education, research, health inst. bailouts** Support for non-profit institutions suffering financial stress.	M	**Healthcare investment** Funding to support targeted increases in public health capital, preventative measures, training health-care professionals and associated infrastructure (hospitals, IT systems for health care).
G	**Reduction in VAT, other goods and services taxes** Reduction in the rate of regressive value-added taxes (VAT) or goods and service taxes (GST) on consumption. *E.g.* taxation of alcohol.	N	**Worker retraining** Retraining members of current or soon-to-be displaced workforces with new skills and modern apprenticeships suitable for future industries (complementary to artificial intelligence, robotics, distributed

manufacturing, new energy, new food systems).

O Targeted direct cash transfers or temporary wage increases
Direct cash transfers targeted to lower income workers or in the form of a bonus to COVID-19 essential workers. Wage increases for those with government-controlled wages (public sector, minimum wage).

P Rural support policies
Support for rural communities such as debt forgiveness for small landholders; employment guarantee schemes (minimum period of employment in state-run entities at minimum wage).

Q Traditional transport infrastructure investment
Spending on traditional infrastructure – road upgrades, airports, ports infrastructure.

R Project-based local infrastructure grants
Funding for schools, hospitals, social housing and local councils to improve local asset bases.

S Connectivity infrastructure investment
Clean transport infrastructure and communications infrastructure investment; charging networks for electric vehicles, 5G networks.

T Clean energy infrastructure investment
Increased spending in clean electricity and heat generation and storage; upgraded transmission or hydrogen infrastructure.

U Buildings upgrades (energy efficiency)
Increase thermal efficiency through improved insulation, improved energy efficiency of appliances, clean heating (heat pumps or heat networks).

V Green spaces and natural infrastructure investment
Upgrading public parks, green spaces, national parks, tree planting and biodiversity protection, ecological conservation initiatives, ecological system services.

W Disaster preparedness, capacity building
Cash spending in preparation for future pandemics, fires, floods, cyclones, other extreme events.

X General R&D spending
Cash support for technology-agnostic research and development programmes.

Y Clean R&D spending
Cash support for R&D in green technologies, including electrolysis, heat pumps, energy storage, plant genetics, greenhouse gas removal.

B.3. Selection of Leading Experts

Targeting a representative expert perspective on fiscal policy measures, we sampled five categories of experts in fiscal stimulus policy, namely: leading elite academics in the field, G20 senior central bankers, global senior development bankers, G20 finance ministers and senior staff, and leading global policy think tank experts.

B3.1. Academics

Four potential approaches for elite expert selection appear in the literature. The first and most rigorous approach, as used prominently by Drupp *et al.* (2018), is identification by publication. In this case, elite academics are selected based on the strength and relevance of their research output using stringent filtering rules. See also Howard and Sylvan (2015) who used a working paper version of Drupp *et al.* (2015) as the basis for their methodology. A second, similarly useful but arguably more biased, approach is identification using peer nomination (Christensen *et al.*, 2018). Here, a broad group of peers nominate experts to a topic area and vote to distinguish those they deem most appropriate for sampling. However, this process is unlikely to be purely meritocratic or representative. Peers are likely to nominate colleagues with whom they have positive personal relationships and/or who have perspectives similar to their own. A third common approach is using conference attendance as an indicator of elite expertise, as in Necker (2014). While this may be an effective means of identifying academics with research interests in a particular field, it is likely to over-index on junior researchers and is not collectively exhaustive. It would also exclude any prominent leaders who were not in attendance at the conference. The final approach is expert selection through personal relationships, as used by Nordhaus (1994). This approach, while simple, time-efficient and in some cases useful for directional understanding, lacks rigour in ensuring complete representation and bias-control.

In this paper, leading academics were selected by virtue of their publications. Using the Scopus engine, we searched for articles containing key terms relating to fiscal policy, including “fiscal stimulus”, “fiscal

austerity" and "countercyclical policy". A complete list of all search terms is included in Table A1. The same method was applied using the Google Scholar search engine to supplement the Scopus results. However no additional articles were identified. As the article main text often provides passing comment to themes tangential to the main content, the search was constrained to article abstracts and titles only. Following the approach of Drupp *et al.* (2018) we limited articles to those published within top economics journals, specifically the 102 'A', 'AA', and 'AAA' journals identified by Combes and Linnemer (2010). This produced a preliminary valid article count of 162. Subsequently, we manually reviewed each article, using a weak relevancy test to filter out pieces that feature fiscal stimulus terms in their abstract but fail to either discuss these terms in a meaningful way or provide broader commentary that would suggest expertise in the area. In this step we eliminated 32 articles, leaving 130 remaining.

Permitting all named authors of these works and accounting for authors who featured in multiple pieces, we were left with a set of 246 academic experts. Using manual internet search processes, we identified email addresses for 217 academic experts. We failed to identify contact details for 29 who were either deceased or without published details online. 12 of the located email addresses were found to be invalid and generated 'bounce-backs' during the send process, yielding an adjusted contact pool of 205. In most cases these bounce-backs were presumably due to recent changes in employment.

The Scopus engine search code used was *ISSN(0033-5533, OR 0002-8282, OR 0022-3808, OR 0012-9682, OR 0034-6527, OR 0304-405X, OR*

0304-3932, OR 0034-6535, OR 0022-0531, OR 0022-1082, OR 0304-4076, OR 0013-0133, OR 0741-6261, OR 0047-2727, OR 0022-1996, OR 1542-4766, OR 0014-2921, OR 0734-306X, OR 0020-6598, OR 0899-8256, OR 0893-9454, OR 1537-2707, OR 0167-6296, OR 0304-3878, OR 0022-166X, OR 0022-2879, OR 0022-2186, OR 0165-4101, OR 0094-1190, OR 0095-0696, OR 1381-4338, OR 0165-1889, OR 0167-2681, OR 0305-750X, OR 1096-6099, OR 0883-7252, OR 0938-2259, OR 0266-4666, OR 8756-6222, OR 1057-9230, OR 0002-9092, OR 0022-1821, OR 0167-7187, OR 0022-0507, OR 0895-3309, OR 0165-1765, OR 0895-5646, OR 0347-0520, OR 0022-1090, OR 0921-8009, OR 0304-4068, OR 0021-9398, OR 1058-6407, OR 0022-0515, OR 0030-7653, OR 0162-1459, OR 2162-2434, OR 0048-5829, OR 0013-0427, OR 0003-0554, OR 0378-4266, OR 0008-4085, OR 0021-9886, OR 1365-1005, OR 0023-7639, OR 0960-6491, OR 0095-2583, OR 0308-5147, OR 0166-0462, OR 0927-5371, OR 0147-5967, OR 0167-6687, OR 0020-7276, OR 0261-5606, OR 0013-0079, OR 0305-9049, OR 0028-0283, OR 0014-4983, OR 0924-6460, OR 0176-1714, OR 0933-1433, OR 0272-7757, OR 0043-1397, OR 0195-6574, OR 2214-8043, OR 0895562X, OR 0034-6586, OR 0922-680X, OR 1042-9573, OR 0747-4938, OR 1573-045X, OR 1468-2702, OR 0927-5940, OR 0038-4038, OR 0378-5920, OR 0019-7939, OR 0007-2303, OR 0167-4870, OR 0013-0117, OR 0928-7655, OR 0022-4367, OR 0003-6846), ABS("fiscal stimulus" OR "fiscal austerity" OR "contracyclical polic"OR "contracyclical fiscal" OR "countercyclical poli*" OR "countercyclical fiscal" OR "contra-cyclical polic*" OR "contra-cyclical fiscal" OR "counter-cyclical poli*" OR "counter-cyclical fiscal" OR "expansionary polic*" OR "fiscal boost" OR "fiscal" AND "economic stimulus" OR "fiscal" AND "policy" AND "global*

financial crisis" OR "fiscal" AND "policy" AND "global financial crisis" OR "fiscal" AND "Asian Financial Crisis" OR "fiscal" AND "COVID" OR "fiscal" AND "Corona virus")

Table B2. Number of articles retrieved per search term.

Search term	Number of articles
contracyclical polic* OR contra-cyclical polic*	0
contracyclical fiscal OR contra-cyclical fiscal	0
countercyclical poli* OR counter-cyclical poli*	19
countercyclical fiscal OR counter-cyclical fiscal	23
expansionary polic*	25
fiscal AND Asian Financial Crisis	0
fiscal austerity	20
fiscal boost	0
fiscal AND Corona virus	0
fiscal AND COVID	0
fiscal AND economic stimulus	1
fiscal AND policy AND global financial crisis	15
fiscal stimulus	59

B3.1.1. G20 central bank officials

Senior central bank officials were identified through comprehensive desktop searches of public data for relevant Level 1 - Level 4 employees at all G20 national central banks as well as the European Central Bank. Translation services were used for banks with non-English websites. Employees were primarily identified using corporate organograms, visual hierarchies and organisational charts. 'Relevant' employees were those with job titles that suggested an essential role in setting or advising economic policy. Examples of these included *Head of Economic Analysis Department*, *Head of Research*, *Executive Director* and *Governor*. Support staff were excluded.

We observed a range of public openness and website transparency across the set of banks. We were able to locate a minimum of five names for each bank. Email addresses were identified manually through internet research. A total of 484 senior central bank officials were identified with 226 email addresses.

B3.2. G20 finance ministry staff

Senior policymakers in G20 finance and treasury ministries were identified in a similar manner to central bank officials. Manual comprehensive internet searches of public data were used to identify relevant Level 1 - Level 4 employees. Translating services were used for banks with non-English websites. As in central banks, employees were predominantly identified using corporate organograms, visual hierarchies and organisational charts. Again, 'relevant' employees were those with job titles that suggested an essential role in setting or advising economic policy. Examples of these included *Minister of Finance*, *Head of Economic Policy*, *Head of Department of Budget Policy* and *Senior Expert*. The range of public openness and transparency across ministries was even greater than that among central banks. A total of 390 senior finance ministry officials were identified with 147 email addresses.

B3.3. Global development bank officials

Senior development bank officials were selected for the target group based on listing as a Level 1 - Level 4 relevant employee at any prominent multinational development bank or the International Monetary Fund (IMF). Prominent multinational development banks were considered to be the ten major banks by scale of operation as in Faure *et al.* (2015), as well as the Asian Infrastructure Investment Bank (AIIB), which was established

in 2016 and is rapidly raising and distributing funds in a manner to rival the size of others on the 2015 list. Employee titles and email addresses were extracted from publicly available online resources using internet research. Translating services were used for banks with non-English websites. As with central banks and finance ministries, employees were predominantly identified using corporate organograms, visual hierarchies and organisational charts. 'Relevant' employees were those with job titles that suggested an essential role in setting or advising economic policy. Examples of these included *President*, *Director and Vice President of Equitable Growth*, *Director of Finance and Institutions*. Support staff were excluded. A total of 347 senior development bank officials were identified with 301 email addresses.

B3.4. Global think tank experts

A broad-based approach was used to engage leading global experts and commentators at top-tier economic Think Tanks. We combined two preeminent ranking systems with different methodologies to identify a set of 120 'top-tier' economic think tanks. The University of Pennsylvania's *2019 Global Go To Think Tank Index Report (GGTTT)* (McGann 2020) ranked 2019's top 144 domestic economic think tanks in the world (from a much larger list) based on 528 survey responses elicited from a hand-picked panel of experts who reviewed each think tank against 28 criteria. IDEA's *Top 25% Think Tank Ranking for March 2020* (Zimmermann 2020) employed a contrasting strategy to provide a ranking of 55 leading think tanks based on the quantified academic impact of the works put forth by think tank contributors. The top 100 GGTTT think tanks were combined

with the top 50 IDEA think tanks to form a total set of 120 top tier think tanks. The existing contact database of the GGTTT was used to identify email addresses for the most senior 2 levels of economics experts at each think tank.

B3.5. Limitations in expert selection methodology

This selection process will inevitably have not identified all relevant experts. Practical feasibility limited the engagement we had with some potential experts, particularly those from non-English G20 nations (*e.g.*, Russia) and some G20 LMICs (*e.g.* Mexico, South Africa). Inferior information for these locations, largely driven by incomplete or unavailable website listings, meant that we were unable to collate a significant number of expert names and email addresses for some nations. Multilingual research assistants were engaged to source and interpret native language web pages when available.

A potential source of process inefficiency is the likelihood that some emails to target group experts were quarantined by corporate spam filters and either kept from recipients or redirected to junk folders. Whilst we were unable to determine the percentage of emails that were incorrectly quarantined, spam testing using *mail-tester.com* and *GlockApps* indicated low spam risk. As such we have no reason to believe that a significant number of emails were kept from recipients.

B3.6. Expert Groupings

To differentiate between survey responses, we created 10 identical surveys, one for each sub-group A1, A2, C1, C2, D1, D2, F1, F2, T1 and T2. The target expert group and supplementary expert group each consisted of 5

sub-groups as in the table below. As described in Appendix B3, two survey links were sent to each target expert: a personalised link for self-reporting and a secondary link for sharing with colleagues. In order to ensure no accidental contamination of the target group, these links were designed so that they could only be opened from the mailbox associated with the email address of the specific target group recipient. We developed additional country-specific comparison groups (LIC, MIC, HIC, LMIC, G20, NG20) based on respondent answers to the question, *What national economy do you spend most of your time working on?*.

Table B3. Full list of expert groupings and associated ID codes.

Group ID code	Group Description	Form
A1	Expert academics - systematically identified	self-contained
A2	Expert academics - referrals	self-contained
A3	Expert academics - combined set	A1 + A2
C1	Central bank officials - systematically identified	self-contained
C2	Central bank officials - referrals	self-contained
C3	Central bank officials - combined set	C1 + C2
D1	Development bank officials - systematically identified	self-contained
D2	Development bank officials - referrals	self-contained
D3	Development bank officials - combined set	D1 + D2
F1	Finance ministry officials - systematically identified	self-contained
F2	Finance ministry officials - referrals	self-contained
F3	Finance ministry officials - combined set	F1 + F2
T1	Think tank experts - systematically identified	self-contained
T2	Think tank experts - referrals	self-contained
T3	Think tank experts - combined set	T1 + T2
Z1	Target group - all systematically identified experts	A1 + C1 + D1 + F1 + T1
Z2	Supplementary group - all referred experts	A2 + C2 + D1 + F2 + T2

Z3	Total group - all experts	Z1 + Z2
Z1-exA	Target group ex. expert academics	Z1 - A1
Z1-exC	Target group ex. central bank officials	Z1 - C1
Z1-exD	Target group ex. development bank officials	Z1 - D1
Z1-exF	Target group ex. finance ministry officials	Z1 - F1
Z1-exT	Target group ex. think tank experts	Z1 - T1
HIC	Experts focused on high-income countries	self-contained
MIC	Experts focused on middle-income countries	self-contained
LIC	Experts focused on low-income countries	self-contained
LMIC	Experts focused on low- and middle-income countries	MIC + LIC
G20	Experts focused on G20 countries	self-contained
NG20	Experts focused on non-G20 countries	self-contained

B3.7. Survey Design

B3.7.1. Text of first email

Send date: 15 April 2020

Subject: Urgent COVID-19 request for assistance

Text: Dear <name>,

You have been identified as an expert in fiscal policy based on your status as an expert in economics/finance. Our objective is to elicit your assessment and recommendations on fiscal recovery policies in response to COVID-19 to help guide significant government spending, by G20 and other national governments. The output of the survey is intended to be published in a commissioned paper by the *Oxford Review of Economic Policy*.

We would be most grateful if you could find the time to immediately complete the short survey included here: <individual survey link> Note

that this is best completed on a desktop computer or laptop (not mobile phone).

In the interest of collecting a sample from a broader range of experts, we welcome responses from any of your contacts (or their contacts) who you regard as leaders in fiscal economics or policy. **Please do share the following link with any such individuals: <general survey link for group>** (your own link above is unique and will expire if not accessed from your email account).

Your individual response will be held in the strictest confidence. If you wish to be acknowledged and thanked for contributing your expertise to this effort, you will be given the option of including your name at the end of the survey.

Many thanks for your time and cooperation,

Professor Cameron Hepburn, Director of the Smith School — University of Oxford

Professor Joseph Stiglitz, Nobel Laureate — Columbia University

Professor Lord Nicholas Stern, Former President of the Royal Economic Society — London School of Economics

Dimitri Zenghelis — University of Cambridge

B3.7.2. Text of first follow-up email

Send date: 16th of April 2020

Subject: Urgent COVID-19 request for assistance

Text: Dear <name>,

This email is sent on behalf of Prof. Joseph Stiglitz, Prof. Lord Nicholas Stern, Dimitri Zenghelis and Prof. Cameron Hepburn.

We notice that you have not yet responded to the *urgent survey request* we sent to you on Tuesday. **The survey will be closing tomorrow**. You have been *individually identified* as a part of a **very small group of experts in fiscal policy**. Your response to the survey is vital and will aid in effectively and efficiently guiding trillions of dollars in eminent G20 government spending in response to COVID-19.

We would be most grateful if you could find the time to immediately complete the very short survey included here: **<individual survey link>**

In the interest of collecting a sample from a broader range of experts, we welcome responses from any of your contacts (or their contacts) who you regard as leaders in fiscal economics or policy. Please do share the following link with any such individuals: **<general survey link for group>** (your own link is unique and will expire if not accessed from your email account).

Your individual response will be held in the strictest confidence.

Many thanks for your time and cooperation,

Cameron Hepburn, Director of the Smith School — University of Oxford

Professor Joseph Stiglitz, Nobel Laureate — Columbia University

Professor Lord Nicholas Stern, Former President of the Royal Economic Society — London School of Economics

Dimitri Zenghelis — University of Cambridge

B3.7.3. Text of second follow-up email

Send date: 17th of April 2020

Subject: Final reminder: Urgent COVID-19 request for assistance

Text: Dear <name>,

This is a final request to action the survey sent to you on Tuesday. **The survey will close tonight (11.59pm GMT).** You were *individually identified as a part of a small group* and as such, your response to this survey is important. The results of this survey will be helpful in guiding government spending in response to COVID-19.

We would be most grateful if you could find the time to complete the very short survey included here: **<individual survey link>**

In the interest of collecting a sample from a broader range of experts, we welcome responses from any of your contacts (or their contacts) who you regard as leaders in fiscal economics or policy. Please do share the following link with any such individuals: **<general survey link for group>** (your own link is unique and will expire if not accessed from your email account).

Your individual response will be held in the strictest confidence.

Many thanks for your time and cooperation,

Professor Cameron Hepburn, Director of the Smith School — University of Oxford

Professor Joseph Stiglitz, Nobel Laureate — Columbia University

Professor Lord Nicholas Stern, Former President of the Royal Economic Society — London School of Economics

B3.7.4. Survey text

Respondents were asked to rate each policy type according to four metrics: speed of impact, long-run economic multiplier, climate impact potential and overall desirability. To provide opportunity for introduction of additional policy archetypes excluded from the core set of 25, a free response question was also included. Additionally, respondents were asked to provide demographic data in the form of 6 drop-down responses. Collected demographic information included addressing country of research/work focus, country of domicile, educational background, length of time working in the broad fields of economics and/or policy, highest level of educational attainment and gender. A final question allowed participants to provide their name for inclusion as a listed expert in the published paper.

The full survey text was as follows:

Page 1: Welcome

This policy survey aims to assess possible fiscal recovery responses to the COVID-19 crisis. Expected completion time is 15 minutes or less.

Imagine that you are asked by your national government to rate a number of potential fiscal policies against four criteria:

1. Speed of implementation: time for policy to achieve half of its total impact.

2. Economic multiplier: multiplier effect of the policy, from low to high.

3. Potential climate impact: implications of this policy for Paris 2015 net-zero targets.

4. Overall desirability: on balance, should this policy be implemented by your government?

For additional information about any policy, hover over the underlined title. For example, hover your mouse over the following (functionality may be limited on some mobile devices): Direct Cash Payments to Consumers. [Cash transfers to consumers in the forms of direct bank transfers or mailed cheques. *E.g.* direct transfer of US$1,200 to US citizens through the CARES Act in 2020.]

Your response will help assess the possible long-term impact of COVID-19 on the economy and the climate.

Responses will be kept in the strictest confidence.

CUREC Ethics Approval: SOGE 1A2020-44

Demographic Data

a. What national economy do you spend most of your time working on? [Drop-down menu; all UN member states plus, Kosovo, the Palestinian Territories, Malta and Taiwan]

b. What is the category of your current place of work? [Radio bubble options; University, Central Bank, Ministry of Finance, Development Bank, Think Tank, Other - Please specify (with free entry box)]

Privacy

I consent to having my information collected and shared. View Privacy Policy. [Check box question]

Page 2: Speed of implementation

Please estimate how quickly you would expect each policy to achieve **half** of its total impact in your country of focus from its date of legislation.

Question mechanics

- Type: 25 slider response questions, one for each policy archetype (see *Appendix B2)*
- Left-hand scale label: slow (3+ years)
- Middle scale label: none
- Right-hand scale label: fast (less than one month)
- Scale: 100-point slider
- Default starting value: 50

Page 3: Economic multiplier

Please estimate the relative size of the long-run economic multiplier of each policy. A low multiplier (*e.g.* 0) implies a net loss. A high multiplier implies an increase in output that is a number of times greater than expenditure.

Question mechanics

- Type: 25 slider response questions, one for each policy archetype (see *Appendix B2)*
- Left-hand scale label: very low (stimulus completely crowds-out private activity)
- Middle scale label: none
- Right-hand scale label: very high (stimulus crowds-in significant additional private activity)
- Scale: 100-point slider
- Default starting value: 50

Page 4: Climate impact potential

Please subjectively estimate the relative potential impact of each policy on reducing greenhouse gas emissions if enacted in your country of focus.

Question mechanics

- Type: 25 slider response questions, one for each policy archetype (see *Appendix B2)*
- Left-hand scale label: Extremely negative impact
- Middle scale label: none
- Right-hand scale label: Extremely positive impact
- Scale: 100-point slider, -50 to 50
- Default starting value: 0

Page 5: Overall desirability

What is your overall opinion on the implementation of each policy as a recovery package item in your country over the coming 12-month period?

Question mechanics

- Type: 25 slider response questions, one for each policy archetype (see *Appendix B2)*
- Left-hand scale label: Strongly opposed
- Middle scale label: Agnostic
- Right-hand scale label: Strongly support
- Scale: 100-point slider, -50 to 50
- Default starting value: 0

Page 6: Additional input

a. What other fiscal policy approaches should governments be considering? How would you rate these for speed of implementation, economic multiplier and potential to impact the climate? [Free response]

b. Where do you live? [Drop-down menu; all UN member states plus Kosovo, the Palestinian Territories, Malta and Taiwan]

c. In total, how many years have you worked in the broad fields of economics and/or policy? [Drop-down menu; integer numbers between 1 and 50, as well as 0-1]

d. What is your highest level of educational attainment? [Drop-down menu; High school, Bachelor degree, Masters by Coursework, Masters by Research, PhD]

e. To which gender identity do you most identify? [Radio bubble options; Female, Male, Not listed (with free entry box), Prefer not to answer]

f. Please enter your name if you would like to be included in the list of experts that are acknowledged in the published paper; your individual answers will remain anonymous. [Free response]

Page 7: Thank you!

Thank you for taking our survey. Your response is very important to us.

Privacy Policy

Fiscal Recovery Options: Global Survey Privacy Policy

Summary

This privacy notice specifically refers to our use of data collected through the *2020 Fiscal Recovery Options: Global Survey*. There are 2 types of information collected by the survey.

1. Anonymised survey data: This consists almost entirely of answers to slider and multiple-choice questions, none of which contain personally identifiable data. One question provides free-text options for written answers. We ask participants not to use these fields to provide any personal information

2. Optional name: Individuals can optionally provide their name if they wish to be acknowledged in the published paper. These names will be reprinted publicly.

Purpose of processing

The anonymised survey data will be used to gain insight into the preferences and opinions of participants. These insights will be used to inform ongoing research into optimal COVID-19 fiscal recovery pathways.

If you choose to provide us with your name, we will acknowledge you as a contributing expert in the published paper. Your name will not be shared for other purposes.

Lawful basis for processing

By opting in to provide your name, you are providing consent to our processing of your personal data for the purpose specified.

Who we share data with

The data is stored by our survey service supplier, SurveyGizmo. This information is stored in the EU.

Retention period and criteria

Anonymised survey data will be kept for the purposes of analysing the data for an indeterminate amount of time (until we no longer need it).

Rights

The GDPR provides certain rights that individuals may exercise in respect of their own personal data. If you would like to exercise any of the rights in the GDPR, in respect of personal data you have submitted, please contact the Data Protection Officer using the contact details below. Please note that there may be some circumstances in which your request cannot be complied with—for instance if we have a legal obligation to keep data, or to process it in a particular way. All requests to exercise GDPR rights will be handled on a case by case basis.

Identity and contact details of controller and representative

The Oxford COVID-19 Stimulus Research Team (led by Professor Cameron Hepburn) is the controller of your personal data. This means that it is the Research Team which decides how and why your personal data is processed. Cameron can be contacted at cameron.hepburn@smithschool.ox.ac.uk.

Contact details of the Oxford University Information Compliance Team

The University of Oxford staffs its own Compliance Team separate from the Research Team. They can be contacted at information.compliance@admin.ox.ac.uk.

Right to lodge a complaint

If you are dissatisfied with the way we are managing your personal data, please let us know in the first instance by writing to Cameron Hepburn (cameron.hepburn@smithschool.ox.ac.uk). If you remain dissatisfied, you are entitled to raise your concerns with the University of Oxford Compliance Team (information.compliance@admin.ox.ac.uk).

B.4. Descriptive Statistics of Survey Respondents

Table B4. Summary of survey response distribution.

Respondents who fully completed survey (all compulsory questions)[66]	231
Slider question responses	23,100
Qualitative 'free answer' question responses	71
Drop-down menu responses	1,386
Names recorded	146
Respondents who partially completed survey (excluded from analysis)	45
Total Number of Respondents (complete and partial)	276

[66] All slider questions were compulsory. All drop-down responses were compulsory. The free-form response question *What other fiscal policy approaches should governments be considering?*, and personal identification question *Please enter your name if you would like to be included in the list of experts*, were both optional.



Figure B1. Geographic coverage of respondents by *country of focus*. Dark green indicates at least one respondent. Full responses only.

B.5. Survey Results

Survey results were exported from the host platform, *SurveyGizmo*, and aggregated for statistical analysis on a continuous relativity-adjusted zero-mean, zero-sum basis to account for response relativity biases.

Respondents rated each policy item in a relative and subjective manner using 100-point sliding scales. The point value of each response was not visible to respondents, rather it was used to compute, for each respondent, the relative performance of policy archetypes. Respondents were not homogenous in their use of the sliding scales; some employed the full 100-point range whilst others constrained their responses to within a tight range (*e.g.* ffi 20 from the centre value). Each respondent's scores were re-based or 'relativity-adjusted' for each of the four sliding response questions so that in all cases the 25 archetypes were collectively zero-mean, zero-sum.

We achieved an overall survey response rate of 19.7% for the target group. This reflected 19.9% for central bank officials, 13.6% for development bank officials, 15.6% for finance officials, 32.7% for academics and 16.4% for think tanks. By comparison, with our response rate of 32.7%, previous surveys of expert academic economists have achieved equivalent response rates of 33% (Howard and Sylvan, 2015), 30% (Drupp *et al.*, 2018), 17% (Necker, 2014), and 7% (Enders and Hoover, 2006). Given the accelerated timeline of our survey—4 days rather than a typical response windows of 3-4 weeks, a 32.7% academic response rate is high. Surveys of finance officials and central bank executives are rare in the academic literature. No comparable study was identified outside of a select group of opaque corporate surveys (Barontini and Holden, 2019). This subset did not provide data on response rates. Given the high academic response rate, we have no reason to presume that response rates for other target groups were unacceptably low.

Table B5 shows that, of the 25 policy archetypes, on a relativity-adjusted basis, five feature in the top quartile of target group scores for more than one core criteria; D, K and O for speed and economic multiplier, S and X for economic multiplier and climate, but no policies for both speed and climate. Four policies feature in the bottom quartile across two or more metrics; B, E, I and Q.

Categorical comparisons took the mean responses of each expert group (A1, C1, D1, F1, T1, HIC and LMIC in Appendix B4) and compared these to the mean responses of the target group (see tables B5 to B9). To ensure mutual exclusivity between comparison groups, expert group

participants were removed from the target group to create 'adjusted target groups' as in Appendix B4 (Z1-exA, Z1-exC, Z1-exD, Z1-exF, Z1-exT). Adjusted target groups were not needed for HIC/LMIC comparisons as these groups are already mutually exclusive. The mean variation between groups was calculated by averaging the absolute value of the mean expert group scores minus the mean adjusted target group score for each of the 25 policy archetypes, as in Equation 1.

$$\frac{\sum_{n=1}^{25} |\overline{expert\ group\ score} - \overline{adjusted\ target\ group\ score}|}{25} \quad (1)$$

Table B5. Performance of target group relativity-adjusted policy archetypes. Expressed in the form: relativity adjusted score (ranking).

