Understanding & Incentivising Innovation for a Climate Compatible Future

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To the child whose beanstalks grew tall,

To the mother whose toes sank into the warm sand,

To the father who stood tall atop the mountain,

To the hare that took shelter from the storm,

To the bioluminescent worm that hung from a stalactite,

To the ancient bacteria that lived for eons in the planet's crust,

To all beings,

We are Earth, we will be, Earth.

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I dedicate this thesis to my nana.

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Abstract

Net-zero emissions are needed to stabilise mean global temperatures. This is one of the greatest challenges of our generation. Innovation will play a fundamental role in ensuring economic activity becomes "climate-compatible". Yet, robust empirical evidence on how to best incentivise investment and innovation in low-carbon technologies is limited. This thesis explores this question using rich datasets related to energy generators, firms, and patents. It is divided into three papers which respectively seek to understand (i) the role of price and risk-mitigation policies, such as feed-in-tariffs, in bringing breakthrough clean technologies to market, (ii) the joint impact of different policies on firms' incentives to undertake clean innovation, and (iii) patterns of learning and knowledge diffusion across clean and dirty technologies. This thesis deploys tools from modern econometrics, causal inference, and network analysis to study these questions. It finds that risk reduction policies alongside subsidies are important in bringing nascent clean technologies to market, that environmental and innovation policy, if not well-coordinated, can lead to un-intended impacts, and that, on aggregate, knowledge embedded in clean inventions is intellectually distant to that embedded in dirty inventions, despite a few areas of close proximity. Collectively, the papers demonstrate the importance of understanding innovation processes and policies for the net-zero transition.

DPhil Papers

1. Bringing Breakthrough Technologies to Market: Evidence from Renewable Energy Feed-in-Tariffs

Sugandha Srivastav

2. The Unintended Consequences of Environmental and Innovation Policy Interactions

Jacquelyn Pless and Sugandha Srivastav

3. Knowledge Spillovers Between Clean and Dirty Technologies

Su Jung Jee and Sugandha Srivastav

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I. Introduction

A. Motivation

Modern civilisation has been built around hydrocarbons. Materials such as coal, oil, gas, steel, cement and fertilisers, have made production processes more efficient, electrified populations, and catalysed the mechanisation of agriculture. However, the carbon-intensive resources that once improved livelihoods, now threaten them due to the growing impacts of anthropogenic climate change (IPCC 2018).

Scientific evidence shows that 2°C of warming will negatively affect agricultural productivity, fish stocks, coral reefs, and make extreme weather events such as fires, storms and floods more frequent and intense (IPCC 2018). Accumulating scientific evidence and growing political momentum has led to the widescale adoption of net-zero emissions targets. Till date, 136 countries have announced such pledges which together cover 83% of global emissions (The Net Zero Tracker 2022). These targets are often accompanied by a vision of future economic activity that is clean, efficient, and welfare-improving.

This thesis explores *how* economic activity can transition to a climate compatible future, focusing particularly on firm-level incentives to undertake clean innovation. It explores the implications of risk, policy interactions and knowledge spillovers for innovation and investment. It examines how policies, such as feed-in-tariffs, carbon pricing, and R&D tax credits, have fared in facilitating the net-zero objective.

In doing so, the thesis feeds into the debate around policies for effective and rapid decarbonisation. It finds that if policymakers have a target to bring breakthrough low-carbon technologies to market, it is important to address barriers related to the high cost of capital which arise due to uncertainties and incomplete information over new technologies. This issue is particularly relevant for second-generation clean

energy technologies such as green ammonia, long-duration storage and electrified long-haul transport which will likely play an important role in achieving net-zero emissions.

Relatedly, this thesis investigates whether policymakers should use technology-neutral or technology-specific innovation policy to support decarbonisation. It examines how each type of innovation policy interacts with environmental policy, and finds that technology-neutral innovation policy can counteract the effects of carbon pricing under certain circumstances. This inquiry marries the literature on innovation economics and environmental economics.

Finally, this thesis explores if knowledge embedded within dirty technologies has relevance for clean technologies using patent citation data. Due to the enormous pressure on hydrocarbon companies to diversify (Colgan et al. 2021), it is interesting to see if there are "adjacent" clean technologies which dirty R&D incumbents can more easily pivot into, leveraging their existing skills and knowledge. It finds that on aggregate, knowledge spillovers from dirty to clean technologies are very limited, but there are certain areas of proximity when sectoral results are examined.

The institutional context of the first two papers is the United Kingdom, which has a legally binding net-zero emissions target by 2050 and a goal to fully decarbonise its power sector by 2035. The third paper studies the global innovation frontier, which is proxied by the United States Patent and Trademark Office's (USPTO) patents (Granstrand 2018). Methodologically, this work uses tools in applied econometrics, including bunching estimation, as well as methods in network analysis. Detailed micro-data on balance sheets, power sector projects, and patents supports this thesis.

The rest of the synthesis document is structured as follows: Section I.B presents a summary of each paper, Section I.C highlights contributions, Section I.D discusses policy recommendations and Section I.E deliberates limitations and extensions.

Section II does a literature review. Section III concludes. Individual papers are appended at the end of this document.

B. Summary

Paper 1 - The inquiry begins with Paper 1, which asks how nascent, socially-beneficial technologies can be brought to market to meet power sector decarbonisation targets. This question is motivated by the hypothesis that due to credit market imperfections and positive externalities, investment in clean technologies is sub-optimally low. Using a bunching estimator, the paper finds that the UK's renewable energy feed-in-tariff (FiT) is highly effective in incentivising entry by utility-scale solar generators and results in large net capacity additions. In terms of value for money, a social cost of carbon worth £100 per tonne of CO2 is enough to make the FiT a net gain, but this ignores the market creation benefits of the policy.[1]

Key results can be summarised as follows (empirical strategies contained in parentheses):

- Relative to a no-FiT counterfactual, there are at least 43 times more commercial solar projects thanks to the policy, resulting in a net increase of 2.3 GW of low-carbon capacity. This is roughly equal to one-fifth of UK's total installed solar capacity today (bunching estimation).
- In the first phase of the FiT (April 2010 to July 2012), there are 27 times more projects relative to a counterfactual with no FiT. In the second phase (August 2012 to December2015) this effect is enhanced to 41 times. Several factors related to risk reduction explain this increase since subsidies were higher in phase 1.

[1] This paper investigates the impact of the FiT on commercial generation, not on residential generation which was covered by a separate rate.

- The FiT's eligibility threshold does not result in significant strategic downsizing: out of the observed bunching mass, only 6% can be attributed to strategic downsizing while the remaining 94% reflects new entry (bunching estimation).

Evidence on how much capacity can be *causally* attributed to the FiT is useful as without it, policymakers cannot accurately assess the scheme's cost-effectiveness. The paper's exploration of the role of risk-reduction in bringing breakthrough technologies to market likely has implications for other socially-beneficial early-stage technologies across a host of other contexts (e.g. climate change adaptation, healthcare, second-generation clean technologies, etc.)

Paper 2 - Next, Paper 2 investigates how to incentivise innovation by energy-intensive firms in the context of two market failures: knowledge spillovers which create a wedge between the social and private value of innovation and environmental externalities which lead to an oversupply of socially harmful dirty innovation (Jaffe, Newell and Stavins 2005). R&D tax credits and carbon pricing are used to address these externalities respectively. However, since carbon prices are politically constrained to be below their optimal level (Klenert et al. 2018, Borenstein 2012), the "first-best" innovation policy may no longer be best (Lipsey and Lancaster 1956). Using a "discontinuity-in-effects" estimation strategy, the paper discovers that the positive marginal effect of carbon pricing on innovation by firms in the UK manufacturing and energy sectors is dampened by access to more generous R&D tax credits.

Key results can be summarised as follows:

- Firms in industries that are directly regulated under the European Union Emissions Trading Scheme (EU ETS), increase capital expenditures by 1.2% in response to a 1 GBP increase in the carbon price. However, this

effect is dampened to 0.8% for firms receiving more generous R&D tax credits.

- For firms in indirectly exposed industries, a 1 GBP rise in carbon price increases total factor productivity (TFP) by 2.3% but this effect is dampened to -0.8% for firms receiving more generous R&D tax credits.

These results indicate how carbon pricing and R&D tax credits are substitutes in their effects for both regulated and indirectly exposed firms. This has implications for policymakers interested in inducing innovation and productivity gains in energy-intensive sectors.

Paper 3 - Finally, Paper 3 uses 50 years' worth of patent data from the USPTO to explore if clean and dirty technologies systematically learn from each other. The assumption that clean and dirty technologies do not learn from each other underpins the canonical result that carbon pricing needs to be complemented by directed clean subsidies to overcome the "market size effect" (Acemoglu et al 2012). Paper 3 finds that on aggregate, there is limited knowledge spillovers between clean and dirty technologies, but aggregate results conceal sector-specific heterogeneity.

Key results can be summarised as follows:

- Less than one-tenth of clean patents directly cite prior dirty patents.
- Most clean technologies are indirectly linked to dirty technologies in the patent citation network.
- The median clean patent is connected to a dirty one by three degrees of separation.
- Geothermal energy, long-haul transportation, and carbon capture & storage are the clean sectors that have the highest degree of cross-citation with dirty technologies while solar PV has the lowest.

C. Contributions

Together, the papers in this thesis provide evidence on policies to incentivise innovation for the clean energy transition. An overarching theme is the empirical examination of policies and situations that fall outside the realm of Pigouvian "first-best". This is of importance as frictions and political constraints prevent such policies from being feasible (Klenert et al. 2018; Borenstein 2012).

Feed-in tariffs are one such example intervention. They have been deployed around the world, yet there is limited causal evidence of the impact of feed-in-tariffs on entry and investment in the commercial renewable energy sector.[2] Paper 1 remedies this gap, with an analysis that allows policymakers to understand how much of the observed capacity additions can be causally attributed to this policy. Additionally, this paper underscores how apart from the carbon externality, other market failures such as those related to credit market imperfections and incomplete information, affect renewable energy deployment and warrant policymakers to consider a range of instruments.

Similarly, a priori one would not expect that R&D tax credits need to be directed specifically towards clean innovation. However, since the ability to set optimal prices on carbon is politically constrained, it becomes important to re-visit this conventional wisdom. Paper 2 develops a theoretical model which shows how technology-neutral R&D tax credits can either be complements or substitutes to carbon pricing, and how this ambiguity is removed when the tax credits are directed towards clean innovation. It generates novel causal evidence on the interaction between environmental and innovation policy. It finds that the positive effect of carbon pricing on innovation and productivity is attenuated by technology-neutral R&D tax credits,

[2] Smith and Urpelainen (2014), Jenner et al. (2013) and Dijkgraaf, et al. (2018) generate evidence that is most likely to be correlational rather than causal due to the difficulty in controlling for confounding factors in cross-country regressions that try to estimate the impact of the FiT on share of renewable generation.

lending support to the idea that policymakers should consider these interactions carefully.

Finally, there is an implicit assumption that underpins many analyses related to diversification, innovation policy and environmental policy, which is that clean and dirty knowledge are mutually exclusive. This leads to the canonical result that even optimally set carbon prices require directed clean technology subsidies because there is hysteresis in the innovation system that leads to sub-optimally high levels of dirty innovation (Acemoglu et al. 2012). However, if clean technologies can learn from their dirty counterparts, we may be overstating the extent of path dependencies that favour dirty innovation. Paper 3 systematically investigates the knowledge spillovers between clean and dirty technologies, leveraging 50 years' worth of patent data, classifying patents as clean, dirty or grey. It finds a limited share of direct citations between clean and dirty patents; and discovers that the median clean patent is connected a dirty one by three degrees of separation. This points towards limited knowledge spillovers between the two technology classes. However, the paper does find sectoral heterogeneity and highlights clean sectors that are more intellectually close to dirty technologies.

Methodologically, this thesis has several contributions which include applying the bunching estimator to a novel context with a large extensive margin response, using a "discontinuities-in-effects" identification strategy which is inspired by the "difference-in-discontinuities" strategy employed in Grembi et al. (2016) and Pless (2022). Paper 3 creates a new metric to proxy indirect inter-technology learning which builds off the work in Ahmadpoor and Jones (2017).

D. Policy Recommendations

Several policy recommendations emerge from this thesis:

1. **Risk reduction is important for early-stage technologies.** These technologies suffer from a chicken and egg problem, where due to fundamental uncertainty, private investors do not invest, but this makes it harder to determine what the risk-profile looks like. Government intervention in the form of guaranteed demand or price, can help incentivise investment and attenuate the problem of incomplete information by demonstrating the realised costs and revenues. Support can be phased out as the technology matures and the problem of incomplete information is attenuated.
2. **Complement carbon pricing with *directed* clean technology subsidies.** Carbon prices are constrained to be below the true value of the social cost of carbon. Under such circumstances, directed clean innovation subsides are likely necessary to ensure the direction of innovation is climate compatible. Furthermore, even if carbon prices are optimal, hysteresis in the innovation system may still warrant targeted clean innovation subsidies to overcome the market size effect.
3. **Dirty R&D incumbents can consider pivoting into adjacent clean sectors.** Clean technologies, such as geothermal energy, tidal power, offshore wind, and carbon capture & storage are relatively more proximate to dirty technologies due to commonalities related to geologic surveying, operating out at sea, and understanding chemistries. These areas of intellectual proximity may offer potential pathways through which dirty R&D incumbents can leverage *existing* skills and knowledge to pivot into adjacent clean industries.

E. Limitations, Extensions & Ideas

This section briefly discusses the scope, limitations, and possible extensions of each paper as well as broader areas for intellectual inquiry.

Paper 1 concerns itself with the case of policy for nascent breakthrough technologies, which occupy a small share of the overall market. Its conclusions do not have external validity when applied to technologies with higher market shares. This is because the distortionary effects of dampening price volatility on overall market outcomes can no longer be approximated away. In these cases, FiTs may lead to an over or under-supply of electricity and dampen the incentive to invest in valuable technologies related to energy storage or demand-side response. There may also be distortions in the credit market because of the policy. In future work, it would be worthwhile to model the FiT in a full general equilibrium setup with an explicit credit market to be able to comment on the optimal deployment of the policy.

In *Paper 2*, the estimated impact is a local average treatment effect and hence interpretations hold within a small window around the R&D tax credit generosity threshold. In future, it would be worthwhile to identify settings in which causal estimation is possible without the limiting condition of estimating local average treatment effects. Further analysis on the direction of R&D expenditures and alternative measures for innovative activity (e.g. survey data to precisely pin down how firms are innovating) could be helpful in better understanding the mechanisms at play.

In *Paper 3*, the analysis is limited to a measure of innovation that is based on patent data, which is biased towards (i) products rather than processes and (ii) higher-end innovation rather than low-value innovation (OECD 2009). Paper 3 measures knowledge spillovers between clean and dirty technologies, as is relevant to the technological frontier. An extension could be to trace learning between clean and dirty technologies in bibliometric data, using academic citations as a proxy for learning. Furthermore, while citations are a proxy for knowledge spillovers, they are an imperfect measure. As such, future work could try to use natural language

processing to determine the degree of similarity between clean and dirty inventions by reading the explanatory text of these patents.

More broadly, there are important questions related to policy design that are worth exploring further. One example is how to best design a feed-in-tariff. Instead of setting an eligibility threshold based on size, the policy could have a tender-based approach to allocation (Green and Vasilakos 2011) e.g. one could use a reverse auction as was done in the allocation of contract-for-differences in the UK. Comparing different design elements could be based on leveraging existing empirical evaluations of FiTs that have different design features or it could involve modelling efforts that simulate the impacts of each.

While this thesis makes an initial foray into understanding innovation for a climate compatible future, open questions remain. In particular, three significant areas for future inquiry emerge: (i) the interplay between market power and clean innovation, which is not only important for the electricity sector, but also for hard-to-decarbonize sectors such as iron & steel, aviation, and shipping; (ii) incentivizing clean innovation in low and middle-income countries; and (iii) designing policies to better support fundamental research in clean technologies.

II. Literature Review

Although each paper enclosed in this thesis contains its own literature review, an overall contextualisation of the literature this thesis most closely connects to is provided below.

A. Theory of Clean Innovation

The literature on the economics of clean innovation is theoretically embedded in the idea of "directed technical change" (e.g. Acemoglu 2002) which posits that there are two major forces that determine the direction in which innovation occurs: the

price effect and the *market size effect*. The price effect leads to innovation that is directed towards scarce factors while the market size effect favours abundant factors due to path dependencies.

An application of this theory to the low-carbon transition finds that the market size effect and the initial productivity advantage of dirty inputs directs innovation and production towards dirty sectors, contributing to environmental degradation and net welfare losses (Acemoglu et al. 2012). The theory finds that carbon taxes and directed clean research subsidies are sufficient to redirect technical change to clean sectors and that these policies need to be in place only temporarily, because once clean technologies are sufficiently advanced, research would be directed towards clean technologies without further government intervention.

This theoretical work is complemented by a series of empirical studies on the price and market size effects. For the price effect: Newell, Jaffe and Stavins (1999) and Popp (2002) show how energy price hikes lead to more patents in energy-saving innovations. Aghion et al. (2016) discover that increases in fuel price due to carbon taxation induce clean innovation in the automobile sector. Calel and Dechezlepretre (2016) observe that the European Union Emissions Trading Scheme (EU ETS) increased low-carbon innovation. The empirical literature confirms that changes that evoke scarcity on carbon emissions direct innovation towards low-carbon products and processes.

For the market size effect evidence is more limited. A general network analysis of patents and their citations shows that technological progress builds upon itself (Acemoglu, Ufuk and Kerr 2016). There is also evidence that in the auto-industry, firms with history of dirty innovation are more likely to focus on dirty innovation in the future (Aghion et al. 2016).

In the canonical model of the environment and directed technical change (Acemoglu et al. 2012), scientific labour for dirty innovation is modelled as distinct

to scientific labour for clean innovation. This is critical to the market size effect and is another way of implicitly saying there are no knowledge spillovers between clean and dirty innovation. This assumption underpins the key result that carbon pricing needs to be complemented by directed clean technology subsidies. However, till date, no study has systematically evaluated the extent to which clean and dirty technologies learn from each other. This is the contribution of Paper 3.

The scope for higher knowledge-spillovers is often used support clean innovation subsidies. However, ex-ante it is not clear that clean innovation generates higher knowledge spillovers than dirty innovation. Dechezleprêtre, Martin, and Mohnen (2014) conduct a citation analysis of clean and dirty patents and find that there are 40% higher levels of spillovers from clean technologies than dirty ones. Noailly and Shestalova (2017) similarly use patent data from Europe over 1978-2006 to observe that patents in wind, storage and solar technologies are generally cited more frequently than other technologies, and that innovations in solar energy and storage technologies find applications outside the field of power generation. These are examples of other arguments which may justify directed clean innovation subsidies.

B. Understanding Technological Responses to Environmental Policy

A related strand of literature evaluates the technological responses to environmental policy. Important questions in this area include whether policy leads to incremental or radical clean innovation; whether policymakers should use targeted measures or broad-based interventions; and what the impact of overlapping policies is on the direction of innovation.

Calel (2018) hypothesises that there is a hierarchy of response to environmental regulation whereby firms first seek to: adopt existing abatement technologies and once adoption opportunities are exhausted, invent new clean products/processes. Using reductions in emissions intensity to proxy adoption and clean patents to proxy

innovation, Calel (2018) finds while in some cap & trade schemes the hypothesis is confirmed, in the EU ETS, expectations of high future carbon prices incentivise innovation before adoption.

On the question of targeted versus broad-based interventions, Johnstone, Haščič, and Popp (2010) argue that broad-based policies such as tradable energy certificates are more likely to induce innovation in technologies that are already cost-competitive with fossil fuels (i.e. incremental innovation) whereas targeted schemes such as feed-in-tariffs are likely to induce innovation in more costly technologies such as solar power (radical, product innovation).

While there are many studies that estimate the impact of broad-based measures such as carbon taxation (Martin et al. 2014, Andersson 2019, Leroutier 2022) and cap & trade schemes (Calel and. Dechezlepretre 2018, Colmer et al. 2022, Rafaty et al. 2020, Martin et al 2020), there are relatively few studies that generate evidence on more targeted measures such as feed-in-tariffs (Smith and Urpelainen 2014, Jenner et al. 2013 and Dijkgraaf, et al. 2018) and renewable portfolio standards (Greenstone and Nath 2020). The evidence that exists on feed-in-tariffs largely consists of cross-country studies which suffer from endogeneity issues. This is a gap that Paper 1 aims to fill by robustly causally estimating the impact of the UK renewable energy feed-in-tariff.

Finally, conceptual work has emphasised how clean innovation suffers from two externalities: the climate externality and knowledge spillovers (Jaffe, Newell and Stavins 2005). Fixing these market failures requires carbon pricing and innovation subsidies. Paper 2 empirically estimates the effect of these two policies and finds that, if not properly coordinated, they can lead to unintended consequences for the direction of innovation. This work marries two separate stands of literature, one which empirically estimates the effect of carbon prices on innovation-related outcomes (Popp 2002; Martin, De Preuxand Wagner 2014; Calel and Dechezlepretre

2016; Aghion et al. 2016), and the other which measures the impact of R&D tax credits (Guceri and Liu 2019, Howell 2017, Simcoe et al. 2019, Guzman et al. 2019, Dechezlepretre et al. 2016, Bøler et al. 2015, Bronzini and Iachini 2014 and Pless 2021).

C. Financing Clean Energy Innovation

Finally, by looking at the role of risk-reduction in incentivising entry and investment by clean energy firms, this thesis also connects to the general literature on clean energy finance.

Clean energy innovation is particularly sensitive to credit market imperfections because it has long time horizons (often in excess of 20 years); higher uncertainty due to technological nascency, intermittent output, and exposure to fluctuating electricity prices; as well as irreversibility due to the site-specific nature of investments and sunk costs related to due diligence, permitting, etc (Polzin et al. 2019; Dixit and Pindyck 1994). For these reasons, it is often said that clean energy, much like other large infrastructure projects, needs patient capital and models of financing that can address credit market imperfections and incomplete information (Steffan 2018). Any potential underinvestment due to these issues is likely to be exacerbated by the lack of carbon pricing, which results in firms failing to account for the harmful effects of dirty energy. These problems are non-trivial and have been cited as one of the main barriers to the widescale deployment of clean energy that is needed to achieve net-zero emissions (Polzin et al. 2019).

Existing work has examined the suitability of venture capital and crowdfunding as methods to finance low-carbon technologies. Nanda et al. (2015) and Gaddy et al. (2017) find that the venture capital (VC) model of financing is ill-suited to clean energy innovation due to long project horizons which are incompatible with VC horizons. Cumming et al. (2017) find that crowdfunding is also not a suitable

alternative. It is in this vein that Paper 1 explores how policies can bring breakthrough clean energy technologies to market, examining the efficacy of risk-reduction instruments such as feed-in-tariffs.

However, much more empirical work is needed in this field to establish which policies work well. Open questions include how to make insurance markets for nascent technologies more liquid and developed. In the early stages of solar energy, for example, the sheer lack of insurance products made it difficult for developers to enter (Speer, Mendelsohn and Cory 2010). Furthermore, if government intervention is the solution, which forms of government intervention are best suited to achieve societal goals whilst avoiding "pork barrel", that is, the wastage or crony use of public monies (Cullenward and Victor 2020)?