ID	Policy archetype titles	Speed	Multiplier	Green	Overall
A	Temporary waiver of interest payments	21.5 (4)	-4.1 (18)	-7.3 (18)	4.6 (8)
B	Assisted bankruptcy (super Chapter 11)	-3.3 (14)	-10.1 (24)	-7.9 (19)	-3.8 (16)
C	Liquidity support for large corporations	18.1 (5)	-4.7 (20)	-10.4 (23)	-7 (20)
D	Liquidity support for households, SME's	26.7 (3)	10.9 (1)	-5 (17)	17.7 (1)
E	Airline bailouts	2.2 (10)	-14.5 (25)	-22.4 (25)	-17.1 (25)
F	NFP, education, research, health bailouts	1.7 (11)	-4.9 (21)	0.3 (10)	5.6 (7)
G	Reduction in VAT and other goods & services taxes	12.3 (7)	-0.4 (13)	-9.2 (21)	-9.9 (22)
H	Income tax cuts	3.8 (8)	-1.5 (15)	-7.9 (20)	-10.3 (23)
I	Business tax deferrals	13.1 (6)	-6.2 (22)	-9.5 (22)	-7 (19)
J	Business tax relief for strategic and structural adj.	0.8 (12)	-3.3 (16)	-3.5 (13)	-3.3 (15)
K	Direct provision of basic needs	28 (1)	6.7 (4)	-4.1 (14)	10.7 (3)
v	Education capital investment	-14.9 (21)	5.4 (7)	4.2 (8)	3.9 (10)
M	Healthcare capital investment	2.2 (9)	7.7 (3)	0.2 (11)	12.1 (2)
N	Worker retraining	-11.4 (17)	2.1 (11)	0.3 (9)	2.6 (12)
O	Targeted direct cash transfers or temp. wage rises	26.8 (2)	6.5 (5)	-4.8 (16)	8.1 (4)

P	Rural support policies	0.6 (13)	-8 (23)	-4.1 (15)	-7.3 (21)
Q	Traditional transport infrastructure	-16.4 (22)	3.2 (10)	-11.1 (24)	-12.2 (24)
R	Project-based local infrastructure grants	-11.9 (18)	4.4 (8)	-3.3 (12)	-5.7 (18)
S	Clean connectivity infrastructure	-10.9 (16)	8.1 (2)	9 (5)	2.8 (11)
T	Clean energy infrastructure investment	-18 (24)	3.7 (9)	24.5 (1)	3.9 (9)
U	Buildings upgrades	-13.5 (19)	-3.7 (17)	14.1 (4)	-4.2 (17)
V	Green spaces and natural infrastructure	-17.6 (23)	-4.4 (19)	21.4 (3)	0.3 (14)
W	Disaster preparedness	-6.5 (15)	-0.9 (14)	6 (7)	7.1 (5)
X	General R&D spending	-14.8 (20)	6.5 (6)	7.1 (6)	2.4 (13)
Y	Clean R&D spending	-18.5 (25)	1.6 (12)	23.3 (2)	6.1 (6)

Table B6. Mean **speed of implementation** responses by expert group. Figures are expert group average minus adjusted target group average. For HICs/LMICs figures are a subtraction of LMIC group averages from HIC group averages. For all columns, a positive (negative) number indicates that the expert group believes the policy to be faster (slower) than what others believe.

	Policy archetypes	Academics	Finance officials	Central bank officials	Development bank officials	Think tank experts	HICs - LMICs
A	Temporary waiver of interest payments	-1.6	-6.0	11.0	-0.6	-8.4	3.6
B	Assisted bankruptcy (super Chapter 11)	8.6	-15.5	1.5	-7.2	5.7	5.8
C	Liquidity support for large corporations	-8.2	1.5	13.6	-4.2	1.1	4.9
D	Liquidity support for households and SME's	3.1	5.4	-0.6	-6.9	-0.3	6.2
E	Airline bailouts	-0.7	7.8	-0.9	-12.8	17.0	11.8
F	NFP, education, research, health inst. Bailouts	4.9	-0.3	4.7	-9.7	-3.2	9.4
G	Reduction in VAT and other goods & services taxes	0.6	-11.1	-1.3	5.3	3.7	-8.4
H	Income tax cuts	-2.2	-3.6	-2.2	3.8	6.6	-3.2
I	Business tax deferrals	-3.7	1.4	6.6	-2.6	0.2	0.2
J	Business tax relief for strategic and structural adj.	-1.9	-1.1	0.3	3.0	0.2	-5.6
K	Direct provision of basic needs	6.4	-4.4	-0.9	-1.5	-6.4	2.6
L	Education capital investment	-0.2	-0.5	-1.4	4.1	-3.5	0.8
M	Healthcare capital investment	-6.8	5.7	1.1	3.5	2.3	-4.4
N	Worker retraining	1.4	6.7	-7.6	4.1	-4.1	-2.9
O	Targeted direct cash transfers or temp. wage rises	4.2	-2.0	-3.7	-2.6	3.3	-1.8
P	Rural support policies	-4.0	2.3	-1.7	9.7	-6.5	-13.9
Q	Traditional transport infrastructure	3.8	-1.7	1.8	-8.1	3.3	1.3

R	Project-based local infrastructure grants	-1.0	-2.7	-1.1	-1.5	9.9	-1.9
S	Clean connectivity infrastructure	-1.6	1.2	0.2	-0.7	3.5	0.8
T	Clean energy infrastructure investment	2.2	3.0	-6.8	2.3	-0.4	2.4
U	Buildings upgrades	-1.4	-1.8	-0.6	4.5	-1.4	0.2
V	Green spaces and natural infrastructure	2.5	0.5	-1.9	7.0	-15.4	-1.3
W	Disaster preparedness	-2.4	3.5	-7.3	7.1	3.0	-3.7
X	General R&D spending	-3.4	6.2	-1.5	0.5	3.5	-1.2
Y	Clean R&D spending	1.1	5.7	-1.0	3.7	-13.6	-1.9

Table B7. Mean **long-run economic multiplier** responses by expert group. Figures are expert group average minus adjusted target group average. For HICs/LMICs figures are a subtraction of LMIC group averages from HIC group averages. For all columns, a positive (negative) number indicates that the expert group believes the policy to be faster (slower) than what others believe.

	Policy archetypes	Academics	Finance officials	Central bank officials	Development bank officials	Think tank experts	HICs - LMICs
A	Temporary waiver of interest payments	0.1	-6.6	0.3	3.9	-0.4	-5.9
B	Assisted bankruptcy (super Chapter 11)	6.7	-0.4	-7.9	-6.6	9.9	8.9
C	Liquidity support for large corporations	-5.1	1.6	3.6	0.4	3.6	-1.0
D	Liquidity support for households and SME's	3.2	3.1	-3.0	-5.9	4.4	2.8
E	Airline bailouts	-3.5	3.7	-0.8	-1.4	8.3	2.7
F	NFP, education, research, health inst. Bailouts	5.5	-4.6	-8.1	0.4	5.3	-1.0
G	Reduction in VAT and other goods & services taxes	4.0	-7.9	-2.2	0.0	2.8	-4.1
H	Income tax cuts	2.0	-0.7	0.0	-3.8	2.4	1.9
I	Business tax deferrals	-4.1	1.5	2.6	0.9	2.0	-2.8
J	Business tax relief for strategic and structural adj.	-6.5	11.9	2.4	-4.9	7.1	3.4
K	Direct provision of basic needs	4.8	-6.9	4.2	-1.5	-9.1	0.7
L	Education capital investment	-2.7	4.4	0.1	3.9	-5.1	-3.5
M	Healthcare capital investment	-1.9	4.2	0.2	4.9	-8.6	-4.5
N	Worker retraining	-0.4	5.1	-4.1	0.9	1.2	-0.1
O	Targeted direct cash transfers or temp. wage rises	6.2	-6.5	-2.5	-3.4	2.4	-4.3
P	Rural support policies	-1.0	-2.9	-5.6	9.0	0.0	-9.6
Q	Traditional transport infrastructure	-0.2	-1.1	1.3	-5.1	8.3	-0.7

R	Project-based local infrastructure grants	-1.1	1.5	0.4	-4.0	7.3	1.7
S	Clean connectivity infrastructure	-6.3	5.5	8.5	-5.4	3.5	2.4
T	Clean energy infrastructure investment	-1.3	4.5	2.2	-0.6	-4.6	7.4
U	Buildings upgrades	0.8	-2.2	5.1	-4.4	-1.0	3.8
V	Green spaces and natural infrastructure	-0.5	-4.3	-1.0	7.1	-4.7	0.8
W	Disaster preparedness	-1.5	0.2	-5.9	7.1	1.6	-1.5
X	General R&D spending	-2.5	-2.2	6.0	1.4	-4.6	-0.1
Y	Clean R&D spending	5.3	-1.0	4.4	7.1	-8.1	2.4

Table B8. Mean **climate impact potential** responses by expert group. Figures are expert group average minus adjusted target group average. For HICs/LMICs figures are a subtraction of LMIC group averages from HIC group averages. For all columns, a positive (negative) number indicates that the expert group believes the policy to be faster (slower) than what others believe.

	Policy archetypes	Academics	Finance officials	Central bank officials	Development bank officials	Think tank experts	HICs - LMICs
A	Temporary waiver of interest payments	2.3	-3.5	0.5	-1.7	0.2	0.9
B	Assisted bankruptcy (super Chapter 11)	0.3	-0.5	0.3	1.2	-2.7	0.0
C	Liquidity support for large corporations	-1.6	-1.3	1.1	3.1	-2.0	-0.7
D	Liquidity support for households and SME's	2.0	-0.6	-1.0	0.0	-2.4	1.5
E	Airline bailouts	-5.9	8.1	0.7	1.1	2.5	-3.8
F	NFP, education, research, health inst. Bailouts	0.9	-0.8	-3.8	2.5	1.2	-0.7
G	Reduction in VAT and other goods & services taxes	2.6	-2.9	-1.8	1.0	-1.7	-0.2
H	Income tax cuts	0.2	-3.7	1.6	1.8	-2.3	-0.7
I	Business tax deferrals	-1.5	0.4	1.1	1.0	-0.4	-0.4
J	Business tax relief for strategic and structural adj.	-5.4	6.0	2.2	0.0	2.7	1.0
K	Direct provision of basic needs	1.3	-4.7	-2.1	3.6	-0.5	-2.6
L	Education capital investment	-3.9	1.7	1.5	1.8	2.0	-1.9
M	Healthcare capital investment	-0.3	0.9	-3.3	3.9	-1.2	-2.7
N	Worker retraining	0.3	2.7	-3.4	1.3	0.4	-0.6
O	Targeted direct cash transfers or temp. wage rises	2.6	-3.6	-4.5	3.2	0.1	-1.7
P	Rural support policies	-7.5	2.8	0.3	6.8	2.9	-6.0
Q	Traditional transport infrastructure	-0.9	3.4	-1.4	3.0	-4.3	-3.2

R	Project-based local infrastructure grants	-1.9	3.9	1.4	-1.6	0.6	0.0
S	Clean connectivity infrastructure	13.4	0.7	-4.1	-12.1	-4.9	6.5
T	Clean energy infrastructure investment	0.9	-1.8	0.2	-5.5	9.0	7.4
U	Buildings upgrades	3.6	2.8	0.4	-5.4	-3.1	7.1
V	Green spaces and natural infrastructure	-2.3	-5.1	6.3	-6.7	11.5	1.5
W	Disaster preparedness	-0.5	1.6	-3.6	5.7	-3.9	-4.9
X	General R&D spending	-0.2	-1.9	4.6	-2.5	-1.4	-1.7
Y	Clean R&D spending	1.6	-4.4	7.0	-5.5	-2.1	5.9

Table B9. Mean **overall desirability** responses by expert group. Figures are expert group average minus adjusted target group average. For HICs/LMICs figures are a subtraction of LMIC group averages from HIC group averages. For all columns, a positive (negative) number indicates that the expert group believes the policy to be faster (slower) than what others believe.

	Policy archetypes	Academics	Finance officials	Central bank officials	Development bank officials	Think tank experts	HICs - LMICs
A	Temporary waiver of interest payments	1.2	0.1	1.1	0.5	-5.8	-4.5
B	Assisted bankruptcy (super Chapter 11)	5.6	2.4	-3.7	-5.0	-1.0	5.7
C	Liquidity support for large corporations	-8.6	2.7	12.6	0.2	-5.0	-0.9
D	Liquidity support for households and SME's	0.5	-0.4	2.6	-1.9	-2.1	-0.1
E	Airline bailouts	-4.7	3.7	2.1	-0.8	4.9	-0.2
F	NFP, education, research, health inst. Bailouts	4.9	-4.2	-1.7	-2.6	0.1	3.7
G	Reduction in VAT and other goods & services taxes	7.5	-13.1	-4.4	-1.2	5.9	-2.8
H	Income tax cuts	2.1	0.9	1.9	-1.8	-6.5	-4.4
I	Business tax deferrals	-2.9	6.7	2.8	1.7	-8.1	-3.7
J	Business tax relief for strategic and structural adj.	-4.0	5.2	1.3	1.4	-0.8	2.4
K	Direct provision of basic needs	5.7	-11.3	-1.4	2.1	-2.6	-0.2
L	Education capital investment	-1.2	0.0	2.1	-1.3	1.3	0.7
M	Healthcare capital investment	-3.7	1.2	1.4	-2.3	9.1	-0.9
N	Worker retraining	0.1	2.4	-3.3	2.4	-1.0	-0.6
O	Targeted direct cash transfers or temp. wage rises	4.0	-13.4	-3.2	3.8	4.1	-5.6
P	Rural support policies	-6.2	-4.5	-0.6	10.6	2.6	-12.7
Q	Traditional transport infrastructure	-0.3	4.0	-0.4	-1.0	-1.3	-3.9

R	Project-based local infrastructure grants	-2.0	7.8	-3.4	-0.6	3.4	-0.9
S	Clean connectivity infrastructure	-1.2	8.7	1.9	-7.7	3.6	1.6
T	Clean energy infrastructure investment	1.2	1.0	-5.7	3.9	-0.6	6.1
U	Buildings upgrades	1.4	2.0	-1.8	0.0	-2.2	5.5
V	Green spaces and natural infrastructure	-0.9	-2.2	-3.4	6.5	-0.7	1.3
W	Disaster preparedness	0.4	-2.7	-0.3	-0.3	2.9	3.3
X	General R&D spending	-0.8	0.8	4.2	-5.2	2.7	2.6
Y	Clean R&D spending	1.8	2.0	-0.8	-1.3	-3.0	8.4

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C

Supplementary Materials for

Reviewing the COVID-19 "Green Recovery": rhetoric or reality?

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C0. Introductory note

This document forms the supplementary methods component to the paper *Reviewing COVID-19 Fiscal Policy: climate action or carbon lock in.*

Additional supplementary materials are available in two datasets:

- Supplementary Data: *Global Recovery Observatory*[1]
  - 8,001 COVID-19 fiscal policies archetyped using the original fiscal recovery taxonomy described in the paper
  - 58,704 datapoints
  - Covers 88 countries
  - Download at: http://dx.doi.org/10.6084/m9.figshare.20338395
- Supplementary Data: *Global COVID-19 Speech Database*[2]
  - 3,817 English speeches
  - Covers 43 countries
  - Download at: http://dx.doi.org/10.6084/m9.figshare.20338533

C1. Building the Global Recovery Observatory (GRO)

The GRO includes 8,001 policies between 01/01/2020 – 31/12/2021, covering 88 countries.[1] It is available at the following link: http://dx.doi.org/10.6084/m9.figshare.20338395 .

C1.1. Data fields in GRO

In its raw form, the Global Recovery Observatory includes nine fields per policy:

- Country (8,001 entries)
- Bill and bill section(s) (4,322 entries)
- Alternative reference in government document (1,961 entries)
- Policy name (8,001 entries)

- Policy description (8,001 entries)
- Total value, local currency (billions) (6,211 entries)
- Total value, USD (billions) calculated on date of announcement (6,211 entries)
- Date of confirmation (8,001 entries)
- Source (7,995 entries, with gaps due to websites subsequently removed)

The policies are organised by country and then by date. Categorisations including policy archetype, subarchetype, sector, function, short-term GHG impact, and long-term GHG impact are provided for all 8,001 entries using the fiscal taxonomy described in section C2 of these supplementary methods.

C1.2. Data criteria and validation for GRO

In their weekly policy tracking, Oxford research assistants relied on publicly available press releases, budgetary documents, and other government publications. Reliable press reporting was occasionally used in supplement to these government documents. To be included in the database, fiscal allocations needed to be confirmed (either through legislation or other equivalent process with similar certainty of implementation), tagged as COVID-19 related expenditure, and to be clearly additional beyond prior commitments. In several cases, researchers found evidence to suggest that government and press reporting incorrectly claimed additionally; such spending measures were not included in the database.

Three validation processes were used to ensure full coverage of fiscal announcements. First, regular cross-checking was conducted against other trackers including Yale's *COVID-19 Response Tracker*,[3] the IMF's *Fiscal Policy Responses to COVID-19* database,[4] and, while it was active, Vivid Economics'

Greenness of Stimulus Index.[5] The Yale Tracker proved the most useful for this purpose—very few missed and applicable policies were identified in either the Vivid Economics or IMF trackers. Some additional policies identified in IMF tracking did not meet our criteria for inclusion as they were not publicly reported.[67] Secondary validation was conducted by requesting national governments to review the dataset and identify errors for correction. This was facilitated on four occasions, each facilitated by the United Nations Environment Programme. Specifically: a headline review of numbers in September 2020 and September 2021 with all national governments for the Emissions Gap Reports of 2020 and 2021, a headline review of numbers by the world's 50 largest nations for the release of *Are We Building Back Better?*,[6] and detailed policy-by-policy review of all governments in Latin America and the Caribbean for the release of *Is the COVID-19 economic recovery building a sustainable future?*.[7] Government corrections identified ~3 demonstrable errors in the 8,001-policy dataset, out of ~16 claimed errors, however, most governments did not provide any comment on the datasets in the requests for review, focusing instead on written content. As such, it is unclear whether governments provided genuine review of the data. The third type of validation came through invited corrections from the 60,000 users of the GRO database through the Oxford University and United Nations websites. Corrections suggested by the public were infrequent, totalling less than 10, of which only 2 were accepted. Rejected suggestions were typically found to be inaccurate after deeper investigation or did not have a verifiable public source.

[67] The IMF relies on direct reporting of governments rather than interpretation of publicly released materials.

Validation of internal consistency in the dataset came by constructing recurrent neural network models that predict policy characteristics from the textual descriptions in the policy dataset (see section CC5 of the supplementary materials). High predictive accuracy in these models suggests a strong and consistent underlying dataset and taxonomy. Of course, high predictive accuracy does not indicate dataset completeness—the pre-described validation approaches are used for this purpose. Further details on the construction of the neural networks are available in section CC5.

C1.3. Country aggregate data in GRO (without archetypes)

National-level variation in spending is apparent for many dimensions in the dataset. The broadest aggregate national summary is presented in extended data table 1. See the GRO supplementary dataset for full policy details.

C2. Fiscal taxonomy for environment and economy

C2.1. Inherent limitations in ex-ante policy impact considerations

Ex-ante assessments of potential fiscal policy impacts are a coarse placeholder for detailed ex-post studies. While every effort has been made in the present work to maximise the accuracy of generalised assessments, the nature of fiscal policy is such that minor variations in policy design and macroeconomic environment can and regularly do have major effects on impact.

At least three core limitations should be considered: generalisation is required to deal with large numbers of policies; policies sometimes change before implementation; and policy implementation sometimes fails. First, when considering global collections of policy packages, the large number of individual policies prevents tailored impact assessment. Archetype methods allow for like policies to be grouped into a set of categories or 'archetypes'. In this case, archetypes are assessed instead of individual policies. The higher the number of

archetypes, the more individualized the impact assessment and the higher the accuracy. However, even with hundreds of archetypes, there will always be some level of policy variation that cannot be captured amongst the thousands of policies. Importantly, when considering aggregate global views on policy impact, concerns on policy variation might be withdrawn as a very high sample size might mean that impact variations effectively cancel each other around a global mean, defined by each archetype.

Second, since the time between initial policy announcement and policy implementation can be significant—sometimes several years for recovery investments—the details of a policy can change significantly before any funds are spent. This is particularly true in periods of economic uncertainty, as seen over 2020-2021. We refer to this as the spending-expenditure anomaly, where fiscal spending describes initial ratified plans and expenditure describes actuals. Unfortunately, the details of this anomaly are seldom clear as policy changes are seldom released by governments on a timely basis, if at all. Beyond that, GRO researchers focus on new policies rather than changes to old policies as they update the dataset. Where data is available (*e.g.*, the UK), I have attempted to record expenditure progress against spending. Future work should consider forthcoming government expenditure disclosures and reconcile these against the policy data of the present study.

Third, any number of factors can stifle policy implementation, meaning that policy outcomes do not match original intent. Such factors might be influenced by internal and/or macroeconomic circumstances. To this end, it is essential that rigorous ex-post analyses are built into investment programs. With significantly more ex-post data, across regions, ex-post assessments could be dramatically improved. For instance, with a large enough training set of data,

deep learning processes might identify factors likely to influence implementation and shape policy impact.

Despite clear limitations in ex-ante assessment, there is nevertheless value in developing an as-good-as-possible understanding of policy impacts. Fiscal policy in any country signals government priorities, thereby driving business investment, academic research, and civil society actions, as well as influencing the investment patterns of other nations. Additionally, in the context of climate change, better leading indicators on transition progress would be invaluable for understanding where national commitments are being met and where additional focus is required. These indicators would also filter into global climate modelling exercises, which currently do not appropriately integrate fiscal policy commitments.

Precedent works, including Barbier's analysis of Global Financial Crisis (GFC) fiscal policy,[8] show that even simple frameworks can be useful for understanding environmental impacts ex-ante. Barbier's work identifies five policy types that are classified as low carbon (equivalent to archetypes in the GRO fiscal taxonomy); these are used to categorise the fiscal announcements of G20 countries into green and non-green spending. This approach lay the foundation for ex-ante fiscal policy environmental assessment and has shaped our methodology.

C2.2. Comparison of GRO to other COVID-19 fiscal policy trackers

So far as I am aware, the first published COVID-19 fiscal tracking database was contained in annex to Hepburn *et al.* (2020).[9] However, several policy tracking initiatives were underway at a similar time, including by the IMF,[4] Vivid Economics,[5] and Yale's Program on Financial Stability.[3] The unprecedented scale of fiscal commitments continued to capture the attention

of other researchers as the pandemic progressed, leading to additional tracking initiatives from CarbonBrief,[10] Covid Money Tracker,[11] Energy Policy Tracker,[12] Green Recovery Tracker,[13] IEA Sustainable Recovery Tracker,[14] the OECD,[15] and most recently, Nahm *et al.* (2022).[16] Each of these trackers were developed to serve slightly varied functions and as a result, each cover a different subset of countries, sectors, policy granularity, and time periods. The details of the variations between trackers are described in table C1.

Distinct from other efforts, GRO intends to serve as a research resource for all fiscal policy analysis across sectors. It covers the largest number of countries and tracks at high policy granularity; while most others track at the package level, GRO tracks at the policy level, serving to capture the full depth of information provided by governments. As a result, GRO covers 2.3x more policies than the next largest dataset and 4.6x more than the next largest dataset with environmental impact assessments.

Table C1. Comparison of existing COVID-19 fiscal policy trackers.

	Number of fiscal policies	Geographic coverage	Sectoral coverage	Granularity of coverage	Approach to categorising policies	Approach to assessing GHG impact	Academic methodology available?	Data available to download?	Data sources
Global Recovery Observatory (present study)	8,001	88 countries + EU (50 largest economies + 39 additional countries)	All sectors	Policy level	Original environmental-economic taxonomy with 42 archetypes and 221 subarchetypes, all mapped to sectors	Archetype-based 5-point Likert scale; both short- and long-term impact; assessments based on literature, experts, and Hepburn *et al.* (2020)[9] survey	Yes, both for policy categorisation and GHG impact assessment	Yes	Manually compiled from public sources; links provided
CarbonBrief Green Recovery Tracking[10]	204	21 countries	Green initiatives only	Inconsistent; some policy level and some package level	9 sectors and 22 green subsectors	All policies in database considered relevant to GHGs, but no assessment provided	No	Yes	Manually compiled from public sources; all links provided
Covid Money Tracker[11]	2,808 (including some sub-policies)	United States only	All sectors	Sub-policy level. N.B. appears to include some allocations that might not be incremental above pre-COVID-19 levels	24 recipient industries	GHG impact not considered	No; provided methodology does not relate to categorisation or GHG assessment.	Yes	Manually compiled from public sources; all links provided
Energy Policy Tracker[12]	1,725	35 countries + 9 multilateral institutions	Energy production and consumption only	Policy level	Original energy taxonomy with 17 energy types and 9 energy stages	Archetype-based 4-point Likert scale; long-term impact only	Yes, both for policy categorisation and GHG impact assessment	Yes	Manually compiled from public sources; links provided

	Number of fiscal policies	Geographic coverage	Sectoral coverage	Granularity of coverage	Approach to categorising policies	Approach to assessing GHG impact	Academic methodology available?	Data available to download?	Data sources
Green Recovery Tracker[13]	1,184	20 Eurozone countries	Only policies that impact GHG emissions	Inconsistent; some policy level and some package level	7 sectors	Broadly follows EU standards with notes on "controversial cases"; long-term impact only	No; brief note available for GHG impact	Yes	Manually compiled from public sources; links not provided
IEA Sustainable Recovery Tracker[14]	1,188	42 countries	Only clean energy measures	Policy level	Original energy taxonomy with 7 archetypes and 44 subarchetypes	World Energy Model provided CO_2 impact assessment	Yes, both for policy categorisation and GHG impact assessment	Yes	IEA policies and measures database
IMF Fiscal Policy responses to COVID-19[4]	~850	66 countries	All sectors	Package level	6 broad economic categories	GHG impact not considered. N.B. the October 2020 IMF Fiscal Monitor[17] included a useful box (1.1) covering ~100 green policies	No	Yes	Country submissions
G20's US$14-trillion economic stimulus (Nahm *et al.*, 2022)[16]	366	19 countries + EU	All sectors	Package level	None	Bottom-up (policy-by-policy) 3-point Likert scale; no consistent assessment categories; short- and long-term impact	No; supplementary materials only provide definitions	Yes	Manually compiled from public sources; all links provided
OECD Green Recovery Database[15]	1,494	44 countries plus EU	Only recovery policies with "environme	Inconsistent; some policy level and some package level	14 sectors and 7 policy types	Bottom-up (policy-by-policy) 3-point Likert scale; no consistent assessment	No; brief note available for GHG impact	No	Led by country submissions, supplemented by public sources

	Number of fiscal policies	Geographic coverage	Sectoral coverage	Granularity of coverage	Approach to categorising policies	Approach to assessing GHG impact	Academic methodology available?	Data available to download?	Data sources
			ntal relevance"			categories; long-term impact only			
Vivid Economics Greenness of Stimulus Index[5]	~1,500	30 countries (G20 + 10 additional countries)	All sectors	Inconsistent; some policy level and some package level	Original environmental taxonomy with 43 archetypes, all mapped to sectors	Archetype-based 5-point Likert scale; long-term impact only; no apparent assessment method for archetypes	Yes for categorisation ; No for GHG impact	No	Manually compiled from the IMF Policy Tracker and the public domain
Yale COVID-19 Response Tracker Visualisation[3]	3,492	184 countries	All sectors	Inconsistent; some policy level and some package level	27 policy tools, 59 ultimate beneficiaries, 65 target subsectors, and 48 conduits	GHG impact not considered	No	Yes	Manually compiled from public sources; all links provided

C2.3. Fiscal taxonomy for recessionary investment—archetypes and subarchetypes

As described in the paper methods, the taxonomy considers in environmental and economic characteristics of different fiscal policy measures to categorise all policies into 42 archetypes and 221 subarchetypes. The taxonomy targets four additional criteria for each archetype and subarchetype—policies should:

- be sufficiently granular to reflect the policy detail provided by governments;
- be of similar granularity at each level (*i.e.* archetype and subarchetype);
- be mutually exclusive; and
- be collectively exhaustive.