Finally, what lessons from innovative financing models in the realm of general infrastructure projects can carry over to clean energy innovation, and what changes might be necessary? Paper 1 represents an initial foray into these questions using methods in causal inference. There is space to bring more econometric methods to these questions to complement the already-rich base of evidence based on qualitative assessments, systems analysis, and modelling efforts (see the literature review in Polzin et al. 2019).

III. Conclusion

Directed technical change towards climate compatible growth requires the consideration of several market and government failures. Till date, the literature in environmental economics has heavily focused on addressing the environmental externality. However, there are other relevant market failures for the net-zero transition such as credit market imperfections and knowledge spillovers. Crucially, optimal carbon pricing seems to be politically unfeasible. These empirical realities coupled with the target to reach net-zero emissions by 2050 create the space to

explore novel ways to achieve climate change pledges. This thesis focuses on empirically evaluating policies and contexts that are not "first-best". Using methods in reduced-form causal inference and network analysis, this thesis looks at risk-reduction instruments, policy interactions, and knowledge spillovers to empirically test what has been successful so far and what may be promising in the future. The papers enclosed in this thesis represent a first step towards answering a suite of much broader questions around climate compatible growth.

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Bringing Breakthrough Technologies to Market: Evidence from Solar Power and Feed-in Tariffs

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Solving societal problems such as climate change requires commercializing new technologies. Yet, due to incomplete information, there are under-developed markets for finance and insurance for these new technologies. Temporary support to bring the first set of projects to market may be warranted to resolve this credit market failure. I investigate the impact of the UK's feed-in tariff (FiT) which provides revenue certainty by offering a fixed price for power generated by solar farms over 25 years. Exploiting the presence of bunching at the policy's eligibility threshold, I find the FiT supported the first tranche of commercial solar investments in the country, contributing to at least 2.3 GW of additional capacity from 2010-2015 (equal to one-fifth of all solar in the UK today). Tradable certificates for clean energy that provided similar subsidies at the point of entry, but without the long-term guarantee over price, were not able to induce the same degree of market-creation, illustrating the value of risk reduction. A social cost of carbon equal to £100/tCO_2 makes the FiT a net benefit.

Keywords: risk reduction, market creation, commercialization, incomplete information, early-stage technologies, cost of capital, feed-in-tariffs, solar energy, bunching.

JEL Codes: Q55 (Environmental Economics Technological Innovation), D22 (Firm Behaviour Empirical Analysis), Q42 (Alternative Energy Sources), H23 (Environmental Taxes & Subsidies), D8 (Information, Knowledge, Uncertainty), H0 (Public Economics), O38 (Innovation Government Policy)

I. Introduction

To stabilise global mean temperatures, the world must achieve net zero emissions, a target that has now been widely adopted by most major economies (Net Zero Tracker 2022). Achieving net zero emissions will require the rapid introduction and diffusion of novel technologies. However, these technologies remain under-provided (Aghion et al. 2009; Stern and Valero 2021), not only because of uncorrected environmental externalities but also because of incomplete markets for finance and insurance.

For early-stage technologies with no prior commercial history, investors do not know the distribution of risk and returns, nor do they know the full range of contingencies that need to be insured against. This creates a chicken and egg problem where finance is needed for a project to get developed but it also helps to have a few projects to get (cost-effective) finance. First-mover projects have an important "demonstration effect" as they help fill critical informational gaps that can deepen markets over time (for example, as market agents learn about solar, ancillary markets for solar insurance, solar finance, solar output forecasting etc. can develop and deepen).[1]

I examine the effect of a temporary subsidy and risk-reduction instrument in the commercialisation of utility-scale solar in the United Kingdom (UK). Utility-scale solar a capital-intensive technology which went from being non-existent in 2009 to accounting for 4.3% of total electricity generation in 2020 (BEIS 2020). While there is literature on how to support technologies in the early research and development stage (e.g. Williams 2017) and help further diffuse those that have already reached market (e.g. Popp 2019), there is relatively little about how to bring the first set of

[1] It has been shown that the cost of capital falls time due to "financing experience" for new technologies (Egli et al 2018)

new technologies to market. Investigating market creation for new technologies is the aim of this paper.

The main policy instrument to support the creation of the solar industry in the UK was the feed-in tariff (FiT) which reduced revenue risk by giving generators a guaranteed price at which power would be bought over a 25 years. The aim was to create a predictable stream of revenues to reduce the cost of capital for financiers who would otherwise charge higher lending rates. To be eligible, solar generators had to be at or below 5 MW of installed capacity. The FiT was introduced at a time when there were very limited private risk-hedging instruments for utility-scale solar, presumably because such a project had never been seen before (Speer, Mendelsohn and Cory 2010). In the absence of the FiT, solar generators face price volatility because they are price-takers in the power market and cannot strategically control when they produce power to take advantage of anticipated price spikes. [2]

My research design leverages bunching at the FiT's eligibility threshold to measure the extent to which the policy incentivised entry and investment (Kleven and Waseem 2013). I also develop a simple model to explain to firms' behaviour. In each period, a solar firm chooses how much to invest and whether to wait or enter today, with or without the FiT. Since solar farms are capital-intensive, firms need to borrow to finance their project. The FiT, by providing a fixed price for power, acts as a shield against market volatility thereby reducing the cost of capital ("risk reduction effect").[3,4] Further, if the difference between the fixed tariff and the expected market price is positive, then the FiT also has a "subsidy effect". The model predicts bunching at the eligibility threshold: some generators that would have entered at larger

[2] Solar generators with battery storage are able to choose when to dispatch power. However, during my time period of analysis, battery storage was not common.

[3] In standard CAPM models, it is typical for the cost of capital to fall when correlation with market risk falls.

[4] In practice, the FiT also reduces quantity risk by ensuring each unit of power is bought. Without it, solar generators face transaction costs linked to brokering their own power purchase agreements with retailers (if such agreements are ever reached).

capacities in a no-FiT world strategically downsize to take advantage of the FiT (this represents lost solar capacity and carbon abatement) and entry thanks to the policy (which represents additional solar capacity and carbon abatement).

I find that the FiT had a highly significant and large impact on solar deployment. Relative to a no-FiT counterfactual, there are at least 43 times more commercial utility-scale solar projects thanks to the FiT, resulting in 2.3 GW of additional solar capacity over a period of just five years (April 2010 to December 2015), which is equal to one-fifth of all solar capacity today.[5] This represents some of the first solar capacity since in January 2010, there were 0 MW of commercial solar. Only 6% of projects are inframarginal due to strategic downsizing and the remaining 94% are new entrants. Estimates are lower bounds due to the local nature of the estimation. When the FiT is heavily diluted in 2016, bunching at 5 MW completely disappears, suggesting that the earlier bunching is indeed driven by the FiT as opposed to other factors that could differ at the 5 MW threshold.

Since the FiT acts as a subsidy in addition to being a risk reduction tool, both characteristics of the policy could be driving the results. I isolate the value of risk reduction by looking at periods when the price offered by tradable clean energy certificates is similar to that offered by the FiT. This happens roughly between 2012 to 2015. I find that in this period, the vast majority of firms still enter at the FiT cut-off. While the tradable certificate provides the same subsidy in that period, it is much more risky as the price can change in future periods due to fluctuating market conditions. This illustrates how there is a tension between market-based schemes that have dynamic efficiency but more risk (Ciarreta, Espinosa and Pizzarro-Irizar 2014), and interventions that forgo this efficiency like FiTs but provide stable

[5] Based on solar capacity figures from April 2022.

incentives. For early-stage technologies, the results suggest that the presence of stable long-term risk hedges is critical for entry and investment.

Analysis of relative bunching over different periods shows that bunching peaks when expectations take hold that the FiT will be diluted, even though the subsidy is sizably lower in this period. Firms' expectations are observed through public consultations conducted by the government. When firms expect the FiT would stay, they are strategic about whether they enter this period or next. Waiting has value because of persistent declines in the cost of solar panels (learning-by-doing externalities). However, when faced with the prospect that the FiT will be removed, and there will no longer by any type of long-term risk hedge, many generators advance their decision to enter the market, creating a surge in bunching.

Finally, it is possible that the size-based eligibility criterion may have introduced inefficiencies.[6] If there are economies of scale to solar farms, then the accumulation of new projects at 5 MW is inefficient. However, for larger projects there are step-changes in costs linked to permitting land due to NIMBYism (Jarvis 2023). Further, since the transmission and distribution network is fixed in the medium term, keeping solar projects small helps facilitate integration without having to build out new power lines (i.e. increase system costs).[7,8] The histogram of UK solar farm sizes in post-FiT years does not show more entry at capacities larger than 5 MW. In post-FiT years, entry drops and remains low, and is largely concentrated at capacities near or below 1 MW (Figure 10).[9]

[6] Pollinger 2021 considers kinks in the German FiT and how the participation margin (i.e., the extensive margin response) affects structural estimates of elasticity. However, in this paper, I will not be estimating the elasticity structurally since at the notch, two variables are changing: subsidy level and exposure to risk.

[7] In the UK, congestion on the grid is a major problem with many new projects having to wait for significant periods of time to secure a grid connection (Call for Evidence on Onshore Solar, 2022, UK Parliament).

[8] Author's interview with representative of Aurora Energy Ltd.

[9] There are some projects just under 50 MW but these are considered as a separate class of "mega" investments that are not comparable.

I undertake simple value-for-money calculations by comparing the benefit of the FiT in terms of displaced carbon dioxide and sulphur dioxide emissions against the cost of payments in excess of the market price of electricity (i.e., the subsidy). I do this only for the years in which I have real data rather than for the entire 25 year contract period, which would involve forecasting future power system prices. I find that the FiT leads to a net gain for society with a social cost of carbon of £100/tCO_2 and higher.

While this paper conducts an empirical case study on utility-scale solar, the broader question on the role of risk reduction in bringing new capital-intensive technologies to market has relevance to a broad set of domains from healthcare to agriculture. Commercialisation requires addressing incomplete information such that the cost of capital is not prohibitively large, and temporary risk reduction may have a role to play in kick-starting the ecosystem such that ancillary markets, such as that for specialised finance and insurance, that are critical in bringing the technology to market emerge.

In terms of contributions, this paper generates novel empirical evidence on the efficacy of risk reduction instruments in bringing early-stage technologies to market. More specifically, it evaluates the impact of FiTs for solar. Despite the fact that FiTs have been implemented in almost 90 countries around the world to promote the development and deployment of renewable energy,[10] reduced form causal evidence on their impact remains surprisingly scarce, particularly at the utility-scale level. There are some studies that evaluate the impact of FiTs on residential/rooftop solar (e.g. Cherrington et al. 2013, Grover 2013, Germeshausen 2018, De Groote and Verboven 2019, Pollinger 2021, Taveli 2022) but this is a very different economic context since the agents analysed are households rather than firms, and the installation size and

[10] The number of countries that have FiTs is subject to some debate due to variations in the definition of a FiT.

the upfront investment are orders of magnitude smaller.[11] Some work has conducted cross-country regressions on FiTs and share of renewable capacity (e.g. Jenner et al. 2013, Smith and Urpelainen 2014, Dijkgraaf et al. 2018), which comes closer to this paper in terms of aims, but FiTs across countries can be very different in their design and it is unlikely that endogeneity concerns are adequately addressed.

Methodologically, since many environmental policies have cut-offs around which there is active selection (thereby ruling out regression discontinuity designs), the bunching estimator can be deployed more widely to estimate how firms value these policies. This paper is part of a small set of relatively new studies that try to do this (e.g. Pollinger 2021 uses kinks to analyse FiTs and rooftop solar and Damen et al. 2022 use a notch to analyse an energy efficiency policy).

More broadly, this paper seeks to build upon an emergent literature that discusses how market failures, beyond the carbon externality, affect the transition to a low-carbon future. Existing work has already highlighted the importance of knowledge spillovers and innovation subsidies for clean technologies (e.g. Jaffe et al. 2005, Acemoglu et al. 2012, Howell 2017, Popp et al. 2020). I contribute to this by considering how incomplete markets for finance and insurance may hold back the commercialisation of capital-intensive clean technologies, many of which are essential for net zero. The closest related study is by Ryan (2022) who examines how counterparty risk has a bearing on renewable investments in India. My work also connects to a rich literature on real options and infrastructure investment (Dixit and Pindyck 1994, Aguerrevere 2003, Boomsma et al. 2012, Kellogg 2014).

This paper also touches upon (i) the efficiency costs of policy thresholds, (ii) the effect of learning-by-doing externalities on increasing the value of waiting and how

[11] Rooftop solar studies focus on factors relevant for households such as: peer effects (Bollinger and Gillingham 2012 and Graziano and Gillingham 2015), private valuations over new technology (Langer and Lemoine 2022), household discounting (De Groote and Verboven 2019, Talevi 2022) and self-consumption (McKenna, Pless and Darby 2018).

the temporary nature of policy support can counteract this waiting dynamic to induce entry, and (iii) the effect of solar subsidies. Methodologically it connects to the bunching literature that leverages notches (e.g., Kleven and Waseem 2013, Kleven, Landais and Søgaard 2016, Best and Kleven 2018), but is different from most studies since the observed bunching is driven primarily by new entry rather than strategic downsizing.

II. Institutional Context

A. Feed-in-Tariff Design

The UK has a target to achieve a zero-carbon power grid by 2035 and integrate 30 GW of solar by 2030. Prior to 2010, there was no utility-scale solar in the country. The FiT, introduced in April 2010 and phased out by April 2019, provides a fixed price for electricity generated and sold to the grid by a renewable energy generator which is less than or equal to 5 MW in size. The price is guaranteed over 20-25 years.[12] Solar photovoltaics, wind, hydro, anaerobic digestion, and micro combined heat & power are all eligible.[13] All electricity generated receives the "generation tariff" and that which is exported to the grid receives an additional "export tariff". For solar farms that export 100% of their electricity, which is vast majority of utility-scale farms, the effective fixed tariff is the sum of the generation and export tariffs which is adjusted for inflation each year.[14] In early years, the tariff is 8 times higher than the market price of power while towards the end of the sample, it is much lower (Figure 1). Changes in the FiT impact only new applicants, while those farms that

[12] The contract duration for all technologies except for solar is 20 years. Solar benefits from 25 year contracts.

[13] Micro combined heat & power had a different eligibility threshold due to its smaller size.

[14] In practice, every year, generators can decide whether they opt for the export tariff or the market rate for that year. During my sample period, it was always better to select the offered export tariff, which was higher. Further, the majority of the FiT's benefit which is the larger of the two tariffs, sometimes being up to ten times greater than the export tariff.

have already been accredited remain on the tariff they entered at for the entire contract duration.

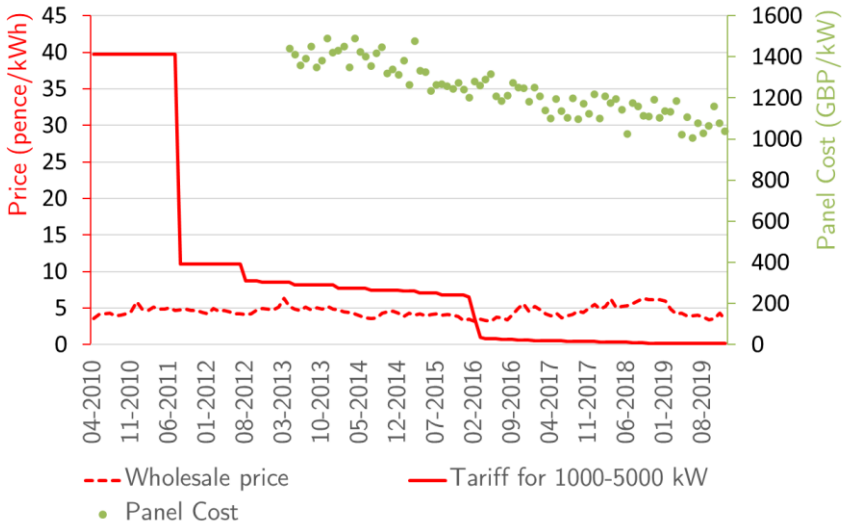


FIGURE 1. FIT GENERATION TARIFF VERSUS THE MARKET RATE OVER TIME

In terms of how the scheme was financed, electricity retailers made payments to accredited FiT generators at the specified tariff. The extent to which the tariff exceeded the wholesale electricity price reflected the cost, which was passed onto to consumers through bills. The government set a cap on annual FiT-related payments. Once this cap was hit, additional installations entered a queue and could be considered when the cap reset.

B. Incomplete Markets & Risk-Hedging

Although solar panels are more commonplace today, they were regarded as expensive and risky technologies in the recent past. Utility-scale solar projects contend with long project horizons, volatile wholesale electricity prices, and uncertainties related to the technology, policy environment, land acquisition, and power market. These factors affect the cost of capital which makes up a significant portion of overall project costs (Egli, Steffen and Schmidt 2018, Steffen 2020, Polzin et al 2021). For example, estimates suggest financing costs make up one-one-third of

total project costs (European Photovoltaic Industry Association, 2016) and the weighted average cost of capital can account for 20-50% of the levelized cost of electricity of utility-scale solar PV projects (IEA 2021a).

During the early years of the FiT's implementation period (2010 onwards), it was the one of the main risk hedging instruments on the market. There were incomplete markets for solar finance and insurance: corporate power purchase agreements for solar energy were almost non-existent/very scarce (Figure 2) as were insurance products (Speer, Mendelsohn and Cory 2010). FiTs provided hassle-free, off-the-shelf guarantees that a new renewable energy generator's power will be purchased at a set tariff. In the absence of FiTs, these generators would have had to incur the transaction costs of negotiating power purchase agreements with utilities and face the risks linked with brokering such a deal (if it was ever reached).[15]

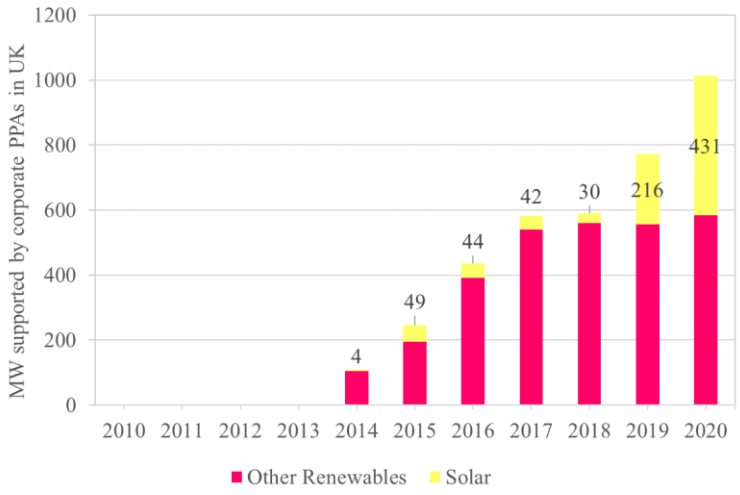


FIGURE 2. POWER PURCHASE AGREEMENTS IN THE UK

Notes: RESource 2022

Investor guidance reveals how an "offtake agreement" was a pre-requisite to get any sort of financing (Groobey, Pierce, Faber and Broome 2010). Such agreements could take the form power purchase agreements or, indeed feed-in-tariffs. Higher project

[15] Based on author's interview with a private renewable energy developer.

risk translated into a higher cost of capital due to risk aversion by investors (Polzin et al. 2019). Often risk could not be fully diversified away due to unknown elements of the early-stage technology.

Solar projects also typically had no recourse to the parent corporation's balance sheet or credit worthiness, and the only collateral available to financiers was the renewable energy asset and its expected future cash flows, making any guarantee over future revenues particularly valuable as it helped reduce the cost of capital (Steffen 2018).

C. Policy Environment around the Cut-Off

The UK introduced its Renewables Obligation (RO) scheme in 2002 which required electricity retailers to source a certain amount of their power from renewable energy generators. The sourcing could be done through the purchase of tradable renewable obligation certificates (ROCs). The RO formally closed to all new generating capacity in March 2017. Unlike the FiT, the RO did not reduce price risk since ROC prices could fluctuate according to demand and supply conditions. However, like the FiT, the RO did offer a subsidy, which at certain points in time, was similar in value to the FiT (see Figure 3, 2012-2015). At or below the 5 MW threshold, generators could qualify for the FiT but if they opted for it, they would need to relinquish the ability to claim ROCs.

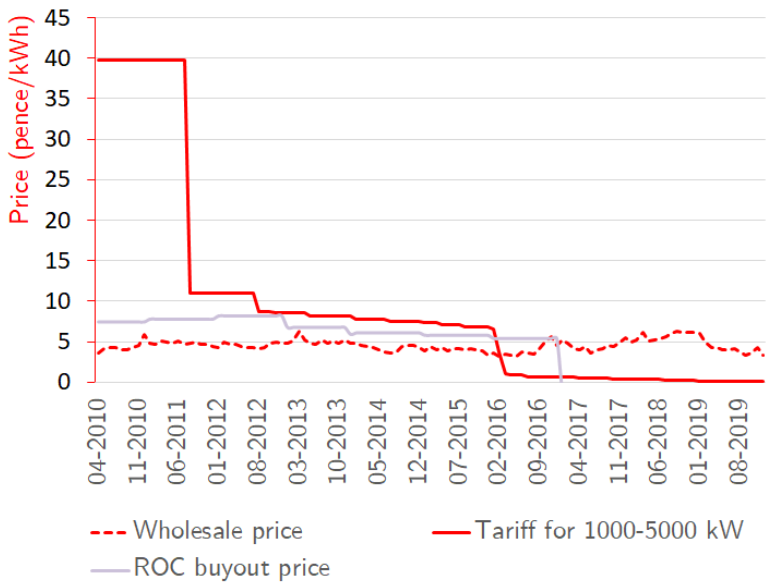


FIGURE 3. WHOLESALE POWER PRICE, GENERATION TARIFF AND PRICE OF ROCS

III. Theoretical Framework

A. The Model

The Environment — Solar generators are price-takers,[16] have zero marginal cost,[17] and decide on installed capacity (q_i) which determines their variable output (ηq_i) where η represents the capacity factor and i, the generator.[18] Generators cannot manipulate the quantity of electricity they produce as this depends on exogenous weather conditions. They can, however, select q_i which determines their maximum output. I assume generators know their own capacity factor (Kellogg 2014), meaning they have access to accurate weather predictions in the medium-term.

[16] Renewable energy generators' electricity production is driven by exogenous weather conditions and cannot be strategically manipulated.

[17] Marginal costs are close to zero for renewable energy generators because their "fuel input" e.g. sunshine and wind is freely available. There are some very minimal variable costs linked to grid fees and maintenance but these can be ignored for modelling purposes.

[18] The capacity factor is the ratio of actual electricity output over the theoretical maximum. For solar energy, this captures the impact of weather variability on realised generation.

The market price for electricity (p_t) is volatile with mean μ_p with variance σ_p. Each generator is in a unique location which is associated with site-specific cost-shocks that may vary over time (χ_{it}) and has mean μ_{χ_i}. For example, χ_{it} could be land licensing costs. Fixed costs (I_{it}) are irreversible and financed by borrowing. I assume $I_{it} = (1 + \sigma_p)(1 + \chi_{it})\alpha_t q_i$ where α_t represents the cost per solar panel. This is exogenously determined and declining over time due to learning-by-doing (LBD) externalities. In the baseline model, I abstract away from LBD externalities and assume $\alpha_t = \alpha$. This assumption is relaxed in an extension.

The inclusion of $(1 + \sigma_p)$ captures how price volatility increases the cost of capital. This is an empirically documented fact for renewable energy projects and can be conceptualised in terms of risk aversion by investors who command a higher return for a larger spread (Byoun et al. 2013, Steffen 2018, Polzin et al. 2019).[19] In this model, I show how the FiT reduces the cost of capital by switching from $\sigma_p = \delta > 0$ to $\sigma_{\bar{p}} = 0$. However, this is the simplest case. In practice, σ_p could be more broadly conceptualised as revenue volatility. Anything to reduce revenue volatility, including managing quantity risks, would have the same effect. Importantly, since early-stage technologies are associated with uncertainty over the distribution of risk, investors may not know the value of σ_p and consequently, over-estimate it: $\hat{\sigma}_p > \sigma_p$. The FiT deals with this informational problem by stating the price at which renewable power would be purchased and ensuring that there is a buyer for it, essentially reducing or eliminating revenue risk. All of these scenarios rely of the same fundamental dynamic. Therefore, I choose to model the simplest one. For expositional simplicity and without loss of generality, I model I_{it} as a one-off fixed cost, though in practice it will be a flow of payments over time.

[19] This is standard CAPM models where the Sharpe ratio describes how much excess return investors need for larger standard deviations

Firm Choice — In each period, generators decide whether to invest with or without the FiT, or wait. This choice is the maximum of the value of waiting (V_t^w), the value of investing today with a FiT (V_t^{FiT}) and the value of investing today without any risk-hedging (V_t^I) (see Equation 1):

$$\max\{V_t^w, V_t^{FiT}, V_t^I\} \tag{1}$$

The discount rate is $\beta = \frac{1}{1+r}$ where r is the risk-free interest rate and $\beta \in (0,1)$. The value of waiting is given by Equation 2, where E_t is the expectations operator. V_t^w is solved recursively in Appendix A assuming no LBD externalities.

$$\max_q V_t^w = \beta\left\{E_t V_{t+1}^w, E_t V_{t+1}^{FiT}, E_t V_{t+1}^I\right\} = \beta \max\{\widehat{V}^{FiT}, \widehat{V}^I\} \tag{2}$$

Generators observe market prices (p_t) and period cost shocks (χ_{it}), and assess whether these values lie above their expected values. If the value of entering today is lower than the value of entering in the future, a generator will choose to wait.

The value of V_t^{FiT} is given by Equation 3.[20] The price at which FiT generators sell power is given by $\bar{p}_t = \bar{p}_{gen} + max(\bar{p}_{exp}, p_t)$. This captures how solar generators get the fixed generation tariff ($\bar{p}_{gen}$) which is assured over 25 years, and can decide annually whether they top that up with the market price of power (p_t) or the fixed export tariff ($\bar{p}_{exp}$), which is guaranteed over the contract period. In practice, on average, $\bar{p}_{exp} \geq p_t$, making the choice to select p_t weakly dominated. Therefore, for expositional simplicity, I assume $\bar{p}_t = \bar{p}$ and $\sigma_{\bar{p}} = 0$. This makes the firm problem more tractable and essentially just theoretically under-values the FiT.

[20] Note: $\sum_{s=1}^{\infty} \beta^{s-1}(\bar{p}\eta q_i^f) = \frac{\bar{p}\eta q_i^f}{1-\beta}$

The optimal quantity of installed capacity is given by q^f and $\bar{q}$ represents the FiT eligibility threshold, which is 5 MW.[21] The generator selects its project size subject to the FiT constraint.

$$\max_q V_t^{FiT} = \frac{\bar{p}\eta q_i^f}{1-\beta} - (1+\chi_{it})\alpha_t q_i^f \quad s.t. \quad q_i^f \leq \bar{q} \tag{3}$$

V_t^I is given by Equation 4, where q^I represents the optimal quantity of installed capacity. Note, a generator can enter at $q \leq \bar{q}$ and choose to not opt for the FiT, therefore there is no size constraint. Since entering as a merchant project mains facing price volatility, σ_p is in Equation 4.

$$\max_q V_t^I = p_t \eta q_i^I + \eta q_i^I \left(\sum_{s=1}^{\infty} \beta^s E_t p_{t+s}\right) - (1+\chi_{it})\left(1+\sigma_p\right)\alpha_t q_i^I \tag{4}$$

Assuming a firm decides to invest in period t, its choice to enter with a FiT depends on whether $R_t \equiv V_t^{FiT} - V_t^I > 0$. As η just scales quantity produced, it has been removed for notational simplicity.

$$R_t \equiv \left(\bar{p}q_i^f - p_t^m q_i^I\right) + \left(\frac{\bar{p}q_i^f - \mu_p q_i^I}{1-\beta}\right) - \frac{\alpha(1+\chi_{it})}{\eta}\left(q_i^f - \left(1+\sigma_{p^m}\right)q_i^I\right) \tag{5}$$

The two channels of impacts, the "subsidy effect" and "volatility effect" can be seen respectively: as the tariff rate increases, the incentive to take-up a FiT goes up ($\frac{\partial R}{\partial \bar{p}} > 0$) and similarly, higher electricity price volatility increases the value of the policy ($\frac{\partial R}{\partial \sigma_p} > 0$).

[21] For analytical ease I assume an infinite lifetime for each project. Adding a fixed time horizon T would merely scale the entry decisions for generators. Given my primary interest is the conditions under which a firm finds it optimal to bunch, this would not introduce a meaningful effect.

B. Model Predictions

Proposition 1: Timely Entry — If the FiT is at least equal to the average electricity price/ROC price ($\bar{p} \geq \mu_p$), then there is more timely entry with a FiT.

Proof of 1 — To see how, consider the following: as σ_p increases, holding all else constant, the value of entering with a FiT today will increase relative to the value of entering without it or waiting. This is because:

- higher σ_p *reduces* the value of V_t^I as implied by Equation 4
- higher σ_p does not affect V_t^{FiT} since the FiT delinks revenues from p_t.
- higher σ_p decreases the value of waiting if in $V_t^W = \beta \, max\{\hat{V}^{FiT}, \hat{V}^I\}$, $\hat{V}^I$ is larger, or leaves it leaves the value of waiting unchanged if $\hat{V}^{FiT}$ is larger. Since $\hat{V}^{FiT} > \beta \hat{V}^{FiT}$, in expectation it is better to enter with a FiT today than tomorrow.

Proposition 2: Strategic Downsizing — Some generators who initially planned to install $\bar{q} + \Delta$ worth of capacity will revise their plans and re-locate to the FiT threshold, $\bar{q}$. These are *inframarginal generators* as they would have entered even without the FiT.

Proof of 2 — The bunching upper bound, Δ, for which the generator is indifferent between downsizing and being at a higher capacity is obtained by setting V_t^{FiT} equal to V_t^I and solving for Δ:

$$\Delta = \bar{q}\left(\frac{p^F - \widehat{p_t}}{\widehat{p_t}}\right) - \frac{\alpha(1+\chi_{it})}{\eta}\left(q_i^f - (1+\sigma_p)q_i^I\right) \tag{6}$$

where $p^F \equiv \frac{\bar{p}}{1-\beta}$ and $\widehat{p_t} \equiv p_t + \beta \frac{\mu_p}{1-\beta}$. The value of Δ at which generators are indifferent increases with the monetary benefits of the FiT and decreases with its costs (Equation 6). Since $\frac{\partial \Delta}{\partial \sigma_p} > 0$, as volatility increases, generators will make bigger

reductions in size to strategically benefit from the FiT. Δ is empirically important as it will define the area over which we will observe strategic downsizing.

Proposition 3: New entry due to the FiT — There is also an *extensive margin* response to the FiT, where the policy will induce new entry if it draws from the pool of waiting firms.

Proof of 3 — To see how, prior to the introduction of the FiT, a new project chooses between V_t^I and $\beta\hat{V}^I$ (the value of entering today as a merchant vs. the discounted expected value of entering in the future). A firm delays entry if the realised cost shock in time period t is higher than its average value ($\chi_{it} > \mu_{\chi_i}$) implying that $V_t^I < \beta\hat{V}^I$. However, with the FiT, it is possible that even with the unfavourable cost draw, $V_t^I < \beta\hat{V}^I < V_t^F$ and $V_t^F > 0$. This depends on the extent to which the FiT reduces investment costs through reducing σ_p and/or tops up revenues, with $\bar{p} \geq \mu_p$.

Empirically, by using a bunching estimator, I will determine the extent to which the FiT resulted in strategic downsizing versus new entry for different assumed values of Δ.

Proposition 4: Extensive Margin Bunching — A proportion of new generators will be constrained to enter at the FiT cut-off when they may have entered at larger capacities in a world where the FiT had no size-based threshold.

Discussion of 4 — If the FiT were smooth, generators could enter at any capacity $\bar{q} + \Delta$,but since the FiT has a cut-off, some generators who would have found it optimal to select a larger size will be constrained to entering at $\bar{q}$ (details in Appendix).

C. *Learning-by-doing*

Finally, if there are learning-by-doing externalities, α_t is declining over time and the expected value of entering with a FiT or as a merchant project will change by more than just discounting (i.e. Equations A.3 and A.4 of the Appendix will no longer hold). Firms will have to trade-off delaying entry to take advantage of cost declines with lost revenue from the delay. There will be an optimal point in time where these values are equal. Although this extension means we can no longer find an simplified representation of the value of waiting as in Equation 2, we can represent the problem diagrammatically (Figure 4). This leads to our fifth proposition:

Proposition 5: Entry induced through temporary support — If the FiT will be removed next period, some generators will advance their decision to enter the market. If there are learning-by-doing externalities, a generator may find it preferable to enter with a FiT in a future time period, when the cost of solar panels is lower than the current period and the benefits of this outweigh the lost revenue from entering later ($V_{t+1}^{FiT} > V_t^{FiT}$). However, if in the subsequent time period, there will be no FiT, then the generator may advance their decision and enter today if $V_t^{FiT} > V_t^I$.

D. *Model Boundaries*

This model does not consider the distortionary effects of price volatility reduction on overall market outcomes. If FiT projects comprised a large share of the market, such distortions would be important to study. However, in the UK power market, solar is less than 2% of installed capacity, and FiT-accredited solar is less than half of all solar. Therefore, these general equilibrium effects linked to how price volatility dampening could affect market clearing and investment are assumed away. This paper is concerned with the role of FiTs for early-stage technologies that, by definition, have very low market shares.

IV. Data & Descriptive Statistics

A. Data

The Renewable Energy Planning Database managed by the UK Department for Business, Energy & Industrial Strategy keeps a record of *all* commercial renewable energy projects as they move through the planning and development process. It has detailed information on the project name, size, geo-location, status, types of policy support, among other variables. There are 2,481 unique commercial solar projects from 2010 to 2019. The total number of clean energy projects across all technologies is 6,624.

The median and the mode for commercial solar project size is 5 MW, while the mean is 9.3 MW. Out of all solar project proposals, the status of 1,900 is known.[22] Out of these 84% have successfully entered the market while the rest have had their planning permit rejected or have chosen to exit before construction. For the analysis, I assume a project "enters" when it applies for planning permission – this is the earliest date in the dataset. To ensure my results and analysis reflect actual added capacity, I filter out projects that subsequently backed out or were denied permission, leading to a sample size of 1,596 commercial solar projects.

Data on electricity prices at 30-minute frequencies is collected from Aurora Energy. The UK power market does not have regional variation in electricity prices since it operates as one zone. The electricity prices that are relevant to solar energy are those that occur during daylight hours. To construct the appropriate wholesale electricity price variable, I use daily sunrise and sunset times to filter out night-time prices.[23]

[22] Projects labelled as unknown have applied for a permit but have not yet started construction, therefore it is unclear if they will be cancelled or will go ahead.

[23] In my time period, solar plus battery technology is highly limited, therefore it is safe to assume that the vast majority of solar generators only sell power during daylight hours. In the future, as battery penetration increases, solar generators may be able to sell much more power at night.

Using these "sunshine prices", I construct the average daily electricity price that solar generators would be exposed to. This is aggregated up further to construct monthly averages. I also use 30-minute daylight prices to calculate monthly volatility.

Data on solar panel costs is from Bloomberg New Energy Finance and NREL.

B. Descriptive Evidence

Between 2010 and 2019, 1,596 commercial solar generators successfully entered the power market, adding 12.5 GW of new capacity. The UK solar industry's beginning coincides with the introduction of the FiT in 2010 (Figure 5). Prior to that, there were no commercial solar projects.

The amount of new solar capacity steadily increases from 2010 to the end of 2015. The jagged structure of the plot reflects seasonality as each winter, the number of new solar projects falls. In 2016, there is a sudden drop in new capacity. This is when the pre-accreditation process of the FiT was removed.

The pre-accreditation process ensured that generators larger than 50 kW received a guaranteed tariff level before beginning construction. This guarantee played an important role because construction can take time and without pre-accreditation, generators could find themselves in a situation where, by the time are ready to operate, the tariff has changed and the project's economics are no longer favourable.

An event study plot, which is presented in the spirit of descriptive evidence since confounding factors are not controlled for, illustrates how prior to the removal of the pre-accreditation process, there was an anticipatory increase in entry rates and how a month after the policy change, there is huge drop in new projects. Solar project proposals start rebounding in 2018 but never returned to previous levels. Sub-section C discusses the event study in more detail.

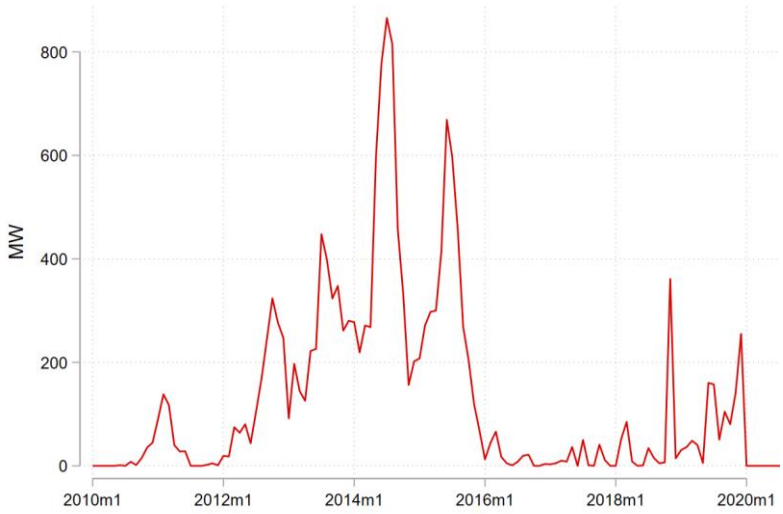


FIGURE 5. MONTHLY NEW COMMERCIAL SOLAR CAPACITY IN THE UK

Notes: The project entry date corresponds to when planning permission was sought. Projects that are denied planning permits are not shown to ensure only actual new capacity is reflected.

C. Event Study Regression

I consider observations preceding October 2015 as "treated" (i.e., in a world with an effective FiT) and those after the date as "untreated" (i.e., in a world where the policy was diluted significantly). Using a Poisson specification which is well-suited to count data, I examine how the number of new solar project proposals changes after pre-accreditation was formally removed. Equation 7 describes the estimation where y_t is the number of new solar projects, β_j captures the effect of the change in the FiT in the months after the shock, and the third term controls for seasonality.

$$y_t = \alpha_t + \sum_{j=1}^{T} \beta_j \cdot \mathbb{1}\{t \geq t_{start}\} + \sum_{i=1}^{11} \gamma_i \cdot m_i + \varepsilon_t \tag{7}$$

As the event study plot shows, there is a highly statistically significant and sizable decline in entry rates. A month after the policy change, there is a 78% drop in new projects, which becomes a 95% drop 7 months after (albeit with higher errors around the estimate), after controlling for seasonality.

The event study plot also suggests that there were anticipation effects prior to the removal of the pre-accreditation scheme, as indicated by the increased entry rates from June 2015 onwards.[24] This aligns with the prediction of the model in Section III.C.

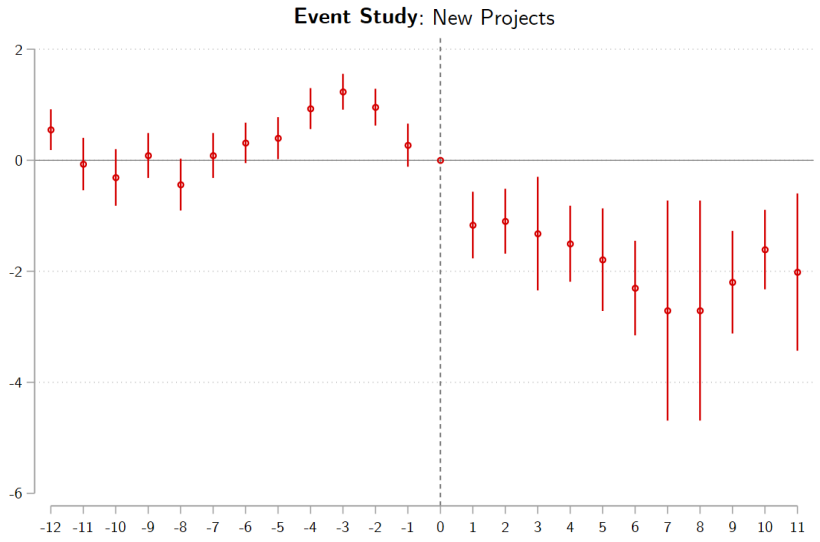


FIGURE 6. EVENT STUDY PLOT OF MONTHLY DECLINE IN NEW SOLAR PROJECTS

One cannot control for all changes across time that may have affected entry in such an empirical design. Therefore, the results are presented in the spirit of descriptive evidence. Section V will present the bunching estimation which is the main empirical strategy.

[24] On 22 July 2015, it was announced that a consultation would be held on whether pre-accreditation should be removed. Even though almost all generators opposed the removal of the pre-accreditation process, it was nevertheless announced in September 2015, that it would be removed. The policy took effect on October 2015.

V. Bunching Estimation

A. Empirical Strategy

The FiT creates a sharp discontinuity at 5 MW where generators below the threshold are eligible for the fixed tariff while those above are subject to fluctuating wholesale electricity prices or ROC prices. I exploit this discontinuity to estimate the impact of the FiT on entry and investment in commercial solar, where investment is proxied by installed capacity.

Recall that firms can either wait, enter without any risk-reduction policy, or enter with a FiT. The bunching estimation will disentangle how much of the observed effect is driven by those who switch from waiting to entering (new entry/extensive margin) versus those who switch from entering at higher capacities to downsizing and entering with a FiT (inframarginal/intensive margin). While new entry results in solar capacity additions which is helpful for decarbonisation, downsizing reflects lost capacity/abatement and support to inframarginal generators, which is inefficient.

There is a third potential behavioural response which is upsizing by generators who would have entered at lower capacities but decide to scale-up to 5 MW thanks to enhanced profitability due to the FiT. However, I do not find evidence of this (see Section V.E.). Consequently, the main results will only consider bunching that occurs due to movement from the right of the notch.

The bunching estimation is as follows:

$$(8) \qquad c_j = \sum_{i=0}^{n} \gamma_i (q_j)^i + \sum_{r \in N} \rho_r \cdot 1[q_r] + \sum_{i=q-}^{q+} \psi_i \cdot 1[q_j = i] + v_j$$

where c_j is the number of generators in bin j (each bin represents 0.1 MW increments of capacity), q_j is the installed capacity, n is the order of the polynomial, $[q\text{-}, q+]$ is the excluded range, and N is the set of round numbers (r) excluding the FiT eligibility

threshold and including 2.5 and 1.5, where there is a tendency to bunch which is not driven by discontinuous incentives but rather the salience of certain numbers (natural reference points). The counterfactual distribution is defined as the predicted values from the regression in Equation 8 omitting the contribution of the dummies around the notch (third term) but keeping the contribution of round-number dummies (second term) (Kleven and Waseem 2013).

The bunching estimation creates a local no-FiT counterfactual and compares to the with-FiT observed data to determine how much "excess mass" there is at the notch due to the policy (Figure 7). To determine what proportion of this excess mass is due to strategic downsizing, the "missing mass" is calculated. This is the difference between the no-FiT counterfactual and the with-FiT observed data to the right of the notch. The amount of new entry is the difference between the excess mass and the missing mass.

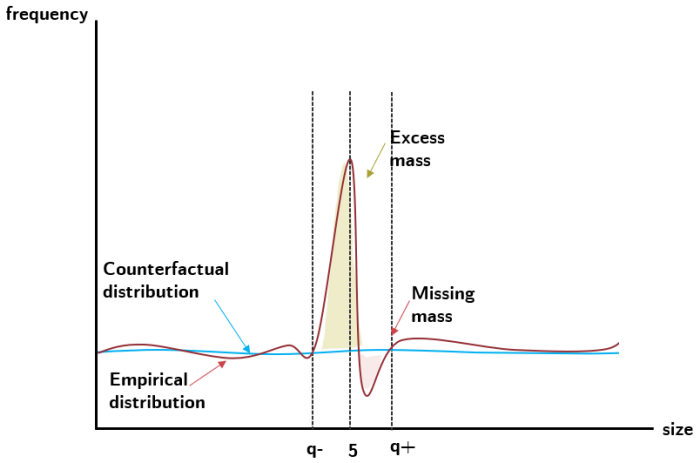


FIGURE 7. SCHEMATIC OF BUNCHING ESTIMATION

Deciding appropriate values for [q-, q+] is subjective: q+ reflects our expectation of the upper bound from where generators will strategically downsize, while q- is 5 MW since generators who downsize have no incentive to go below this value. In practice, I find q- is 4.9 since many firms mistakenly think the eligibility criterion is

a strict inequality. In settings where the response is entirely on the intensive margin, the value of $q+$ is found by equating the missing mass towards the right of the notch to the excess mass under the notch. However, in my setting this is not possible since there is a large extensive margin response.

In the baseline specification, I assume $q+ = 6.5$ MW. This choice is informed by a series of robustness tests that find that there is limited evidence for strategic downsizing beyond 6.5 MW. Using values of $q+ > 6.5$ MW results in a negative missing mass, which is not compatible with downsizing (see Section V.E.).

Adjustment costs can attenuate the amount of bunching and create a downward bias in the estimate of how much firms respond to discontinuous incentives (Chetty et al. 2011). In my setting, this is less of a concern since projects are "paper proposals" where adjustment costs related to revising installed capacity plans are relatively low, and there is high salience around where discontinuities occur.

B. Identification Assumptions & Caveats

Identification via bunching at a threshold requires that there are no other policies or market features that could create incentives to invest in solar at the 5 MW cut-off apart from those created by the FiT (Kleven 2016). I explore this assumption by checking the empirical distribution of solar project size post-2016 when the FiT was highly diluted. There is no observable bunching anymore, suggesting that this main identification assumption holds (Figure 8).