The taxonomy is functionally built on four levels: subarchetypes as a subset of archetypes as a subset of typologies as a subset of policy functions. These are defined as follows:

- **Policy function:** rescue, recovery, or unclear
    - Rescue policies operate in the immediate- to short-term and are typically designed to keep people and businesses alive. They might include unemployment insurance, food stamps, business liquidity support, immediate tax holidays, vaccine development, and more.
    - Recovery policies operate in the medium- to long-term and are typically designed to reinvigorate economic growth. They

might include investments in infrastructure, true stimulus cheques, and various business incentives.

  - Unclear policies are those for which insufficient public detail is available. They might be rescue, recovery, or a mixture of both.

  - Reinforcement policies are not considered in GRO at the time of writing. Reinforcement measures typically operate in the long- to very long-term. They intend to build directly on policy measures introduced in response to the crisis, often reinforcing new economic, social, or environmental trajectories (*i.e.*, different from those in place prior to the crisis).

- **Typology:** 5 in total, of which 3 are rescue typologies and 2 are recovery taxonomies

  - Temporary liquidity measures (rescue) aim to support businesses, non-profits, and/or subnational entities facing shortfalls in liquidity. These measures may also act to alleviate the costs of servicing debt, often in the form of interest waivers.

  - Temporary life and livelihood measures (rescue) aim to support individuals and families, either through direct payments, health support, or other welfare support. These measures might be provided direct to the individual, through

a subnational entity, through a non-profit, or through an employer or business.

  - Temporary tax and payment relief measures (rescue) aim to support individuals or businesses that are unable to fill scheduled or unscheduled non-interest payments due to the crisis.

  - Incentive measures (recovery) broadly aim to stimulate consumer demand through direct subsidies and/or measures to otherwise decrease the costs (financial and/or non-financial) of procuring products and services.

  - Investment measures (recovery) broadly aim to stimulate economic production, for instance through direct public investment in infrastructure.

- **Policy archetype:** 42 in total, spread between temporary liquidity measures (5), temporary life and livelihood measures (6), temporary tax and payment relief measures (6), incentive measures (6), and investment measures (20) (1 archetype is "unclear"). Policy archetypes are listed in table C2, organised by policy function and typology. Table C3 provides brief archetype definitions.

- **Policy subarchetype:** 221 in total, with wide variation in the number of subarchetypes per archetype. Some archetypes include as little as 2 subarchetypes, and some as many as 14 subarchetypes. Policy subarchetypes are listed in table C3 with example policies.

Table C2. Summary of GRO fiscal policy archetypes.

Rescue: Temporary liquidity measures	
A	Liquidity support for subnational public entities
B	Liquidity support for large businesses
C	Liquidity support for start-ups and SMEs
D	Liquidity support for not-for-profit organisations
E	Temporary waiver of interest payments for businesses
Rescue: Temporary life and livelihood measures	
F	Direct provision of basic needs
G	Targeted welfare cash transfers
H	Job continuation support
I	Temporary waiver of interest payments for individuals
J	Healthcare services support
K	Emergency services (disaster management) support
Rescue: Temporary tax and payment relief measures	
L	Income tax cuts
M	VAT and other goods and services tax cuts
N	Business tax cuts
O	Business tax deferrals
P	Reduced prices for centrally-controlled products and services
Q	Other tax cuts and deferrals
Recovery: incentive measures	
R	Targeted recovery cash transfers
S	Tourism and leisure industry incentives
T	Electric vehicle incentives
U	Electronic appliance and efficiency incentives
V	Green market creation
W	Other incentive measures
Recovery: investment measures	
X	Worker retraining and job creation
Y	Education investment (non-infrastructure)
Z	Healthcare investment (non-infrastructure)
α	Social and cultural investment (non-infrastructure)
β	Communications infrastructure investment
γ	Traditional transport infrastructure investment
δ	Clean transport infrastructure investment
ε	Traditional energy infrastructure investment

η	Clean energy infrastructure investment
θ	Local (project-based) infrastructure investment
λ	Buildings upgrades and energy efficiency infrastructure investment
μ	Natural infrastructure and green spaces investment
ω	Agriculture and fisheries
π	Other large-scale infrastructure investments
σ	Armed forces investment
τ	Disaster preparedness and capacity building investment
φ	General research and development investment
ψ	Clean research and development investment
Unclear	

Table C3. Details of GRO fiscal policy archetypes and subarchetypes, with example policies. Archetype names are in bold. Subarchetype names follow shaded circular bullets. Example policies are italicised and follow hollow circular bullets. Not shown are "unclear" subarchetypes, of which there was one used for each archetype.

Rescue: Temporary Liquidity Measures

A. Liquidity support for subnational public entities

Transfer of funds from the national government to provinces, municipalities, federal states, state-owned enterprises etc. to service immediate liquidity shortfalls or otherwise finance new rescue programs.

- A1. Support for states/regions
  - *Federal aid to states to combat coronavirus*
  - *Loans to states*
- A2. Support for localities
  - *Ring-fenced funding for municipalities*
  - *Restructuring cities' debt*
  - *Finance for provinces*
  - *Transfer of funds to autonomous communities*

B. Liquidity support for large businesses

Government support for rapid liquidity to large corporations, including emergency grants to named and unspecified sectors.

- B1. Support for agriculture, forestry, and fishing (no green conditions)
  - *Agricultural bank equity investment*
- B2. Support for agriculture, forestry, and fishing (with green conditions)
- B3. Support for airlines and other transport (no green conditions)
  - *Loan guarantees for airlines*
- B4. Support for airlines and other transport (with green conditions)
  - *Loans to airlines conditional on carbon offsets*
- B5. Support for energy (no green conditions)

- *Support for electricity distribution companies*

- B6. Support for energy (with green conditions)
- B7. Support for holiday and leisure (no green conditions)
  - *Emergency funds for entertainment industry*
- B8. Support for holiday and leisure (with green conditions)
- B9. Support for retail (no green conditions)
  - *Emergency cash grants for businesses in retail*
- B10. Support for retail (with green conditions)
- B11. Support for specified other industry (no green conditions)
  - *Support for exporting industries*
- B12. Support for specified other industry (with green conditions)
  - *Support for car manufacturer on condition of participation in battery development program*
- B13. Support for unspecified industry
  - *Direct equity stakes in companies*

C. Liquidity support for start-ups and SMEs

Government support for rapid liquidity to small and medium sized enterprises (SMEs) including start-ups.

- C1. Support for agriculture, forestry, and fishing
  - *Direct support for fishing businesses*
- C2. Support for energy
- C3. Support for holiday and leisure
  - *Credit line for tourism SMEs*
- C4. Support for retail
  - *Direct support for small retailers*
- C5. Support for specified other industry
  - *Compensation for childcare businesses*
- C6. Support for unspecified other industry
  - *Co-lending program for SMEs*

D. Liquidity support for not-for-profit organisations

Government support for rapid liquidity to not-for-profit organisations, including through emergency grant programs.

- D1. Support for arts and culture
  - *Emergency funds for cultural institutions*
- D2. Support for social care and health care
  - *Support for self-help groups*
- D3. Support for education and research institutions
  - *Funding for specific universities and research offices*
- D4. General non-profit support
  - *Emergency cash grants for charities*
- D5. Support for animal services

E. Temporary waiver of interest payments for businesses

Holidays on interest payments or other relief on commercial rent and loans.

- E1. Commercial rent interest relief
  - *Loan principal payment deferrals*
  - *Loan payment delays for struggling companies*
  - *Suspension of interest payments for tourism industry*
- E2. Automotive interest relief
  - *Motor finance and high-cost credit support*
- E3. Utility payment interest relief (*i.e.* electricity, gas, water)
  - *Increased flexibility for utility payments*
  - *Postponement of collection of electricity and natural gas consumption fees*
- E4. Microcredit interest relief
  - *Support for small companies using credit*
- E5. Rural investment interest relief
  - *Postponement of farmer's debt without interest*
- E6. General and other
  - *Reduction in interest rates for borrowers*
  - *Reduced interest rates for small taxpayers*

Rescue: Temporary life and livelihood measures

F. Direct provision of basic needs

Direct funds to support the immediate local production and distribution of essential goods such as food, health, and transport, either in the formal or informal economies.

- F1. Provision of nutrition
  - *Food banks support*
  - *Indigenous food support*
- F2. Provision of short-term shelter
  - *Housing the homeless*
- F3. Provision of social services
  - *Exploitation prevention fund*
  - *Funding for children in care*
- F4. Provision of utility access (including electricity and water)
  - *Allocation to social water funds*
  - *Free cooking gas cylinders to poor families*
  - *Covering heating costs*
- F5. General and other support
  - *Subsidising basic needs*

G. Targeted welfare cash transfers

Direct cash transfers targeted to individuals and families.

- G1. Payments targeted to families
  - *Payments to families with children*
  - *Payments to families with COVID-19 deaths*
- G2. Payments targeted to low income individuals
  - *Bill exemptions*
- G3. Payments targeted to individuals (other)
  - *Payments to out-of work individuals with (suspected) COVID-19*
  - *Payments to self-employed workers*
  - *Payments to workers with reduced hours/remuneration*
  - *Payments to COVID-19 emergency workers*
  - *Payments to workers who have been made redundant/furloughed*
  - *Extending/increasing unemployment benefits*
  - *Increase in government-controlled wages*
- G4. Indirect payments through social programs
  - *Insurance expansion/reduced payments*
  - *Pension support*

H. Job continuation support

Schemes to support employment, either indiscriminately across the economy or targeted to sectors under threat. Includes furlough schemes and related incentives.

- H1. Job continuation subsidies
  - *Furlough schemes*
  - *Credit for salary payments*
- H2. Job continuation incentives
  - *Firm payouts for bringing back furloughed workers*

I. Temporary waiver of interest payments for individuals

Permitted delays in payments relating to rents, mortgages, student loans and other individual payments.

- I1. Mortgage interest and rental relief
  - *Foreclosure and eviction moratorium and mortgage restrictions*
  - *Mortgage support, including six-month mortgage payment deferment*
  - *Business rent reductions in special zones*
  - *Delay rent payments and debts for households and SMEs*
- I2. Student debt interest relief
  - *Removal of tax on employer student loan repayment benefits*
  - *Suspending repayment and interest on student and apprentice loans*
- I3. General and other relief
  - *Allowed deferral of payments on credit and interest*
- I4. Automotive interest relief
  - *3-month payment freeze on car loan repayments*

J. Healthcare services support

Emergency health measures to respond to the health impacts of the COVID-19 pandemic, including with development of treatments and vaccines.

- J1. General medical equipment/services spending (including PPE)
  - *Expanding stockpile of flu drug*
  - *Purchases of masks and medical equipment*
- J2. Mental health support
  - *Funding for mental health phone line*
- J3. Aged care support
  - *Funding for aged care facilities*
- J4. General medical personnel support
  - *Medical insurance for frontline workers*
- J5. Vaccine and COVID-19 research, manufacturing and application
  - *Funding for vaccine development program*

K. Emergency services (disaster management) support

Measures to facilitate the management of the COVID-19 pandemic, particularly of outside the healthcare industry.

- K1. Administrative support for emergency response
  - *Funding for media campaigns regarding COVID-safety*
- K2. Procurement of emergency response equipment

Rescue: Temporary tax and payment relief measures

L. Income tax cuts

Includes any reduction in marginal income tax rates, increase in tax-free thresholds, or expansion of permitted deductions.

- L1. Reduction in marginal rates (including increases in tax-free thresholds)
  - *Reduced rates for lowest income tax bracket*
- L2. Expanded deductions
  - *Tax deductions for childcare household spending*
  - *Tax credit for taxpayers spending on accommodation, food, and non-alcoholic beverages*
- L3. New tax exemptions
  - *Income tax exemption for health and security personnel*
- L4. Permitted delays in payment
  - *Relaxation of tax payment schedules*
  - *Temporary suspension of payments for over 65s*

M. VAT and other goods and services tax cuts

Reduction in the rate of value-added taxes (VAT) or goods and service taxes (GST) on consumption. Includes changes to taxes on specific goods, as well as adjustments to import tariffs.

- M1. VAT reductions
  - *Reduction of VAT by 15%*
  - *Taxable sales income of 3% exempt from VAT*
  - *30% reduction in auto sales tax*
  - *Increase in stamp duty threshold*
- M2. VAT deferrals
  - *Deferral of VAT payments for 3 months*
  - *Extend payment deadline of import duties*
- M3. Non-discretionary payment relief
  - *ATM charge suspension*
  - *Toll road charge suspension*
  - *License fee waivers*
- M4. Reduced taxes for emergency medical imports
  - *Duty and tax exemption for emergency medical imports*

N. Business tax cuts

Includes temporary or permanent reductions in business tax, changes to tax-free thresholds, or expanded deductions.

- N1. Reduction in rates
  - *Corporate investment tax discounts*
- N2. Expanded deductions
  - *Tax deductions for materials in production during the pandemic*
- N3. New tax exemptions for clean and/or resilient investments
- N4. New tax exemptions for general and other investments
  - *Tax waivers for hoteliers and restaurants*

O. Business tax deferrals

Permitted deferral of payment of corporate taxes or strengthening of carry-back provisions in tax loss offsets.

- O1. Tax deferrals for dirty industries
  - *Freezing fees and charges for coal and gas explorers*
- O2. Tax deferrals for other industries
  - *General business tax deferrals*

P. Reduced prices for centrally-controlled products and services

Measures that reduce the price of goods and services controlled by a government entity.

- P1. Public service payments
- P2. Fuel prices (oil and gas)
- P3. Utility prices (electricity and water)
  - *Electricity cost cuts for businesses*

Q. Other tax cuts and deferrals

Any tax-related measures not covered by archetypes L, M, N and P.

- Q1. Other tax cuts and deferrals

Recovery: Incentive Measures

R. Targeted recovery cash transfers

Recovery-type direct cash transfers to individuals to promote spending and restore consumer demand. Does not include cash transfers designed to meet basic needs due to COVID-19.

- R1. Payments targeted to families
- R2. Payments targeted to low-income individuals
- R3. Payments targeted to individuals (other)
- R4. Indirect payments through social programs

S. Tourism and leisure industry incentives

Government subsidies for consumers of leisure activities and measures to promote leisure participation.

- S1. Incentives for general tourism
  - *Reduced fees on public transport routes that directly serve tourist activities*
- S2. Incentives for greener and/or more resilient tourism including ecotourism
- S3. Incentives for hospitality services
  - *50% off all meals from Monday to Wednesday*
  - *Discounts for individuals using hotels*
- S4. Incentives for arts and cultural activities
  - *Discounts for going to the theatre*
- S5. Measures to promote leisure participation
  - *Tourism marketing support*
  - *Arts and culture sector support*

T. Electric vehicle incentives

Support for electric vehicle production and consumption, including schemes like cash-for-clunkers programs which, act to replace inefficient vehicle fleets with more efficient or electric vehicles.

- T1. Vehicle transfer programs
  - *Fleet exchange program for new EVs*
- T2. Efficient vehicle and EV subsidies
  - *Electric and hybrid car purchase subsidy*

U. Electronic appliance incentives

Incentives for individuals to purchase appliances, specifically with energy efficiency conditions, through transfer schemes or subsidies.

- U1. Electronic appliance specific 'cash for clunkers' programs
- U2. Electronic appliance subsidies
  - *Energy-efficient home appliances partial refunds*

V. Green market creation

Investments to promote the creation and expansion of green markets that are not covered by other archetypes. For instance, investments that prompt the integration of more renewable energy generation into electricity markets but do not provide funds for new assets, or investments that direct new focus to emerging green industries.

- V1. Increased clean energy market participation
  - *Cutting the renewable energy levy on electricity bills*
  - *Allow major energy users to be rewarded for scaling down demand during peak periods*
- V2. Modernisation and transition investments
  - *Establishment of an Emissions Reduction Fund, supporting workers and reducing emissions in the oil and gas sector, with a specific focus on methane*
  - *Promoting more efficient aircraft fleets*
  - *Promoting modernisation of shipping, including traffic innovation and support for renewing government vessels*
  - *Funding to clean up orphan and inactive oil and gas wells*
  - *Support for auto industry transformation*
- V3. Capacity investments
  - *Building an industrial cluster for green tech*
  - *Promoting low-carbon manufacturing such as by building an energy efficient testing platform in smart industrial complexes*
  - *Support for regional innovation clusters*
- V4. Payments and other incentives for ecosystem services

W Other incentive measures

Incentive measures that are not covered by archetype R, S, T, U or V.

- W1. Other incentive measures

Recovery: Investment Measures

X. Worker retraining and job creation

Measures designed to train and retrain workers for new and growing industries.

- X1. Green worker retraining and job creation—climate transition/mitigation
  - *Retraining for green transition*
- X2. Green worker retraining and job creation—adaptation
- X3. Green worker retraining and job creation—unclassified/mixed
  - *Investing in green jobs for long-term unemployed*
- X4. General and other worker retraining and job creation
  - *Investing in training workers in innovative industries*
  - *Retraining fund for general reskilling*
  - *Subsidising jobs for young people*

Y. Education investment

Capital injections to fund improved hard and soft infrastructure for teaching in pre-primary, primary, secondary, and tertiary subsectors. Includes scholarship funding.

- Y1. Education capital and equipment
  - *Funding for placement of teachers and teaching assistants*
  - *ICT and equipment funding*
- Y2. Scholarship funding
  - *Creation of new arts scholarships*
- Y3. Staff funding
  - *Increased non-research university staff*
  - *Increased school administration staff*
  - *Funding for new teachers*
  - *Funding for new research posts*
  - *Support to nurses and careers in education*
- Y4. Education physical infrastructure
- Y5. Funding to support understanding of climate change mitigation, adaptation, and/or resilience

Z. Healthcare investment

Investments in the healthcare system beyond those required to deal with the immediate impacts of the COVID-19 pandemic. Investments might include physical health, mental health, aged care, technological upgrades, and more.

- Z1. General medical
- Z2. Mental health
- Z3. Aged care
- Z4. Healthcare capital
  - *Purchase of IT systems*
- Z5. Physical healthcare infrastructure

α. Social and cultural investment

Non-emergency, non-infrastructural investments in social and cultural sectors including non-profits.

- α1. Support for arts and culture sector
  - *Establishing a new institute of music*
- α2. Support for social care
- α3. General and other non-profit investment

β. Communications infrastructure investment

Investments to expand existing communication infrastructure or introduce new infrastructure, including provisions for remote learning and broadband. Soft infrastructure including digital programs and cybersecurity are also included.

- β1. Broadband investment
  - *Simplify fibre broadband expansion*
  - *5G infrastructure acceleration with focus on remaining white spots*
- β2. Remote working infrastructure investment
  - *Production of equipment to ensure telework modality*

- *Buying new computers to improve connectivity in education*
- β3. Civil cybersecurity programmes
  - *Cybersecurity implementation funding*
- β4. Implementation of digital programmes
  - *AI networks implementation funding*
- β5. Improve resilience of existing communications infrastructure

γ. Traditional transport infrastructure investment

Investments in traditional transport infrastructure including road upgrades, airports, and ports infrastructure.

- γ1. Road construction
  - *Funding for road upgrades*
  - *Funding for new highways*
  - *Funding for bridge repairs*
- γ2. ICE engine automobile support
  - *Relief for road transport passengers*
  - *Loans for autoparts industry*
- γ3. Aviation infrastructure
  - *Purchase of air routes*
  - *Building new airports*
  - *Building new airplanes*
- γ4. Port and ship construction
  - *Funding for upgrading ships*
  - *Funding for port repairs*
- γ5. Rail construction and capacity
  - *Expansion of rail network and system*
  - *Building new trains*

δ. Clean transport infrastructure investment

Investments in new or expanded public transport systems, including to increase capacity and transport digitalisation, in cycling and walking infrastructure, and in electric vehicle (EV) charging infrastructure.

- δ1. New public transport systems or line expansions
  - *Investment in major public infrastructure programme aiming to expand and improve city metro, bus, and tram services*
- δ2. Existing public transport capacity expansions
  - *Funding to increase frequency and capacity*
- δ3. EV charging infrastructure
  - *All petrol stations to be required to offer EV charging points*
  - *Investment in JET EV charging*
- δ4. Public transport digitalisation efforts
  - *Improved internet access on metro services*
- δ5. Cycling and walking infrastructure
  - *Investments in bike lanes, wider pavements, safer junctions*
- δ6. Improve efficiency in dirty transport
- δ7. Improve resilience of existing transportation infrastructure and networks

ε. Traditional energy infrastructure investment

Investment into fossil fuel and related infrastructure.

- ε1. New or refurbished power plants
  - *Finance for restarting coal power projects*
- ε2. New or refurbished refineries
  - *Construction of new oil refineries*
- ε3. New or refurbished coal mine and oil/gas fields
  - *Expansion of existing coal mines*
- ε4. New of refurbished infrastructure for transport and transmission of fossil energy
  - *Building rail capacity for the sole purpose of coal transport*
  - *Increasing transmission capacity to allow for higher fossil fuel use*
- ε5. Improve resilience of existing traditional energy infrastructure

η. Clean energy infrastructure investment

Investments in clean electricity and heat, including for generation, storage and transport for electricity and heat.

- η1. New or refurbished renewable energy generation facilities
  - *Abolishing the national solar capacity cap*
  - *Raising expansion target for offshore wind raised and removal of restricting the development of onshore wind within 1,000m of homes*
  - *Investment in offshore windfarms and hydropower infrastructure*
- η2. New or refurbished nuclear energy generation facilities
- η3. New biofuel and other renewable fuel infrastructure
- η4. Upgraded (or new) transmission infrastructure
  - *Funding to extend the national electricity grid and support a high voltage transmission line*
- η5. Upgraded (or new) distribution infrastructure including smart grids
  - *Establish a State Power Grid and Study Program to invest in and develop responsible grid infrastructure*
- η6. Hydrogen infrastructure
  - *Develop new domestic supply chains, export infrastructure and to help grow domestic demand for hydrogen*
  - *National hydrogen strategy backed by investment in domestic hydrogen production, transport*
- η7. Battery and storage infrastructure
  - *Procuring large-scale battery system to help balance the local electricity grid*
  - *Advancement of geothermal and lithium battery projects*
  - *Utility customers will be able to access "Community Power Banks," or neighbourhood batteries that store solar energy and help neighbourhoods balance the grid*
- η8. Carbon capture and storage/utilisation
- η9. Other initiatives to clean dirty energy assets
- η10. Improve resilience of existing clean energy infrastructure

θ. Local (project-based) infrastructure investment

Investments to improve local housing, utility, and other infrastructure.

- θ1. Urban development programs
  - *Smart City' program, which targets sustainable and integrated urban development (including linkage of information and communication technologies to coordinate energy, buildings, traffic, sewage, and water)*
- θ2. General new housing investment
  - *Social housing building*
- θ3. Clean and/or resilient new housing investment
- θ4. General investment in new public buildings
  - *Building schools*
  - *Renovating courts of justice*
- θ5. Clean and/or resilient investment in new public buildings
- θ6. General investment in local utilities
  - *Financing gas, electric, and sanitary infrastructure*
- θ7. Clean and/or resilient investment in local utilities

λ. Buildings upgrades and energy efficiency infrastructure investment

Investments to reduce carbon emissions in existing buildings. This includes investments to improve thermal efficiency (for instance through improved insulation), improve energy efficiency of appliances, and shift to cleaner heating (for instance through heat pumps or heat networks).

- λ1. Green retrofitting programs (including daylighting, electricity and electrification, insulation)
  - *Funding for a CO_2-focused building renovation programme*
- λ2. Rooftop solar support
  - *Financial support scheme for household solar procurement*
  - *Enacts new feed-in tariffs for solar projects in order to stimulate solar power development.*
- λ3. Other building upgrade support

μ. Natural infrastructure and green spaces investment

Investments in nature.

- μ1. Public parks and green spaces investment
  - *Funding for community gardens, outdoor spaces and allotments*
- μ2. Environmental re(building) initiatives including afforestation, reforestation, and environmental rehabilitation
  - *Tree planting*
  - *Reforesting 30,000 honey plants*
- μ3. Environmental protection initiatives including conservation and natural infrastructure resilience
  - *Funds for the conservation and sustainable management of forests*
  - *Funds for a marine observation network*

ω. Agriculture and fisheries

Investments in hard and soft infrastructure in the agriculture and fisheries sectors.

- ω1. General agriculture investment
- ω2. Clean and/or resilient agricultural practices (*e.g.*, adaptive cropping, education on A&R, agroecology etc)
    - *Supporting green restructuring of agricultural sector*
    - *Promotion of climate-smart and precision agriculture*
- ω3. General fisheries investment
- ω4. Clean and/or resilient fisheries practices (*e.g.*, wild fishery management)
    - *Execute War on Waste programme at harbours and landing sites*
- ω5. General investment in resilient land management
    - *Watershed management projects*

π. Other large-scale infrastructure investments

Investments in other large-scale construction projects.

- π1. Large-scale urban infrastructure—general
    - *Finance for stadiums*
    - *Construction of major government buildings*
- π2. Large-scale urban infrastructure for climate resilience
- π3. Large-scale regional infrastructure—general
    - *Dam construction*
    - *Non-coal mining*
    - *Land reclamation activities*
- π4. Large-scale regional infrastructure for climate resilience
- π5. Large-scale space infrastructure

σ. Armed forces investment

Investments in the capacity and arsenals of armed forces including police and defence.

- σ1. Arsenal funding
    - *Finance for purchasing military equipment, such as tanks, bombs, and planes*
    - *Expanding police capacity through purchasing police vehicles*
- σ2. Administration funding
    - *Expanding armed forces and police administration networks*
    - *Military digital technology investment*

τ. Disaster preparedness

Investments to prepare for future pandemics, fires, floods, cyclones, and other unpredictable but high-consequence events.

- τ1. Future epidemic reaction capabilities
    - *Investment in production facilities of pharmaceuticals, medical devices, PPE*
    - *Stocking pharmaceuticals, medical devices, PPE*
- τ2. Investment in risk assessment and early warning systems

- τ3. Procurement of emergency response equipment
  - *Fire backburning*
  - *Flood protection walls*
- τ4. Investment in emergency response systems
- τ5. Other direct (physical) climate change adaptation and resilience measures
- τ6. Other indirect (economic, political) climate change adaptation and resilience measures

φ. General research and development investment

Support for research and development programmes and innovative businesses.

- φ1. Health and science programmes
  - *Budget reallocation for health and science projects*
  - *Coronavirus related R&D*
- φ2. Digitisation and AI programmes
  - *Funding start-ups and SMEs in technology industries*
  - *Cybersecurity research investment*
  - *Quantum research investment*
- φ3. Space programmes
  - *Support for innovation in satellite telecommunications, earth observations, and nanosatellite technologies*
- φ4. General and other programmes

ψ. Clean research and development investment

Support for research and development with explicitly green technologies and innovative businesses.

- ψ1. Clean energy R&D programmes
  - *Focus on digitalisation and "sector coupling"*
  - *Supporting vehicle manufacturers and the associated supply industry in the form of a bonus program.*
  - *Accelerating digitalisation in forestry, including investment in modern operating machines and devices*
  - *Investing in R&D on electromobility and batteries*
  - *Support the development of hydrogen transport options*
- ψ2. Agriculture R&D programmes
  - *Investments to develop a more secure and sustainable forestry sector*
  - *Launching an agricultural flexibility program meant to support the agriculture sector as it adapts to new pressures*
- ψ3. Industrial R&D programmes
  - *R&D of low-carbon manufacturing, such as building an energy efficient testing platform in smart industrial complexes*
- ψ4. Other sectoral R&D programmes
  - *Investment in R&D of CCS technology*
- ψ5. Other climate resilience R&D programmes

C2.4. Green definitions and taxonomy tables

C2.5. 1.Low-, neutral-, and high-GHG investments (3-point Likert scale)

In this investigation a low-GHG investment is one that is likely to reduce greenhouse gas emissions compared to a scenario in which the investment is not made (score = +1). A high-GHG investment is likely to increase emissions compared to a scenario in which no investment is made (score = -1). A neutral-GHG investment is either (i) unlikely to have a net impact on emissions in either direction or (ii) is not defined enough to enable analysis (score = 0). 2-point analyses in the present study group neutral- and high-GHG investments into a single category, as both support the economic status quo—*i.e.*, 2-point analyses assign low-GHG investment a score of 1 and all other investment a score of 0. Throughout the analysis, GHG impact is considered in both the short-term, during policy implementation, and in the long-term, after policy implementation. Long-term GHG impacts generally outlast the economic impacts of the crisis that spawned the investment. Net GHG impact can be derived either on a national or global basis using typical weighting assumptions per archetype, however these considerations are left for future work. GHG impact definitions are explored with simplified, illustrative, examples:

Example A: Investment to build a new coal-fired power plant (subarchetype ε1)

In most nations it is highly unlikely that a new coal plant is built without public funds.[68] Instead, if additional power capacity is

[68] Poor financial returns and high risk of asset stranding render coal power an unattractive investment.

required, it is likely that lower emission alternatives are built, perhaps by private operators, and perhaps at a later time. Hence, the no intervention baseline is some level of long-term emissions, $x_{A,0}$ *per year*, but no significant additional short-term emissions $y_{A,0}$. If the coal plant were built with public funds (scenario A), significant material use would bring short-term emissions $y_{A,1}$, and long-term emissions would increase to $x_{A,1}$ *per year* through the burning of additional coal such that $x_{A,1} > x_{A,0}$. Hence, the post-intervention emissions profile is significantly higher than the no intervention profile, and the investment would be considered a high-GHG emissions policy in both the short- and long-term.