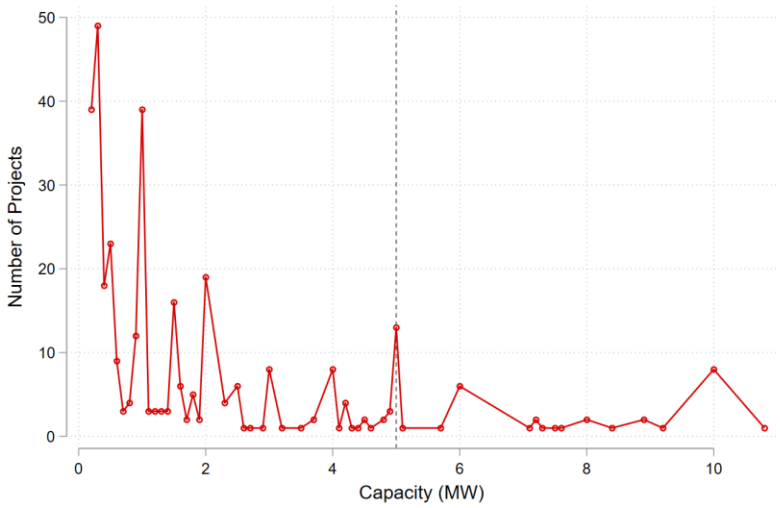


FIGURE 8. ABSENCE OF BUNCHING POST 2016

Notes: The small peak at 5 MW is the standard round number clustering.

Since observations below the notch still benefit from the FiT but are used to create a "no-FiT" counterfactual, the approach likely under-estimates the true effect. An alternative is to estimate the counterfactual only using observations to the right of the notch outside the excluded zone. However, this brings its own set of challenges — these projects may serve as a less valid control group since larger projects may have different economic characteristics relative to smaller ones. It also results in the loss of statistical power. Therefore, I choose to over-estimate the level of the counterfactual distribution and produce a lower-bound estimate of entry and capacity additions due to the FiT.

I also assume the marginal solar project does not influence prices in the power market. If the marginal solar project affected prices, firms' decisions would not only consider the change in financial incentives at the 5 MW discontinuity but also expectations of how other solar generators would react to it. For example, if one project's entry depressed prices, this would impact the next project's calculation of expected profits. This would contaminate our interpretation of the effect of the discontinuity. However, it is reasonable to assume a single 5 MW solar project does

not affect prices as it is extremely small compared to the total UK power market, which is 4-5 orders of magnitude larger.

C. Main Results

This section presents the results from estimating Equation 8, where the exclusion zone is [$q- = 4.9$ $q+ = 6.5$], capacity bins are defined in terms of increments of 0.1 MW and a 4^{th}-order polynomial is used. Results with lower and higher order polynomials are reported in Section V.E. but since the data outside the notch is relatively flat, it is unlikely that higher order polynomials are needed.

There is a significant and very large bunching response at the FiT threshold (Figure 9). Around 6% of projects strategically downsize. The remaining 94% are new entrants. This shows how the FiT's effect is largely on the extensive margin: that is, it "created the market" by incentivising large amounts of entry and new capacity in commercial, utility-scale solar energy. Visually, it is intuitive that the response is largely on the extensive margin, since if it were driven by strategic downsizing, we would expect to see a hole above 5 MW.

Taking into account the capacity lost from strategic downsizing, I find there are *at least* 43 times more solar projects thanks to the FiT, leading to net capacity additions worth 2.3 GW (equal to one-fifth of all installed solar capacity in the UK using 2021 figures).[25] In terms of absolute numbers, there are at least 490 new utility-scale commercial solar projects due to the FiT (for context, the total number of solar projects from 2010-2019 is 2,481). As noted earlier, these estimates are likely lower than the true effect because there could be more entry driven by the FiT below $q-$ that the estimator is unable to capture.

[25] The reason it is "at least" 43 times is because the excess mass is only calculated around the bunching zone. There could be additional solar projects that are attributable to the FiT below the bunching area (i.e., between 0-4.9 MW) but these are not captured by the bunching estimation since causal identification requires restricting analysis to a local area.

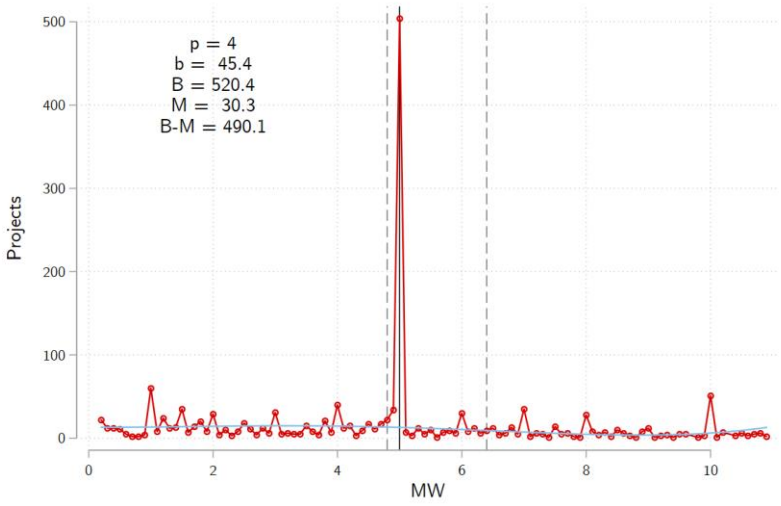


FIGURE 9. MAIN BUNCHING ESTIMATION

Notes: p represents the polynomial, b is the ratio of excess mass to counterfactual mass, B is the excess mass, M is the missing mass.

D. Differences in Bunching

Examining how the extent of bunching changes over time can shed light on how the changing characteristics of the FiT affect firms' incentives. Figure 10 plots the histogram of project size over the last decade. From this descriptive evidence, one can see that bunching peaks in 2015, right before the heavy dilution of the FiT scheme. This aligns with the evidence presented in the event study (Section IV.C) as well as the theoretical predictions that there will be expedited entry by generators if the FiT will be removed, since those who were previously deferring entry to take advantage of learning-by-doing externalities, now find it more advantageous to enter with a FiT today than to lose the option to have the risk hedge in the future (Section III.B).

Furthermore, concerns related to efficiency losses due to extensive margin bunching can be partially allayed, not only by considering the cost curve for solar which is U-shaped, but also by the fact that post-2016, when there is effectively no FiT, there is no significant entry at higher capacities. If after 2016, there were many projects at

higher capacities, this would raise concerns that during FiT years, entry was artificially constrained at 5 MW. Instead, it seems like the FiT played a key role in creating that entry and market itself.

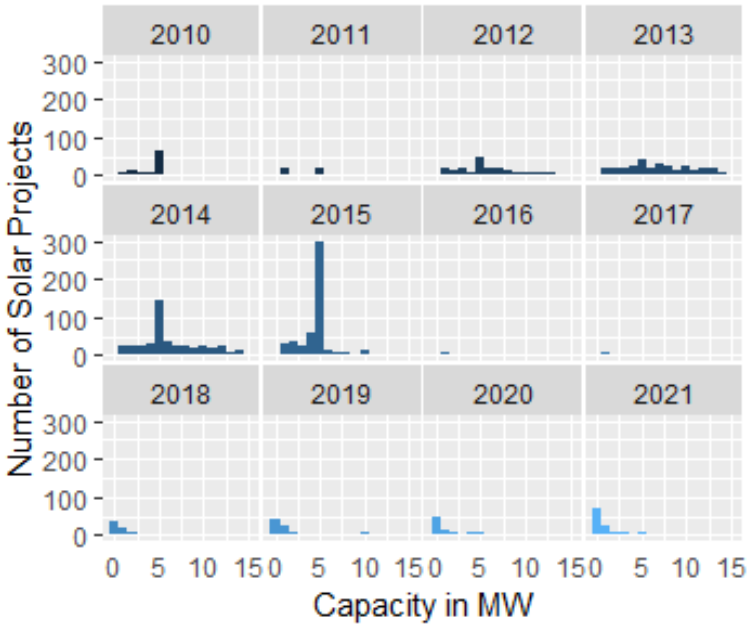


FIGURE 10. HISTOGRAM OF SOLAR PROJECTS BY YEAR

To more formally check how bunching changes over time, it is necessary to estimate the change in *relative* bunching by creating no-FiT counterfactuals for each period. I choose to estimate these in groups of years rather than individual years to avoid sample size reductions and loss of statistical power. I therefore, estimate the amount of relative bunching over three different time periods: (i) phase 1 - April 2010 to July 2012, (ii) phase 2 - August 2012 to December 2015, and (iii) phase 3 - January 2016 to December 2019. In phase 1, generators get 27 p/kWh while in phase 2, they get 9 p/kWh. Phase 3 is when the pre-accreditation process was removed and the rate fell further to 2 p/kWh.

The bunching estimates presented in Figure 11 show that in phase 2 there are at least 41 times more projects relative to a no-FiT counterfactual, while in phase 1,

there are 27 times more projects. In both cases, new entry is driving the vast majority of bunching.[26]

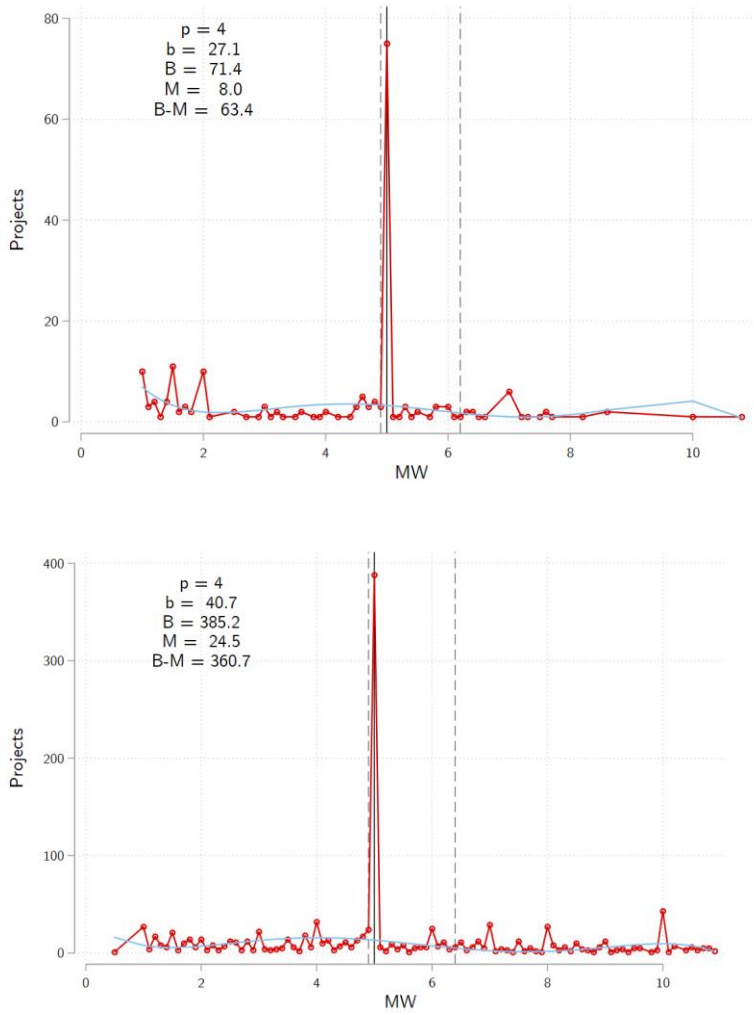


FIGURE 11: BUNCHING OVER TIME

Notes: Top: Bunching from April 2010- July 2012 , Bottom: Bunching from August 2012 - December 2015

The increase in bunching mass in phase 2 relative to phase 1 is, in the first instance, surprising since the subsidy is lower. General solar panel cost declines should not explain why the *relative* difference between the no-FiT counterfactual and with-FiT

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data increases. Only variables that change at the 5 MW threshold should be affecting the relative amount of bunching. However, as already discussed, a notable change between the phases was that while in phase 1, there was an option to enter with a FiT next period, in phase 2, the imminent removal of the FiT was clear (as evidenced by public consultations) thereby increasing the value of taking it up immediately.

In a with-FiT world, firms may rationally choose to enter with a FiT tomorrow instead of today to take advantage of accumulated experience and future cost declines. However, when the prospect of FiT removal/dilution is imminent, the choice to enter with a FiT today dominates the choice of entering tomorrow without this risk hedge.

Additionally, even though the tradable certificate scheme was offering similar prices to the FiT in phase 2 (on the other side of the cut-off), the vast majority of firms still bunched at 4.9 and 5 MW, illustrating the value of a long-term risk hedges over market-based schemes that are risky due to changing prices.

Finally, in phase 3, 2016 onwards, there is no bunching, as would be expected since the scheme is highly diluted/has no guarantees for generators.

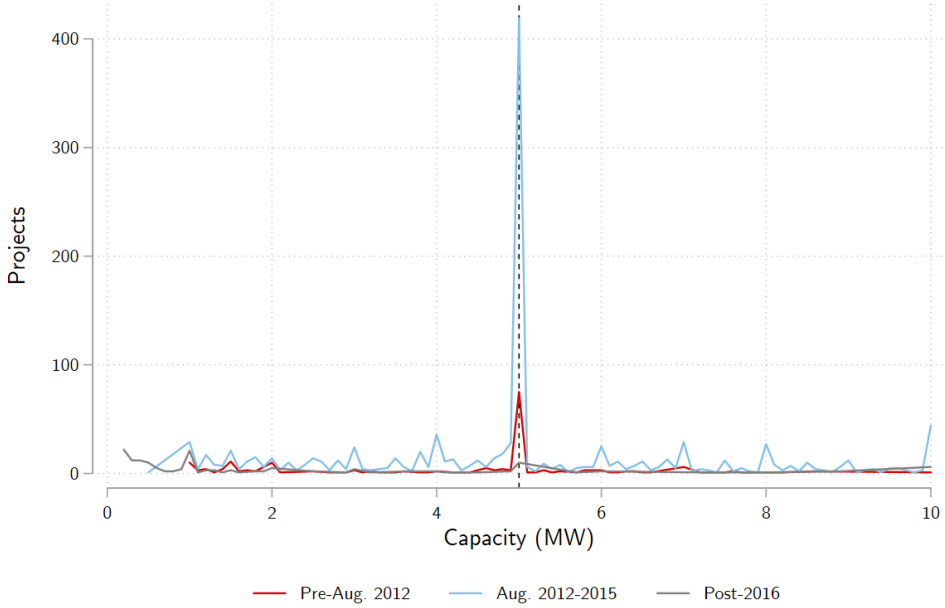


FIGURE 12. BUNCHING OVER DIFFERENT PERIODS OF TIME

Note: Counterfactuals are not shown in this plot.

E. Robustness Checks and Falsification Tests

Upsizing — Upsizing is unlikely to be a concern since there is no visible hole towards the left of the notch. However, this is tested more formally via a bunching estimator that calculates bunching from the left (see below). The missing mass is negative which means that there are *fewer* projects towards the left of the notch in a no-FiT world relative to the with-FiT reality. This highlights that there is no upsizing and is, in fact, suggestive that the FiT created new entry at lower capacities. This is in line with the idea that the UK FiT's effect is largely about "creating the market" by incentivising large amounts of entry and new capacity. This is also aligned with descriptive evidence that finds that there were no commercial solar projects prior to the introduction of the FiT in 2010.

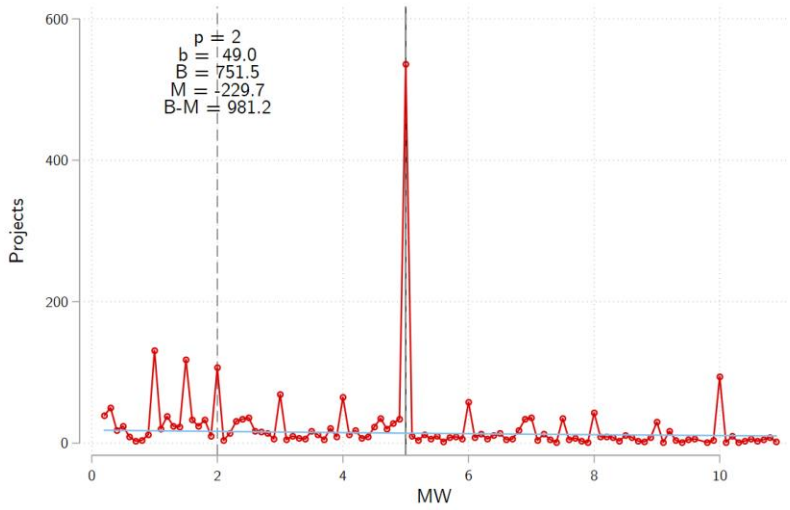


FIGURE 13 TEST FOR UPSIZING

Reference Point Effects — One cannot rule out the possibility that the FiT makes 5 MW a reference point, that is, developers decide to build farms that are 5 MW in size because it becomes salient due to the policy threshold. This has been documented in the bunching literature where agents cluster around certain values (e.g. marathon finish times, statistical results that are just under certain p-values, etc.). If this is the case, then "bunching confounds the incentive effect with a reference point effect" (Kleven 2016). I compare bunching across different time periods when the 5 MW reference point is the same but other elements of the policy change. This holds constant any reference point effects. I find that firms are indeed responding strongly to changes to FiT policy characteristics as shown by the change in relative bunching mass (Section V.D).

Cheating through co-location — One may also question whether there is "cheating" whereby a 10 MW project passes by as two separate 5 MW projects. I can test this by using geolocation data and measuring the distance between all 5 MW projects. Only 20 of 511 projects (3.9%) have identical locations, raising suspicions that they might be cheating. I find that these projects are registered under legally separate

entities. Since this is such a small share of the overall sample, the main results still hold.

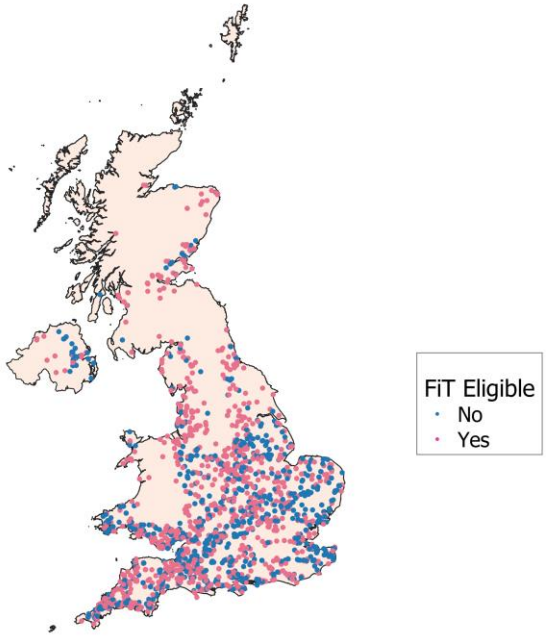


FIGURE 14: GEO-LOCATION DATA OF FIT AND NON-FIT SOLAR PROJECTS IN THE UK

Sensitivity to Order of Polynomial — Finally, Kleven (2016) highlights how in the case of notches, behavioural responses can be very spread out. Sensitivity analyses with respect to the order of the polynomial and the excluded range are recommended. Tests show that results are stable across alternative specifications.

Using a lower bound at 4.9 MW and upper bound between 6-6.5MW, I see that strategic downsizing accounts for 1-3% of the response for a third order polynomial and 3-6% of the response for a fifth order polynomial. These estimates suggest that if anything, my baseline specification is on the conservate side by presenting the larger estimate of strategic downsizing/lower estimate of new entry.

Once the upper bound is assumed to be 7 or 8 MW, for third, fourth and fifth order polynomials, the amount of strategic downsizing takes on negative values - this is the opposite of what one would expect if we believed 7-8 MW projects were

downsizing to take advantage of the FiT. In other words, there is no statistically significant evidence of a "hole" up to these capacities.

VI. Value for Money

To close my analysis, I consider whether the FiT represented value for money. I do a very simple back-of-the-envelope style calculation that uses the (lower-bound) estimates of net solar capacity additions due to the FiT. I assume that this generation crowds out coal-fired generation. During the growth period of solar, all other types of generation also increased except for coal, which declined. This produced climate and air quality benefits, which are weighed against the cost of subsidizing the FiT-accredited generation, which is measured in terms of the average weighted difference between the wholesale price and the fixed tariff (See Appendix D for full details related to the calculation).

I find that it takes a social cost of carbon worth £100 per tonne of CO_2 to make the FiT a net gain for society, after accounting for the health benefits of reducing SO_2 emissions/particulate matter. For comparison, lower bound estimates of the social cost of carbon from the literature are £60 t/CO2 (Pindyck 2018) and prevailing carbon market prices in the EU ETS (as of August 2022) are about £96.5/tCO2.

However, the government's objectives with the commercial FiT were primarily around market development rather than CO_2 reductions. Government consultations reveal how the UK was ahead of Denmark in wind power R&D in the 1980s but lost out in terms of commercialising the technology. This past experience created strong motivation to bring solar technology to market via some sort of support scheme that could eventually be phased out. Other aims included improving grid diversity, ensuring local buy-in for the energy transition, fostering innovation, and increasing local-level energy independence (DECC 2015a).

VII. Conclusion

This paper explores the role of risk reduction, via feed-in-tariffs, in bringing early-stage technologies to market, focusing on the case of utility-scale solar energy. This question is

motivated by the hypothesis that due to credit market imperfections, incomplete information and positive externalities, investment in clean energy is sub-optimally low.

Using a bunching estimator, I find that the UK's renewable energy feed-in-tariff, a policy intervention that reduced the risk of investing in renewable energy projects, was effective in incentivising large amounts of entry and investment by solar generators. Since the policy's design also created incentives for strategic downsizing of projects that would have entered anyway, I also quantify the degree of such downsizing and find that it is minimal. The net effect is positive and suggests that the policy induced significant low-carbon capacity additions. The very large extensive margin response shows how this policy helped bring utility-scale solar energy to market, especially since prior to the FiT, such projects did not exist in the UK power grid.

Value for money calculations show it takes a social cost of carbon worth £100/tCO2 to make the policy a net gain. Bunching by different time periods shows how even when the FiT provides a low subsidy, there is still significant bunching because firms value price volatility elimination and the prospect of the scheme being removed triggers a surge in entry. This also emphasizes the potential importance of phasing out support to counter the waiting dynamic that emerges from learning-by-doing externalities.

While this paper conducts an empirical case study on solar energy, the broader question on the role of risk reduction in bringing breakthrough technologies to market is likely to have relevance to other technologies such as second-generation low carbon technologies (e.g. green fuels, long duration storage, zero-carbon steel, etc.) and healthcare innovation. Technologies in these domains also generate positive externalities and, face risks and credit market imperfections.

In terms of limitations, this work concerns itself with case of policy for nascent technologies, which occupy a small share of the market and can be modelled a price-takers. To explore broader questions around the optimal deployment of the FiT, beyond the case

of early-stage technologies, a new model with endogenous prices and a market for credit will be needed. This is a promising avenue for future work.

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IX. Appendix

A. Solving for the Wait Value Function

The value of waiting is given by Equation A.1:

$$V_t^W = \max \beta E_t\{\mathrm{V}_{t+1}^{\mathrm{w}}, \mathrm{V}_{t+1}^{\mathrm{FiT}}, \mathrm{V}_{t+1}^{\mathrm{I}}\} \tag{A.1}$$

The expected value of entering with a FiT next period is (the capacity factor has been omitted for notational convenience):

$$E_t V_{t+1}^{FiT} = \beta \left[\frac{\bar{p}}{1-\beta} - (1 + \mu_{\chi_i})\alpha \right] q_{t+1}^{f*} \tag{A.2}$$

Recall that $\sigma_{\bar{p}} = 0$. Further, the choice of optimal installed capacity across time periods under a FiT is the same, $E_t q_{t+1}^{f*} = E_t q_{t+2}^{f*} = \cdots = E_t q_{t+T}^{f*}$ because the variables that affect this choice do not change in expectation: $\bar{p}$, μ_{χ_i} and α are constant. This also means that the value of entering with a FiT is the same in expectation across periods:

$$E_t V_{t+1}^{FiT} = E_t V_{t+2}^{FiT} = \cdots = E_t V_{t+T}^{FiT} \equiv \hat{V}^{FiT} \tag{A.3}$$

This implies that it is always better to enter with a FiT today rather than tomorrow in expectation since $\hat{V}^{FiT} > \beta \hat{V}^{FiT}$.

A similar logic applies to the value of investing without any policy support.

$$E_t V_{t+1}^{I} = E_t V_{t+2}^{I} = \cdots = E_t V_{t+T}^{I} \equiv \hat{V}^{I} \tag{A.4}$$

It is important to note that this is in *expectation*. Once the cost shock of the current time period is realized, it may be unfavourable such that waiting till the next period is optimal. This creates a distribution over entry timings.

Substituting A.4. and A.3. into A.1. and recursively solving the value of waiting yields:

$$V_t^W = \beta \max\{\widehat{V}^{FiT}, \widehat{V}^I\} \tag{A.5}$$

In words, the value of waiting is the discounted expected value of entering with a FiT or entering as a merchant project, whichever is larger. Note that as $T \to \infty$, $\beta^T \to 0$ and $\beta^T V_{t+T}^w \to 0$. Without the FiT, V_t^W will be the discounted expected value of entering as a merchant project, as shown in Equation A.6.

$$V_t^w = \beta \widehat{V}^I \tag{A.6}$$

B. Value for Money Calculations

Table 1

	Variables	Values	Comments
1	Net Capacity Additions due to FiT (MW)	2,270	Obtained from bunching estimates
2	Solar Load Factor	0.11	Annual average
3	Days in a Year	365	
4	Hours in a day	24	
5	Annual Solar Generation due to FiT (MWh)	2,187,372	Capacity*Days*Hours*Load Factor (lines 1-4)
6	Emissions intensity of coal displaced by solar (tCO2/MWh)	0.90	Using the carbon intensity of coal production in the UK
7	Emissions displaced by FiT Solar (tCO2/year)	1,968,635	Generation*Emissions Intensity (line 5* line 6)
8	SO2 intensity of coal production (tSO2/MWh)	0.002	Using the SO2 intensity of coal production in the UK
9	SO2 reduction from coal displaced by solar (tSO2/year)	3,991	Generation*SO2 Intensity (line 5* line 8)
10	Price of CO2 (£/tonne)	96.5	Carbon Price in EU ETS allowances (August 2022)
11	Social Cost of SO2 (£/tonne)	6,000	Social Cost of SO2, EU Commission Calculation for UK
12	Annual benefit of reduced SO2 emissions (£)	23,946,221	Line 11*Line 9
13	Annual benefit of reduced CO2 emissions (£)	189,973,258	Line 10*Line 7
14	Net subsidy given to FiT accredited solar (£/MWh)	112.0	FiT tariff - wholesale electricity price (weighted average value)
15	Annual cost of FiT solar subsidy (£)	244,985,664	Generation*Subsidy (line 5*line 10)
16	Annual benefit less cost (£)	- 31,066,185	Line 13 + Line 12 - Line 15
17	Minimum social cost of carbon to make FiT net gain	112.28	Line 15 - Line 12 / Line 7

C. Figures

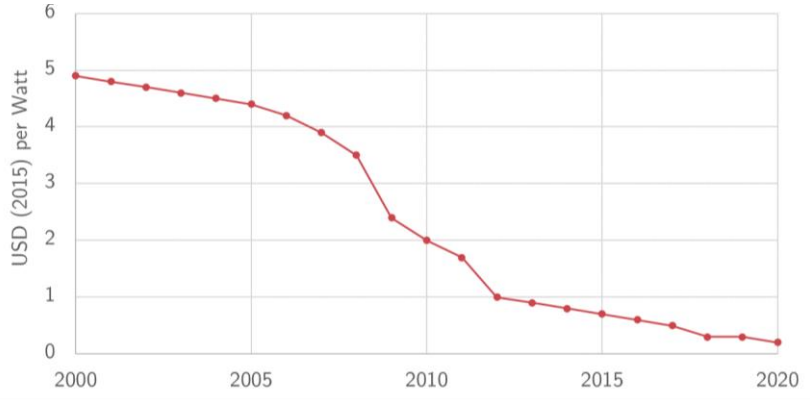


FIGURE A.1. SOLAR PANEL COSTS. SOURCE: BNEF AND NREL.

The Unintended Consequences of Environmental and Innovation Policy Interactions

By Jacquelyn Pless[1] and Sugandha Srivastav[2]

Improving the productivity and innovative performance of energy-intensive firms can help meet important development and environmental objectives. Energy-intensive firms are often exposed to both carbon pricing and innovation subsidies, yet there is little evidence on how these two instruments interact. To address this gap, we use a "discontinuity-in-effects" specification, and find that the effects of carbon pricing on different measures of productivity and innovation are attenuated by more generous R&D tax credits, making the two policies substitutes. We develop a theoretical model to explain the mechanisms behind why carbon pricing and technology-neutral R&D tax credits can be either substitutes or complements on different types of innovation.

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I. Introduction

Innovation and productivity growth in energy-intensive sectors is crucial for achieving important development and environmental objectives. Energy innovation is often characterized by two market failures: knowledge spillovers which create a wedge between the social and private value of innovation (Nelson 1959; Arrow 1962) and environmental externalities (Jaffe, Newell and Stavins 2005). R&D tax credits and carbon pricing have been used to address these externalities respectively. However, since carbon prices are often below their optimal levels due to political constraints (Klenert et al. 2018, Borenstein 2012),[1] it is important to investigate how these two policies interact and whether innovation subsidies are complements or substitutes to carbon pricing (Lipsey and Lancaster 1956).

We develop a theoretical framework to illustrate how environmental and innovation policies may interact. The set-up features a final goods market with a constant elasticity of substitution between clean and dirty inputs to produce a homogenous product (e.g. energy). There is an intermediate goods market, where clean and dirty inputs are manufactured, and R&D takes place via quality improvements. While carbon pricing increases the relative demand for clean inputs, undirected (i.e., technology-neutral) innovation policy reduces the marginal cost of both clean and dirty inputs. Therefore, the interaction cross-partial is ambiguous as it depends on the extent to which the R&D tax credits, and embedded innovation incentives, support clean versus dirty inputs.

We estimate the interaction effects of carbon pricing and technology-neutral R&D tax credits on energy-intensive firms' innovative and productive activities in the UK manufacturing and power sectors. Due to data limitations, we are unable to directly measure clean and dirty innovation, however, we are able to measure improvements

[1] For example, in 2021, only 3.7% of emissions were covered by a carbon price above USD 40/tCO2e while the literature's accepted lower bound of social cost of carbon is USD 80/tCO2 (Pindyck 2019).

in productivity which typically have positive implications for the environment as they reduce the materials/energy-intensity of output. Our dataset includes firms in sectors such as cement, iron & steel, paper & pulp, chemicals, textiles, and petroleum. We develop a "discontinuity-in-effects" research design which estimates the effect of carbon prices on each side of an exogenous sharp discontinuity in the R&D tax credit generosity.

We find that carbon pricing and technology neutral R&D tax credits act as substitutes on innovative activity and productivity as indicated by a variety of different outcome variables (e.g. total factor productivity (TFP), capital expenditures, R&D expenditures, labour/capital productivity, expenditure on plants & vehicles, expenditure on buildings & land, etc.). Firms in industries that are directly regulated under the European Union Emissions Trading Scheme (EU ETS), increase capital expenditures by 1.2% in response to a 1 GBP increase in the carbon price. However, this effect is dampened to 0.8% for firms receiving more generous R&D tax credits.

For firms in indirectly exposed industries,[2] carbon pricing has no statistically significant impact on capital expenditures. However, a 1 GBP rise in carbon price increases TFP by 2.3% but this effect is dampened to -0.8% for firms receiving more generous R&D tax credits. These results indicate how carbon pricing and R&D tax credits are substitutes in their effects for both regulated and indirectly exposed firms. This has implications for policymakers interested in inducing innovation and productivity gains in energy-intensive sectors.

We make several contributions to the literature. We empirically demonstrate the importance of innovation and environmental policy interactions. This is worthy of investigation since optimal carbon prices are difficult to achieve in practice.

[2] These are firms that are not in sectors directly under the EU ETS but which have supply chain links to regulated sectors.

Consequently, the "first-best" innovation policy may no longer be best (Lipsey and Lancaster 1956).

We also marry the innovation and environment literature. The existing empirical literature has studied these market failures and their corrective instruments in silos. For example, there is growing scholarship on whether carbon pricing induces innovation (e.g., Martin et al. 2014, Calel and. Dechezlepretre 2016, Colmer et al. 2022, Martin et al 2020). There is a separate literature on how subsidies for R&D impact innovation (e.g., Guceri and Liu 2019, Howell 2017, Agarwal et al. 2020, Fazio et al. 2019, Dechezlepretre et al. 2016, Bøler et al. 2015, Bronzini and Iachini 2014 and Pless 2022). However, since firms frequently face both types of policies simultaneously, it is worth understanding their *joint* effect. This requires estimating the cross-partial or interaction effect of innovation and environmental policy, which is the contribution of this paper.

Finally, studying innovation and productivity in energy-intensive sectors is a critical and timely issue given the need to improve resilience to energy price shocks and lower the environmental footprint of production. This makes our empirical results important in their own right.

The rest of our paper is organized as follows. Section 2 develops a theoretical framework for studying policy interactions, Section 3 discusses the institutional context in which we conduct our empirical analysis, Section 4 describes our empirical strategy and data, Section 5 provides results and Section 6 concludes.

II. Theoretical Framework

Environment — Similar to Acemoglu et al. (2012), there is a competitive final goods market and an intermediate goods market with monopolistic competition. Innovation takes place in the intermediate goods market. A representative household supplies specialized labour and rents technology to firms.

Final Goods Market — Dirty and clean intermediate products (y_d and y_c) are used to make a final good Y with a constant elasticity of substitution, $\sigma > 1$.[3] We conceptualise the final good as energy, which can be produced using either clean or dirty generation, or as mobility which can be achieved via an electric vehicle or internal combustion engine.

$$Y = \left(\sum_{n=1}^{N} y_{cn}^{\frac{\sigma-1}{\sigma}} + \sum_{j=1}^{J} y_{dj}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

There are N discrete clean products and J discrete dirty products. Let η denote the emissions intensity, where $\eta_{dj} > \eta_{dj+1}$ (i.e. dirty products with a lower j have more emissions per unit.) Within the power sector, y_{dj} could be coal, while y_{dj+1} could be gas. y_{cn} could represent wind power or solar photovoltaics. A tax τ per unit of emissions is applied to dirty goods.

Intermediate Goods Market — Firms operate in an environment of monopolistic competition. Each firm makes a single differentiated product, either y_{dj} or y_{cn}, using specialized labour. y_{dj} or y_{cn} represent quality-adjusted units that can increase either with improvements in quality or quantity. We depart from Acemoglu et al (2012), by explicitly modelling R&D expenditure (m) and assume it results in product-quality improvements from a normalized quality level of 1 ($M \equiv 1 + m$).[4] One can

[3] Clean and dirty inputs are modelled as substitutes.

[4] Since M is increasing in m, we will simply consider M.

conceptualize R&D expenditure as the cost of hiring scientists, while K represents capital.

$$y_{dj} = A_d M_{dj}^{\alpha} K_{dj}^{\phi} \tag{2}$$
$$y_{cn} = A_c M_{cn}^{\alpha} K_{cn}^{\phi}$$

We assume $\alpha, \phi \in (0,1)$ and $\alpha + \phi \leq 1$. Firm productivity is captured by A which varies between clean and dirty manufacturers.[5]

An intermediate firm's profit function is shown below. The R&D tax credit rate per unit of investment is represented by Λ and applies to both clean and dirty intermediate inputs i.e., it is technology neutral. The marginal cost of R&D and capital are given by w and μ respectively (for notational convenience, we will drop subscripts n and j).

$$\pi_d = p_d y_d(p_d) - (1-\Lambda) w_d m_d - \mu_d K_d \tag{3}$$
$$\pi_c = p_c y_c(p_c) - (1-\Lambda) w_c m_c - \mu_c K_c$$

PROPOSITION 1: The R&D tax credit's marginal impact on clean and dirty innovation is positive. Subscript x denotes *cn* or *dj*.

$$\frac{\partial \Psi_x^*}{\partial \Lambda} = -w_x \left[\frac{\mu_x}{\phi}\right]^{\phi} \left[\frac{(1-\Lambda)w_x}{\alpha}\right]^{\alpha-1} A^{-1} < 0 \tag{4}$$

[5] Although one could consider other specifications of how R&D enters the production function, this simple form helps produce a tractable solution that illustrates the key intuition that R&D tax credits can affect the marginal cost of producing clean/dirty inputs.

PROOF: See Appendix A. Since the R&D tax credit can be claimed by both clean and dirty intermediate input manufacturers, it reduces marginal costs for both technologies.

PROPOSITION 2: A marginal increases in the carbon price raises clean R&D and reduces dirty R&D.

$$\frac{\partial M_{cn}^{*}}{\partial \tau} = \Omega_c \, \eta_{dj} \left[\frac{\Psi_{\mathrm{dj}}}{\Psi_{\mathrm{cn}}}\right]^{\frac{\sigma}{\alpha}} \left[\kappa_{dj}\right]^{\frac{\sigma-\alpha}{\alpha}} > 0 \tag{5}$$

$$\frac{\partial M_{dj}^{*}}{\partial \tau} = -\,\Omega_d \frac{\sigma}{\alpha} \left[\frac{\Psi_{\mathrm{dj+1}}}{\Psi_{\mathrm{dj}}}\right]^{\frac{\sigma}{\alpha}} \left[\frac{(1+\tau\eta_{dj})}{(1+\tau\eta_{dj+1})}\right]^{\frac{-\sigma-\alpha}{\alpha}} \left[\frac{\eta_{dj}-\eta_{dj+1}}{(1+\tau\eta_{dj+1})^{2}}\right] < 0 \tag{6}$$

PROOF: See Appendix A. A carbon price reduces the demand for dirty intermediate inputs and increases the demand for clean intermediate inputs which shifts R&D activity accordingly.

PROPOSITION 3: Assuming, $\sigma > 1$, it is theoretically ambiguous whether a technology neutral R&D tax credit is a complement or substitute to carbon pricing in terms of its impact on clean or dirty innovation.

$$\frac{\partial^{2} M_{cn}^{*}}{\partial \tau \, \partial \Lambda} = \Omega_c \, \eta_{dj} \frac{\sigma}{\alpha} \left[\kappa_{dj}\right]^{\frac{\sigma-\alpha}{\alpha}} \left[\frac{\Psi_{\mathrm{dj}}}{\Psi_{\mathrm{cn}}}\right]^{\frac{\sigma-\alpha}{\alpha}} \left[\frac{1}{\Psi_{cn}} \Big(\underbrace{\frac{\partial \Psi_{dj}}{\partial \Lambda}}_{D} - \underbrace{\frac{\Psi_{\mathrm{dj}}}{\Psi_{\mathrm{cn}}} \frac{\partial \Psi_{\mathrm{cn}}}{\partial \Lambda}}_{R} \Big)\right] \tag{7}$$

$$\frac{\partial^{2} M_{dj}^{*}}{\partial \tau \, \partial \Lambda} = -\,\Omega_d \left(\frac{\sigma}{\alpha}\right)^{2} \left[\frac{\Psi_{\mathrm{dj+1}}}{\Psi_{\mathrm{dj}}}\right]^{\frac{\sigma-\alpha}{\alpha}} \left[\frac{\kappa_{dj}}{\kappa_{dj+1}}\right]^{\frac{-\sigma-\alpha}{\alpha}} \left[\frac{\eta_{dj}-\eta_{dj+1}}{{\kappa_{dj+1}}^{2}}\right] \left[\frac{1}{\Psi_{\mathrm{dj+1}}} \Big(\underbrace{\frac{\partial \Psi_{\mathrm{dj}}}{\partial \Lambda}}_{D} - \underbrace{\frac{\Psi_{\mathrm{dj}}}{\Psi_{\mathrm{dj+1}}} \frac{\partial \Psi_{\mathrm{dj+1}}}{\partial \Lambda}}_{R} \Big)\right] \tag{8}$$

PROOF: See Appendix A. This is the main novel result of our model.

The sign of $\frac{\partial^{2} M_{cn}^{*}}{\partial \tau \, \partial \Lambda}$ is ambiguous. If $\left|\frac{\partial \Psi_{\mathrm{dj}}}{\partial \Lambda}\right| < \left|\frac{\Psi_{\mathrm{dj}}}{\Psi_{\mathrm{cn}}} \frac{\partial \Psi_{\mathrm{cn}}}{\partial \Lambda}\right|$, then $\frac{\partial^{2} M_{cn}^{*}}{\partial \tau \, \partial \Lambda} > 0$, i.e., carbon pricing and R&D tax credits are complements. However, if $\left|\frac{\partial \Psi_{\mathrm{dj}}}{\partial \Lambda}\right| > \left|\frac{\Psi_{\mathrm{dj}}}{\Psi_{\mathrm{cn}}} \frac{\partial \Psi_{\mathrm{cn}}}{\partial \Lambda}\right|$, then $\frac{\partial^{2} M_{cn}^{*}}{\partial \tau \, \partial \Lambda} < 0$ i.e., carbon pricing and R&D tax credits are substitutes. The dampening term $(\frac{\partial \Psi_{\mathrm{dj}}}{\partial \Lambda})$

reflects how R&D tax credits reduce the marginal cost of dirty innovation, while the reinforcing term ($\frac{\Psi_{dj}}{\Psi_{cn}}\frac{\partial \Psi_{cn}}{\partial \Lambda}$) reflects how R&D tax credits reduce the marginal cost of clean innovation, and this is scaled by the degree to which dirty inputs are costlier than clean inputs.

Similarly, the interaction effect, $\frac{\partial^2 M_{dj}}{\partial \tau \partial \Lambda}$, is ambiguous. The negative effect of τ on innovation for y_{dj} is dampened by R&D tax credits reducing the marginal cost of the dirtier input, y_{dj} (see D label) but reinforced by the scaled marginal effect of R&D tax credits reducing the marginal cost of the less dirty input, y_{dj+1} (see R label).

PROPOSITION 4: Assuming $\sigma > 1$, if R&D tax credits were targeted only towards clean technologies, then the two instruments would be unambiguously complements.

$$\frac{\partial^2 M^*_{cn}}{\partial \tau \, \partial \Lambda} = \Omega_c \, \eta_{dj} \frac{\sigma}{\alpha} \left[\kappa_{dj}\right]^{\frac{\sigma-\alpha}{\alpha}} \left[\frac{\Psi_{dj}}{\Psi_{cn}}\right]^{\frac{\sigma-\alpha}{\alpha}} \left[-\frac{\Psi_{dj}}{\Psi_{cn}}\frac{\partial \Psi_{cn}}{\partial \Lambda}\right] > 0 \tag{9}$$

PROOF: See Appendix A. If R&D tax credits were targeted only towards clean technologies, then $\frac{\partial \Psi_{dj}}{\partial \Lambda} = 0$ which would eliminate the dampening term from Equation 7 and the R&D tax credits would reinforce the positive effect of carbon pricing on clean innovation.

The total effect of each instrument on the level and thus direction of innovation depends on the sum of the direct and indirect effects ($\frac{\partial M_{cn}}{\partial \Lambda}, \frac{\partial M_{cn}}{\partial \tau}, \frac{\partial^2 M_{cn}}{\partial \tau \partial \Lambda}, \frac{\partial M_{dj}}{\partial \Lambda}, \frac{\partial M_{dj}}{\partial \tau}, \frac{\partial^2 M_{dj}}{\partial \tau \partial \Lambda}$). Fundamental to the ambiguity is that R&D tax credits are technology-neutral and clean and dirty inputs are imperfect substitutes $\sigma > 1$. However, if the tax credits were directed towards clean technologies only, the

total effect would be the sum of: $\frac{\partial M_{cn}}{\partial \Lambda}, \frac{\partial M_{cn}}{\partial \tau}, \frac{\partial^2 M_{cn}}{\partial \tau \partial \Lambda}, \frac{\partial M_{dj}}{\partial \tau}$ which is unambiguously positive.

We have developed a simple theoretical framework to study the interaction of policy instruments that aim to correct two market failures: knowledge externalities and environmental externalities. Approaching the two market failures and their respective instruments, through a multiplicative rather than additive lens, emphasizes that technology neutral innovation subsidies can potentially work against the desired directional effects of environmental regulation. Such considerations are of relevance in a world with Paretian constraints (Lipsey and Lancaster 1956).

III. Institutional Context

Our empirical setting is the UK, which has a carbon price and R&D tax credit. The UK government's R&D Corporation Tax Relief scheme, introduced in 2000, was the first financial incentive scheme aimed at fostering innovation. It provides tax relief on lump-sum R&D expenditures across all sectors such that both profit- and loss-making firms benefit. Qualifying costs include those related to labour but not capital expenditure (see Appendix C for further details).

Small and medium enterprises (SMEs) benefit from much more generous tax credit benefits relative to larger firms, and the threshold for what defines SMEs for the R&D tax credit purposes is twice as high as the threshold for all other contexts in which SMEs benefit from favourable policies or incentives.[6] The mechanism through which the R&D tax credit works is as follows: expenditure that qualifies for R&D is artificially "enhanced" at a specified rate which reduces the company's taxable profit for that financial year, effectively creating a "tax credit". The enhancement rate

[6] The standard threshold for small enterprises is less than 50 employees and an annual turnover under €10 million. For medium-sized enterprises it is less than 250 employees and an annual turnover under €50 million. For more generous R&D tax credits it is less 500 employees and an annual turnover under €86 million post 2008, which is the period of our analysis.

changes over time but in some years, it is as high as a 230% deduction for profit-making firms and 14.5% for loss-making firms.[7]

The amount relief depends on (i) the firm's R&D expenditure, (ii) the rate at which its profits are ordinarily taxed (which depends on revenue), and (iii) whether the firm is loss-making. As an example, if a profit-making company in the first-tax bracket spends £100 on R&D, it can receive £19 in rebates under the regular R&D tax credit, and £44 under the enhanced R&D tax credit.