Example B: Investment in new clean public transport (subarchetype $\delta 1$)

In this scenario assume that without public funding a new public transport asset is unlikely to be built in a city.[69] It follows that without intervention, at least in the short-term, existing transportation systems continue to function without change. In most cities, existing transportation systems are highly dependent on internal combustion engine (ICE) automobiles and maintain a high CO_2 burden. As such, the no-intervention baseline in the given high-emissions city is then some level of long-term emissions, $x_{B,0}$ per year, with no significant additional short-term emissions $y_{B,0} = 0$. If a new public transport asset is built, significant material use results

[69] Public transport is almost always an impure public good and uncommonly provided by private investors without government support.

in short-term emissions $y_{B,1}$, where $y_{B,1} > y_{B,0}$, but the replacement of automobile transport with more efficient public transport reduces net sector emissions over the long-term to $x_{B,1}$ *per year* where $x_{B,1} < x_{B,0}$. Hence, the post-intervention emissions profile is higher than the no intervention profile (high GHG investment) in the short-term but lower in the long-term (low GHG investment).

Example C: Direct liquidity support for an airline without green conditions (subarchetype B3)

Without liquidity support, in the extreme case, a desperate airline unable to secure private investment is likely to scale down operations or otherwise face liquidation. In time, it is assumed that another airline, either a new operation or an emboldened competitor, would grow to take its place and meet the demand that it would have otherwise met. Ceteris paribus, it is likely that the replacement airline takes on a similar long-term emissions profile, $x_{C,0}$ *per year*, to that which the liquidated airline had pre-crisis, $x_{C,-1}$ *per year,* such that $x_{C,0} \approx x_{C,-1}$. However, because airlines are capital intensive businesses, and liquidity can be low in the sector during downturns, it is likely that there will be a period of unmet demand where short-term emissions, $y_{C,0}$ *per year,* are less than $x_{C,-1}$. With unconditional liquidity support, the airline is likely to continue operations post-crisis as they would have pre-crisis so that long-term emissions, $x_{C,1}$ *per year*, and short-term emissions, $y_{C,1}$ *per year*, are both roughly equivalent so that $y_{C,1} \approx x_{C,1} \approx x_{C,0} \approx x_{C,-1} > y_{c,0}$. Compared to the no intervention baseline, the unconditional

liquidity support is considered a high GHG investment in terms of short-term impact but a neutral GHG investment for the long-term.

Example D: Direct liquidity support for arts and culture not for profit (NFP) (subarchetype D1)

Without liquidity support, a desperate NFP is likely to scale down operations or be liquidated. In time, it is assumed that another NFP takes its place. With liquidity support, it is assumed that the NFP would likely continue operations largely without change. Since the emissions of the NFP are likely to be minimal with or without intervention, the policy is deemed to have little influence on the national rate of emissions in either the short- or long-term, *i.e.*, a neutral GHG investment.

C2.5.2 A range of -2 to +2 (5-point Likert scale)

Building on definitions used for the 2- and 3-point scales, archetypes in the fiscal taxonomy consider GHG impact on a five-point scale: large increase in GHG emissions (-2), moderate increase (-1), minor or no impact (0), medium decrease (+1), and large decrease (+2).

Under the stated baseline, which refers to a scenario in which no policy intervention is made, archetypes may have a different GHG impact in different nations, according to variations in existing emissions trajectory. In other words, one policy may be more/less positive in one country versus another. This varied impact is particularly noteworthy for liquidity support of incumbent corporations, business tax deferrals, and business tax cuts. For high-emitters (versus low-emitters), economy-wide liquidity support is likely to impact future emissions more negatively in contrast to a scenario

without intervention. To address these deviations between countries, "emissions intensity adjustment factors" can be applied to subarchetypes A1, A2, B13, C6, E6, N1, N2, N4, and O2 (at least), which collectively account for ~30% of spending.

The emissions intensity adjustment factor accounts for heterogeneity in the impact of broad-base support for incumbent corporations. The size of an economy is a factor in the magnitude of liquidity support provided to businesses operating in that economy. The adjustment factor considers national CO_2 emissions as a proportion of GDP. The taxonomy takes the GDP-weighted global mean of CO_2 emissions per $ of GDP and then linearly assigns scores to individual nations based on deviation in emissions intensity from the global mean. Scores are distributed on a 0 to 1 scale according to the deviation from the mean. A score of 1 represents the large economy with the highest emissions intensity and therefore the highest positive deviation from the mean (South Africa has the biggest large nation deviation of +156%), while the lowest score is the nation with the lowest emissions intensity (Switzerland has a deviation from the mean of -76% and an adjustment factor of 0.09).

C3. Fiscal taxonomy for recessionary investment—GHG potential impact assessments

As discussed in the paper methods, assessments of potential GHG impact are based on (a) results of the Hepburn *et al.* (2020) global survey of leading economists,[9] (b) a first-principles literature assessment linked to each policy archetype, and (c) extended peer input and review. A summary of archetype and subarchetype scores is included in extended data table 2. Scoring details and literature are provided in sections C3.1 to C3.41.

C3.1. Archetype A: Liquidity support for subnational public entities

There is wide variation in industries and practices that may ultimately be supported by spending in this archetype; it is therefore difficult to assign a universal impact score for GHG emissions. Yet, in general, considering broad impacts across industries, policies in this archetype are expected to increase consumption relative to the level before the policy was implemented and this increase in consumer behaviour is likely to cause a moderate increase in short-term GHG emissions.[18] These policies are, however, temporary and in the general case there is little evidence to suggest that they will have significant GHG emissions impacts in the long-term, compared to a state without intervention. We therefore expect a moderate increase in GHG emissions short term (-1), but little net change long-term (0).

C3.2. Archetype B: Liquidity support for large businesses

Though there is wide variation in the policies under this archetype, it is expected that they will, in general, result in an increase in material use, manufacturing, and a general increase in consumption, relative to a scenario in which there was no intervention. Increased material use, manufacturing and consumption have broadly been shown to increase GHG emissions short-term.[19,20] We therefore expect, in general, a moderate increase (-1) in short-term GHG emissions because of these policies.

- For support for airlines, other transport and energy (B3, B4, B5 and B6), we expect even greater increases in GHG emissions (-2) relative to a scenario in which these policies were not implemented (*i.e.* where airlines would become insolvent), as these are both emissions-intensive sectorshttps://www.zotero.org/google-docs/?broken=BnPLwz.[21]

For long-term GHG impacts, there is significant variation by subarchetype, based on green conditionality and industry:

- For liquidity support that is not green-conditional (B1, B3, B7, B9, B11, B13), we expect little net change in long-term GHG effects, as support for individual companies is unlikely to alter business as usual emissions without intervention due to competitive market dynamics. In other words, if these corporations were not kept solvent, they would disappear in time, but the demand that they previously satisfied would continue and other corporations would rise to take their place. The reader should be reminded that in the no-intervention scenario, businesses would face significant risk of insolvency or down-scaling of operations. We therefore expect little net change (0) in long-term GHG emissions because of these policies.
    - An important exception is non-green conditional liquidity support for the energy industry (B5). Energy is an emissions-intensive sector, and it is expected that many traditional energy assets will become stranded under business-as-usual conditions with no intervention.[22] We therefore expect liquidity support for these businesses to result in increased long-term GHG emissions for an economy (-1).
- For liquidity support that is green conditional (B2, B4, B6, B8, B10, B12), we expect improvements in GHG emissions in the long term, as large corporations are unlikely to have implemented the green changes without the intervention. We therefore expect some decrease in long-term GHG emissions (+1) because of these policies.

C3.3. Archetype C: Liquidity support for startups and SMEs

Though there is wide variation in the policies supported under this archetype, it is expected that they will, in general, increase material use, manufacturing and consumption, relative to before the policy was implemented. These factors have broadly been shown to increase GHG emissions short-term.[19,20] We therefore expect, in general, a moderate increase (-1) in short-term GHG emissions because of these policies.

- For support for energy (C2), we expect significant increases in GHG emissions relative to before these policies were implemented, as these are both emissions-intensive sectors.[21] We therefore expect large short-term GHG increases (-2) because of these policies.

There is little evidence to suggest that liquidity support for startups and SMEs will have significant long-term GHG impacts. Due to competitive market dynamics, we expect that liquidity support for individual companies, especially smaller companies, will have little long-term effect compared to business-as-usual BAU practices without intervention. We therefore expect little net change (0) because of these policies.

- We note that for archetype B (liquidity support for large corporations), non-green conditional support for large energy companies was assessed as -1 for long-term GHG emissions. For energy SMEs and startups (subarchetype C1), we assume that because most of these operations are much smaller, their long-term GHG impacts are unlikely to be comparable in magnitude to the long-term GHG impacts of larger energy companies. It is likely that

in many cases smaller energy corporations skew towards clean energy operations (including for distributed energy resources, and emerging clean energy technologies). Hence, on balance, we perceive little net change (0) for C1 in the long term.

C3.4. Archetype D: Liquidity support for not-for-profit organisations

As not-for-profit organisations rarely rely on large-scale manufacturing or other material-heavy programs, they do not rank among the most emissions-intensive sectorshttps://www.zotero.org/google-docs/?broken=FoGcnd,[21] and there is little evidence to suggest that they have significant GHG impacts over any time horizon. We therefore expect little net change in GHG emissions (0) in both the short-term and long-term because of these policies.

C3.5. Archetype E: Temporary waiver of interest payments for businesses

In general, these interest waivers allow businesses to direct the resources that they would have otherwise used for these payments towards other business practices. This may result in an increase in material use, manufacturing, and ultimately increased consumption of end products by individuals, relative to before the policy was implemented. These factors have broadly been shown to increase GHG emissions in the short term.[20] However, there is little evidence that significant new long-term GHG emissions will come from these measures, especially as they are only temporary in nature. We therefore expect some increases in GHG emissions short-term (-1), but little net change in long-term GHG emissions (0).

C3.6. Archetype F: Direct provision of basic needs

There is little evidence of significant GHG effects from the direct provision of basic needs, as policies are usually relatively small and fund manufacturing or supply that would have occurred anyway and may have otherwise been wasted as in the case of food supply (morbidity implications are intentionally excluded from this analysis). Though there may be some manufacturing-related emissions involved here, they are not likely to be comparable in scale to other emissions-intensive industries. Therefore, we expect little net change (0) because of these policies in either the short or long term.

C3.7. Archetype G: Targeted welfare cash transfers

Policies in this archetype are usually designed to help consumers meet any direct and urgent needs resulting from the pandemic, and as an added benefit, support the businesses at which these individuals might spend. In the short-term, these policies might therefore increase consumption relative to a state in which the policy was not implemented (although of course this is not always the case in practice as marginal propensities to consume can vary widely). In general, increased consumption brings some increase in GHG emissions.[20] In the long term, however, there is little evidence to suggest that these policies have significant impacts on emissions, especially given their temporary nature (morbidity implications which are intentionally exclude from this analysis). We therefore expect a moderate increase in short-term GHG emissions (-1), but little net change in long-term emissions (0) because of these policies.

C3.8. Archetype H: Job continuation support

In allowing companies to keep individuals employed when they may not have otherwise been able to, these policies increase the amount of disposable income of those who would otherwise have lost their jobs. This is naturally expected to result in increased consumer activity by those individuals relative to a scenario with no policy intervention. Increased consumption increases GHG emissions.[20] However, there is little evidence to suggest that these policies have long-term impacts on GHG emissions (morbidity implications are intentionally exclude from this analysis). We therefore expect some increases in short-term GHG emissions (-1), but little net change in the long term (0).

C3.9. Archetype I: Temporary waiver of interest payments for individuals

These policies are expected to function similarly to welfare cash transfers to individuals, in that they are intended to increase the disposable income of the individual, thereby precipitating an increase in consumption. In general, increased consumer spending do result in some increases in GHG emissions.[20] In the long term, however, there is little evidence to suggest that these policies have significant impacts on emissions, especially given their temporary nature. We therefore expect a moderate increase in short-term GHG emissions (-1), but little net change in long-term emissions (0) because of these policies

C3.10. Archetype J:Healthcare services support

Most of the policies in this archetype are designed to rapidly scale-up healthcare capacity to manage the impact of the COVID-19 pandemic. In practice, this involves rapid increases in manufacturing of medical goods,

which raises short-term GHG emissions.[23] These policies are largely temporary, and there is little to suggest that they have significant long-term GHG impacts (morbidity implications are intentionally exclude from this analysis). We therefore expect moderate increases in GHG emissions in the short term (-1) and little net change in the long term (0).

- Measures categorized as mental health support (J2), aged care support (J3), and general medical personnel support (J4) are either largely digital because of physical distancing requirements or otherwise involve little manufacturing. There is little evidence to suggest meaningful negative GHG impacts of these subarchetypes at any stage of their implementation; therefore, we expect little net change (0) in short-term GHG emissions from this subarchetype.

C3.11. Archetype K: Emergency services (disaster management) support

Support for emergency services is vital, but in the short term, often involves manufacturing to ensure that sufficient resources for crisis management are available. This manufacturing is likely to bring a short-term increase in GHG emissions, driven by energy and materials usage.[19] In the long term, however, there is little evidence to suggest significant GHG impacts. We therefore expect a moderate increase in emissions short-term (-1), but little net change in the long term (0).

- Subarchetype K1 (administrative support for emergency response) is not likely to involve significant marginal manufacturing, and therefore we expect lower short-term GHG impacts than other subarchetypes. We therefore expect little net change (0) for both short and long-term GHG impacts for subarchetype K1.

C3.12. Archetype L: Income tax cuts

Policies in this archetype increase the disposable income of individuals. They are designed to both support direct urgent needs and, as a supplementary benefit, support the businesses at which these individuals spend. As such, in the short-term, these policies are likely to increase consumption relative to the counterfactual. In general, increased consumer spending increases GHG emissions.[20] In the long-term, however, there is little evidence to suggest that these policies will significantly impact emissions, especially given their temporary nature. We therefore expect a moderate increase in short-term GHG emissions (-1), but little net change in long-term emissions (0) because of these policies.

C3.13. Archetype M: VAT and other goods and services tax cuts

There is evidence to suggest that reductions in VAT could result in increased demand for consumer goods.[24] In general, increased consumption is expected to somewhat raise short-term GHG emissions,[20] however studies have shown that temporary VAT changes are unlikely to increase long-term demand,[25] so long-term GHG impacts may not be significant. We hence expect a moderate increase in GHG emission in the short term (-1), but little net change in long-term emissions (0).

C3.14. Archetype N: Business tax cuts

In general, tax cuts allow businesses to direct the resources that they would have otherwise used for tax payments to other business practices. This may bring an increase in material use, manufacturing, and consumption of end products by individuals, relative to before the policy was implemented. These factors have broadly been shown to increase GHG emissions in the

short-term.[19,20] However, there is little evidence that these kinds of policies will increase long-term GHG impacts except if they precipitate a downward price shift in the supply curve. Yet, since this archetype speaks explicitly to temporary business tax cuts, any shift in the supply curve would also be temporary. We therefore expect some increase in short-term GHG emissions (-1), but little net change in long-term GHG emissions (0).

- For subarchetype N3 (new tax exemptions for clean and/or resilient investments), we expect a different emissions profile as policies in this archetype should support cleaner modes of business and consumption. While few GHG impacts are expected short term, in the long term, the new clean investments that are likely to result from these policies are expected to lower net GHG emissions. We therefore expect little net change in short-term GHG emissions (0), but a reduction in emissions in the long term (1).

C3.15. Archetype O. Business tax deferrals

In general, tax deferrals allow businesses to direct the resources that they would have otherwise used for these payments towards other business practices. This might increase material use, manufacturing, and ultimately consumption of end products by individuals, relative to before the policy was implemented. These factors have broadly been shown to increase GHG emissions in the short term.[19,20] However, there is little evidence that these measures will impact long-term GHG emissions as they are temporary in nature. We therefore expect some increases in GHG emissions in the short term (-1), but little net change in long-term GHG emissions (0).

- For subarchetype O1 (tax deferrals for dirty industries), we naturally expect increases in short-term GHG emissions to be larger in magnitude than they would be for other industries, as these have particularly high emissions intensities. Long-term impacts, however, are still expected to be minimal due to the temporary nature of the policies. We expect large increases in GHG emissions in the short term (-2), but little net change in long-term GHG emissions (0) for policies on subarchetype O1. Researcher discretion is advised for considering tax deferrals for fossil energy operators which face stranded asset risk if the deferrals are not made.

C3.16. Archetype P: Reduced prices for centrally controlled products and services

There is little evidence of significant GHG effects resulting directly from reduced prices for centrally controlled products, either in the short or long term, especially given the temporary nature of the changes. Therefore, we expect little net change (0) because of these policies in either the short or long-term. There is likely to be high variation at the country level for this archetype—unfortunately these variations cannot be captured in the present assessment.

- The subarchetype relating to fuel prices including oil and gas (P2) is expected to have different short-term effects to the other subarchetypes. Though variation is expected on a country-by-country basis, the reduction of the prices of these items should increase their consumption, and since they are fossil fuels, this is expected to increase GHG emissions in the short term. Long-term however, these measures are theoretically temporary and therefore

expected to have minimal effect unless they lead to a permanent change in consumer habits (researcher discretion is advised). We therefore expect a significant increase in short-term GHG emissions (-2), but little net change in the long term (0) for subarchetype P2.

C3.17. Archetype Q: Other tax cuts and deferrals

This is a particularly broad archetype, and differences in assessment may exist at the policy level that we are unfortunately unable to capture with this assessment model.

Though there is wide variation in the policies that might be covered in this category, we can reasonably assume that the final output they ultimately allow for increases materials use, manufacturing, or consumption relative to no policy intervention. These factors have short-term GHG impacts,[19,20] though due to the temporary nature of these policies, there is little expectation of significant long-term GHG impacts. In the most general of cases, we therefore expect some increases in GHG emissions short-term (-1), but little net change long-term (0). Researcher discretion is advised.

C3.18. Archetype R: Targeted recovery cash transfers

The aim of targeted recovery cash transfers is usually to promote spending and therefore a return to BAU practices. Several studies have shown that direct transfers do, by and large, lead to higher consumption,[26,27] and heightened consumption is associated with increases in GHG emissions.[28] However, these measures are usually only implemented during a crisis and intended as temporary. Long-term emissions impacts are low, considering the temporary nature of targeted recovery cash transfers, as they should not affect life-long consumption patterns. Hence, targeted transfers are

generally expected to increase short-term GHG emissions (-1) as BAU practices return but bring little net change (0) to long-term emissions.

C3.19. Archetype S: Tourism and leisure industry incentives

Overall, the tourism and leisure industries contribute significantly to global GHG emissions.[29–31] Depending on the scope of emissions included and assessment methodology used, these industries generate between 4.4% - 8% of worldwide CO_2e emissions[30,31] The sector is growing due to heightened demand, entailing upward trends in GHG emissions.[29,30] Further, there seems to be limited scope to reduce emissions through technological or processual improvements.[29,30] Recent assessments have placed tourism and leisure behind manufacturing and construction in terms of the carbon multiplier, which is a ratio of CO_2e emissions per US$ generated in economic value, demonstrating the high carbon intensity of the industry.[30] The high carbon intensity of tourism and leisure is driven primarily by its extensive transportation needs, entailing a strong correlation between the level of emissions per tourist and distance traveled.[30,32–34]

General hospitality infrastructure also contributes significantly to sectoral GHG emissions.[35] Hospitality sites, and in particular large hotels, are among the least sustainable building types in terms of energy consumption (Beccali *et al.*, 2009; Rahman *et al.*, 2011).[35,36] Further, the active tourism and leisure industries require the support of manufacturing (to meet often high shopping demands of tourists) and agriculture (to provide the necessary quantity of food and beverages). The above general evidence is supported by a wide array of national case studies, showcasing substantial increases in CO_2e emissions due to the growth of the tourism

and leisure industries.[37–39] Domestic practices, most importantly sourcing energy from renewable sources, decrease the carbon footprint associated with providing for tourists.[30]

S1 (Incentives for general tourism) and S3 (Incentives for hospitality services) could allow a swifter return to carbon-heavy BAU practices in the leisure and tourism sector in the short term (-2). We expect these policies to have lower, but substantial, effects in long run (-1).

S2 (incentives for greener and/or more resilient tourism including ecotourism) is likely to reduce long-term emissions compared to the status quo scenario of no green investment. Green or sustainable tourism initiatives can be categorised as either: i) making existing tourism more sustainable, such as through energy efficiency improvements, switching to renewable energy sources and encouraging shorter travel distances; or ii) investing in new eco-tourism initiatives, such as sustainable safaris and lodging. Efforts to make existing tourism more sustainable have typically been outweighed by simultaneous growth in the industry in general, resulting on net in higher GHG emissions in the short-term, despite ongoing efforts to reduce the industry's GHG impact.[30] In the case of new investment in eco-tourism, Higham (2007) finds that eco-tourism has a high transportation component and, in some cases, can outweigh conventional tourism in terms of its carbon footprint, due to the high material costs of infrastructure construction, the fossil fuel intensive profile of current transportation options, and the reluctance of consumers to voluntarily reduce their personal tourism carbon footprints.[40,41] However, many other green tourism initiatives, like improving energy efficiency in hotels, can demonstrably reduce carbon emissions. Overall, compared to a scenario in

which these policies were not implemented, we therefore expect them to have little net impact on GHG emissions in the short-term (0) and a small positive impact in the long-term (+1).

S4 (Incentives for arts and cultural activities) are expected to bring limited impact to GHG emissions in both the short and long run (0) as these policies do not target the biggest factors contributing to the tourism and leisure industries' carbon footprint.

S5 (Measures to promote leisure participation) are expected to bring some effects on GHG emission levels in the short run (-1) and little impact in the long run (0). While it depends very much on the initiative in question, incentives to promote leisure participation usually occur at the domestic level, thus incentivizing shorter distances for travel, with corresponding reductions in GHG emissions.

C3.20. Archetype T: Electric vehicle incentives

EV incentives spur heightened demand, especially in countries with sufficient infrastructure supporting easy utilization.[42,43] EV production brings a moderate increase in GHG emissions, in some cases even more than conventional vehicles due to the resources and energy consumed during battery production.[44] That said, the difference can be relatively small.[45] Further, there is substantial scope for recycling and repurposing of batteries, driving down the yearly average of GHG emissions associated with the production phase of EVs.[46–48] The strongest driver of EV emissions is the energy-mix used for powering the car.[49,50] EVs powered with a coal-heavy energy mix, assuming an extreme case, may have a higher carbon footprint than highly efficient ICEVs.[45,51–53] Regional case studies,

performed in coal-powered regions in China, Poland, and the US corroborate this.[51,54] Nevertheless, assuming a moderately clean energy mix, higher utilisation of EVs is associated with substantial reductions in GHG emissions over the vehicle's full lifecycle.[44] Further, in the case of a sustainable energy mix, like that in Scandinavia, lifecycle emissions are lower than that of traditional internal combustion vehicles by a significant margin.[49,50] Hence, incentivising EV purchases, in conjunction with a clean energy mix, is a crucial component of the transition towards a clean economy.[50,55]

Considering the above, we assume an increase in GHG emissions in the short term (-1) for both T1 (EV transfer programs) and T2 (EV subsidies) due to the carbon footprint of the manufacturing process. In the long run, investment in both T1 and T2 is expected to lower GHG emissions, with the size of the benefit determined by the domestic energy-mix. The countries under assessment vary significantly with respect to said factor. An average of (+1) is assigned, unless the correction factor of O'Callaghan and Murdock (2021) is applied,[6] in which case a value of +2 should be used.

C3.21. Archetype U: Electronic appliance and efficiency incentives

Incentivising electronic appliance purchases leads to increased manufacturing to match subsidised demand. This is likely to bring a moderate short-term increase in GHG emissions (-1) due to the materials and energy used during the production processes.[19]

Speaking to the long-term impact, it is likely that in the absence of an incentive program, consumers would be less likely to purchase the more

efficient appliance. There appears to be a large "energy efficiency gap", consumers sometimes fail to make energy-saving purchases with a positive net present value.[56,57] Incentive programs attempt to address this gap, but the impact of any program will vary depending on many context-dependent factors. [58,59]

Furthermore, the Jevons paradox explains that the incentive measures might not always bring the desired energy savings.[57,60,61] Higher efficiency may lead to a rebound effect of increased consumption because every unit of consumption is cheaper (Sorrell, 2007).[62] Preexisting consumer patterns, and appliance choice, will play a key role in the energy use outcome of the policy.[63] Accounting for these different factors, a moderate reduction in GHG emissions is expected for the archetype in the long term (+1).

C3.22. Archetype V: Green market creation

Considering the extensive time frame needed to develop and expand green markets, little to no GHG emission impact is expected in the short term (see Duke and Kammen, 1999; Jacobsson and Lauber 2006).[64,65] In the long term, increasing energy market participation for renewables (V1), investing in transitional technologies (V2), and incentivizing ecosystem services (V4) are vital for sustainability. There is substantial empirical backing for the efficiency of such policies. In OECD and EU countries, public investment schemes likely contributed significantly to the attractiveness of green markets, drawing an influx of private capital and spurring long-term development.[66,67] Similar conclusions on the role of state-led green market creation have been reached in national studies, for instance, in Germany,[65] Korea,[68] and Turkey.[69] Policy can significantly accelerate the emergence

and early performance of green markets.[70,71] The accessibility of finance seems to contribute substantially to the effectiveness of fiscal policy for this archetype, but the general assessments of this taxonomy are not capable of capturing variation across countries and so researcher discretion is advised.

We, therefore, expect little net change in GHG emission from this archetype in the short-term (0) but large improvements in emissions (+2) in the long-term.

C3.23. Archetype W: Other incentive measures

Many varied policies are likely to be categorized to this archetype, with corresponding variance in GHG impact. In their most general sense, incentives aim to promote consumption of some good or service. Sometimes the incentive might promote one good or service at the direct disadvantage of another (*i.e.*, zero sum) and sometimes there might be no losers. In the former case, we would expect a lower impact on net GHG emissions in the short term when compared to the latter case. Given a high degree of uncertainty, we suggest that a neutral GHG expectation (0) is used as a baseline for both the short and long term. Researcher discretion is advised.

C3.24. Archetype X: Worker retraining and job creation

In the short term, while training programs are ongoing, there is little evidence that spending will induce significant GHG impacts. In the long term, there is naturally variation in GHG impacts dependent on the industry for which individuals are being trained. In general, determining what employment a worker is likely to secure because of their training is not straightforward. Further, it is difficult to attribute GHG emissions from the employing industries to the original worker retraining programs. We,

therefore, expect little net change in both short-term and long-term GHG emissions (0) because of such policies.

- For subarchetypes X1, X2, and X3 (green worker retraining and job creation), it is well documented that for emissions to be reduced in accordance with current targets, there will need to be a significant shift in worker skills to meet the needs of a decarbonized economy.[72–74] In the short-term, we expect these policies to have little impact on GHG emissions (0), as the emissions benefits from relevant adaptation projects are a step removed from the training itself. In the longer term, however, green worker retraining programs (of which adaptation and resilience training is a subset) are expected to have positive impacts on greenhouse gas emissions as they begin to redirect economic activity towards decarbonisation initiatives.[75] The adaptation and unclassified green policies are therefore expected to have a moderate, positive (1) impact on GHG emissions in the long-term. The mitigation policies are expected to have a higher positive (+2) impact.

C3.25. Archetype Y: Education investment

In the short-term, investment in physical infrastructure and equipment in the education sector (Y4) is expected to cause significant increases in GHG emissions (-2), due to the emissions intensity of the construction process.[76,77] Investments in equipment are likely to have a smaller immediate impact, but still increase emissions (-1). Staff and scholarships are unlikely to have a significant impact beyond the status quo (0). In the longer term, the majority of new GHG emissions is likely to be from electricity consumption

and manufacturing of educational materials, which is only indirectly linked to the presence of educational infrastructure. Therefore, we expect little net change long-term (0) from educational infrastructure investments.

- For Y5 (Funding to support understanding of climate change mitigation, adaptation, and/or resilience), funding could conceivably reduce GHG emissions in the long term. Educational programs can mitigate climate change by instilling behavioural change towards lower-emissions lifestyles, social structures, and economies.[78] However, the pathways through which educational programs impact GHG emissions are indirect, and there has been limited evidence demonstrating tangible outcomes of educational programs on emissions reductions so far.[78] In the absence of greater evidence, it is difficult to decisively assess the impact of these policies; we suggest a low direct impact (0) on GHG emissions in the short-term and a hopefully positive impact in the longer-term (+1).

C3.26. Archetype Z: Healthcare investment

Healthcare contributes substantially to global GHG emission levels, although the impact varies based country-to-country. A US healthcare sector assessment for 2013 notes an increase in sectoral emissions from 8% to 10% of total national emissions.[79,80] The biggest contributors were hospital care (36%), physician and clinical services (12%), and the prescription drugs sector (10%). While the US is an outlier, it is not the case that the emissions from the healthcare sector are of a negligible magnitude. In Australia, the sector contributes 7% of the general GHG emissions.[81] In Japan, healthcare contributed 5.2% of the country's carbon

footprint.[82] In Canada, the negative impact of the sector is smaller but still significant.[83] Pichler *et al.* (2019) found in a cross-national study that in a group of 35 countries including both HICs and developing nations like India, Mexico, and Turkey, the mean share of healthcare related GHG emissions was 5.4%, with the highest levels occurring in the Netherlands, the US, and Belgium.[84] Although there is variability on the domestic level, the linkage between the broadened healthcare sector and increase in GHG emissions is well-established.

Subarchetype Z5 (physical healthcare infrastructure investment) is likely to have a larger emissions role than other subarchetypes, due to its focus on infrastructure. Most other subarchetypes are focused on non-infrastructural initiatives, bringing correspondingly less impact on GHG emissions. Policies supporting the emergence of efficient telemedicine can decrease the GHG emissions associated with commuting to healthcare facilities.

All considered, there is likely to be a small detrimental change (-1) in short-term and ambiguous changes in long-term (0) GHG emissions resulting from these varied policies. The exception is subarchetype Z5, where large detrimental GHG emissions (-2) are expected in the short term. There is substantial heterogeneity in emissions from country-to-country that this assessment is not able to capture.

C3.27. Archetype α: Social and cultural investment (non-infrastructure)

There is little evidence to suggest that social and cultural initiatives, in general, have any significant impact on greenhouse house emissions. We, therefore, expect little net change (0) because of these policies.

C3.28. Archetype β: Communications infrastructure investment

Infrastructural investments are, in general, high emissions initiatives, thus short-term increases in GHG emissions are expected. In the long run, mixed effects will follow. First, considering the complementary nature of infrastructure and ICT devices, we assume an increase in demand for such goods will be seen as soon as the investments are completed. The manufacturing of ICT devices, mobiles, laptops, and the like carries a substantial carbon footprint.[85] Further, the utilisation phase of such appliances entails energy usage, which in a setting with a carbon-heavy energy mix can mean heightened GHG emissions.[86,87] Infrastructure maintenance and operations contribute somewhat to the national carbon footprint through electricity used for power and cooling.[88] Nevertheless, the ICT sector has been at the forefront of efficiency increases in terms of energy usage, which is tracked by its substantial lobal carbon footprint.[86,89]

In the long term, improved communication network coverage will presumably alter the day-to-day behaviours of individuals and.[90–95] Digitalisation could lead to some positive effects on national GHG emissions. As just one practical example, electronic invoicing can substantially reduce energy consumption compared to traditional invoicing.[96] Similar arguments regarding the possible environmental benefits spurring from digitalisation are shown by Weber *et al.* (2010) for downloading music and by Amasawa *et al.* (2018) for the adoption of e-readers.[97,98]

ICT development has been widely associated with decreased vehicle use and reduced traffic, which has a double emissions benefit.[92–95] Practices like remote working and internet conferencing are among the drivers of this relationship.[90,95] Nevertheless, general positive impacts on GHG emissions

from efficiency gains may not be realised if rebound effects are included in the evaluation.[61,99] Increases in efficiency may spur lower savings rates and "substitution effects. The ICT sector is arguably especially prone to substantial rebound effects, as it greatly decreases the costs of service delivery.[85] Per sale, internet retail reduces the GHG emissions of distribution, but if the ease of purchase leads to increased demand, the net effects on emissions are mixed.[100–102]

Further, rebound effects might include accelerated economic growth, associated with increased productivity and production.[85] This has been supported by regional studies in OECD countries, US, Finland, and several South Asian countries.[85,103–108] Nevertheless, the causal relationship between ICT development and economic growth remains controversial.[85]

For $\beta 1$ (broadband investment), we expect substantial increases in GHG emissions in the short term (-2) due to the manufacturing and production phase of investment. $\beta 2$ (Remote working infrastructure investment) attracts the score of (-1) in the short term. $\beta 3$ (civil cybersecurity programmes) and $\beta 4$ (implementation of digital programmes) do not come with significant short-term impacts on GHG emissions due to the lack of a construction phase. In general, as the archetype in question facilitates the long-term development of ICT technologies on the national scale, we assume mixed and ambiguous effects, and therefore a score of (0).

For $\beta 5$ (Improve resilience of existing communications infrastructure), improvements may include upgrades to physical structures and networks, such as enhanced diversity of systems, improved spatial and environmental planning, and the introduction of additional network nodes for at-risk

regions that do not have diversified network coverage.[109,110] Other improvements may include new technologies, such as the use of cloud computing to shift computational loads away from regions experiencing extreme weather conditions, and improved contingency planning and use of early warning systems.[109] Many of these solutions involve enhanced planning and use of existing systems, thus limiting short-term GHG emissions. While some new construction may be required (such as the installation of additional nodes to diversity network coverage), this is anticipated to be limited in scope compared to other sectors and infrastructural projects. We therefore expect little net change (0) in short-term and long-term greenhouse gas emissions from these policies.

C3.29. Archetype γ: Traditional transport infrastructure investment

In the short term, traditional transport infrastructure projects are highly carbon intensive in construction (-2), driven by material and energy use.[76,111,112] In the long term, traditional transport infrastructure investment, in particular, funding for aviation sites and road construction, increases the general utility of transportation vehicles, including planes and ICEV, thus delivering heightened use of those assets and increased GHG emissions in the long run. However, in the case of road construction, increasing electric vehicle sales complicate the assessment of long-term emissions impact. In most major geographies, and particularly in the advanced economies that are making major road investments, higher road investment is not guaranteed to increase long-term emissions because new roads might decrease travel length and could disproportionately advantage EVs. Therefore, adopting a conservative interpretation, traditional transport

infrastructure investments falling under the $\gamma 1$ (road construction) archetype brings an unclear (0) impact on long-term GHG emissions. $\gamma 2$ (ICE automobile support) will impact demand for fossil-fuel-burning vehicles, which carries a long-term negative impact on GHG emissions (-2). For $\gamma 3$ (aviation infrastructure), no near-term shift towards non-fossil airplanes means that increased investment is likely to significantly increase GHG emissions (-2) in the long term. $\gamma 4$ (Port and ship construction) supports freight, which tends to be a carbon-intensive mode of transportation, but not as intensive as other options.[113–115] Therefore, the $\gamma 4$ archetype attracts the scores of (-1) in the long run. $\gamma 5$ (Rail construction and capacity) increases the ease of public transportation and the efficiency of rail shipment, which could lower national GHG emissions associated with transportation in the long term (+1).

C3.30. Archetype δ: Clean transport infrastructure investment

In the short term, clean transport infrastructure projects are carbon intensive during the implementation phase due to the materials and energy used.[76] Long term, clean transport infrastructure plays a vital role in reducing GHG emissions, as it directly disincentivizes the use of high-emission traditional transport modes such as personal ICEVs.[42,43,116] It is therefore expected that clean transport investment brings significant short-term increases in GHG (-2), but large improvements in GHG emissions long-term (+2). $\delta 4$ (public transport digitalisation efforts) is an exception, with no short-term impacts on GHG emissions.

Efforts to increase the physical resilience of transportation infrastructure to climate change ($\delta 7$) are varied, including: switching paving materials, conducting more frequent maintenance, upgrading drainage systems, increasing shading, elevation, relocation and fortification of roads, tunnels, and bridges, and adding additional infrastructure such as levees and seawalls.[117] While transportation infrastructure in general contributes to greenhouse gas emissions by facilitating the use of combustion vehicles,[118] those impacts are attributed to BAU use of existing infrastructure, not to additional resilience measures, specifically. Some of these policy options involve construction and materials use, which is a greenhouse gas emissions intensive process.[76,77] However, the extent of construction required is smaller in scope than the construction of new transportation infrastructure. These policies are thus expected to increase greenhouse gas emissions by a modest amount (-1) in the short term. The long-term impacts of more resilient transportation infrastructure on GHG emissions are expected to be neutral (0).

C3.31. Archetype ε. Traditional energy infrastructure investment

As with almost all construction projects, traditional energy infrastructure projects are expected to have negative GHG impacts in the short term, mainly derived from material use (Behrens, 2016). As these policies directly perpetuate fossil fuel production and consumption, they are likely to cause large increases in GHG emissions long term. Therefore, these policies are expected to result in significant increases in GHG emissions (-2) both the short and long term.

For $\varepsilon 5$ (improve resilience of existing energy infrastructure), measures range from management and technical solutions to technological and structural solutions. Management and technical measures can include vegetation management, underground transmission and distribution networks, load forecasting, and improved early warning systems .[119] Technological and structural measures can include fortifying flood-prone and offshore infrastructure, relocating infrastructure away from high-risk zones, and the implementation of smart grids and micro grids to better manage generation and distribution.[119] Some of these solutions require construction and materials use, which is an emissions intensive,[76,77] thus resulting in a moderate increase (-1) in short-term GHG emissions. The long-term emissions implications of increased resilience of traditional energy infrastructure are complex. On the one hand, improving the resilience of traditional energy infrastructure, which emits high volumes of greenhouse gases,[120] will prolong its usage, thus increasing the overall emissions from each of these facilities. On the other hand, prolonging the usage of existing facilities may slow the installation of new traditional energy facilities. The latter hypothesis has however been at least somewhat overstated in political discourse. While new installations of traditional energy facilities, such as coal power plants, have slowed in recent years, the primary reasons are lower-cost renewable alternatives, greater awareness of environmental risk, and scarce financing options, rather than the lifetime of existing facilities.[120] As such, increasing resilience of existing traditional energy infrastructure is expected to have a moderate but negative (-1) net long-term impact on GHG emissions.

C3.32. Archetype η: Clean energy infrastructure investment

As with almost all construction projects, clean energy infrastructure is expected to have negative GHG impacts in the short term, mainly due to material use.[19] Long term, however, clean energy projects facilitate the transition away from fossil fuels and therefore significantly reduce GHG emissions.[121] Hence, these policies are expected to result in a significant increase in GHG emissions short term (-2), but a significant decrease long term (+2).

For $\eta 5$ (improve resilience of existing clean energy infrastructure), measures range from management and technical solutions to technological and structural measures. Management and technical measures can include load forecasting and improved early warning systems.[119] Technological and structural measures can include designing wind turbines for higher wind speeds, fortifying flood-prone and offshore infrastructure, relocating infrastructure away from high-risk zones, and the implementation of smart grids and micro grids to better manage generation and distribution.[119] Some of these solutions require construction and materials use, which is an emissions intensive process,[76,77] but the magnitude of impact is likely to be less than that of investment in new infrastructure. As such, we expect moderate negative (-1) short-term greenhouse gas emissions. In the long-run, more resilient clean energy infrastructure will prolong the lifespan of these facilities, thus enabling greater renewable energy consumption, which in turn decreases greenhouse gas emissions.[120,121] These policies are thus expected to have a positive (+1) long-term impact on greenhouse gas emissions.

C3.33. Archetype θ: Local (project-based) infrastructure investment

In the short term, these, like almost all construction projects, are expected to cause significant increases in GHG emissions because of the various stages of the construction process involved.[77] However, there is little evidence of significant GHG effects on local infrastructure investment. Therefore, we expect significant increases in short-term GHG emissions (-2) and little net change in the long term (0).

Clean and/or resilient investments in housing (θ3) and public buildings (θ5) are generally expected to be similar to the equivalent general investments in terms of short-term GHG emissions due to the construction process (-2), but in the long term, these buildings are expected to be more energy efficient than others and often use clean energy through rooftop solar power or other means.[122] Therefore, it is expected that these investments will reduce GHG emissions in the long term (+1).

For clean and/or resilient investment in local utilities (θ7), impacts are likely to be similar to those of traditional investments in utilities. However, as in the case of clean housing and public buildings, the long-term impacts could be moderately to significantly positive, depending on the scale of the investment. As a baseline, in the absence of capacity expansion, most clean and resilient utilities are expected to see reductions in greenhouse gas emissions (+1), due to improved energy efficiency.

C3.34. Archetype λ: Building upgrades and energy efficiency infrastructure investment

In the short term, these programs involve construction and manufacturing, which have been shown to cause significant GHG emissions by using materials and energy.[19] Long term, however, energy efficiency

improvements associated with building upgrades are expected to bring large decreases in GHG emissions.[123] We, therefore, expect these policies to cause a large increase in GHG emissions short-term (-2) and a large decrease in emissions long-term (+2).

Other building upgrades and support ($\lambda 3$) policies are not explicitly related to clean energy or energy efficiency. There is little evidence to suggest that these policies will cause significant changes in long-term GHG emissions. Therefore, these are expected to result in little net change (0) in long-term GHG emissions.

C3.35. Archetype μ: Natural infrastructure and green spaces investment

Though there may be some negative GHG impacts resulting from short-term construction efforts through some of these policies, for the vast majority, there is evidence that the expansion of green spaces results in decreased emissions in both the short and long term.[124] We, therefore, expect moderate improvements in GHG emissions (+1) in both cases.

For subarchetypes $\mu 2$ (Environmental re(building) initiatives including afforestation, reforestation, and environmental rehabilitation) and $\mu 3$ (Environmental protection initiatives including conservation and natural infrastructure resilience), we expect large long-term GHG benefits (+2) as they likely support carbon sequestration.[125–127]

C3.36. Archetype ω. Agriculture and fisheries

While agriculture is a high GHG-emitting sector,[128–130] additional investments in general agricultural projects (ω1) are not expected to substantially alter the BAU trajectory. Population growth and

demographic change drive increases in calorific demand and therein facilitate growth in private investment. New public investment generally acts to either (i) shift current growing/rearing patterns rather than total calorific content, wherein the GHG impact of those shifts depend entirely on which patterns are being supported and which are being put aside, or (ii) promote more efficient practices of agricultural production, which might reduce energy use but possibly simultaneously boost total production—again, it depends entirely on the policy. Therefore, in the absence of more specific policy-level details, this subarchetype is expected to bring little net change (0) to GHG emissions, both in the short-term and long-term.

By contrast, clean and/or resilient agricultural practices (ω2) have a positive impact on short-term (+1) and long-term (+2) GHG emissions, via two key pathways. First, by encouraging carbon sequestration in soils and vegetation at significant magnitudes, both in the short-term and long-term (while soil carbon sequestration potential is not indefinite, it is nonetheless maintained over longer time horizons of decades under certain environmental conditions).[131–135] Second, by avoiding GHG emissions that would have been released under conventional agricultural practices, such as reducing the use of synthetic chemicals (which produce GHG emissions, such as nitrous oxide and carbon dioxide), with both short-term and long-term positive impacts.[131,135]

Fisheries represent a notable source of GHG emissions and additional public investments in general fisheries projects without environmental controls (ω3) can significantly change local marine environments, reducing GHG sequestration and/or increasing GHG release.[136–140] However, the

GHG impact per dollar will vary by project, with many projects likely having little to no impact or even shifting demand away from farmed or overfished regions. As such, we provide a low negative score (-1) for GHG impact in both the short and long term.

Clean and/or resilient fishery practices (ω4) have been shown to reduce GHG emissions from fishing through two main pathways. First, practices such as switching to sustainable harvesting equipment (such as substituting passive fisheries, trap fisheries, or gillnets for conventional dredging, bottom-trawling, and beam-trawling equipment) might have co-benefits for emissions, as they are less energy-intensive, resulting in a lower GHG emissions output.[141] Second, sustainable aquaculture practices, such as improved feed and nutrition management and integrated aquaculture, result in lower GHG emissions.[142] Clean and/or resilient fishery practices thus have a positive (+1) impact on short and long term GHG emissions.

C3.37. Archetype π: Other large-scale infrastructure investments

As with most physical infrastructure projects, there are significant GHG emissions associated with the construction process of this archetype, impacting short-term emissions.[143,144] Long term, there is little evidence to suggest GHG emissions are significantly impacted by these general policies. Therefore, we expect a large increase in GHG emissions in the short term (-2) and little net change in the long term (0).

Large-scale space infrastructure (π3) may have long-term GHG emissions consequences resulting from ongoing fuel and servicing costs, though this is small relative to other GHG sources.[145] We, therefore, expect some increase in long-term GHG emissions because of these policies (-1). Of course, some

space initiatives might involve satellite monitoring of the earth for environmental purposes (for instance, the space agencies of New Zealand and Gabon); in these cases, we suggest that the relevant policies might be better archetyped as $\psi 4$ (other sectoral R&D programmed), but the researcher should use their discretion.

C3.38. Archetype σ: Armed forces investment

Investment in the capacity and arsenals of armed forces, including police and defence, is likely to cause significant increases in GHG emissions, both in the short and long term. Short-term impacts are likely to be coupled to the construction of new military equipment and enhancement of capabilities, while long-term effects will result from continued use of hydrocarbon fuels.[146,147] We, therefore, expect large increases in GHG emissions (-2) in both the short and long term for this archetype.

In the case of administration funding ($\sigma 2$), GHG effects are likely to be smaller (-1) in the short term for administrative investments, but in the long term, this subarchetype still directly facilitates carbon-intensive operations, thus the long-term score (-2) remains.

Researchers should note that some governments mobilise their military personnel for environmental initiatives that might indirectly support lower GHG emissions. For instance, the Seychelles Coast Guard is a branch of the defense force that actively engages in environmental protection. In the case that military support is clearly divided into those programs which do and don't serve environmental objectives, we consider that the relevant environmentally positive designations might be better categorized to another archetype (with the most appropriate archetype determined by the

sector that is supported). As always, the researcher should use their discretion.

C3.39. Archetype τ: Disaster preparedness and capacity building investment

Most policies with a procurement or construction requirement are likely to rely on manufacturing and construction processes, bringing a short-term increase in GHG emissions.[19,148] In the long term, however, there is little evidence to suggest significant GHG impacts will be major. We therefore expect a moderate increase in emissions in the short term (-1), but little net change in the long term (0).

Most investments in risk assessment and early warning systems (τ2) will primarily entail administrative activities and the use of existing computational and communications equipment, thus requiring little additional GHG emissions. In some contexts, additional communications and computational infrastructure may be required, thus necessitating construction and material use, both of which bring GHG emissions.[19,76,77] However, the additional construction and materials requirements are expected to be limited in scope compared to other sectors and to large-scale infrastructural projects. We therefore expect little net change (0) in short-term and long-term GHG emissions from these policies.

For indirect climate change adaptation and resilience measures (τ6), GHG impacts are likely to be subdued. These policies typically centre around socioeconomic, political, administrative, and planning activities,[149] which have a limited first order impacts on GHG emissions. As such, we

expect little net impact (0) on GHG emissions in both the short and long term from these policies.

C3.40. Archetype φ: General research and development investment

Research projects, in general, have little short-term impact on GHG emissions as they do not usually involve large-scale manufacturing or other high-emission activities. Of course, there is wide variation between projects, with some having quite high emissions impacts per dollar of investment. However, even research projects that are not explicitly 'clean' often aim to reduce costs in existing processes and bring some energy efficiency improvements through innovation. Therefore, for the general case, we expect little net change in short-term GHG emissions (0). In the long term, for health and science programs ($\varphi 1$) as well as digitization and AI programs ($\varphi 2$), we expect moderate improvements (+1). For space programmes, the GHG impact will depend on the nature of the funded initiatives; overwhelmingly, initiatives are likely to increase long-term GHGs by enabling more emissions-heavy space operations (-1), but climate change satellite monitoring initiatives could clearly have a positive impact. For general and other programs ($\varphi 4$), given high variability in initiatives, we assume a negligible long-term baseline impact (0). We advise that the researcher use their personal discretion in making related impact assessments.

C3.41. Archetype ψ: Clean research and development investment

Research projects, in general, have little short-term impact on GHG emissions as they do not usually involve large-scale manufacturing or other high-emission activities. Of course, there is wide variation between projects,

with some having quite high emissions impacts per dollar of investment. By their nature, clean research and development projects are designed to assist in reducing GHG emissions in the long term, and this is often effective.[150–152] Therefore, we expect little net change in short-term GHG emissions (0), but large improvements in the long term (+2)

For R&D programs targeted to the areas of adaptation and resilience (ψ5), GHG impacts are likely to vary between initiatives, in large part due to differing spillover effects. Measures for climate resilience often have synergies with, or co-benefits for, climate change mitigation objectives, specifically GHG emissions reduction.[153] This is particularly true for land-related initiatives in agriculture and forestry (*e.g.*, agroecology reduces GHG emissions and enhances climate resilience), as well as green infrastructure and urban greening initiatives.[153,154] Given the synergies and co-benefits between climate change resilience and mitigation initiatives, green R&D programmes that focus on climate resilience are therefore expected to have positive GHG outcomes in the long-term (+1).

C4. Total and green recovery data using the fiscal taxonomy

C4.1. GRO data summary—total

Tables C4a-C6d provides a summary of spending by subarchetype in each country tracked in the GRO, organised alphabetically. Table C4a considers Antigua and Barbuda to Egypt; table C4b considers El Salvador to Mexico; table C4c considers Mongolia to Spain; table C4d considers Suriname to Vietnam. Archetype definitions and examples are included in table C3. Rows might not sum to total due to rounding.

Table C4a. Total spending per subarchetype per region: Antigua and Barbuda to Egypt.

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
A1		2	0.6							0.3	41														
A2		0						0						0.4		0.2			0.6	0	1.4				
AUnclear																									
B1	0	0							0			0	0.5							0.1	2.1		0.1		
B2																									
B3	0	0	1.6				0	0.6		0	0.7					0				0	3.5				0.1
B4				0.7							0														
B5		0	0		0																				

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
B6											0.3														
B7		0		0.4		0.1	0.1	0.1	0		0		0.4			0					1				1.5
B8																									
B9																									
B10																									
B11		2	0.2		0						0.4		2.5	0	0.1	0.4	0.1		14.5	0.1	1.5		0		0.4
B12												0.1	0								0				
B13	0	4.8	16.8	30.8		3.5	0	56.6					1.1	2.8	5.4	0.1			0.4	0	23.3		0.7		
BUnclear																									
C1		0											7			0	0			0			0		
C2							0																		
C3		0	0.2	0.6																					
C4																									
C5		0.1	9	0.1	0	0.2		0	0			0	0	0	16.6					0.1	0.1	0	0		0.3
C6	0	0.5	36.1	4.6	0.1	2.4		3.6		1.8	19.6	0.1	97.2	1.7	401	0	0		5.9	0.3	16.6			1.4	
CUnclear																									
D1			0.3										0						0		0.1				
D2		0	0		0		0	0			0.3		0	5.6						0	0				
D3		0	0					0		0			1.9		12.3	0.1			0	0.1	0.1			0	
D4				0.8				0			1		0.6						0						

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
D5																									
DUnclear																									
E1													2	1.5											
E2																									
E3										0															
E4																									
E5																									
E6								0.1		0.2		0	0.1												
EUnclear																									
F1	0				0	0		0	0				0.2	0.1						0.1	0.2				6.8
F2		0				0.2							0.7												
F3			0.3				0	0					0.6	0.1	3.7					0.1					
F4								0							0.3					0					0.2
F5		0			0				0				0.6							0				0	0
FUnclear																				0.1					12.4
G1			0			0.2		0	0		0.4						0.1			0	0		0.5		1.5
G2		5.5	3.5	0.1		0.1		0.1		0.3	77.5		2.8	2.2	234.7	0				0.1					0
G3			13.4	1.6	0	0.4	0	1.2		0.8	12		29.1	0.6	0	0			1	0	1.2	0	0.7		4.1
G4		1.1	14.2	2.2		0.1	0	6.1			0.4	0.1	8.4	2.4	42.1				0.7		0				1.2

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
GUnclear													0.9					0.1		0					
H1		0.1	54.2	13.4		0.1		0.1			16.2	0	62.5	0.5					0.4		1.6		0.3		0
H2		0	22.2					0	0						3.1	0	1.7			0	3.5		0		
HUnclear																				0					
I1											0.6														0.1
I2																					0.2				
I3																									
I4																									
IUnclear													1.5												
J1		0.3	4.1		0		0	1.3		0	7.4	0	0.3	0.9	0.8	0.5			2.9	0.1	0.8	0		0.1	0.8
J2			0.2								0.1		0.2							0	0				
J3			0.3																	0					
J4		0	0.2	0	0						0.4									0					
J5		0.5	5.7		0	0.5	0	0		0	12.2	0	8.4	1.1		0.2	0.1	0.4		0.3	0.1		0.8		
JUnclear			1.3								1.3		0.3	14						0.3					1
K1		0.1	0.7				0.1			0	0.4	0	4.6		17.1	0	0.5			0.4			0	0.4	
K2										0.2	2.1		0.3			0.2				0					
KUnclear						0						0													
L1			12.7	1.8																					0.3
L2													0.3												

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
L3			6.1																						
L4								0													0.9				
LUnclear																									
M1								0												0					
M2																					12.7				
M3	0																			0					
M4																									
MUnclear																									
N1											1.1				98.4										
N2			2					0																	
N3																									
N4																									
NUnclear																									
O1													0.1												
O2				11	0.2						10.3				4.8						11.1				
OUnclear																									
P1																									
P2																							0.2		
P3	0														43.7					0.1					1.6
PUnclear																							0		

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
Q1			3.5					2.4			0.1				350.6										
QUnclear																									
R1									0	0.2															
R2																								0.1	
R3			0.1		0										16.1								0		
R4																0.3							0.7		
RUnclear													0									0			
S1		0	0					0.2			0.4		0	0		0			0.2		0.2				
S2			0				0.1																		
S3			0.2																		0.1				
S4			0.2										0								0				
S5			0.9					0.3					0.1		1.5										
SUnclear															14.3										
T1													0.2												
T2																									
TUnclear																							0		
U1																									
U2																									
UUnclear																									

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
V1								0					0.1												
V2			0					0.1																	
V3		0	0.2											0		0.2					0.1				
V4		0											0.2							0					
VUnclear								0.1							1.4								0		
W1		0		1.1						0.1					0.7										
WUnclear																									
X1																									
X2																									
X3						0										0									
X4		0	13.4			0.1		0.3			0.2		0.2	0.4	4.8					0.2	2.4		0		
XUnclear																									
Y1		0						0.3					0										0.1		
Y2		0											0.3			0									0.1
Y3																									0.4
Y4								0.4					0.1												
Y5																				0					
YUnclear		0	0.6		0			0.1						15.3	0.2					0			0.1		
Z1		0.3	21.7								0.6									0					
Z2								0			0														

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
Z3			1.3																		0.1				
Z4		0.1	0.2																						
Z5		0																							
ZUnclear					0.3						0.1														
α1		0	0.3										0.4												
α2		0													0					0	1				
α3			0.1												1.5										
αUnclear																									
β1		0.6						0.1					1.6												
β2		0																		0					
β3								0.1																	
β4		0.1	0.3		0			1			0.1		0.1		212.4					0					
β5																									
βUnclear		0					0													0					
γ1		1.2	6.2					0					1.6				0						0.3		
γ2																									
γ3								0.1					0												

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
$\gamma 4$		0.1					0	0															0		
$\gamma 5$								0							7										
γUnclear			11.9																						
$\delta 1$													1.2	0.1											
$\delta 2$		0	5.1	0.3				0.7					0.1										0.1		
$\delta 3$			0					0					0.1												
$\delta 4$								0																	
$\delta 5$								0.5															0		
$\delta 6$								0																	
$\delta 7$																							0		
δUnclear								1.2													0.8				
$\varepsilon 1$			0																	0					
$\varepsilon 2$			0.2												0.5										
$\varepsilon 3$															2.4										
$\varepsilon 4$			0.2																	0					0.2
$\varepsilon 5$															19										
εUnclear			0										0.1												

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
$\eta 1$						0.4		0.1			0.2				11.1					0	1.1		0.6		
$\eta 2$															10.2					0					
$\eta 3$													1.2		2						0.2				
$\eta 4$			0.3																						
$\eta 5$																									
$\eta 6$		0.1	0.5					0.6																	
$\eta 7$			0																						
$\eta 8$			0.2																		0.4				
$\eta 9$													5.7												
$\eta 10$																									
ηUnclear			1.4										2.2			0									
$\theta 1$		0.5	0.7		0		0	0							69.3	0.1									
$\theta 2$		1.5	1.1				0	0.2		0.7			0.8	13.9	3.6								0.2		0.4
$\theta 3$								0.1													0				
$\theta 4$		0			0		0	0.3					0.1												
$\theta 5$								0.1																	
$\theta 6$	0.1	0	0.7													0				0			0		

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
θ7																				0					
θUnclear		1.4								0.2			0												
λ1								0.1			0		3.6								4.9				
λ2							0																		
λ3							0													0					
λUnclear								1.2																	
μ1														0.3											
μ2		0	0										3		15.2										
μ3		0	0					0.1							8.5					0			0		
μUnclear																					0				
ω1		0	0.2				0						1.2							4.7			0.1		
ω2																									
ω3																									
ω4		0																							
ω5																									
ωUnclear																				0					
π1		0														0							0.1		

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
$\pi 2$		0	0.1																						
$\pi 3$		0	0.2																						
$\pi 4$																									
$\pi 5$																									
πUnclear										0.3															
$\sigma 1$		0.5	0.9																		0.4				
$\sigma 2$																									
σUnclear																									
$\tau 1$						0.1							0.1							0					
$\tau 2$																				0					
$\tau 3$																									
$\tau 4$																									
$\tau 5$		0																		0		0			
$\tau 6$																				0					
τUnclear																									
$\varphi 1$		0.4						0			0		10.5								0				
$\varphi 2$								0																	

Subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt
φ3								0																	
φ4		0	2.7			0							0.2		4.8	0				0	0.4		0		
φUnclear																									
ψ1			0.5					0					2.9												
ψ2			0																	0			0		
ψ3			0.2					0																	
ψ4																				0					
ψ5				0																					
ψUnclear						0								0.9							0.1				
Unclear			0.3		0.2		0	6.1		0.2			0.1	20.6	573.2			0.2		0.1		0	0		
Total	**0.1**	**23.8**	**282.5**	**69.5**	**0.8**	**8.4**	**0.3**	**86.6**	**0**	**5.3**	**207.4**	**0.3**	**273.1**	**85.4**	**2214.4**	**2.3**	**2.5**	**0.7**	**26.6**	**7.3**	**94.2**	**0**	**5.6**	**2**	**33.4**

Table C4b. Total spending per subarchetype per region: El Salvador to Mexico.