Carbon pricing in the UK operates through the EU ETS which covers firms in sectors that are highly energy-intensive (e.g. petroleum, iron & steel, metals, chemicals, pulp & paper, glass, cement, etc.).[8] The UK joined the EU ETS in 2005. From 2013 onwards, the UK also implemented a Carbon Price Floor. In reality, rather than operating as a price floor to the EU ETS, it was a top-up, effectively increasing the carbon price firms were exposed to. Our analysis takes place from 2009 up to 2018, while the UK was still in the European Union. Therefore, we do not have to consider its subsequent departure from the EU ETS and the implementation of the UK ETS.

IV. Data & Empirical Strategy

A. Data and Summary Statistics

We use Bureau van Dijk's (BvD) Financial Analysis Made Easy (FAME) database to gather balance sheet and ownership information for manufacturing and power sector firms in the UK. This provides us with information such as employment, total assets, and turnover, which are required for determining whether a firm is eligible for

[7] See Guceri and Liu 2019 and Pless 2022 for in-depth institutional details.

[8] The directly regulated EU ETS firms in our paper, therefore, belong to NACE codes 17, 19, 20, 22, 23, 24, 25, 35.

more generous R&D tax credits.[9] It also provides detailed production information so that we can measure firm-level productivity. Our sample includes manufacturing and power sector firms in England, Wales, Scotland, and Northern Ireland from 2000 to 2019. The initial download results in a total of 963,940 firm-year observations across 47,954 unique firms (see Appendix D for details on data cleaning and preparation).

We use ICE Market Data to obtain daily data on the carbon price from the European Climate Exchange (ECX) which is the largest EUA trading venue, capturing two-thirds of total traded volume (Mizrach et al 2014). We use the annual average of daily one-month ahead futures price. The vast majority of EUA trades happen in the futures market rather than the spot market, making the futures market more relevant for price discovery and firm behaviour. In the years after 2012, we also account for the carbon price floor which, via the carbon support price, topped up EU ETS allowance prices.[10]

Table I provides summary statistics for manufacturing and power sector firms in the 200-800 employee window. The firms are capital-intensive and spend about 3% of annual revenue on R&D. About 86% of the sample is in industries directly regulated by the EU ETS. The mean value of TFP (logged) is 5.2 with a standard deviation of 1.7. These figures are very similar to other estimates of TFP for UK manufacturing firms when using multiple production function estimation approaches (Bournakis and Mallick 2018).

Table I: Summary Statistics for Manufacturing and Power Sector Firms

[9] We gather consumer price index and exchange rate information from FRED to convert monetary figures into real terms and to convert GBP into Euros for determining tax credit threshold eligibility.

[10] We use data from Leroutier 2022 on the CPF levels across time.

	Mean	St. Dev.	Observations
Panel A: Outcomes			
R&D Expenditures (000s GBP)	2,933	14,766	1,322
R&D as Percent of Revenue	0.030	0.133	1,321
TFP (log)	5.213	1.680	4,543
Capital Productivity (log) (revenue / capital)	1.762	1.198	4,552
Labor Productivity (log) (revenue / labor)	5.249	0.876	4,622
Panel B: Inputs			
Employment	374	156	4,709
Capital (log)	9.312	1.445	4,575
Capital-Labor Ratio	3.482	1.304	4,562
Investment (000s GBP)	7.699	1.563	4,205
Panel C: Other Firm Characteristics			
Age (years)	35.0	29.1	4,709
Pr[Regulated Industry = 1]	0.864	0.343	4,709
Turnover (log)	11.075	1.035	4,633
Total Assets (log)	10.90	1.278	4,707

Notes: Summary statistics for the main outcomes, inputs, and firm characteristics. Sample includes firms with 200 to 800 employees from 2008 onward. The number of observations falls across some variables because of non-reporting.

B. Estimation Strategy

To estimate the interaction effect of R&D tax credits and carbon pricing, we develop a discontinuity-in-effects research design which leverages the R&D tax credit generosity threshold and checks if the impact of carbon pricing changes across it, to infer whether the two policies are independent or, complements or substitutes (this empirical strategy is adapted from Pless 2022). This estimation is done for firms that are directly regulated in the EU ETS and those that are indirectly exposed. The main specification is therefore, as follows:

$$(10)\ Y_{it} = \beta_1(C_t * J_{it} * R_i) + \beta_2(C_t * J_{it}) + \beta_3(C_t * R_i) + \beta_4(J_{it} * R_i) + \beta_5 C_t + \beta_6 R_i + J_{it}(\beta_7 + \beta_8 A_i^*) + \beta_9 A_i^* + \boldsymbol{X}_{it} + \epsilon_{it}$$

where Y_{it} is the outcome variable for firm i in year t, $\mathrm{C_t}$ is the carbon price, and R_i is an indicator if the firm is directly regulated under the EU ETS and $\mathrm{J_{it}}$ is an indicator if the firm is eligible for a more generous R&D tax credit. $\mathrm{J_{it}}$ equals one if

a firm's lagged employment is less than 500 employees and either its lagged turnover or total assets are less than 100m GBP or 86m GBP, respectively.

β_5 is the direct effect of carbon pricing for indirectly exposed firms, and β_2 shows how this changes for firms with more generous R&D tax credits. β_3 captures the *additional* effect of carbon pricing for directly regulated firms in the EU ETS and β_1 shows how this changes for firms with more generous R&D tax credits. These coefficients identify the interaction effects we are most interested in. The remaining coefficients control for the direct impact of the R&D tax credits on innovation outcomes via an embedded regression discontinuity design and remaining interaction effects.

Although we define treatment status precisely using all three eligibility criteria, we use lagged employment as the only running variable since it is the primary determinant of treatment status. We normalize the running variable function, $A_i^* = A_i - A_c$ at the 500-employee cut-off point, allowing the slope to differ on each side of the cut-off. Additional control variables are captured by the matrix $\mathbf{X}_{\mathrm{it}}$ include firm, industry, year, and county fixed effects as well as industry-year specific time trends. Standard errors are clustered at the industry-year level to adjust for potential serial correlation in errors. For the years 2009-2018, we estimate local linear regressions around the running variable cut-off and restrict the data to $A_{it} \in [A_c - h, A_c + h]$, where h represents the bandwidth around the threshold.

All firms in the sample face costs associated with carbon pricing, as they are all polluters to some degree, but shocks to the marginal cost of production induced by carbon prices are highest for emissions-intensive firms. Cost shocks therefore vary not only over time but also across firms based on a firm's emissions-intensity. The split between directly and indirectly exposed firms allows for an additional source of identifying variation that proxies for intensity of treatment (e.g., see Lu and Pless

2021 who also allow for varying effects using a heterogenous diff-in-diff estimation that distinguishes between very dirty and less dirty firms).

There are four main identification assumptions that must be satisfied for our research design to identify the causal effects of carbon prices and R&D tax credits on their own and their interaction: (i) the thresholds determining R&D tax credit generosity are arbitrary and there are no other policies or incentives that vary sharply at the same thresholds, (ii) the R&D tax credit policy has relevance, as otherwise, a discontinuity in the carbon price effect at the threshold would not be attributed to the difference in tax credit generosity, (iii) carbon pricing is not determined by UK firms' input choices or productivity, and (iv) the effect of carbon pricing does not differ at the R&D tax credit generosity cut-off absent the threshold. We conduct a series of empirical tests to provide confidence that these assumptions hold in Section IV.C.

Innovative activity is measured by a host of different outcome variables (e.g. TFP, capital expenditures, R&D expenditures, labour/capital productivity, expenditure on plants & vehicles, etc.). To measure productivity, we use the semi-parametric estimator of Olley and Pakes (1996) (OP) to construct firm-level measures of TFP.[11] We estimate labour and capital coefficients separately by industry given differences in input intensities across industries while controlling for production choice dynamics within each industry using year fixed effects. To have a sufficient number of observations for each industry-specific estimation, we use the first two digits of firms' NACE codes. We then use these coefficient estimates to construct firm-level TFP. When exploring mechanisms and firm choices that drive productivity changes, we also break down our baseline measure and examine input levels, ratios, and single-factor productivity measures. The single factor productivity measures also serve as a robustness check to our TFP estimates (see Appendix E).

[11] Due to data limitations, this is the TFP measure we are able to estimate. See Appendix E.

C. Validity of Research Design

The first key identifying assumption is that the thresholds determining R&D tax credit generosity status are set randomly by the government in a way that is not correlated with differences in firm characteristics around the thresholds and that no other policy varies at that discontinuity. This is not only important for identifying the causal direct effect of R&D tax credits but also the interaction effect. We focus on the year 2009 onwards as this is the time period where the R&D tax credit generosity threshold was double the size of thresholds that define SMEs for all other purposes. We find no other policies in the UK that create changes in incentives around the 500-employee cut-off.

Second, we conduct a covariate balance test which shows that observable characteristics do not change around the cut-off in pre-policy years. Assigning firms that would have been treated under the new eligibility regime as treated in pre-policy years (2002-2008), we estimate the effect of a "pseudo-treatment" on firm R&D investments within a regression discontinuity framework as follows:

$$Y_i = \delta_0 + \delta_1 A_i^* + J_i(\gamma_0 + \gamma_i A_i^*) + \epsilon_i \tag{10}$$

where each variable takes on the same definition as before. The coefficient γ_0 captures whether there is any effect at the threshold in pre-policy years. Results are presented in Table II show that there is no discontinuity in revenue, the capital-labour ratio, capital, labour, or investment.[12] Furthermore, the covariate balance also suggests that the government did not select these thresholds based on any specific firm characteristics.

[12] We are unable to estimate these effects on R&D expenditures when we narrow the sample around the threshold because this variable is not sufficiently reported in the early years of our data.

Table II: Covariate Balance in R&D Tax Credit Pre-Policy Years

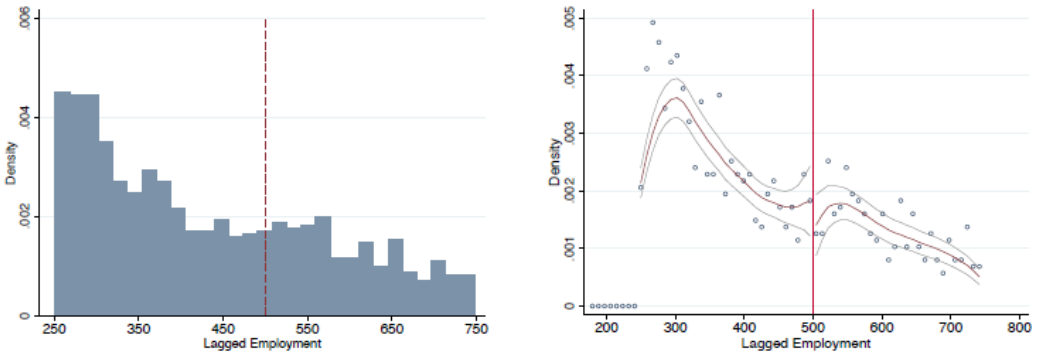
Dep. var (log)	Revenue (1)	K-L Ratio (2)	Capital (3)	Labor (4)	Investment (5)
Treated	-0.027	0.061	0.060	0.012	0.076
	(0.037)	(0.040)	(0.042)	(0.025)	(0.109)
Observations	2263	2246	2250	2278	1977
Mean Dep. Var.	11.16	3.57	9.55	5.96	7.88
Firm fixed effects	x	x	x	x	x
Industry fixed effects	x	x	x	x	x
Year fixed effects	x	x	x	x	x
County fixed effects	x	x	x	x	x

Notes: Regression discontinuity results demonstrating no discontinuities in covariates around the tax credit threshold in pre-policy years. Firms with 250 to 750 employees are included. First order polynomials of the (centered) running variable are included separately for each side of the threshold. The number of observations changes across variables because of non-reporting. Asterisks denote $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

We also examine the firm size distribution to check whether there is evidence of firms strategically downsizing to take advantage of the more generous tax credits, as this behavior would suggest that firms below the threshold in post-policy years are systematically different in ways that could bias our results. For instance, firms that do engage in such firm size manipulation might be particularly savvy or R&D-intensive.

Panel A of Figure 1 shows the density of firms for those with 250 to 750 employees for all post-policy years. Panel B provides a formal McCrary density test. We also include analogous figures in Appendix B that use data only for the years 2013-2018 to ensure that such behavior did not evolve over time (Figure B.1). In both cases, there is no evidence of firms bunching below the threshold, and the log differences in density height at the threshold are not statistically significant.

Figure 1: No Evidence of Manipulation around the R&D TC Threshold



(a) Histogram Based Upon Employment

(b) McCrary Density Test Based Upon Employment

Note: Histogram and McCrary test for discontinuity in distribution density of total employment at the tax credit generosity threshold. Sample includes firms reporting R&D expenditures with 250 to 750 employees. Log difference in density height of -0.350 with a standard error of 0.300.

The second key identifying assumption is that the R&D tax credit is relevant. A causal interpretation of our estimates relies on the assumption that the tax credit policy on its own is effective, as there is no reason to expect an interaction effect with carbon pricing otherwise. Existing evidence using quasi-experimental methods and administrative data suggests that the UK's R&D tax credit policy has had large, positive effects on firm R&D expenditures and innovation outcomes (Guceri and Liu 2019, Dechezlepretre et al. 2016, Pless 2022). We complement these findings with our own estimates to ensure that this is the case for firms in our data and confirm that it is (see Appendix B).

Our third assumption concerns the exogeneity of the carbon price. Firms in the UK contribute to a relatively small share of emissions in the EU ETS and are therefore, price-takers. We address any remaining endogeneity associated with general macroeconomic trends with a rich set of controls (this is similar to the empirical strategy followed in Fabra and Reguant 2014).

Lastly, if firm responsiveness to carbon pricing does not vary sharply at the threshold absent the tax credit policy, the discontinuities-in-effects estimate will

capture the causal effect of the policy interaction because it is driven strictly by the exogenous discontinuity in the size of the R&D tax credit. Our preceding tests showing the validity of our identification strategy for the R&D tax credit policy on its own provides evidence that this is the case. No other policies introduce sharp changes in incentives for firms that align with the tax credit generosity thresholds, and thus there should be no other drivers of discontinuities-in-effects besides the tax credit policy.

V. Main Results

A. R&D and Productivity in the Manufacturing Sector

We estimate the discontinuity-in-effects model of Equation 10 for various measures of innovation and output-related outcomes. We include various specifications that change the bandwidth around the threshold, the type of weights, and the polynomial. The baseline uses a window of +/- 250 employees, uniform weights and a quadratic polynomial, as recommended by Gelman and Imbens (2019). Reported results are tested for joint significance.

We first focus on the most energy-intensive firms, i.e. those that are in directly regulated EU ETS sectors. Firms in directly regulated industries increase capital expenditures by 1.2% in response to a 1 GBP increase in the carbon price. [13] However, for firms receiving more generous R&D tax credits, this effect is dampened to 0.8% (Column 3 of Table III).[14] Additionally, a 1 GBP rise in the carbon price increases plant & vehicle investments by 1.2% for directly regulated firms[15] but this is attenuated to 0.9% with more generous R&D tax credits.[16] We do not see a (jointly)

[13] F-test = 13, results jointly significant at 1% level.

[14] F-test = 10.9, results jointly significant at 1% level.

[15] F-test 4.8, results jointly significant at 5% level.

[16] F-test 3.2, results jointly significant at 10% level.

significant impact on labour-related outcomes and capital productivity for regulated firms.

Table III: Effects on Inputs and Single-Factor Productivity

Dep. Var. (log):	K-L Ratio	Labor	Capital	Plant & Veh. Investment	Labor Productivity	Capital Productivity
	(1)	(2)	(3)	(4)	(5)	(6)
Carbon Price * Treated * Regulated	-0.018	-0.024	-0.042***	-0.030**	0.017	0.044***
	(0.012)	(0.016)	(0.013)	(0.014)	(0.012)	(0.013)
Carbon Price * Treated	0.014	0.024	0.038***	0.027**	-0.021*	-0.047***
	(0.011)	(0.016)	(0.012)	(0.013)	(0.011)	(0.012)
Carbon Price * Regulated	0.003	0.024	0.027**	0.024*	-0.012	-0.026**
	(0.012)	(0.019)	(0.013)	(0.013)	(0.010)	(0.011)
Carbon Price	0.008	-0.025	-0.015	-0.013	0.019**	0.024**
	(0.011)	(0.019)	(0.013)	(0.012)	(0.009)	(0.011)
Observations	3968	4065	3978	3664	4034	3965
Mean Dep. Var.	3.48	5.83	9.33	8.60	5.25	1.77

*Note: Estimates are in the 250-750 employee window. *p<0.10, **p<0.05, ***p<0.01*

Table IV shows the results for R&D expenditures. Across all the specifications, the coefficient on "carbon price*treated*regulated", is negative and significant, indicating how R&D tax credits dampen the marginal effect of carbon pricing. Note this does not mean R&D tax credits themselves reduce R&D expenditures, it means they dampen *carbon pricing's* positive effect on R&D expenditures, showing how the instruments are substitutes

Table IV: Effects of Carbon Price and Tax Credits on R&D Expenditure

	250 to 750 Employees (1)	200 to 800 Employees (2)	150 to 850 Employees (3)	Triang. Weights (200-800 Empl.) (4)	Cubic Trends (200-800 Empl.) (5)
Carbon Price * Treated * Regulated	-0.087*	-0.071**	-0.061*	-0.071**	-0.075**
	(0.047)	(0.031)	(0.031)	(0.034)	(0.032)
Carbon Price * Treated	0.081*	0.052*	0.046	0.055*	0.059*
	(0.046)	(0.028)	(0.029)	(0.032)	(0.030)
Carbon Price * Regulated	0.100***	0.075***	0.053**	0.089***	0.087***
	(0.032)	(0.028)	(0.026)	(0.028)	(0.031)
Carbon Price	-0.097***	-0.067**	-0.041*	-0.079**	-0.075**
	(0.031)	(0.029)	(0.024)	(0.030)	(0.031)
Observations	906	1322	1544	1322	1322
Mean Dep. Var.	6.62	6.55	6.42	6.60	6.55

Notes: Estimates for the impacts on (log) R&D. Columns 1-3 include narrow to wider windows around the tax credit generosity threshold. Firm, industry, and county fixed effects are included in each regression. Year-by-industry quadratic trends are included for Columns 1-3. In Column 4, we use triangular weights, and in Column 5, we use cubic industry-year trends rather than quadratic. Standard errors are clustered by industry-year. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

For firms in indirectly exposed industries, a 1 GBP increase in carbon price results in 1.9 and 2.4% increase in labour and capital productivity respectively (Table III). However this effect is dampened with more generous R&D tax credits, as indicated by the negative and statistically significant coefficients on carbon price*treated.[17] Furthermore, for indirectly exposed firms, a 1 GBP increase in carbon price has a negative effect on reported R&D expenditures, but more generous R&D tax credits attenuate this effect (as indicated by the positive and statistically significant coefficients on carbon price*treated in Table IV). The direct effect of a decline in R&D expenditures in response to carbon pricing may be linked to diverting/re-labelling funds for other uses, while specific subsidies for R&D dampen this effect.

Turning to TFP and various output-related measures, a carbon price has a positive and significant direct effect for indirectly exposed firms. However, in almost all cases (i.e., TFP, revenue, value-add), this is dampened by more generous R&D tax credits (as indicated by the negative and statistically significant coefficients on carbon price*treated in Table V).

[17] E.g. A 1 GBP increase in carbon price increases capital productivity by 2.4% which is attenuated to -2.3% with more generous R&D tax credits for indirectly exposed firms. F-stat 11.4, results significant at 1% level.

Table V: Impacts on TFP & Output related Measures

Dep. variable (log)	TFP (baseline)	TFP (alternative)	Revenue	Value-Added	Profit Margin
	(1)	(2)	(3)	(4)	(5)
Carbon Price * Treated * Regulated	0.023*	0.024*	0.012	0.021	0.288
	(0.014)	(0.014)	(0.015)	(0.015)	(0.277)
Carbon Price * Treated	-0.031**	-0.032**	-0.027*	-0.032**	-0.348
	(0.014)	(0.014)	(0.014)	(0.015)	(0.248)
Carbon Price * Regulated	-0.016	-0.016	-0.010	-0.019	-0.493**
	(0.012)	(0.012)	(0.011)	(0.011)	(0.233)
Carbon Price	0.023**	0.023**	0.024**	0.027**	0.382*
	(0.011)	(0.012)	(0.011)	(0.011)	(0.200)
No. of Observations	2,953	2,953	3,025	2,963	2,981

Notes: Estimates for output-related measures around 250-750 employee window. Other controls include firm, industry, and county fixed effects as well as year-by-industry quadratic trends. Standard errors are clustered by industry-year. Asterisks denote $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

An interesting takeaway from this analysis is that carbon pricing can increase productivity as witnessed in the estimates for indirectly exposed firms. This lends some support to the "strong" version of the Porter hypothesis (Porter, 1995). However, more generous R&D tax credits attenuate this effect. These findings indicate that carbon pricing and R&D tax credits are substitutes in their effects on innovation and productivity-related outcomes for firms in both directly regulated and indirectly exposed firms.

B. Falsification and Robustness Checks

We conduct a number of falsification and robustness checks to ensure that the results are not sensitive to our modelling choices or driven by some artefact of our data. We begin with imposing artificial cut-offs in the running variable and test whether R&D and TFP are continuous across the pseudo-thresholds. Both outcomes should be smooth since there are no policies that alter R&D investment costs or provide other incentives for firms that differ at these cut-offs. Table VI below

provides the results for artificial thresholds set at 300 and 700 employees. No statistically significant discontinuities in outcomes are detected.

Results from several additional robustness checks are presented in Appendix B. The effects on R&D and TFP are reported in odd-numbered and even-numbered Columns, respectively. In Columns 1 and 2, we use triangular weights rather than uniform weights, to account for a firm's distance from the employment threshold. Columns 3 and 4 use linear running variable polynomials and Columns 5 and 6 use cubic polynomials rather than quadratic. The results are stable in magnitudes and statistical significance in all cases (Table B.2.).

Table VI: Pseudo-Threshold Falsification Tests

Dep. Var. (log):	R&D (1)	TFP (2)	R&D (3)	TFP (4)
Carbon Price * Treated * Regulated	-0.018	-0.009	0.032	0.000
	(0.023)	(0.010)	(0.049)	(0.017)
Carbon Price * Treated	0.028	0.005	-0.044	-0.006
	(0.028)	(0.009)	(0.046)	(0.017)
Carbon Price * Regulated	0.022	0.006	0.061	0.005
	(0.023)	(0.010)	(0.037)	(0.013)
Carbon Price	-0.020	0.000	-0.039	0.001
	(0.027)	(0.010)	(0.036)	(0.013)
Observations	1263	2164	613	1638

Notes: Dependent variable is (log) total firm R&D expenditures (£000s) in Columns 1 and 3 and (log) TFP in Columns 2 and 4. The pseudo-threshold is 300 employees for Columns 1-2 and 700 employees for Columns 3-4. First order polynomials of the (centered) running variable (employment) are included separately for each side of the threshold. Other controls include firm, industry, and county fixed effects as well as quadratic industry-year trends. Standard errors are clustered by industry-year. Asterisks denote $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

VI. Conclusion

This paper investigates the interaction effect of innovation and climate policy, and finds that the two function as substitutes. Specifically, using a "discontinuity-in-effects" estimation strategy, we discover that the positive effect of carbon pricing on several innovation and productivity related outcomes in the UK manufacturing and power sector is attenuated by access to more generous R&D tax credits. Since

innovation and productivity growth in energy-intensive sectors is a high priority issue, policymakers need to be aware of these potentially unintended consequences to ensure economic and environmental goals are successfully met.