Subarchetypes	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico
A1		0									10.2	6.9					3.3		0						
A2		2.8	5.9	6.6												0	2					0			0
AUnclear																									
B1		0.1	0.1						0	0	6.5						0.4	0	25.3	2.8	0	0			
B2		0.1													2.1										
B3		3.5	16.1	11.8								0	0.4		0.2	4.3	5				0	0			
B4		0.5	9.3														0.3								
B5											11.9														
B6																									
B7		0.2	2.2												0.1	0.2	2		0.7		0				
B8																									
B9			0.8																						
B10			0																						
B11		0.2	11.2		0.1						0.4				0.4	0	220.3		0					0.1	
B12		0	5.6		0.1																				
B13		13.6	355.7	1052.6	0.3					0	19.5	3.2	1.3		3.3	3.7	378.7	0	81.6				9.7		
BUnclear																									
C1			0.1		0					0	9.1				0.1			0	20.7		0				
C2	0																								
C3																	0.1		15.2						

Subarchetypes	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico
C4																	0.4								
C5	0		1		0.3					0		0.9				0.6		0.1			0				
C6	0.1	5.5	31.5	73.5	0.1	0	0.3			0	18.5	22.4			3.1	4.9	18.8	0	242.3		0.1	0.1	14	0.5	0.1
CUnclear																									
D1		0.1	0								0				0.3	0.1			0.5						
D2		0.2	1.9	2.1			0							0.1	0.2				1						
D3		0.2			0										0.1				5.6		0.1				
D4				0				0							0		0.1								
D5																					0				
DUnclear															0										
E1																	0.1		18.9						
E2																									
E3						0																			
E4																									
E5																									
E6		0.8								0.1													22.3		0.1
EUnclear																									
F1		0			0.1				0.1	0	13.2	0.3			0.1	0.2	0.5		0.2			0		0	
F2			0.4	23.3																					
F3		0.8				0												0.1	2.9						0

Subarchetypes	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico
F4					0.2		0				3.6								0.1						
F5	0								0			0													
FUnclear					0																				
G1	0	0.1	3.2	4.8					0				5.2	0.3	0	0.5	0.6		10			0			
G2		2.4	26.2				0.8				3.6	9.2							1.7				6.5		0.3
G3	0	0.6	0				0	0	0		3.6		1.2		10.2	3.1	3		15.6			0	3	0.4	22.1
G4				0.4								16.5				4	2.1		133.2						17.3
GUnclear																									
H1	0	3.5	25.4			0	0.2		0		0.3				4.9		17.5		56.2				4.4		
H2			0.1	10.9	0.1				0		0				0.6	0.1		0		2.2	0.1				
HUnclear																	1.5				0.1				
I1																	0.7								0.1
I2			10.8																						
I3																									
I4																									
IUnclear																2									
J1	0	3.2	8.7	63.7	0		0	0.1		0.1	0.5	11.4	3.5	0.3	0.5	3.5	6.2	0.1	42			0	5.2	0.3	0.2
J2															0										
J3											0.4								5.7						8.4
J4			0.5					0		0	3.6	0.7					0.8		1						2.5

Subarchetypes	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico
J5	0	0.3	35.7	3.4	0.4					0.1	9.8	4.1			0.2	1.1	0.5		39.2		0.2				1.4
JUnclear	0			8.4	0.2					0.2	0								1.2					0.3	5.2
K1	0	0			0				0	0	3.1				0	0.2	0.1		152.2		0	0			
K2					0														5.9		0.1	0			
KUnclear																	1.8		20.2			0			
L1																0.8	9.1								
L2				0.8																					
L3																							8.9		
L4																							2.2		
LUnclear																									
M1		0.8		22.1												0.4	2.8								
M2																									
M3			0.1																						
M4																									
MUnclear																									
N1			1.2									8.6			0.7	1	0								
N2			0														0.4								
N3																									
N4												0					0								
NUnclear																									

Subarchetypes	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico
O1																									
O2		0.8	35.8								3.6											0.6			
OUnclear																									
P1																									
P2																									2.7
P3	0																4.5								
PUnclear											2														
Q1		1														0.8	0.5								
QUnclear																						0			
R1																									
R2					0																0.1				
R3						0									0.1		8.5								
R4					0										0.7							0.1			
RUnclear																					0				
S1		0	0.6									0					7.9		9.9		0			0	
S2															0										
S3																	0.2		0.5						
S4			3.8	1.1																	0.1				
S5			0												0										
SUnclear																	3.2		10						
T1			0.2	4.4											0										

Subarchetypes	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico
T2			3.3	2.5													0.6								
TUnclear																									
U1																									
U2																									
UUnclear																									
V1				12.4															20.7						
V2		0.7	1	6.9											0.6				21.8						
V3				1.2																	0				
V4			0.2														6								
VUnclear																		0	19.2						
W1																								0.1	
WUnclear																									
X1																					0				
X2																									
X3			0																					0	
X4		0.2	12	0.6							5.3				0.6	1.5	9.6				0		0.5		
XUnclear																									
Y1		0	0.4	2.2											0.1		0.5								
Y2		0.1													0.1	0									
Y3																			0.3			0			
Y4										0					0.1						0.1				

Subarchetypes	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico
Y5																									
YUnclear			0.4											0	0.2		21.8				0.1			0	
Z1																									
Z2																									
Z3																									
Z4			2.4	7.9																					
Z5	0		0.1							0											0				
ZUnclear	0																17.6							0	
α1				3											0.1		0.1							0	
α2															1.2										
α3				0.3											0					0.7	0				
αUnclear																								0.1	
β1			2.1	5.6											3.2		1.4	0	0.5						
β2		0													0				0						
β3				0.6																					
β4		0	0.3	4.8											0.4		11.6		7.2						
β5																									
βUnclear			1.5														26.9		0						
γ1		0			1.3									5.4				0.1			0			0	5.1

Subarchetypes	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico
$\gamma 2$																									
$\gamma 3$									0.1						0										
$\gamma 4$																									0.1
$\gamma 5$			5.6																						8.6
γUnclear															0.1										
$\delta 1$																0.6	27.9							0.5	
$\delta 2$				2.8													0.2		0.1						
$\delta 3$																									
$\delta 4$																									
$\delta 5$		0	0																						
$\delta 6$																									
$\delta 7$																									
δUnclear		0.8	2.1																						
$\varepsilon 1$																									2.3
$\varepsilon 2$																									
$\varepsilon 3$											0.4														
$\varepsilon 4$											6.6														
$\varepsilon 5$																									

Subarchetypes	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico
εUnclear																									
η1															0									0	
η2			0.2																						
η3		0.2																							
η4																									
η5																									
η6			8.5	7.9																					
η7		0.5																							
η8																									
η9																									1.8
η10																									0.5
ηUnclear		0															26.8							0.1	
θ1			0.7	0.6						0	0.8				0		0.7	0.1							1
θ2		0.6									2.4	0.1		0			12.6							0.3	7.3
θ3															0.1										
θ4																		0							
θ5			0.4																						
θ6					0									0	0.1	0.1									0

Subarchetypes	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico
θ7		0	0.4																		0.1			0.3	
θUnclear																								0	
λ1		0.1	9.4	2.2						0					0		17.4								
λ2																									
λ3															0										
λUnclear																									
μ1															0										
μ2		0.1	0.3		0										0						0				
μ3		0													0										
μUnclear		0.1									0.8						17								
ω1		0.1	0.7	0.8							13.2							0	0.7		0				
ω2			0.5															0							
ω3											2.6				0										
ω4																									
ω5																									
ωUnclear																									
π1				0.2																					
π2														0.1	0										

Subarchetypes	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico
π3										0					0.1		2.3								
π4																									
π5																									
πUnclear	0				0		0															0			6.6
σ1		0.3	1.6																2.9						
σ2				11.2																					
σUnclear																									
τ1			1.2	2.2															34.1						
τ2																									
τ3																									
τ4																									
τ5			0.4											0					60.8					0.3	
τ6		0																							
τUnclear																			0.2						
φ1			4.9	2.2											0		0								
φ2				4.5															1.3						
φ3			0.7																						
φ4		0.5	27.3	4.5	0										0				96						

Subarchetypes	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico
φUnclear																									
ψ1		0		2.6																					
ψ2																								0	
ψ3			0.6																						
ψ4			5.9																						
ψ5					0										0.2										
ψUnclear			7.1														12.8								
Unclear	0		11.7	16.7			0.1	0.1			322.7				0.3	6.2	24.6	0.2	106.8			0		0.2	9.2
Total	0.1	45.6	708	1396.3	3.2	0	1.4	0.2	0.2	0.5	478.2	84.3	11.6	6.2	35.4	39.9	942.3	0.7	1292.1	5.7	1.2	0.8	76.7	3.5	102.9

Table C4c. Total spending per subarchetype per region: Mongolia to Spain.

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
A1					0.4		0			0.1		0			4										
A2			0.9			0.5				0	0.6	0.4												1	19.7
AUnclear																									
B1	0.2		0.1		1.6	0	0.3			0	1.1	0.1	0.7				0		0		0		0.2		11.8
B2																									
B3		0.2	1.5			1.8					1.4	1	1.7	0	0.8				0		0.1	0.4	1.2	36.8	1.1
B4			5.5			0.1				0													0.4		4.4
B5		0.1				0		0.1													0.1		1.6	1.9	
B6																									
B7			0.2			0.3					1.4	2.9	3.3								0				5
B8	0.1											0.3													
B9			0.2															0						1	
B10																									
B11			18.6			1.3	0.8	0.5				8.5							0	2.7	0.7		0.1	74.3	2.2
B12			2													0.1					0				
B13		0.5	22.8			16.3		0.5		0	1.1	42	8.2		5.6	0.3		0		18.7			10.5	25.5	177.3
BUnclear																									

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
C1	0.1					0	2.1	0.2		0.1	2.5			1.1							0.2		0.2	0.2	0
C2																									
C3						1.3				0.3			0.1										0	0.1	
C4			0.2			3.5				0.1															
C5			3.2			2.4		0.2		0.2		2.7			2.6		0	0	0				0		12.5
C6	0.7	0	34		1.8	14.4	0.3		0.1	0.7	1	17.6	0.7	1.3	23.1		0	0		58.2	0.1	10.1	0	139.5	152.8
CUnclear																									
D1			0.8			0.2	0			0		0.7							0		0		0		
D2	0.7											0.1												0.4	
D3			11			0.2		0													0		0.4	10.7	
D4						0.1						0.1													
D5			0.1			0																			
DUnclear	0.1																								
E1														0.3								1.4			
E2																		0							
E3	0.2							0										0						0.2	0.1
E4			0.7																						
E5																									

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
E6			0.5			0												0		0.2				97	
EUnclear																									
F1	0						0.1	0.9	0		0			0.3					0		0.1		0.4		0
F2													0.7										0.5		
F3					0									0							0.1	0.1			6
F4								2	0.1	0.1															
F5							0.6	0.1		0.5													0	0.8	
FUnclear							0	0		1.8															
G1			0.9		0		0.9			0.1			0	0.6			0	0		0		0		4.1	
G2		1.5			0.2		2.2				5.2						0							9.9	
G3						0	0.6	0	0.4		0				4.7		0	0	0	0.3		0.6	14	2.9	33.5
G4			1.6			0.1		0	0	4.1								0						6	421.9
GUnclear																					0				
H1	0.4	0.7	0.1			0.4	0.6		0.3		3.1	2.7								2.8		6.4		8.2	13.9
H2	0		0.9		0.1			0											0	0.5	0.2	19.8	4.1	3	
HUnclear											30.1														0.1
I1							0					0.6					0								8.2
I2						0.2																			

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
I3			0.2				3.5			0															
I4																									
IUnclear																									
J1	0.1	0.2	0.9		1.3	0.5	0.9	0	0.6	0.4	1.2			0.3				0	0	12.5	0.3		1.2	4.8	23.6
J2			0.2							0															
J3															0										
J4			0.1		0					0.1								0					0	0.6	
J5	0			0.1	0	0.1	0	0		0	0										0.1		0.4	2.8	0.2
JUnclear					0	0.1		0		5.7									0						
K1	0.1			0.2	0	0.1	0.1	0.1		0		2.1					0		0				1.1	1.9	
K2																									
KUnclear																							0.4		
L1																							0.2		
L2																		0							
L3	0.4	0																							
L4																									
LUnclear																									
M1						2.9													0	0.2	0.6				1.3
M2			1.1									0.3											0.6		

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
M3						0	0.4																0.7		
M4																		0							
MUnclear																									
N1						0.8						2.3		0.5										14.5	
N2																							0.1		
N3																									
N4		0.1				0																	0.3		
NUnclear						0.2							1.1										3.9		
O1						0.1																	0.1		
O2						0	0.1																1.6		4.3
OUnclear																									
P1																									
P2	0.4						1.1			0			0.1				0	0							
P3								0												0.2	0				
PUnclear			2.4															0							
Q1																		0					1.1		
QUnclear																									
R1			0.3																						
R2			0.1														0							0.5	

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
R3																	0						1.1		
R4																									
RUnclear																									
S1						0.1				0.2		1.1								4			0		
S2																									1.8
S3													0.1				0								
S4						0.4				0													0		
S5						0.1		0										0						0.4	
SUnclear		1.6								0			0.1		0.3		0					0.1		0.3	0
T1																								1.5	4.2
T2												0.1												10.9	0.6
TUnclear																									
U1																									
U2																								0.2	
UUnclear																									
V1					0.6																				1.7
V2						0	0																	2.1	7.7
V3																	0							6.1	16.9
V4																							0		

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
VUnclear						0							1.2												
W1																			0					3	2.4
WUnclear																									
X1			0.1																						
X2			0			0	0.1																		
X3													0.3										0		0.2
X4	0.2		1.3		6.1	0.3	0			0.3	0.1		1.5		0			0		0.2	0	0	0.8	2.8	8.1
XUnclear																								0.3	
Y1						0							1.1	0.1									0.3		9.3
Y2						0.1																			
Y3																									
Y4																			0				0		
Y5										0.1			0.1												
YUnclear						0.4				8.9			0				0				0.3				2.3
Z1													0.9				0	0							
Z2			0.7										0.1												
Z3																									1.4
Z4													0.4											0.1	
Z5													0.2												

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
ZUnclear													0.9												
α1						0	0			0		0	2.4		0								0		1.1
α2	0.1									2			1											22.2	
α3																							0		0.1
αUnclear																									
β1						0				2.9													0	28.7	1.9
β2																								1.2	0.2
β3													0.1												
β4					0								1.4					0			0		0	0.3	122
β5																									
βUnclear													0.6											3.9	2
γ1					0.2	0.1	0.1	0.1		5.4		1	0.7								0		0	0.1	
γ2						0.1																			
γ3			0.2							0.3															
γ4						0.1		0																	
γ5						0.2	0					0.5													
γUnclear										3.7	13.1														

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
$\delta 1$			1.8					0.2				0.4	1.2						0						
$\delta 2$	0.1		1.2			0.2				2.4			1												
$\delta 3$						0						0													2.5
$\delta 4$																									
$\delta 5$										0															
$\delta 6$						0							0												11.9
$\delta 7$																									1.8
δUnclear													0.1												
$\varepsilon 1$																									
$\varepsilon 2$																									
$\varepsilon 3$					0							0													
$\varepsilon 4$																									
$\varepsilon 5$																									
εUnclear					0.3	0																			
$\eta 1$						1.4						0.1												9.2	
$\eta 2$																									
$\eta 3$																									

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
η4						0																			0.2
η5																								3.1	0.2
η6			0.3										0.2												0.6
η7																									
η8						1.8																			
η9												3.3													
η10																									
ηUnclear													0.2												0.1
θ1										0.8															
θ2	1.1		0.3		0.8			0.1		0			0.5	0.4	0.6		0		0		0.1		0	0.6	
θ3			0.1								0		0.9												
θ4						0		0															0		
θ5																									
θ6										0.1			0.2										0	2.8	
θ7										0.5			0.3										0		
θUnclear																	0	0						12.3	
λ1			0.1									0.8	0.7											5.2	

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
$\lambda 2$												0													
$\lambda 3$						0		0																4.8	
λUnclear																									3.2
$\mu 1$																							0		
$\mu 2$						0				0														2.1	0.4
$\mu 3$						0	0																0		1
μUnclear																									12.2
ω1							0.2			0			0.1				0								
ω2			0.1										0.1								0				0.3
ω3										0.2															
ω4													0										0		0.3
ω5													0.1												
ωUnclear		1.6								1.2							0	0							
$\pi 1$												0.3													
$\pi 2$							1.1																		
$\pi 3$						0				1.4								0			0.1				
$\pi 4$													0.1												

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
π5																									
πUnclear	0.7	1.6	20.4		0					0.1			0.7					0.1							
σ1						0.4																			
σ2																									
σUnclear													0.1												
τ1					0.5		0.6			0											0.1			2	
τ2													0.1												
τ3													0.1												
τ4																									
τ5					0	0	0.1						0.3												
τ6																									
τUnclear										0															
φ1			0.1		0.4					0		0.6			0.2										1.3
φ2			1.1																					16.7	5.9
φ3																									
φ4			0.1			0.8				0			1.5											34.9	3.9
φUnclear																									

Subarchetypes	Mongolia	Morocco	Netherlands	Nicaragua	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore	South Africa	South Korea	Spain
ψ1			0.3			0.3																			7.5
ψ2													0.1												
ψ3						0																		4.4	3.4
ψ4						0																			0.5
ψ5													0.1												
ψUnclear						0							0.4	0.2										2.3	
Unclear			13.2		5.9		10.8				93.8	9.6				0.3	0.1		0		0	3.6		52.4	144.2
Total	**5.7**	**8.1**	**152.5**	**0.3**	**20.2**	**54.7**	**27.6**	**5**	**1.5**	**44.8**	**155.7**	**102.2**	**38.8**	**5.1**	**41.9**	**0.7**	**0.1**	**0.1**	**0**	**100.5**	**3.2**	**42.5**	**47.5**	**685.5**	**1285.2**

Table C4d. Total spending per subarchetype per region: Suriname to Vietnam.

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
A1		3.5	5.7						35.6	152			
A2				0					17.2				

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
AUnclear										0.9			
B1		0		0.2	0.3					10.3			
B2	0			0									
B3		1.6	1.9	0.5				2	2.9	87.7			
B4													
B5									0.4				
B6									0				
B7		0.1	0.7	0.3		0.1		0.2	9.5	3			
B8				0									
B9				0		0		13.6					
B10													
B11	0	9.6		1.7	0.1	0.2	6	0.5	14.2	98.1			12.1
B12				0					0.5				
B13	0	57.6	36.4	1.1		0	4.4		35	71			
BUnclear													
C1				0	0.7				0	10.3			
C2													
C3			0.2		0.3				0	15			
C4													
C5	0	0.9		0		0	0.9			30.6			

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
C6		5.1	20.9	3.1	4.9	0	12.1	2.7	433.6	481.4			
CUnclear													
D1		0.5	0.4	0					2.7	0.7			
D2		0				0			0.1	10.8			2.9
D3	0	0.6		0.9			0.2	0.1	3	278.5			
D4									1.1				
D5										0.1			
DUnclear										14			
E1		0.4		0.2									
E2													
E3				0				1.4					
E4													
E5													
E6				0.2									1.8
EUnclear													
F1	0.1			0	1	0.1			1.2	54.8	0		
F2									0.6	9	0		
F3		0							0.1	13.6			
F4				0		0				0.5			0.5
F5				0						7.9			

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
FUnclear			0.7		0					2.7			
G1	0			0.2					0	1.7			
G2	0				1.2					19.5	0		2.7
G3	0		8.4	4.2	13.4	0	0.8		0	336			0.3
G4		0.7		0.3		0			0.2	22.1			
GUnclear													
H1		20.2	1.6	3.7					18.7	16			
H2		3.6							58.4	660.8			
HUnclear				0									0
I1		1.1							6.6	46.6			
I2													
I3					1.3								
I4													
IUnclear													
J1		1.5	0	1.5	0.3	0		0.1	104.6	173.3			
J2		0		0.1						5.2			
J3		0								0.5			
J4				0.4		0				54.1			
J5	0	0.7	0.4	1.5	0.7	0			8.5	104.5	0		2

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
JUnclear				0.1		0			17.1	8.1			0.6
K1		0.9	0	1.7		0	0		7.5	375.4			
K2	0.1	1.1		0						0.6			
KUnclear										49.1			
L1													
L2									0.6	10			
L3						0.1				4.5			
L4	0.1												
LUnclear													
M1	0								6.3				
M2									2.4				1.2
M3						0.5							
M4													
MUnclear								0.1					
N1		10.1				0			34.8				
N2										20			
N3													
N4													
NUnclear													
O1													

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
O2									1.5				
OUnclear													7.7
P1									0.3				
P2				0.1		0							
P3	0			0.7									0.5
PUnclear													
Q1				0	0	0				0			
QUnclear													
R1										0.1			
R2	0.1												
R3	0	0.1			0.1	0.1				0.5			
R4				0									
RUnclear				0									
S1				0.3	0.7				0				
S2													
S3		0								6			
S4		0.6	0.1	0.1					0				
S5				0.1					0.6				
SUnclear				0									
T1													
T2									2.1				

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
TUnclear													
U1													
U2													
UUnclear													
V1									0.2	6.1			
V2		0.1							2.3	27.2			
V3		0							8.4	0.5			
V4		0											
VUnclear		0								0.1			1
W1				0					0.3	1.5			
WUnclear													
X1									0				
X2										0.1			
X3		0.1											
X4		0.4		0	0.1	0			12	0.6			0.1
XUnclear			0.6	0						0			
Y1	0					0			0.1	7.2			
Y2										0.2			
Y3				0									
Y4									0.7				
Y5									4.2				

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
YUnclear		0.2							2	25			
Z1									7.7	3.1			
Z2		0.1								1.5			
Z3													
Z4									6.6				
Z5													
ZUnclear													
α1						0		0.1	9.6				
α2									0				
α3					0				0.1	0			
αUnclear		0.1							0				1.7
β1		0		0					16.4	66.7			
β2				0									
β3										0.9			
β4				0.1						5.5			
β5													
βUnclear										0.8			1.2
γ1								0.1	40.7	42.8			
γ2													

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
$\gamma 3$			0.3						4.4	25			
$\gamma 4$				0						2.3			
$\gamma 5$		0.1	0.7						10.8	8.2			
γUnclear									77.6	51.5			1
$\delta 1$									5.5	19.8			
$\delta 2$		0	0.8						9	78.2			
$\delta 3$									2.4	7.5			
$\delta 4$		0		0									
$\delta 5$									3	6.6			
$\delta 6$									0.1	6.6			
$\delta 7$										4.8			
δUnclear							2.6		3				
$\varepsilon 1$													
$\varepsilon 2$													
$\varepsilon 3$													
$\varepsilon 4$										1			
$\varepsilon 5$										0			
εUnclear										0.3			

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
$\eta 1$		0	0.6						0.8	11.7			
$\eta 2$									0.7	3.2			
$\eta 3$									0				
$\eta 4$										11			
$\eta 5$		0											
$\eta 6$									1.1	0.5			
$\eta 7$									0.1	6.7			
$\eta 8$									1.3	11.9			
$\eta 9$													
$\eta 10$										4.6			
ηUnclear									0.1	0.9			
$\theta 1$									9.7	2.9			
$\theta 2$	0								42.5	15.7			
$\theta 3$									1.7				
$\theta 4$									0.2	3.4			
$\theta 5$										0.1			
$\theta 6$									0	12.8			
$\theta 7$										12.9			

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
θUnclear				0	0				2.4	0.2			
λ1		0.5	0.1						5.8	3.8			
λ2													
λ3									3.5	0.8			
λUnclear										0.8			
μ1				0					0				
μ2									1.3	19.5			
μ3									0	3			
μUnclear		0.2							0.1	3.4			
ω1					0	0.1			1.5				
ω2										0.1			
ω3				0					0				
ω4													
ω5													
ωUnclear													
π1													
π2									8.4				
π3										1.3			

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
$\pi 4$										4.8			
$\pi 5$													
πUnclear										43			
$\sigma 1$									0				
$\sigma 2$													
σUnclear													
$\tau 1$		0		0.2						50.9			
$\tau 2$													
$\tau 3$										3.4			
$\tau 4$										10.6			
$\tau 5$									6.9	19.7			1
$\tau 6$													
τUnclear													1
$\varphi 1$		0		0					21				
$\varphi 2$									0.2	1			
$\varphi 3$													
$\varphi 4$	0		0.2	0					24.6	1.9			0.2
φUnclear													

Subarchetypes	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
ψ1									0.6	17.4			
ψ2									0				
ψ3									0.1				
ψ4		0							0.4	0.9			
ψ5										0.7			
ψUnclear									0.4				
Unclear		0.1		0			47.5	5.5	77.9	1024.9			
Total	**0.4**	**122.4**	**80.7**	**23.5**	**25.1**	**1.2**	**74.5**	**26.4**	**1268.3**	**4979.5**	**0**	**0**	**39.5**

C4.2. GRO data summary—green

Table C5a-C5e provides a summary of spending with low long-term GHG characteristics. Table C5a considers Antigua and Barbuda to Cuba; table C5b considers the Czech Republic to India; table C5c considers Indonesia to Nicaragua; table C5d considers Nigeria to Singapore; table C5e considers South Africa to Vietnam. Rows might not sum to total due to rounding.

Table C5a. Total low long-term GHG spending per subarchetype per region: Antigua and Barbuda to Cuba. Archetypes and subarchetypes with an asterisk are rescue-type and not included in several figures in the main paper.

Low long-term GHG subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba
B*: Liquidity support w/ green conditions																		
B2*: Green support - agriculture, forestry, & fishing																		
B4*: Green support - airlines & other transport				0.68							0.01							
B6*: Green support - energy											0.33							
B8*: Green support - holiday & leisure																		
B10*: Green support - retail																		
B12*: Green support - specified other industry												0.08	0.03					
N3*: Business tax cuts w/ green conditions																		
S2: Green tourism & leisure incentives			0.00				0.15											
T: Electric vehicle incentives																		
T1: Transfer programs													0.23					
T2: Subsidies																		
TUnclear: Other or unspecified																		
U: Electronic appliance incentives																		

Low long-term GHG subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba
U1: 'Cash for clunkers' programs																		
U2: Electronic appliance subsidies																		
UUnclear: Other or unspecified																		
V: Green market creation																		
V1: Increased clean energy market participation								0.03					0.12					
V2: Modernisation and transition investments			0.03					0.14										
V3: Capacity investments		0.00	0.23											0.04		0.15		
V4: Incentives for ecosystem services		0.01											0.19					
VUnclear: Green market creation - unspecified								0.06							1.43			
X: Worker retraining & job creation																		
X1: Climate transition/mitigation																		
X2: Climate adaptation																		
X3: Unclassified/mixed climate						0.04										0.00		
Y5: Climate-conscious education																		
ω: Agriculture & fisheries																		
ω2: Clean/resilient agriculture																		
ω4: Clean/resilient fisheries		0.00																
ω5: Resilient land management																		

Low long-term GHG subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba
γ5: Traditional rail transport								0.01							7.01			
δ: Clean transport																		
δ1: New/extended public transport lines													1.17	0.08				
δ2: Expanded public transport capacity		0.00	5.11	0.33				0.70					0.07					
δ3: EV charging			0.00					0.04					0.12					
δ4: Public transport digitalisation								0.01										
δ5: Cycling & walking infrastructure								0.49										
δ6: Improving efficiency in dirty transport								0.03										
δUnclear: Other or unspecified								1.19										
η: Clean energy																		
η1: Renewables						0.41		0.12			0.25				11.08			
η2: Nuclear															10.23			
η3: Biofuel & other renewable fuel													1.17		1.95			
η4: Transmission			0.25															
η5: Distribution																		
η6: Hydrogen		0.10	0.45					0.64										

Low long-term GHG subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba
η7: Battery & other storage			0.04															
η8: Carbon capture & storage/utilisation			0.21															
η9: Cleaning existing dirty energy assets													5.71					
η10: Boosting resilience of existing clean energy																		
ηUnclear: Other or unspecified			1.35										2.19			0.00		
θ: Local infrastructure																		
θ3: Clean/resilient new housing								0.08										
θ5: Clean/resilient new public buildings								0.11										
θ7: Clean/resilient local utilities																		
λ: Building upgrades & energy efficiency																		
λ1: Green retrofitting								0.07			0.01		3.57					
λ2: Rooftop solar							0.00											
λUnclear: Other or unspecified								1.22										
μ: Natural infrastructure & green spaces																		
μ1: Public parks & green spaces														0.33				

Low long-term GHG subarchetypes	Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bangladesh	Barbados	Belgium	Belize	Bolivia	Brazil	Burkina Faso	Canada	Chile	China	Colombia	Costa Rica	Cuba
μ2: Environmental re(building)		0.00	0.01										2.97		15.19			
μ3: Environmental protection		0.00	0.02					0.10							8.51			
μUnclear: Other or unspecified																		
φ: General R&D with green co-benefits																		
φ1: Health & science		0.42						0.04			0.00		10.51					
φ2: Digitisation & AI								0.01										
ψ: Clean R&D																		
ψ1: Energy			0.54					0.03					2.93					
ψ2: Agriculture & fisheries			0.05															
ψ3: Industrial			0.18					0.03										
ψ4: Other specified sector																		
ψ5: Climate resilience				0.00														
ψUnclear: Other or unspecified						0.05								0.93				
Total	**0.00**	**0.54**	**8.49**	**1.01**	**0.00**	**0.50**	**0.15**	**5.17**	**0.00**	**0.00**	**0.60**	**0.08**	**30.99**	**1.38**	**55.40**	**0.16**	**0.00**	**0.00**

Table C5b. Total low long-term GHG spending per subarchetype per region: Czech Republic to India. Archetypes and subarchetypes with an asterisk are rescue-type and not included in several figures in the main paper.

Low long-term GHG subarchetypes	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India
B*: Liquidity support w/ green conditions																		
B2*: Green support - agriculture, forestry, & fishing									0.13									
B4*: Green support - airlines & other transport									0.53	9.28								
B6*: Green support - energy																		
B8*: Green support - holiday & leisure																		
B10*: Green support - retail										0.01								
B12*: Green support - specified other industry			0.00						0.00	5.61		0.05						
N3*: Business tax cuts w/ green conditions																		
S2: Green tourism & leisure incentives																		
T: Electric vehicle incentives																		
T1: Transfer programs										0.21	4.38							
T2: Subsidies										3.35	2.47							
TUnclear: Other or unspecified					0.01													

Low long-term GHG subarchetypes	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India
U: Electronic appliance incentives																		
U1: 'Cash for clunkers' programs																		
U2: Electronic appliance subsidies																		
UUnclear: Other or unspecified																		
V: Green market creation																		
V1: Increased clean energy market participation											12.36							
V2: Modernisation and transition investments									0.71	0.99	6.91							
V3: Capacity investments			0.07								1.23							
V4: Incentives for ecosystem services		0.00								0.24								
VUnclear: Green market creation - unspecified					0.02													
X: Worker retraining & job creation																		
X1: Climate transition/mitigation																		
X2: Climate adaptation																		
X3: Unclassified/mixed climate										0.05								
Y5: Climate-conscious education		0.01																
ω: Agriculture & fisheries																		
ω2: Clean/resilient agriculture										0.47								

Low long-term GHG subarchetypes	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India
ω4: Clean/resilient fisheries																		
ω5: Resilient land management																		
γ5: Traditional rail transport										5.56								
δ: Clean transport																		
δ1: New/extended public transport lines																		
δ2: Expanded public transport capacity					0.10						2.81							
δ3: EV charging																		
δ4: Public transport digitalisation																		
δ5: Cycling & walking infrastructure					0.00				0.02	0.02								
δ6: Improving efficiency in dirty transport																		
δUnclear: Other or unspecified			0.80						0.85	2.07								
η: Clean energy																		
η1: Renewables		0.04	1.06		0.58													
η2: Nuclear		0.00								0.24								
η3: Biofuel & other renewable fuel			0.16						0.17									

Low long-term GHG subarchetypes	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India
η4: Transmission																		
η5: Distribution																		
η6: Hydrogen										8.52	7.86							
η7: Battery & other storage									0.50									
η8: Carbon capture & storage/utilisation			0.35															
η9: Cleaning existing dirty energy assets																		
η10: Boosting resilience of existing clean energy																		
ηUnclear: Other or unspecified									0.02									
θ: Local infrastructure																		
θ3: Clean/resilient new housing			0.00															
θ5: Clean/resilient new public buildings										0.43								
θ7: Clean/resilient local utilities		0.01							0.00	0.36								
λ: Building upgrades & energy efficiency																		
λ1: Green retrofitting			4.92						0.05	9.38	2.25						0.00	

Low long-term GHG subarchetypes	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India
λ2: Rooftop solar																		
λUnclear: Other or unspecified																		
μ: Natural infrastructure & green spaces																		
μ1: Public parks & green spaces																		
μ2: Environmental re(building)									0.15	0.30		0.00						
μ3: Environmental protection		0.00			0.00				0.02									
μUnclear: Other or unspecified			0.03						0.06									0.79
φ: General R&D with green co-benefits																		
φ1: Health & science			0.02							4.91	2.25							
φ2: Digitisation & AI											4.49							
ψ: Clean R&D																		
ψ1: Energy									0.04		2.58							
ψ2: Agriculture & fisheries		0.01			0.05													
ψ3: Industrial										0.59								
ψ4: Other specified sector		0.00								5.93								
ψ5: Climate resilience												0.00						

Low long-term GHG subarchetypes	Czech Republic	Democratic Rep of the Congo	Denmark	Dominica	Dominican Republic	Ecuador	Egypt	El Salvador	Finland	France	Germany	Ghana	Grenada	Guatemala	Guyana	Haiti	Honduras	India
ψUnclear: Other or unspecified			0.12							7.08								
Total	**0.00**	**0.08**	**7.54**	**0.00**	**0.76**	**0.00**	**0.00**	**0.00**	**3.26**	**65.61**	**49.60**	**0.06**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.79**

Table C5c. Total low long-term GHG spending per subarchetype per region: Indonesia to Nicaragua. Archetypes and subarchetypes with an asterisk are rescue-type and not included in several figures in the main paper.

Low long-term GHG subarchetypes	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico	Mongolia	Morocco	Netherlands	Nicaragua
B*: Liquidity support w/ green conditions																		
B2*: Green support - agriculture, forestry, & fishing				2.11														
B4*: Green support - airlines & other transport						0.32											5.51	
B6*: Green support - energy																		
B8*: Green support - holiday & leisure															0.07			
B10*: Green support - retail																		

Low long-term GHG subarchetypes	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico	Mongolia	Morocco	Netherlands	Nicaragua
B12*: Green support - specified other industry																	1.98	
N3*: Business tax cuts w/ green conditions																		
S2: Green tourism & leisure incentives				0.03														
T: Electric vehicle incentives																		
T1: Transfer programs				0.02														
T2: Subsidies						0.59												
TUnclear: Other or unspecified																		
U: Electronic appliance incentives																		
U1: 'Cash for clunkers' programs																		
U2: Electronic appliance subsidies																		
UUnclear: Other or unspecified																		
V: Green market creation																		
V1: Increased clean energy market participation								20.70										
V2: Modernisation and transition investments				0.63				21.75										
V3: Capacity investments										0.01								
V4: Incentives for ecosystem services						5.97												

Low long-term GHG subarchetypes	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico	Mongolia	Morocco	Netherlands	Nicaragua
VUnclear: Green market creation - unspecified							0.04	19.20										
X: Worker retraining & job creation																		
X1: Climate transition/mitigation										0.02							0.06	
X2: Climate adaptation																	0.02	
X3: Unclassified/mixed climate													0.01					
Y5: Climate-conscious education																		
ω: Agriculture & fisheries																		
ω2: Clean/resilient agriculture							0.01										0.06	
ω4: Clean/resilient fisheries																		
ω5: Resilient land management																		
γ5: Traditional rail transport														8.58				
δ: Clean transport																		
δ1: New/extended public transport lines					0.59	27.92							0.53				1.78	
δ2: Expanded public transport capacity						0.24		0.14							0.15		1.23	
δ3: EV charging																		
δ4: Public transport digitalisation																		
δ5: Cycling & walking infrastructure																		

Low long-term GHG subarchetypes	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico	Mongolia	Morocco	Netherlands	Nicaragua
δ6: Improving efficiency in dirty transport																		
δUnclear: Other or unspecified																		
η: Clean energy																		
η1: Renewables				0.01									0.02					
η2: Nuclear																		
η3: Biofuel & other renewable fuel																		
η4: Transmission																		
η5: Distribution																		
η6: Hydrogen																	0.27	
η7: Battery & other storage																		
η8: Carbon capture & storage/utilisation																		
η9: Cleaning existing dirty energy assets														1.85				
η10: Boosting resilience of existing clean energy														0.49				
ηUnclear: Other or unspecified						26.79							0.14					
θ: Local infrastructure																		
θ3: Clean/resilient new housing				0.13													0.05	

Low long-term GHG subarchetypes	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico	Mongolia	Morocco	Netherlands	Nicaragua
θ5: Clean/resilient new public buildings																		
θ7: Clean/resilient local utilities										0.07			0.26					
λ: Building upgrades & energy efficiency																		
λ1: Green retrofitting				0.04		17.38											0.12	
λ2: Rooftop solar																		
λUnclear: Other or unspecified																		
μ: Natural infrastructure & green spaces																		
μ1: Public parks & green spaces				0.03														
μ2: Environmental re(building)				0.04						0.01								
μ3: Environmental protection				0.01														
μUnclear: Other or unspecified						17.00												
φ: General R&D with green co-benefits																		
φ1: Health & science				0.00		0.05											0.15	
φ2: Digitisation & AI								1.34									1.06	
ψ: Clean R&D																		
ψ1: Energy																	0.26	

Low long-term GHG subarchetypes	Indonesia	Iran	Iraq	Ireland	Israel	Italy	Jamaica	Japan	Kazakhstan	Kenya	Kyrgyz Republic	Malaysia	Mauritius	Mexico	Mongolia	Morocco	Netherlands	Nicaragua
ψ2: Agriculture & fisheries													0.00					
ψ3: Industrial																		
ψ4: Other specified sector																		
ψ5: Climate resilience				0.18														
ψUnclear: Other or unspecified						12.83												
Total	**0.00**	**0.00**	**0.00**	**3.22**	**0.59**	**109.08**	**0.05**	**63.14**	**0.00**	**0.10**	**0.00**	**0.00**	**0.96**	**10.91**	**0.22**	**0.00**	**12.55**	**0.00**

Table S5d. Total low long-term GHG spending per subarchetype per region: Nigeria to Singapore. Archetypes and subarchetypes with an asterisk are rescue-type and not included in several figures in the main paper.

Low long-term GHG subarchetypes	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore
B*: Liquidity support w/ green conditions																		
B2*: Green support - agriculture, forestry, & fishing																		

Low long-term GHG subarchetypes	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore
B4*: Green support - airlines & other transport		0.07				0.00												
B6*: Green support - energy																		
B8*: Green support - holiday & leisure								0.25										
B10*: Green support - retail																		
B12*: Green support - specified other industry												0.10					0.00	
N3*: Business tax cuts w/ green conditions																		
S2: Green tourism & leisure incentives																		
T: Electric vehicle incentives																		
T1: Transfer programs																		
T2: Subsidies								0.08										
TUnclear: Other or unspecified																		
U: Electronic appliance incentives																		
U1: 'Cash for clunkers' programs																		
U2: Electronic appliance subsidies																		
UUnclear: Other or unspecified																		

Low long-term GHG subarchetypes	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore
V: Green market creation																		
V1: Increased clean energy market participation	0.62																	
V2: Modernisation and transition investments		0.01	0.00															
V3: Capacity investments													0.01					
V4: Incentives for ecosystem services																		
VUnclear: Green market creation - unspecified		0.01							1.16									
X: Worker retraining & job creation																		
X1: Climate transition/mitigation																		
X2: Climate adaptation		0.01	0.09															
X3: Unclassified/mixed climate									0.28									
Y5: Climate-conscious education						0.10			0.06									
ω: Agriculture & fisheries																		
ω2: Clean/resilient agriculture									0.06								0.02	
ω4: Clean/resilient fisheries									0.03									
ω5: Resilient land management									0.10									
γ5: Traditional rail transport		0.16	0.04					0.50										

Low long-term GHG subarchetypes	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore
δ: Clean transport																		
δ1: New/extended public transport lines				0.17				0.43	1.16						0.00			
δ2: Expanded public transport capacity		0.16				2.43			0.95									
δ3: EV charging		0.00						0.04										
δ4: Public transport digitalisation																		
δ5: Cycling & walking infrastructure						0.00												
δ6: Improving efficiency in dirty transport		0.01							0.05									
δUnclear: Other or unspecified									0.12									
η: Clean energy																		
η1: Renewables		1.38						0.10										
η2: Nuclear																		
η3: Biofuel & other renewable fuel																		
η4: Transmission		0.00																
η5: Distribution																		
η6: Hydrogen									0.22									

Low long-term GHG subarchetypes	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore
η7: Battery & other storage																		
η8: Carbon capture & storage/utilisation		1.80																
η9: Cleaning existing dirty energy assets								3.34										
η10: Boosting resilience of existing clean energy																		
ηUnclear: Other or unspecified									0.22									
θ: Local infrastructure																		
θ3: Clean/resilient new housing							0.00		0.93									
θ5: Clean/resilient new public buildings																		
θ7: Clean/resilient local utilities						0.46			0.32									
λ: Building upgrades & energy efficiency																		
λ1: Green retrofitting								0.76	0.73									
λ2: Rooftop solar								0.03										
λUnclear: Other or unspecified																		

Low long-term GHG subarchetypes	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore
μ: Natural infrastructure & green spaces																		
μ1: Public parks & green spaces																		
μ2: Environmental re(building)		0.02				0.05												
μ3: Environmental protection		0.01	0.02															
μUnclear: Other or unspecified																		
φ: General R&D with green co-benefits																		
φ1: Health & science	0.37					0.00		0.59			0.20							
φ2: Digitisation & AI																		
ψ: Clean R&D																		
ψ1: Energy		0.33																
ψ2: Agriculture & fisheries									0.11									
ψ3: Industrial		0.01																
ψ4: Other specified sector		0.00																
ψ5: Climate resilience									0.14									
ψUnclear: Other or unspecified		0.03							0.45	0.19								

Low long-term GHG subarchetypes	Nigeria	Norway	Pakistan	Panama	Paraguay	Peru	Philippines	Poland	Portugal	Romania	Russia	Rwanda	Saint Kitts and Nevis	Saint Lucia	Saint Vincent and the Grenadines	Saudi Arabia	Senegal	Singapore
Total	**0.99**	**4.01**	**0.16**	**0.17**	**0.00**	**3.04**	**0.00**	**6.10**	**7.09**	**0.19**	**0.20**	**0.10**	**0.01**	**0.00**	**0.00**	**0.00**	**0.02**	**0.00**

Table C5e. Total low long-term GHG spending per subarchetype per region: South Africa to Vietnam. Archetypes and subarchetypes with an asterisk are rescue-type and not included in several figures in the main paper.

Low long-term GHG subarchetypes	South Africa	South Korea	Spain	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
B*: Liquidity support w/ green conditions																
B2*: Green support - agriculture, forestry, & fishing				0.00			0.01									
B4*: Green support - airlines & other transport	0.35		4.42													
B6*: Green support - energy												0.04				
B8*: Green support - holiday & leisure							0.00									
B10*: Green support - retail																

Low long-term GHG subarchetypes	South Africa	South Korea	Spain	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
B12*: Green support - specified other industry							0.00					0.55				
N3*: Business tax cuts w/ green conditions																
S2: Green tourism & leisure incentives			1.84													
T: Electric vehicle incentives																
T1: Transfer programs		1.48	4.22													
T2: Subsidies		10.92	0.58									2.12				
TUnclear: Other or unspecified																
U: Electronic appliance incentives																
U1: 'Cash for clunkers' programs																
U2: Electronic appliance subsidies		0.25														
UUnclear: Other or unspecified																
V: Green market creation																
V1: Increased clean energy market participation			1.68									0.23	6.13			
V2: Modernisation and transition investments		2.07	7.65		0.15							2.29	27.18			
V3: Capacity investments		6.14	16.94		0.01							8.36	0.50			
V4: Incentives for ecosystem services	0.02				0.05											
VUnclear: Green market creation - unspecified					0.04								0.10			1.00

Low long-term GHG subarchetypes	South Africa	South Korea	Spain	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
X: Worker retraining & job creation																
X1: Climate transition/mitigation												0.05				
X2: Climate adaptation													0.06			
X3: Unclassified/mixed climate	0.00		0.15		0.05											
Y5: Climate-conscious education												4.21				
ω: Agriculture & fisheries																
ω2: Clean/resilient agriculture			0.28										0.13			
ω4: Clean/resilient fisheries	0.00		0.28													
ω5: Resilient land management																
γ5: Traditional rail transport					0.11	0.67						10.78	8.19			
δ: Clean transport																
δ1: New/extended public transport lines												5.54	19.84			
δ2: Expanded public transport capacity					0.02	0.85						8.99	78.22			
δ3: EV charging			2.51									2.36	7.50			
δ4: Public transport digitalisation					0.01		0.01									
δ5: Cycling & walking infrastructure												2.95	6.62			
δ6: Improving efficiency in dirty transport			11.90									0.07	6.61			

Low long-term GHG subarchetypes	South Africa	South Korea	Spain	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
δUnclear: Other or unspecified										2.63		2.96				
η: Clean energy																
η1: Renewables		9.17			0.03	0.61						0.81	11.74			
η2: Nuclear												0.71	3.21			
η3: Biofuel & other renewable fuel												0.01				
η4: Transmission			0.20										11.01			
η5: Distribution		3.15	0.20		0.00											
η6: Hydrogen			0.63									1.10	0.50			
η7: Battery & other storage												0.09	6.68			
η8: Carbon capture & storage/utilisation												1.29	11.86			
η9: Cleaning existing dirty energy assets																
η10: Boosting resilience of existing clean energy													4.55			
ηUnclear: Other or unspecified			0.12									0.08	0.85			
θ: Local infrastructure																
θ3: Clean/resilient new housing												1.69				
θ5: Clean/resilient new public buildings													0.10			

Low long-term GHG subarchetypes	South Africa	South Korea	Spain	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
θ7: Clean/resilient local utilities	0.03												12.94			
λ: Building upgrades & energy efficiency																
λ1: Green retrofitting		5.17			0.45	0.05						5.76	3.80			
λ2: Rooftop solar																
λUnclear: Other or unspecified			3.21										0.75			
μ: Natural infrastructure & green spaces																
μ1: Public parks & green spaces	0.01						0.00					0.01				
μ2: Environmental re(building)		2.08	0.39									1.33	19.53			
μ3: Environmental protection	0.05		0.97									0.04	2.98			
μUnclear: Other or unspecified			12.23		0.25							0.05	3.36			
φ: General R&D with green co-benefits																
φ1: Health & science			1.26		0.01		0.04					21.03				
φ2: Digitisation & AI		16.67	5.95									0.24	1.00			
ψ: Clean R&D																
ψ1: Energy			7.51									0.64	17.42			
ψ2: Agriculture & fisheries												0.01				
ψ3: Industrial		4.40	3.39									0.07				

Low long-term GHG subarchetypes	South Africa	South Korea	Spain	Suriname	Sweden	Switzerland	Taiwan	Thailand	Trinidad and Tobago	Turkey	UAE	United Kingdom	United States	Uruguay	Venezuela	Vietnam
ψ4: Other specified sector			0.47		0.04							0.39	0.89			
ψ5: Climate resilience													0.66			
ψUnclear: Other or unspecified		2.25										0.39				
Total	**0.47**	**63.74**	**88.97**	**0.00**	**1.22**	**2.18**	**0.06**	**0.00**	**0.00**	**2.63**	**0.00**	**87.26**	**274.91**	**0.00**	**0.00**	**1.00**

C5. Deep learning to predict GHG impacts of policy

Long short-term memory (LSTM) recurrent neural network (RNN) models were used in this work initially to validate the internal consistency of the GRO data set and subsequently to demonstrate the potential of the dataset for future applications in automated assessment of potential policy impact. Necessary details for replicating the procedures used in the core of this paper are included in the paper methods. Model optimisation output is included in additional data figure 4. Further figures documenting the models are included in figures C1-C4. A summary of accuracy achieved by the optimal models is included in extended data table 3.

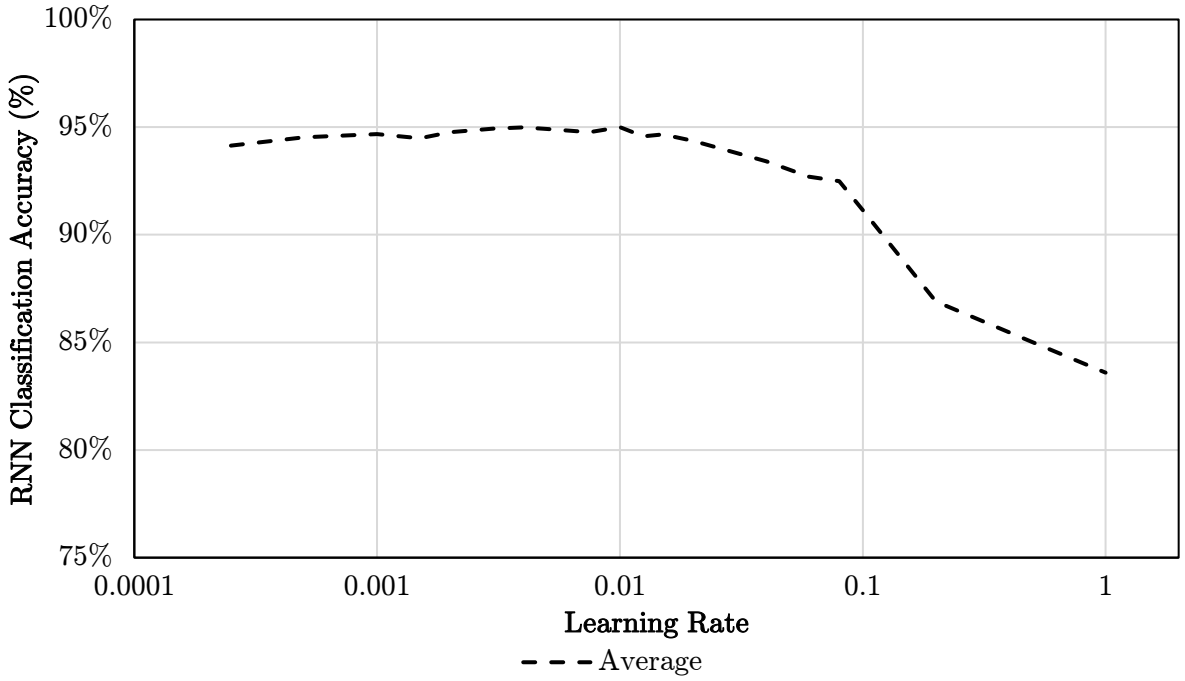


Figure C1. Average accuracy for long-term GHG impact classification trials across batch sizes using a 2-point, positive-other, scale.

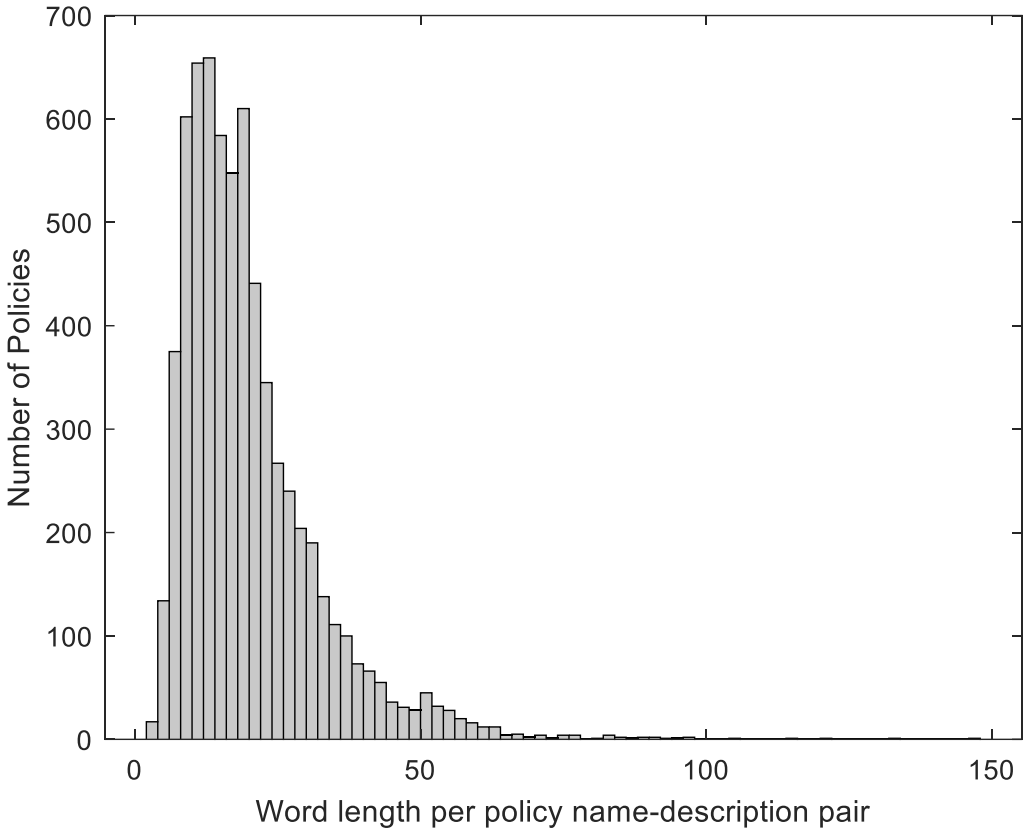


Figure C2. Frequency histogram for word length in the all-policy RNN models.



Figure C3. Example word cloud for training data of the all-policy RNN model.