Our theoretical framework illustrates that while carbon pricing increases the relative demand for clean inputs, undirected innovation subsidies reduce the marginal cost of both clean and dirty inputs, making interaction cross-partial ambiguous. Removing this ambiguity would require making the R&D tax credit technology-specific (i.e., directed towards clean technologies).

Our contributions include empirically demonstrating the importance of innovation and environmental policy interactions, and theoretically modelling why undirected innovation subsidies and carbon pricing can be complements or substitutes. The study of policy interactions is especially important in a world with Paretian constraints (Lipsey and Lancaster 1956). Methodologically, we adapt the estimation strategy in Pless (2022) to another setting to study policy interactions.

Limitations on the empirical side include having to use general measures for innovation. Directly observable metrics such as clean patenting do not work for our analysis because our observations are in a small window around the R&D tax credit generosity threshold and most firms in this bandwidth do not have much patenting. On the theoretical side, we do not propose a general equilibrium model of market failure interdependence which would be illuminating in terms of formally understanding what optimal policy would look like in a second-best world with constrained carbon prices. This would be a promising direction for future work.

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VIII. Appendix

A. Derivations

As in Acemoglu et al (2012), optimal input demands are given by:

(A.1.)
$$\left(\frac{y_{cn}}{y_{dj}}\right)^{*} = \left(\frac{p_{cn}}{(1+\tau\eta_{dj})p_{dj}}\right)^{-\sigma}$$
$$\left(\frac{y_{dj}}{y_{dj+1}}\right)^{*} = \left(\frac{(1+\tau\eta_{dj})p_{dj}}{(1+\tau\eta_{dj+1})p_{dj+1}}\right)^{-\sigma}$$

The first line demonstrates substitution from dirty to clean products due to carbon pricing. The second line demonstrates substitution towards from dirty to less dirty products.

As per the standard result of monopolistic competition, firms that make intermediate inputs set a mark-up over the marginal cost (Ψ), which is as follows:

(A.2.)
$$p^{*}_{cn} = \frac{\sigma}{\sigma-1}\Psi_{cn}$$
$$p^{*}_{dj} = \frac{\sigma}{\sigma-1}\Psi_{dj}$$

Given the Cobb-Douglas specification of the intermediate goods market, we can derive the marginal cost and take its derivate with respect to the R&D tax credits. Subscript x represents *cn* or *dj*:

(A.3.)
$$\Psi^{*}_{x} = A_{x}^{-1}\left[\frac{(1-\Lambda)w_x}{\alpha}\right]^{\alpha}\left[\frac{\mu_x}{\phi}\right]^{\phi}$$
$$\frac{\partial\Psi^{*}_{x}}{\partial\Lambda} = -\,w_x\left[\frac{\mu_x}{\phi}\right]^{\phi}\left[\frac{(1-\Lambda)w_x}{\alpha}\right]^{\alpha-1}A^{-1} < 0$$

Notice that Ψ is decreasing in the value of the R&D tax credit for clean and dirty products alike (recall that subscript x can denote cn or dj).

Market clearing requires that demand equals supply:

(A.4.) $$D_x(p_x^*) = A_s M_x^{\alpha} K_x^{\phi} \; where \; s \in \{c, d\}$$

Inserting input demands from Equation A.1. into Equation A.4. and using A.2. to substitute prices gives optimal R&D investment for firms making y_{dj}:

(A.5.) $$M_{dj}^* = \left[\frac{\left(1+\tau\eta_{dj}\right)\Psi_{\mathrm{dj}}}{\left(1+\tau\eta_{dj+1}\right)\Psi_{\mathrm{dj+1}}}\right]^{-\frac{\sigma}{\alpha}} \left(\frac{y_{dj+1}}{A_d K_{dj}^{\phi}}\right)^{\frac{1}{\alpha}}$$

Taking the derivative of A.5 with respect to τ and defining $\left(\frac{y_{dj+1}}{A_d K_{dj}^{\phi}}\right)^{\frac{1}{\alpha}} \equiv \Omega_d > 0$ gives:

(A.6.) $$\frac{\partial M_{dj}^*}{\partial \tau} = -\Omega_d \frac{\sigma}{\alpha}\left[\frac{\Psi_{\mathrm{dj+1}}}{\Psi_{\mathrm{dj}}}\right]^{\frac{\sigma}{\alpha}}\left[\frac{\left(1+\tau\eta_{dj}\right)}{\left(1+\tau\eta_{dj+1}\right)}\right]^{\frac{-\sigma-\alpha}{\alpha}}\left[\frac{\eta_{dj}-\eta_{dj+1}}{\left(1+\tau\eta_{dj+1}\right)^2}\right] < 0$$

This shows how dirty innovation unambiguously decreases in τ since $\eta_{dj} > \eta_{dj+1}$. We will now check whether R&D tax credits dampen or reinforce this effect by taking the derivative of Equation A.6. with respect to Λ. Define $1 + \tau\eta_{dj} \equiv \kappa_{dj}$

(A.7.) $$\frac{\partial^2 M_{dj}^*}{\partial \tau \, \partial \Lambda} = -\Omega_d \left(\frac{\sigma}{\alpha}\right)^2 \left[\frac{\Psi_{\mathrm{dj+1}}}{\Psi_{\mathrm{dj}}}\right]^{\frac{\sigma-\alpha}{\alpha}}\left[\frac{\kappa_{dj}}{\kappa_{dj+1}}\right]^{\frac{-\sigma-\alpha}{\alpha}}\left[\frac{\eta_{dj}-\eta_{dj+1}}{{\kappa_{dj+1}}^2}\right]\left[\frac{1}{\Psi_{\mathrm{dj+1}}}\left(\underbrace{\frac{\partial \Psi_{\mathrm{dj}}}{\partial \Lambda}}_{D} - \underbrace{\frac{\Psi_{\mathrm{dj}}}{\Psi_{\mathrm{dj+1}}}\frac{\partial \Psi_{\mathrm{dj+1}}}{\partial \Lambda}}_{R}\right)\right]$$

The interaction effect, $\frac{\partial^2 M_{dj}}{\partial\, \tau \partial\, \Lambda}$, is ambiguous. Turning to clean goods, we substitute the first line of Equation A.1. into Equation A.4. and use A.2. to substitute prices, which yields:

(A.8.) $$M_{cn}^{*} = \left[\frac{\Psi_{\mathrm{cn}}}{\kappa_{dj}\Psi_{\mathrm{dj}}}\right]^{-\frac{\sigma}{\alpha}} \left(\frac{y_{dj}}{A_c K_{cn}^{\phi}}\right)^{\frac{1}{\alpha}}$$

Differentiating A.8. with respect to τ and defining $\left(\frac{y_{dj}}{A_c K_{cn}^{\phi}}\right)^{\frac{1}{\alpha}} \equiv \Omega_c > 0$ gives:

(A.9.) $$\frac{\partial M_{cn}^{*}}{\partial \tau} = \Omega_c\, \eta_{dj} \left[\frac{\Psi_{\mathrm{dj}}}{\Psi_{\mathrm{cn}}}\right]^{\frac{\sigma}{\alpha}} \left[\kappa_{dj}\right]^{\frac{\sigma-\alpha}{\alpha}} > 0$$

This shows how clean innovation increases in τ. We can now check whether R&D tax credits reinforce or dampen the effect of τ on clean innovation by taking the derivative of Equation A.9. with respect to Λ.

(A.10.) $$\frac{\partial^2 M_{cn}^{*}}{\partial \tau\, \partial \Lambda} = \Omega_c\, \eta_{dj} \frac{\sigma}{\alpha} \left[\kappa_{dj}\right]^{\frac{\sigma-\alpha}{\alpha}} \left[\frac{\Psi_{\mathrm{dj}}}{\Psi_{\mathrm{cn}}}\right]^{\frac{\sigma-\alpha}{\alpha}} \left[\frac{1}{\Psi_{cn}} \Big(\underbrace{\frac{\partial \Psi_{dj}}{\partial \Lambda}}_{D} - \underbrace{\frac{\Psi_{\mathrm{dj}}}{\Psi_{\mathrm{cn}}} \frac{\partial \Psi_{\mathrm{cn}}}{\partial \Lambda}}_{R} \right]$$

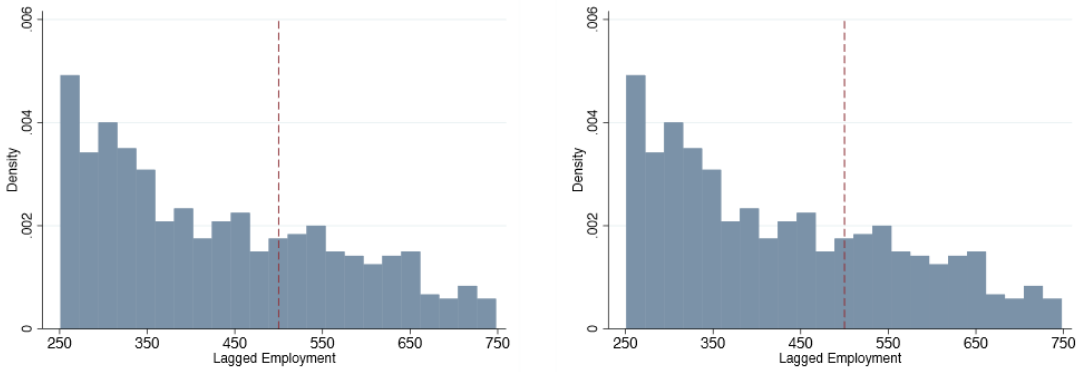
A.10. shows that the sign of $\frac{\partial^2 M_{cn}^{*}}{\partial \tau\, \partial \Lambda}$ is ambiguous.

If R&D tax credits were targeted only towards clean technologies, then $\frac{\partial \Psi_{dj}}{\partial \Lambda} = 0$ and Equation A.10. would become:

(A.11) $$\frac{\partial^2 M_{cn}^{*}}{\partial \tau\, \partial \Lambda} = \Omega_c\, \eta_{dj} \frac{\sigma}{\alpha} \left[\kappa_{dj}\right]^{\frac{\sigma-\alpha}{\alpha}} \left[\frac{\Psi_{\mathrm{dj}}}{\Psi_{\mathrm{cn}}}\right]^{\frac{\sigma-\alpha}{\alpha}} \left[-\frac{\Psi_{\mathrm{dj}}}{\Psi_{\mathrm{cn}}} \frac{\partial \Psi_{\mathrm{cn}}}{\partial \Lambda}\right] > 0$$

which is unambiguously positive since $\frac{\partial \Psi_{\mathrm{cn}}}{\partial \Lambda} < 0$, i.e., directed R&D tax credits would ensure the two instruments are complements.

Figure B.1: No Evidence of Manipulation around the R&D TC Threshold



(a) Histogram Based Upon Employment (b) McCrary Density Test Based Upon Employment

Note: Histogram and McCrary test for discontinuity in distribution density of total employment at the tax credit generosity threshold. Sample includes firms with 250 to 750 employees despite whether their R&D investments are reported in FAME. Log difference in density height of -0.066 with a standard error of 0.314.

Test that R&D TC had an impact

To estimate the R&D tax credit's impact, we implement a difference-in-discontinuities approach as done in Pless (2022):

$$Y_{it} = \delta_0 + \delta_1 A_i^* + J_i(\gamma_0 + \gamma_i A_{it}^*) + T_t[\alpha_0 + \alpha_1 A_{it}^* + J_i(\beta_0 + \beta_1 A_{it}^*)] + \epsilon_{it} \quad \text{(B.1)}$$

where Y_{it}, J_i and A_{it}^* are defined as before, and T_t is an indicator equal to one if the year is post-policy implementation and zero otherwise. In this case we define post-policy as after 2008, when the threshold was doubled.[18] The results from estimating Equation B.1. are presented in the table below. Firms that moved from

[18] As explained in Pless 2022, β_0 is the difference-in-discontinuity estimator since it captures the additional effect of being treated with a more generous tax credit after the eligibility criterion was expanded.

being untreated to treated should experience the highest impact of the new tax credit generosity relative to those that were already benefiting from being a SME under the old regime.

The full sample estimation indicates that R&D expenditures increased by 23% in response to the tax credit generosity change (results jointly significant at the 10% level).[19] Guceri and Liu (2019) similarly estimate the effect to be about 25% using a difference-in-differences framework. Taken together, these results help confirm that the tax credit policy influenced reported R&D expenditures.

Table B.1: Results for the Effect of R&D Tax Credit Only

	Full Sample	250-750 Employees	200 to 800 Employees	Winsorize 5% (200-800 Empl)
	(1)	(2)	(3)	(4)
Treated * Post	0.431*	0.552**	0.477*	0.601**
	(0.260)	(0.260)	(0.276)	(0.305)
Treated	-0.203	-0.428**	-0.229	-0.369
	(0.239)	(0.212)	(0.233)	(0.265)
Observations	4435	1003	1336	1266
Mean Dep. Var.	6.01	6.61	6.54	6.35
Firm fixed effects	x	x	x	x
Industry fixed effects	x	x	x	x
Year fixed effects	x	x	x	x
County fixed effects	x	x	x	x

Notes: Difference-in-discontinuities estimates for the effect of the R&D tax credit on (log) R&D expenditures only. First order polynomials of the (centered) running variable are included separately for each side of the threshold. Asterisks denote $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.2: Main Robustness test of Baseline Specification

[19] The total effect is the sum of the diff-in-disc estimate and the (negative) coefficient associated with the firm size dummy in pre-policy years.

Dep. variable (log)	R&D	TFP	R&D	TFP	R&D	TFP
	(1)	(2)	(3)	(4)	(5)	(6)
Carbon Price * Treated * Regulated	-0.110***	0.020*	-0.110***	0.021	-0.111***	0.024*
	(0.033)	(0.012)	(0.032)	(0.014)	(0.033)	(0.014)
Carbon Price * Treated	0.074**	-0.028**	0.076**	-0.029**	0.079***	-0.031**
	(0.029)	(0.012)	(0.030)	(0.014)	(0.030)	(0.014)
Carbon Price * Regulated	0.111***	-0.014	0.112***	-0.014	0.115***	-0.016
	(0.038)	(0.010)	(0.039)	(0.012)	(0.038)	(0.011)
Carbon Price	-0.084**	0.021**	-0.091**	0.022*	-0.094***	0.024**
	(0.035)	(0.010)	(0.036)	(0.012)	(0.036)	(0.011)
No. of Observations	904	2,953	904	2,953	904	2,953
Triangular weights	x	x				
Uniform weights			x	x	x	x
Linear polynomials			x	x		
Quadratic polynomials	x	x				
Cubic polynomials					x	x

Notes: Main robustness checks of baseline effects on (log) R&D expenditures and (log) TFP. First order polynomials of the running variable are included separately for each side of the threshold. Other controls include firm, industry, and county fixed effects as well as year-by-industry linear trends. Standard errors are clustered by industry-year. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

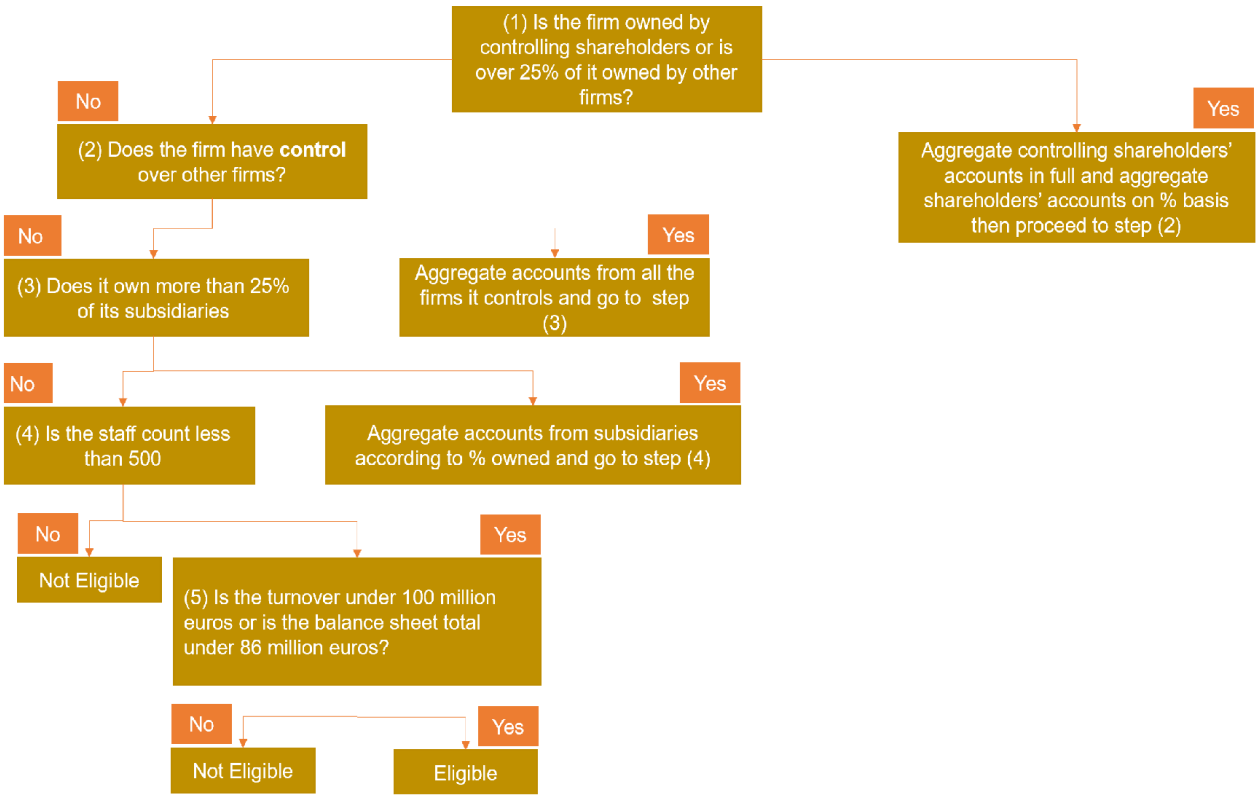
C. Institutional Details

Qualifying Costs— R&D expenditures covered under the R&D Tax Relief Scheme must relate to efforts to develop new processes or products; or improve existing ones. R&D costs that can be claimed under this scheme include employee costs for those working directly on the R&D project, 65 percent of subcontractor costs and costs related to software, consumable items, and clinical trial volunteers. Costs that cannot be claimed include those related to the production and distribution of goods and services, capital expenditure, cost of land, cost of patents and trademarks, and rent or rates.

Qualifying Firms — To qualify for more generous (enhanced) R&D tax credits, the firm has to be an SME, which involves not only considering the firm's own balance sheet but also that of its subsidiaries and owners (see flowchart below). In our assigning of tax credit treatment, we followed this explicitly with the exception of accounting for controlling shareholders that are family members, angel investors, venture capitalists and major investment banks as they are exempt from being considered as part of firm size as per the HMRC rules.

In order to determine R&D tax credit generosity, we follow HMRC guidelines (UK's central tax authority) and add subsidiary employment, total assets, and turnover on a pro rata basis to the enterprise group's totals when the base firm owns more than 25% of the subsidiary and when the subsidiary is based in the UK. We omit subsidiaries from the totals if their information is missing in FAME rather than remove the base firm altogether to preserve our sample. The vast majority (>90%) of controlling shareholders fell into categories for which the HMRC exclude from the eligibility requirements: investment banks, individual angels, venture capitalists, non-profit donors, etc. Missing out on the few controlling shareholders that do not fall into these exception groups as well as the subsidiaries for which we do not have data

is unlikely to affect our results, as there's no reason to believe that the missing cases vary systematically in a narrow window around the R&D tax credit threshold. Furthermore, it is likely that the missed subsidiaries are very small since small firms are not required to report certain variables, and thus omitting low employment, total assets, and turnover figures is unlikely to change many firms' tax credit eligibility status (and certainly not systematically).



Mechanism—SMEs can inflate their stated R&D expenditures at a specified rate, such that their taxable profit is reduced. The amount of tax relief that this amounts to depends on: (i) the firm's R&D expenditure, (ii) the rate at which its profits are ordinarily taxed, and (iii) whether it is loss-making.

For profit-making companies, R&D costs could be inflated by 150% from 2000 until 2008, 175% in 2009, 200% in 2011, 225% in 2012 and 230% in 2020. Loss-making

companies can multiply their R&D expenditure by 230% and claim a tax rebate worth 14.5% of the resultant quantity.

Suppose a company spends £100 on R&D and its corporation tax is 19 percent (i.e. the first tax bracket). With the regular R&D TCs, the company can artificially inflate its R&D expenditure by 100 percent to £200. The extra £100 reduction in taxable profit would yield an effective R&D tax credit worth £19 at the 19 percent corporation tax rate (£100*0.19).

Next, consider a company that also spends £100 on R&D but is eligible for an *enhanced* R&D TC. The company can artificially inflate its R&D expenditure by 230 percent to £330. The extra £230 reduction in taxable profit would yield an effective R&D tax credit worth £44 at the 19 percent corporation tax rate (£230*0.19). For comparison, for £100 of R&D expenditure, the enhanced tax credit gives a rebate that is more than double the size of the normal R&D tax credit.

For loss-making companies, a different mechanism takes place through which losses can be partially recovered through direct cash rebates. Consider the following example: suppose a company spends £100 on R&D and has £0 revenue (i.e. it is loss-making). Its R&D expenditure is artificially inflated by 130 percent to yield £230. This is added to the original expenditure to create a new quantity called "surrenderable loss" equalling £330. The company can apply for a rebate worth 14.5 percent of its surrenderable loss, which in this case means getting back £48. Rather than incurring £100 of loss, the company incurs £52 of loss.

D. Data Preparation

We follow the standard protocols to prepare the FAME data. We define the current year as the one associated with the latest account date if the month is June or later. We convert nominal monetary figures into real 2015 GBP and convert the turnover and total assets figures into Euros when assessing tax credit eligibility. We use the

base firms' real GBP turnover as the outcome variable in the production function estimations.

A key component of determining whether a firm qualifies for the more generous tax credits entails accounting for the employment, turnover, and total assets of other firms connected to the base firm. To do so, we also gathered data on each firm's ownership structure as well as balance sheet information for subsidiaries and controlling shareholders associated with each base firm. This mapping allows us to form "enterprise groups", accounting for connected firms' balance sheet figures for determining tax credit rate eligibility (Appendix C).