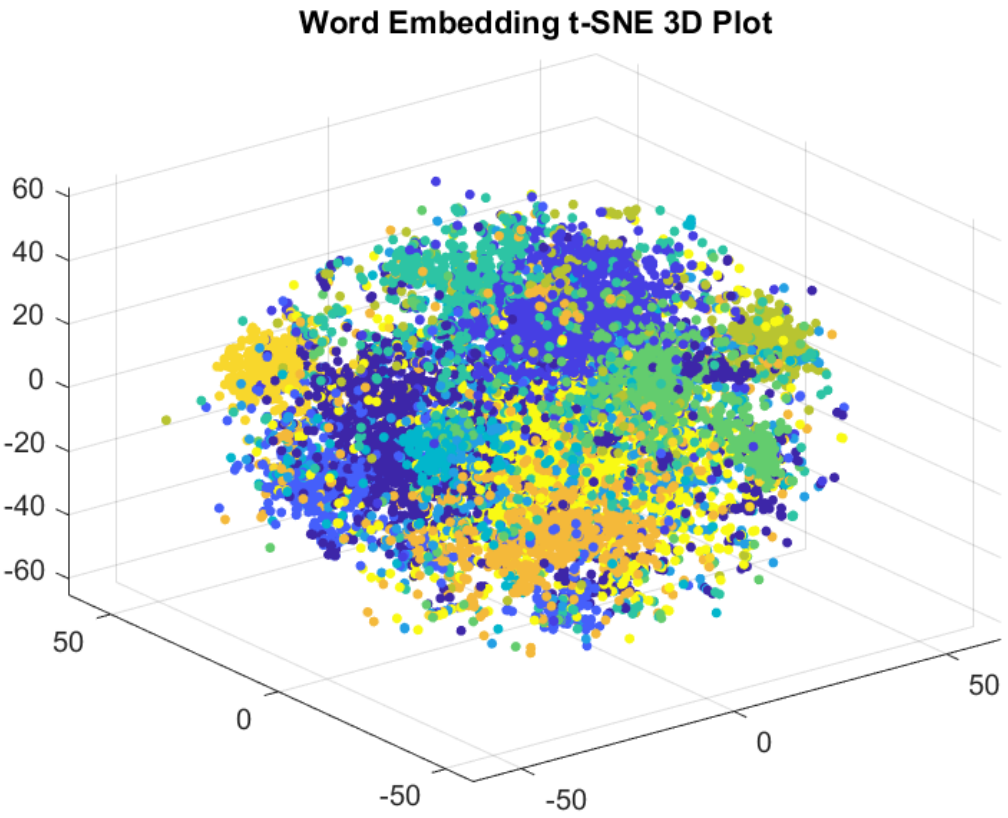


Figure C4. Word embedding t-SNE 3D plot for COVID-19 recovery 3pt long-term GHG impact model. Each colour represents one of twelve algorithmically-identified clusters using a t-SNE algorithm with exaggeration of 60, perplexity of 50, and learn rate 500.

C6. Statistical patterns in recovery investment

C6.1. Independent variables and country groupings

In this study, 47-91 potential independent variables (depending on the sample) were compiled from ten sources to meaningfully cover the universe of plausible independent variables for the four related dependent variables (table C6). This list was reduced from a preliminary set of 1386 variables, including the full set of World Bank Development Indicators and IMF Financial International Financial Statistics measures. First, all incomplete variable sets were eliminated, *i.e.*, those that did not at least fully cover the smallest sample (D). Next, the preliminary set was filtered for relevance by manual elimination of clearly irrelevant variables and inclusion of potentially relevant variables. Eliminated variables included development indicators like 'Adolescent fertility rate (births

per 1,000 women ages 15-19)', 'Battle-related deaths (number of people)', and 'Net bilateral aid flows from DAC donors, Hungary (current US$)' and governance indicators like "Government Effectiveness: Standard Error". Repeated terms were also eliminated, as well as some highly granular subsidiary terms (*e.g.*, 'Population ages 65 and above, total' was maintained, while 'Population ages 65-69, male', 'Population ages 65-69, female' and other 5-year age brackets were dropped). Finally, terms reported in local currency units or USD measures with alternative basing were removed (total of 105 terms). Terms that were products of other terms were mostly left in the independent variable set, with collinearity concerns addressed only when the PcGive model selected all the relevant terms. A summary of the trialled independent variables for each sample is included in extended data table 4 and statistical details of selected variables are included in extended data table 5.

The ten sources for the potential independent variables were:

- **International Monetary Fund:** selection from International Financial Statistics (45 variables)[155]

  Selection includes data fields in 'Central Bank Survey Data', 'Financial, Interest rates', 'International Reserves, Official Reserve Assets', 'Prices', and an assortment of others. Specific variables include 'Treasury bill rate', 'Lending rate', 'Unemployment, Persons', and 'Consumer Price Index'.

- **World Bank:** Global Economic Prospects (4 variables)[156]

  Variables are measures of average historical rates of 'GDP growth'

- **World Bank:** Human Capital Index (7 variables)[157]

Variables range from 'Expected Years of School' to 'Human Capital Index (HCI)'

- **World Bank:** Poverty and Equity dataset (29 variables)[158]

  Variables range from 'Number of Poor at $3.20 a day (PPP)' to 'Survey mean consumption or income per capita, bottom 40% (PPP)'

- **World Bank:** World Development Indicators (556 variables)[159]

  Variables are comprehensive and range from 'Access to Electricity' to 'Birth Rates', 'Deposit interest rate', 'GINI Index', 'GDP', 'Interest payments', and 'Total Population'

- **World Bank:** Worldwide Governance Index (6 variables)[160]

  Variables range from 'Regulatory Quality: Estimate' to 'Government Effectiveness: Estimate'

- **Climate Equity Reference Calculator:** Carbon Fair Share Allocations (9 variables)[161]

  Variables include variations on 'capacity-weighted fair share of responsibility to deal with climate change' and 'responsibility-weighted fair share of responsibility to deal with climate change'. Both with varying dates of reference and measurement.

- **Oxford:** Covid-19 Government Response Tracker (OxCGRT) (88 variables)[162]

  Variables range from averaged index measures like 'C1'School closing' or 'H2'Testing policy' to point in time measures of COVID-19 infections and Deaths.

- **United Nations:** Human Development Index (1 variable)[163]

Independent UN development indicators were not included due to overlap with the World Bank 'World Development Indicators'

- **Assorted sources:** World bond and central bank data (8 variables)
  Variables include various measures of ten-year bond yields, central bank interest rates, bond spreads, and expected default rates.
- **Manually compiled:** election data (4 variables)
  Variables include days to next election at start of pandemic and at January 2021.

The four country groups in the modelling were:

A. **The group of 84 economies:** all nations in the GRO dataset, except three nations with insufficient statistics to build regressor datasets (Cuba, Taiwan, and Venezuela) and Uruguay, which had insufficient published fiscal announcements for tracking of recovery investment.
B. **The group of 81 economies:** group 1, excluding China, Vietnam, and Saudi Arabia, which do not have contested parliamentary or presidential elections.
C. **The group of 50 economies:** consisting of the largest 50 economies by 2020 GDP, as reported by the World Bank.
D. **The group of 47 economies:** group 3, excluding China, Vietnam, and Saudi Arabia, which do not have contested parliamentary or presidential elections.

Since a regression model requires complete data for each independent variable, all country groups were allocated a 'set of complete independent variables', with smaller country groups able to use a larger number of regressors. Interpolation for missing data was avoided in all situations except for providing an expected

12-month and 24-month default rate for the Islamic Republic of Iran. Other default expectations were based on S&P cumulative average default rate tables.

Table C6. Samples and trialled independent variables for GETS analysis.

Sample	Number of trialed independent variables
85 economies	47
82 democracies	51
50 economies	87
47 democracies	91

C6.2. Selected models

Sixteen selection trials were developed to consider the four independent variables for the four samples. As described in the paper methods, automatic model selection was used with size = small for ordinary least squares estimation. During initial trials, prior to variable transformation, Regression Specification Error Tests (RESET tests) identified misspecification in most samples.[164] Transforming the variables to log-log form resolved this issue while also correcting normality issues. Hendry's (1999) Impulse Indicator Saturation (IIS) was used as the primary method for outlier detection,[165] with standardised residual testing used as a comparison point. IIS is a general-to-specific approach which, for cross-sectional analyses, aims to identify an unknown number of outliers with unknown magnitudes. The method introduces impulse dummy variables for every observation in a sample, allowing the model to be saturated by dummy variables—the general-to-specific model selection then selects the dummy variables (and therein outliers) that matter. As such, IIS is a natural fit for general-to-specific applications as in the GRO model selection. IIS applications have featured in several empirical works, including Hendry and Mizon (2011),[166] Reade and Volz (2011),[167] Ericsson and Reisman (2012),[168] Castle *et al.* (2012),[169] Hendry and Pretis (2013),[170] Ericsson (2017),[171] Pretis *et al.* (2018),[172] and Pellini (2021).[173] It has been defended against critiques for two

decades (Castle and Hendry, 2019).[174] The most frequent IIS outliers were the Czech Republic, Indonesia, and Colombia. None of these inclusions are surprising given that all three have provided very little in the way of recovery investment, and in the case of Colombia, also very little recovery spending. Model coefficient values are presented visually in figure S5 alongside residual histograms and predicted log values (x) versus actual log values (y) for the dependent variables.

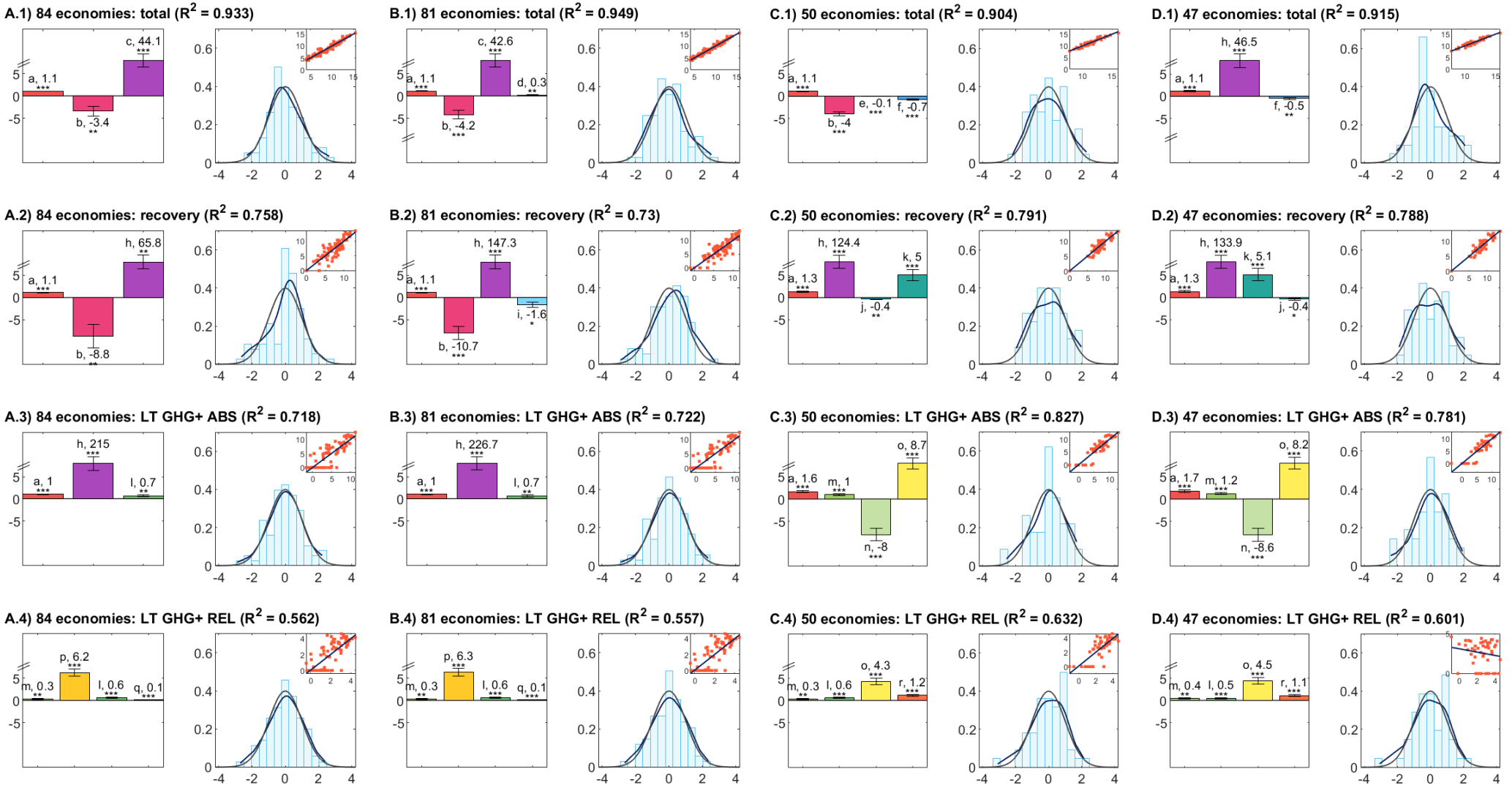


Figure S5. Statistical results of GETS modelling in log-log form for all four dependent variables in four samples, left to right: 84 economies (A), 81 economies (B), 50 economies (C), and 47 economies (D). Bar charts give significant regressors for each model

with coefficient magnitude and standard errors both scaled to the y-axis. Independent variables are grouped thematically by colour. Selected variables are: (a) LN(GDP), (b) LN(GDP growth), (c) LN(Rule of Law), (d) LN(Days until next election˙2020), (e) LN(S&P 24-month cumm avg default rate), (f) LN(Gross domestic savings (% of GDP)), (g) LN(Percentage through maximum election term˙2021), (h) LN(Voice and Accountability), (h) LN(Voice and Accountability), (i) LN(Current health expenditure (% of GDP)), (j) LN(ConfirmedCases per capita (31/12/2020)), (k) LN(StringencyIndex˙2020), (l) LN(Arable land (% of land area)), (m) LN(Renewable energy consumption (% of total final energy consumption)), (n) LN(Access to electricity (% of population)), (o) LN(Human capital index), (p) LN(Human Development Index), (q) LN(Surface area), and (r) LN(Unemployment). Coefficient t-probability (p-value) significance is: * for $p < 0.05$; ** for $p < 0.01$; and *** for $p < 0.005$. Coefficient magnitude is much higher for indexed independent variables; any attempts for practical interpretation should be done with extreme care—standardised coefficients in extended data table 5 might be more useful. Histograms give model residuals, with normal Gaussian kernel density estimates in dark blue and normal distribution density in grey. Inset plots in the top right corner of the histogram charts give predicted log values (x) versus actual log values (y) for the dependent variables. Samples A.1, B.1, C.1, and D.1 consider total COVID-19 investment, on an absolute basis (USD). A.2, B.2, C.2, and D.2 consider total recovery investment, on an absolute basis (USD). A.3, B.3, C.3, and D.3 consider total recovery investment that is long-term GHG-positive, on an absolute basis (USD). A.4, B.4, C.4, and D.4 consider the same, but relative to total recovery investment. IIS outliers in each model were, for A.1: Colombia; A.2: Burkina Faso, Indonesia, Iran, and Paraguay; A.3: China and Czech Republic; A.4: Czech Republic; B.1: Colombia, Mongolia, and Romania; B.2: Paraguay; B.3: Czech Republic; B.4: Czech Republic; C.1: Colombia and Romania; C.2: Czech Republic, C.3: Czech Republic, Indonesia, Singapore and Thailand; D.1: Colombia, Romania, and Spain; D.2: Indonesia and Iran; D.3: Czech Republic, Indonesia, and Thailand. Statistical details and testing available in extended data table 5.

C7. Did investment match political rhetoric?

The *Global COVID-19 Speech Database*[2] is available at the following link: http://dx.doi.org/10.6084/m9.figshare.20338533

C7.1. Green dictionary

Automated text analysis using natural language processing (NLP) continues to grow in popularity. However, these methods often rely heavily on domain-specific dictionaries, which are challenging to create and validate, even with the input of subject matter.[175] A dearth of appropriate premade green dictionaries hence restricts some NLP applications on topics of climate change. Fish-Romito *et al.* (2021) provide only thirteen terms for identifying green literature and twelve for identifying lock-in literature.[176] To address these gaps, O'Callaghan *et al.* (2022) use embedding algorithms to define a green dictionary based on the specific terms used in 908 papers on green investment.[177]

As O'Callaghan *et al.* explain:

> *"Such models operate by identifying how terms in a corpus relate to each other. They vectorise the terms into a n-dimensional space. Here, we use the word2vec word embedding model (61) of dimension 100 with a minimum count of three, to expand our user-defined dictionary to capture groups of related terms (rather than synonyms) that convey similar concepts…*
>
> *…the algorithm teaches itself to find related words to an input dictionary set, uses these new words to identify additional literature, updates the corpus with this new literature, and repeats until no new words or papers are identified. Related words are identified by cycling through each potential term pairing in every dictionary category, taking the average of the term vectors, and finding the closest term to this vectorised location. The cycle repeats by pairing the new term vector with every existing term vector in the dictionary category until the closest term vectors to the average of the pair vectorisation are the input word pair. Papers are identified based on dictionary search terms used with the Web of Science Topic Search (TS) function, which considers titles, abstracts, keyword fields, and*

keyword plus fields. Manual post-processing is applied on every iteration of the cycle to filter unrelated papers."

And in their supplementary materials:

"We used a simple function to expand the initial dictionary set:

1. *The vectorised position of all n initial dictionary terms, $i_1 \rightarrow i_n$, was recorded.*
2. *A loop calculated the vector midpoint between the n x n pairings of the dictionary terms, e.g., for the first two terms,*

$$pairing\ midpoint, i_1, i_2 = \frac{\overrightarrow{i_1} + \overrightarrow{i_2}}{2}$$

3. *For each nxn pairing midpoint, the algorithm identified the most closely located word vector from the corpus and tested if this word vector was already some i_x in the domain dictionary. If the word vector was new, it was recorded as i_{n+1} and step 4 was taken. If the word vector was not new (i.e., some i_x), no action was taken and the loop in step 2 resumed.*
4. *Steps 2 and 3 were repeated using i_{n+1} consecutively as a replacement for i_1 and then for i_2. This continued until no new word vector was discovered and the loop set in step 2 could resume.*

The new domain-specific similar dictionary terms (of number x) were finally added to the original dictionary, expanding the total number of terms to n + x. With these expanded search terms, all steps, from literature identification to text processing to dictionary expansion, were repeated until no further terms were identified."

In the present analysis, I use the ending dictionary of O'Callaghan *et al.* as my initial dictionary. I broaden the dictionary slightly with, amongst others, crisis-specific terms like 'green recovery'. Then, I apply the dictionary-expanding algorithm of O'Callaghan *et al.* to the English speech dataset, deriving a domain-specific dictionary on green policy. The dictionary expansion process identified many new terms, including 'zero˙carbon', 'conserve˙nature', and 'determined˙contribution' (as in 'nationally determined contribution'). The full dictionary is included in table C7.

Table C7. Expanded green dictionary used in rhetoric analysis with terms grouped by category. Not shown are the combined forms of bigrams and trigrams, which were all included in the analysis to account for transcript typos (*e.g.*, "electricvehicle" is included alongside "electric vehicle" and "greenhousegas removal" alongside "greenhouse gas removal"). Also not shown are subsidiary forms of key words (*e.g.*, "green energy" is not included as "green" already is). Finally, bigram hyphenations are excluded (they are read as single words by the algorithm, *e.g.*, "net-zero" and "environmentally-sustainable").

Words	Bigrams	Trigrams
	General environmental	
carbon	determined contribution	decision in paris
clean	efficiency environmental	green new deal[1]
climate	efficiency sustainability	is on fire
cop2*	efficient environmental	save the environment
emission*	efficient fuel*	
ghg	environmental conservation	
ghgs	environmental efficacy	
green	environmental protection	
greener	environmental resilience	
greening	environmental sustainab	
methane	fuel efficien*	
ndc	fuel saving	
unfccc	green recovery[1]	
	net zero	
	paris agreement	
	paris aligned	
	paris commitment	
	paris decision	
	paris framework	
	saving environmental	
	sustainable infrastructure	
	Carbon capture and storage	
ccs	carbon capture[1]	greenhouse gas removal
	carbon removal[1]	
	carbon sequestration[1]	
	carbon storage[1]	
	Electric vehicles	
ev*	charging infrastructure	cash for clunker*

	charging station*	
	electric automobile*	
	electric car*	
	electric charg*	
	electric infrastructure	
	electric vehicle*	
	green automobile*[1]	
	green car*[1]	
	green electricity[1]	
	green vehicle*[1]	
	hybrid automobile*	
	hybrid car*	
	hybrid electric	
	hybrid vehicle*	
	Energy efficiency	
daylighting	appliance efficiency	energy efficient building*
electrification	appliance incentive*	energy efficient retrofit*
	building upgrade*	
	buildings upgrade*	
	efficienct retrofit	
	efficienct retrofits	
	efficiency building*	
	efficiency insulation	
	efficiency retrofit*	
	efficient building	
	efficient buildings	
	energy efficien*	
	green retrofit* [1]	
	insulation building*	
	insulation retrofit*	
	Green energy	
ammonia	battery storage	
hydro	battery infrastructure	
hydrogen	clean energy[1]	
methanol	geothermal energy	
smartgrid	geothermal generation	
solar	geothermal plant*	
wws	geothermal power	
	ghg removal	

green digitalisation[1]	
green electrolysis 1	
green hydrogen[1]	
offshore wind	
renewable energy	
smart grid*	
sustainable energy	
wave energy	
wave power	
wind energy	
wind farm*	
wind power	
wind turbine*	
Green liquidity	
clean bailout*[1]	
clean loan*[1]	
climate bailout*[1]	
climate loan*[1]	
conditional bailout*	
conditional loan*	
green bailout*[1]	
green loan*[1]	
Green R&D	
clean innovation[1]	
clean innovate[1]	
clean r&d[1]	
clean research*[1]	
green innovate[1]	
green innovation[1]	
green research*[1]	
clean innovation[1]	
Green skills	
clean job*[1]	future industries skill
green education[1]	future industries education
green job*[1]	future industries job*
green retraining[1]	future industries retraining
green training[1]	future industries skill*
just transition	future industries training

Natural capital		
biodiversity	agricultural conservation	climate friendly farming[1]
nbs	capital green[1]	climate resilient farming[1]
	carbon store[1]	fish stock management
	coastal restoration	natural environment protection
	conservation agricultur*	natural environment protections
	conservation natur*	nature based solution
	conservation water	nature based solutions
	conserve natur*	
	ecological conservation	
	environmental asset*	
	fishstock management	
	forest management	
	forest rehabilitation	
	forest restoration	
	forests management	
	forests natural	
	forests restoration	
	green capital[1]	
	green resource*[1]	
	green space*[1]	
	management forest*	
	management natur*	
	national park*	
	natural asset*	
	natural evergreen[1]	
	natural forest*	
	natural rehabilitation	
	natural reserve*	
	natural resource*	
	natural sustainability	
	nature conservation	
	nature preservation	
	nature reserve*	
	plant tree*	
	protect natur*	
	regenerative agriculture	
	resource conservation	

	restoration natural	
	soil conservation	
	sustainable fishing	
	tree planting	
	water conservation	
	waterway enhancement	
	waterway protection	
	Sustainable transport	
bike*	clean transport[1]	bike share infrastructure
bus*	micro mobility	
cycl*	pedestrian infrastructure	
ferr*	public transport	
metro	walking infrastructure	
rail		
train*		
tram*		

[1] Term is excluded from counts contributing to the total rhetoric index to avoid double counting in subsidiary terms (*e.g.*, "green energy" is not counted for the total index as "green" is already counted in the general environmental category). These terms are included for category-specific rhetoric indices and term-specific analysis.

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D

Co-authorship Statements

D.1. Paper A: How Stimulating Is a Green Stimulus? The Economic Attributes of Green Fiscal Spending

Co-authors: Cameron Hepburn (University of Oxford) and Nigel Yau (University of Oxford)

ADAPTED CO-AUTHORSHIP DECLARATION

A student whose thesis includes a co-authored chapter/chapters, should complete this form and send it on to their co-author and supervisor for completion. If there is more than one co-author, each should complete a separate form. The student should include the completed form(s) with their own Statement of Authorship when submitting their GSO3 Appointment of Examiners form. The form will be sent on to the examiners with the thesis.

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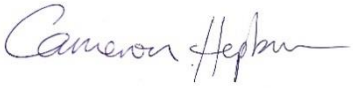
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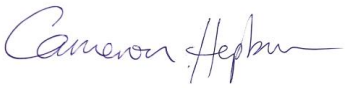
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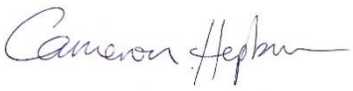
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Please describe the candidate's contribution to the chapter(s).	Brian provided several original and meaningful contributions to our paper: *How Stimulating is a Green Stimulus? The Economic Attributes of Green Fiscal Spending*. These include: • Conceiving of the paper • Developing a structure for the paper • Developing the machine learning approach used in the systematic review and conducting all related analysis • Drafting Sections 1, 3, and 5 • Co-drafting Sections 2 and 4 • Creating all tables and figures • Working alongside co-authors to address reviewer comments and write responses to the reviewers • Checking and refining copy-editing notes provided by editors from the Annual Review of Environment and Resources		
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D.2. Paper B: Will COVID-19 fiscal recovery packages accelerate or retard progress on climate change?

Co-authors: Cameron Hepburn (University of Oxford), Nicholas Stern (London School of Economics), Joseph Stiglitz (Columbia University), and Dimitri Zenghelis (Cambridge University)

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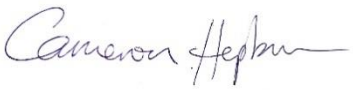
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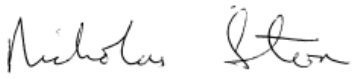
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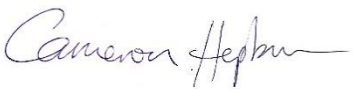
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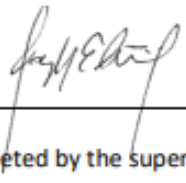
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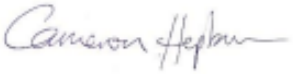
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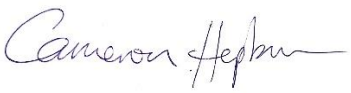
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E

List of My Other Related Works

Economic perspectives on green recovery in a select group of advanced economies:

- *Submission to Covid Recovery Commission Advisory Group (UK),*
- *Submission to BEIS Economic Taskforce (UK)*,
- *Building Long-Term Australian Competitive Advantage Through a Clean Covid-19 Recovery: Submission to the Australian National Covid-19 Coordination Commission*,
- *Prospects for a green COVID-19 recovery in Canada: Submission to the House of Commons Standing Committee on Finance,*
- *Breve guía para contribuir a la reconstrucción y recuperación 'verde' tras la crisis de la COVID-19 en España*, and
- *Prosperity stimulus for Italy: a green COVID-19 recovery*.

Economic characteristics of green recovery in emerging market and developing economies using input-output modelling and more:

- *A Prosperous Green Recovery for South Africa,*
- *Une croissance économique verte pour la République démocratique du Congo*,
- *Shaping a Green and Resilient Recovery for the Republic of Kenya*,
- *Green Economic Recovery for the Arab Republic of Egypt*, and
- *Indonesia: COVID-19 fossil stimulus spending*.

Reflections on COVID-19 policy as instructive for climate policy:

- *Five Lessons from COVID-19 for Advancing Climate Change Mitigation*.

A policy maker handbook on green recovery:

- *Roadmap to Green Recovery.*

Global assessments of the greenness of pandemic responses:

- *Are We Building Back Better? Evidence from 2020 and Pathways for Inclusive Green Recovery Spending,*
- *Chapter 5 of the UNEP Emissions Gap Report 2021: Are COVID-19 fiscal recovery measures bridging or extending the emissions gap?* and
- *Global COVID-19 recovery investment is not aligned with COP rhetoric.*

A draft analysis of the proposed US Build Back Better package:

- *How will the US fiscal response to COVID-19 impact global progress on climate change?*

A methodology document on how to apply the green recovery taxonomy and impact assessments to ordinary budgetary progresses:

- *Introducing The Sustainable Budgeting Approach* (impact assessments include climate, natural capital, air pollution, income inequality, rural inequality, and economic factors).

Assessments of pandemic response in Latin America and the Caribbean:

- *Is the COVID-19 economic recovery building a sustainable future? A snapshot from Latin America and the Caribbean,*
- *Is the COVID-19 economic recovery building a sustainable future? Update: COVID-19 Spending in LAC May - September 2021,* and

- *Is the COVID-19 economic recovery building a sustainable future? Update: COVID-19 Spending in LAC October – December 2021.*

Perspectives on the economic prospects of green hydrogen investment:

- *Briefing for Policymakers: Green Hydrogen as Fiscal Stimulus.*

Perspectives on the economic prospects of clean aviation investment:

- *Why airline bailouts are so unpopular with economists.*

Perspectives on green labour investment:

- *Submission to Environmental Audit Committee – Green Jobs Inquiry.*