E. Production Function Estimation

One limitation of the OP method is that it uses investment as the proxy variable and assumes a (conditional) monotonic relationship between investment and productivity, but firm-level investments tend to be "lumpy". Annual productivity shocks are also more likely to be affected by marginal investments. Levinsohn-Petrin (2003) and Ackerberg et al. (2015) propose using "intermediate inputs" in order to address this. Unfortunately, we do not observe intermediate inputs, so we construct an alternative TFP measure as a robustness check that accounts for investment lumpiness. We already drop cases where investment is zero in our baseline, as the OP estimation then leads to consistent coefficients (Ackerberg et al., 2007). As an alternative measure, we also drop cases where a firm's investment level "spikes" and estimate a second set of industry-specific production functions, following Power (1998) by defining spikes as investment levels that exceed 300% of the firm's average annual investment.[20]

[20] Ackerberg et al. (2015) also address some of the functional dependence problems in OP and LP, however we cannot use this approach without observing intermediate inputs.

Knowledge Spillovers between Clean and Dirty Technologies: Evidence from the Patent Citation Network

By Su Jung Jee[1,2] and Sugandha Srivastav[1,3]

Abstract: Does knowledge from dirty technologies spill over to clean technologies? The answer to this question has implications for the ease of switching from dirty to clean R&D and dirty incumbents' diversification strategies. We measure direct and indirect knowledge spillovers between clean and dirty technologies using the patent citation network. We first examine the proportion of citations in clean patents that directly refer to dirty technologies. Secondly, we systematically explore how clean and dirty technologies are indirectly linked in the citation network and which sectors most frequently "bridge" these two fields. We find that less than one-tenth of clean patents contain a citation to prior dirty patents, but nearly two-thirds are indirectly linked. Geothermal energy, carbon capture and storage, and more efficient industrial processes have the highest proportion of direct connections to dirty knowledge. Patents related to propulsion, chemistry, mechanics, and circuitry frequently serve as "bridges" between clean and dirty technologies in many different sectors. We discuss how our results may inform clean industrial policy and firm-level diversification.

Keywords: Knowledge Spillovers, Directed Technical Change, Clean Technology, Dirty Technology, Measurement, Indirect Connections, Bridge Technologies

JEL Codes: O3, O33, O34, O9, O25, O44

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Highlights:

1. *We present novel evidence on the extent to which clean technologies learn from prior dirty technologies*
2. *We construct a new measure of indirect knowledge spillovers between clean and dirty sectors that captures incremental and indirect ways in which knowledge moves between fields*
3. *We systematically identify "bridge technologies" that connect clean and dirty sectors*
4. *We highlight key implications for diversification from dirty to clean innovation*

1. Introduction

Governments around the world have adopted net-zero emissions targets to limit the impacts of anthropogenic climate change. Achieving these targets will require substantial amounts of innovation in clean technologies, particularly in hard-to-decarbonize sectors (Stern and Valero 2021). Firms, countries, governments and innovators will need to think about how they can pivot to clean innovation and leverage existing competencies to reduce adjustment costs, and the associated risks of stranded labour, skills and assets.

Despite substantial gains in clean innovation, such as the persistent cost reductions in solar panels, wind turbines and batteries (Way et al. 2022), the overall direction of innovation is still unclear (Figure 1). Clean patenting accelerated in the early 2000s partly due to rising energy prices (Newell et al. 1999, Popp 2002, Verdolini and Gaelotti 2011) but in 2010, it peaked and has subsequently fallen. This decline is linked to the burst of the clean tech bubble, challenges in venture capital as a source of finance, and the rise of hydraulic fracturing (Dechezleprêtre 2017, Gaddy et al. 2017, Popp et al. 2020). Advances in hydraulic fracturing contributed to the price of natural gas falling so much that it became the primary fuel for electricity generation in the USA and estimates suggest that it will increase long-run emissions (Popp et al. 2020, Acemoglu et al. 2019). This reversal of trends encapsulated by clean patenting falling, after years of rise, and the rise of fracking, after years of decline in dirty patenting, has raised concerns that current progress is not compatible with the aim to reach net-zero emissions by 2050, which is necessary to keep Earth's temperature within safe bounds (IEA 2020).

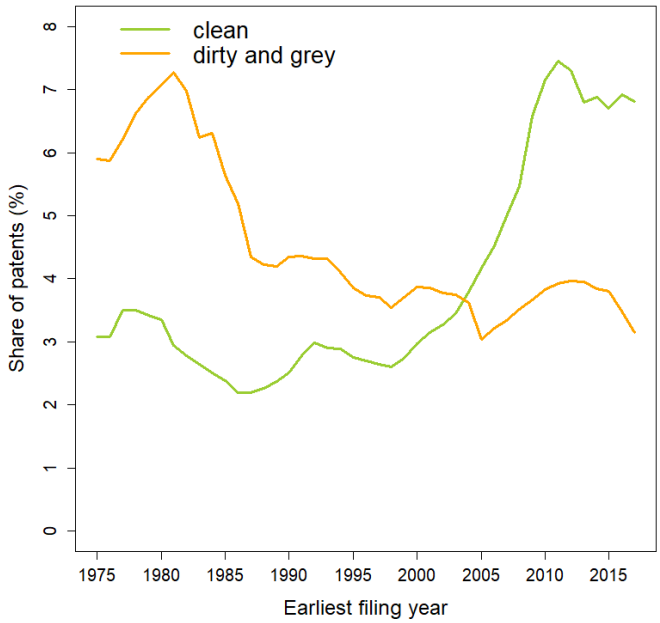


Figure 1. Number of patents as a share of all patents

Notes. The number of clean (green graph) and sum of dirty and grey (orange graph) patents as a share of all US patents by year. Patents are sorted by priority year (i.e., earliest filing year) and counted at DOCDB family-level.

There are many reasons why clean innovation is not near its socially optimal level. Clean innovation suffers from a double externality problem, that is, environmental externalities and knowledge spillovers (Jaffe et al. 2005). The policies to address these market failures, namely carbon pricing and innovation subsidies, have been challenging to implement in full measure (Klenert et al. 2018). Furthermore, access to cost-effective financing has not been easy. Since clean sectors are relatively new, investors face uncertainty over the distribution of risks and returns, which often leads to a higher cost of capital (Egli et al. 2018). Finally, there is path dependency: firms, governments, and buyers of technology may simply continue producing, innovating and buying technology that is familiar as opposed to switching to something new (Aghion et al. 2016). Models of directed technical change state that due to switching costs and the larger market for dirty inputs, firms may be locked-in (Acemoglu et al. 2012 and Acemoglu et al. 2016).

But what if switching costs are overstated? Many of models assume that clean and dirty

technologies are very different and that there is limited shared knowhow.[1] However, this assumption has not been empirically tested in a systematic manner. If clean and dirty technologies do share significant overlaps in their knowledge base, then perhaps a pivot to clean is not as costly or difficult as commonly portrayed in the literature. Intuitively, we know that there are sub-fields where clean and dirty technologies learn from each other. For example, firms engaged in offshore oil have expertise in seabed engineering, floating platforms and materials that can withstand bio-fouling, which have direct applications for innovation in offshore wind or marine energy. In practice, we do witness companies like British Petroleum, that are deeply embedded within in the dirty technology paradigm, bid for seabed rights to build out new offshore wind farms in the North Sea. The question is whether this is an isolated case or if clean technologies have drawn on advances from the dirty technological paradigm more broadly.

To explore this question, we empirically measure the extent of direct and indirect knowledge spillovers between clean and dirty sectors using patent citation data from U.S. Patent and Trademark office (USPTO) from 1976 to 2020. We find that less than one-tenth of clean technologies directly cite dirty patents but most are indirectly connected via intermediate technologies. Amongst clean sectors, geothermal energy, clean metals, carbon capture and storage (CCS), and long-haul transportation have the highest direct links to dirty technologies. Patents related to propulsion, machines for engines, and chemistry often serve as a bridge that indirectly links clean transportation technologies to the dirty technologies. For clean energy, the most common intermediaries are: methods to convert chemical energy into electrical energy (e.g. batteries), circuits, and chemical processes. These areas of connection may shed light on possible diversification pathways for firms. Prior work has shown that knowledge-relatedness is often a key factor in firms' technological diversification choices and can reduce switching costs (Breschi, Lissoni and Malerba 2003).

Our paper makes four contributions: First, we pool together all existing classifications of

[1] This is implicitly assumed by modelling scientific labor for dirty innovation as distinct from that for clean innovation.

"clean" and "dirty" that exist to date in the literature. We supplement it with our own manual tagging efforts to better identify "grey" technologies to create a consolidated tagging system. Second, we leverage methods in network analysis to map out the proximity of clean and dirty technologies in the knowledge space. Third, we provide a detailed sectoral breakdown of which clean technologies are most proximate to their dirty counterparts to inform views on possible diversification pathways for dirty R&D incumbents. Finally, we detail which technologies frequently serve as intermediaries between clean and dirty technologies. Such technologies may represent important "bridges" that could help in the pivot from dirty to clean innovation.

Studies that are most closely related to ours include: Dechezleprêtre et al. (2014) and Noailly and Shestalova (2017) who also use patent citations to measure knowledge spillovers. They focus on how clean technology spills over to general innovation and whether these spillovers exceed those of dirty technologies. They find that on aggregate, clean technologies have higher spillovers than dirty technologies. Our work differs from theirs in two important ways: first, we consider knowledge spillovers *between* clean and dirty technologies, and second, we focus not only on direct links but also, indirect links using a method developed by Ahmadpoor and Jones (2017). Another closely related paper is that of Mealy and Teytelboym (2022) who use export data to document which areas of export specialization frequently coincide with having a clean product specialization. This is conceptually similar to our work as it tries to inform diversification strategies for the low-carbon transition assuming that export data can uncover manufacturing complementarities. Our work focuses on the technological domain, leveraging patent citations to trace diversification opportunities for innovators.

By documenting the proximity of clean and dirty technologies in the knowledge space, we contribute to the thinking on what sort of labour, scientific skills and capital can be re-purposed or re-deployed for the low-carbon transition. There is a rich literature on how external factors such as location matter for innovation due to agglomeration benefits, complementarities, and access to resources (Porter and Stern 2001, Delgado et al 2010). We build upon the thinking that even location in the knowledge space has a bearing on innovation strategy. For example, the patent documentation shows similar machinery is used for: offshore

wind and oil and, for geothermal and upstream hydrocarbons. Insofar as this capital has complementarities with labour, we can also infer that similar types of skilled labour and scientists would be deployed. In short, proximity in the knowledge space likely correlates with similarity across other dimensions.

Furthermore, the pivot to clean innovation is fundamental to the concept of "green growth", that is, the idea that it is possible to respect planetary boundaries and have an economically prosperous future (Ekins 2002, Bowen et al. 2016, Bowen and Hepburn 2014). Since innovation is a long-term driver of growth, and one that often results in the more judicious use of scarce factors of production, our investigation of how distinct the clean innovation paradigm is from the dirty innovation paradigm is useful in terms conceptualizing how difficult this shift may be. This in turn, may be useful for policymakers contemplating green industrial policy or for firms that are deciding on resource allocation to become net zero compliant. Therefore, we see our work as contributing to the broader discussion around industrial policy and firm-level strategies for diversification towards net zero.

2. Literature review

Mapping the knowledge space in which clean and dirty technologies exist can help empirically assess how related they are, and consequently, inform our views on the ease of diversification. Evolutionary economic geography has highlighted how new development pathways are achieved when agents "jump" from one area of expertise to another relatively proximate but different area (Frenken and Boschma 2007, Boschma and Frenken 2011, Hausmann and Klinger 2007 and Hidalgo et al. 2007). Since there are costs linked with searching the knowledge space to find new idea (Binswanger 1974), understanding what is "cognitively closer" as revealed measures such as cross-citations, can give a better understanding of the available recombinant possibilities (Weitzman 1998 and Rigby 2015).

Measures of relatedness can be constructed on the basis of co-classifications in industrial codes (Frenken et al 2007, Boschma and Iammarino 2009, Boschma et al 2009, 2012, and

Hartog et al 2012), co-occurrences of products in countries' export baskets (Hidalgo et al. 2007), cross-citation patterns in patent data (Rigby 2015), and the mobility of labour in occupational networks (Neffke and Henning 2013 and del Rio-Chanona et al 2021), which captures "resource flows".

The choice of which measure to adopt depends on the researcher's goal (Essletzbichler 2015). For example, using the occupational network may be most appropriate for thinking about the mobility of human capital between clean and dirty sectors, while co-occurrences in the export basket may be useful in unravelling complementarities in manufacturing processes. Since our interest is in steering the direction of innovation, we will be focusing on the connectivity between clean and dirty sectors in the patent citation network. Patents have the advantage that citations are active decisions made by inventors and vetted by examiners to prove the invention's novelty over existing work. This means past work is often well cited and provides a more robust measure of connectivity/relatedness than relying on factors such as co-occurrence which may be linked with more inherent randomness.

Several studies have used cross-citation patterns to infer knowledge spillovers between sectors, with a key assumption that if a citation is made, then the citing technology has learnt something from the cited technology (e.g. Dechezleprêtre et al. 2014, Noailly and Shestalova 2017, and Andres et al 2022 who use patent citation data to see whether clean technologies benefit more from AI and ICT technologies than their dirty counterparts). Even if we do not believe each citation is reflective of learning, this measure still has value if we believe that *on average*, a citation link is correlated with learning between those two nodes. As Jaffe et al 1993 state, "knowledge flows do sometimes leave a paper trail, in the form of citations in patents".

The study of knowledge spillovers between clean and dirty technologies can help determine the ease of pivoting from carbon-intensive ("dirty") innovation to low-carbon ("clean") innovation (Breschi, Lissoni and Malerba 2003). Literature to date has focused on whether clean or dirty technologies have higher overall spillovers (Dechezleprêtre et al. 2014, Noailly and Shestalova 2017) but inter-sectoral linkages *between* clean and dirty have not yet been

investigated. Given the path dependent and cumulative nature of knowledge (Nelson and Winter, 1982), many assume that dirty technologies will beget more dirty innovation. Yet, since clean and dirty technologies often have the same goals such as the provision of mobility, power, and industrial growth, they may, in fact, learn from and build-upon each other. The extent to which knowledge from the dirty paradigm can spill over to the clean paradigm is therefore an empirical question.

In practice, diversification requires considering not only knowledge spillovers but also other variables such as production capabilities, access to raw materials, supply chains, etc. Yet since knowledge is a key input into the production process and a driver of the direction of inventive activity (and strategic behaviour), we pay particular attention to it. Prior literature has adopted a similar approach with studies using patent specialisations in clean technologies as an indicator of enhanced competitiveness in a future low-carbon economy (Fankhauser et al. 2013, Srivastav et al. 2018) as well as looking at firms' patenting activity to proxy their position in the product/technology space and infer rivalries (Bloom, Schankerman and Van Reenen 2013).

3. Data

We map out the links between clean and dirty technologies in the patent citation space, using patents granted in the USPTO from 1976 to 2020. [2] Patents grant monopoly rights to inventors over inventions that are novel, non-trivial and of commercial value. The granting of a patent means that all of the details of the invention are released in the public domain alongside information about the inventor, their employer, and technology-class of the invention. To demonstrate novelty, inventors must cite the "technological antecedents of their invention" which are also reflected in citations made to prior art (Jaffe et al. 1993).

[2] The American intellectual property regime is amongst the strongest in the world. For this reason, inventors from all over the world, particularly those whose inventions have high value, have sought protection in the US. In the literature, patents granted by the USPTO are often considered to represent the knowledge frontier (Granstrand, 2018).

Since patents are legal instruments, there is a strict review process linked to ensuring citations are relevant and meaningful. This is arguably different from academic articles where the review process for citations is looser. The inventor has a legal duty to disclose all prior art that they consulted in the development of the invention and the patent examiner, who is a a subject matter expert, vets these citations and adds their own to reflect any missed or concealed prior art (Jaffe et al. 1993, Berchicci and van de Vrande 2019). Jaffe et al. (2000) survey R&D managers and find that citing inventors usually have direct communication with cited inventors, and that the reasons for patent citation include using components of the cited technology and/or leveraging the cited technology to demonstrate the feasibility or use-case of the new invention.

Any study using patents, however, must acknowledge that patents represent only a subset of all innovation (Pavitt 1985 and Griliches 1990) and that despite the citation-vetting process by examiners, references in patents can still contain noise (Jaffe et al. 1992 and Jaffe et al 2000). Notwithstanding various limitations including an incomplete coverage of inventive activity and a bias towards frontier technologies (e.g., OECD 2009), patents are used extensively in the study of innovation (Griliches 1990, Jaffe et al. 1993), and in particular clean innovation thanks to the introduction of classification codes that help identify technologies that reduce or contribute to greenhouse gas emissions (e.g., Dechezleprêtre et al. 2013, Noailly and Shestalova 2017, and Perrons et al. 2021).

In our sample, 62% of citations in patents, are on average, added by the inventor rather than the examiner. For our results we consider all citations regardless of who added them as we are broadly interested in knowledge spillovers across technological domains, rather than specifically, the inventor's knowledge base.

4. Method

Using the universe of patents granted by the USPTO[3] from 1976 to 2020, which yields 6

[3] The American intellectual property regime is amongst the strongest in the world (Granstrand, 2018). For this reason, inventors from all

million patents and 55 million connections, we identify clean and dirty technologies, and assess the extent to which they directly and indirectly cited each other.

We define clean technologies as those mitigate greenhouse gas emissions, dirty technologies as those that contribute to emissions and grey technologies as those that are energy-efficient versions of dirty technologies. We leverage existing classifications schemes in the literature and supplement these with our own tagging efforts to come up with these classifications (Haščič and Migotto 2015, Aghion et al. 2016, Popp et al. 2020 and Dechezleprêtre et al. 2021, IEA 2021). As an indicative illustration: renewable energy is "clean", oil and gas are "dirty", and energy-efficient methods of making steel are "grey".

The tagging strategy gives 258,078 clean patents, 145,753 dirty patents and 98,224 grey patents which are counted at DOCDB family level to avoid double counting the same inventions.[4] There are 31,053 patents that are classified as both clean and dirty, which we exclude from our baseline analysis to focus on the cases where the technologies are obviously clean or dirty (see Supplementary Fig. 1). These co-classifications occur because certain technologies, such as hybrid vehicles, can be both clean and dirty.

We measure direct knowledge spillovers between clean and dirty technologies by the proportion of backward citations in clean patents that directly refer to dirty patents. This metric has been used widely in the environmental innovation literature and we refer to it as the "intensity of connection" (Dechezleprêtre et al. 2014, Noailly and Shestalova 2017).

However, knowledge from a dirty patent may feed into an intermediate technology which may in turn be cited by a clean patent. These indirect links are often overlooked. To address this gap, we calculate the degrees of separation between clean and dirty patents in the citation network. We call this the "minimum distance metric". The minimum distance reveals the incremental and indirect ways in which dirty knowledge has fed into clean inventions

over the world, particularly those whose inventions have high value, have sought protection in the US. Therefore, in the literature, patents granted by the USPTO are often considered to represent the knowledge frontier.

[4] DOCDB families are a cluster of patents that represent the same invention

(Ahmadpoor and Jones 2017). If our measure of minimum distance is 1 ($D_i = 1$), it means that the clean patent directly cites a dirty patent, while if $D_i \geq n$ (where n is larger than 2), a clean patent i must pass through at least *n-1* non-dirty patents within the citation network to reach prior dirty patent(s) (see Fig. 2).[5] Clean patents that cannot be connected to dirty patents at any distance are deemed "unconnected."[6]

D_i measures the proximity of fields of knowledge. Evolutionary economic geography highlights how relatedness can foster the exchange of ideas and open up new pathways of development for regions and firms (Martin and Sunley 2006). All else equal, if D_i is systematically very high between patents of two different technology classes, then the "intellectual distance" between these fields is large and there is less of a "common language" that can help facilitate the diffusion of ideas (Noteboom 2000).

By the same token, "weak connections" at 2 degrees of separation may represent a particularly fruitful direction for ideas exchange as they are not too similar to lead to cognitive lock-in and yet not too different such that there is no practical room for knowledge exchange (Noteboom 2000; Granovetter, 1973).

[5] Measures of distance based on patents have been used to study various questions. For example, Ahmadpoor and Jones (2017) use minimum distance to assess the extent to which scientific knowledge feeds into patented technologies. Bloom, Schankerman and Van Reenen (2013) use a patent-based distance metric to assess competition and product market rivalries across firms.

[6] The D metric is adapted to conduct additional analyses reported in supplementary material (e.g., Supplementary Fig. 3 shows connectivity from dirty to prior clean patents).

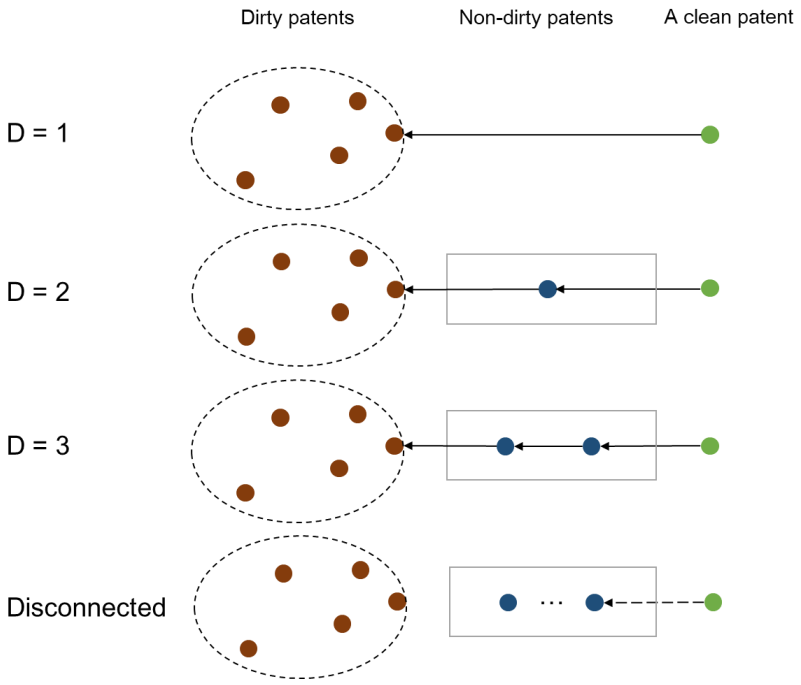


Figure 2. A schematic diagram to explain intellectual distance

Notes. This figure shows how the distance from a clean patent to prior dirty patent is determined. Arrows indicate the citation direction (from citing to cited patents).[7] Intermediary patents can also include other (i.e. different) clean patents that serve as bridges.

5. Results

5.1. Aggregate and sectoral results

We find that nearly one in every ten clean patents contains some reference to a dirty technology. The mode of clean patents' distance to a dirty patent is 3 and over 53% of clean patents are within three degrees of separation from dirty patents. (Fig. 3). By comparison, the average distance between *any* two randomly selected patents in USPTO is 8.5 (Mostafavi et al. 2012). The relative proximity between clean and dirty patents is partly attributable to the fact that many have common goals such as generating electricity, mobility, etc. Yet the limited proportion of direct connections (7.5%) and the relatively high proportion of unconnected patents (27%) highlights that they are different technologies, that sometimes

stem from cognitively dissimilar paradigms. However, these aggregate results conceal significant heterogeneity at the sub-sectoral level.

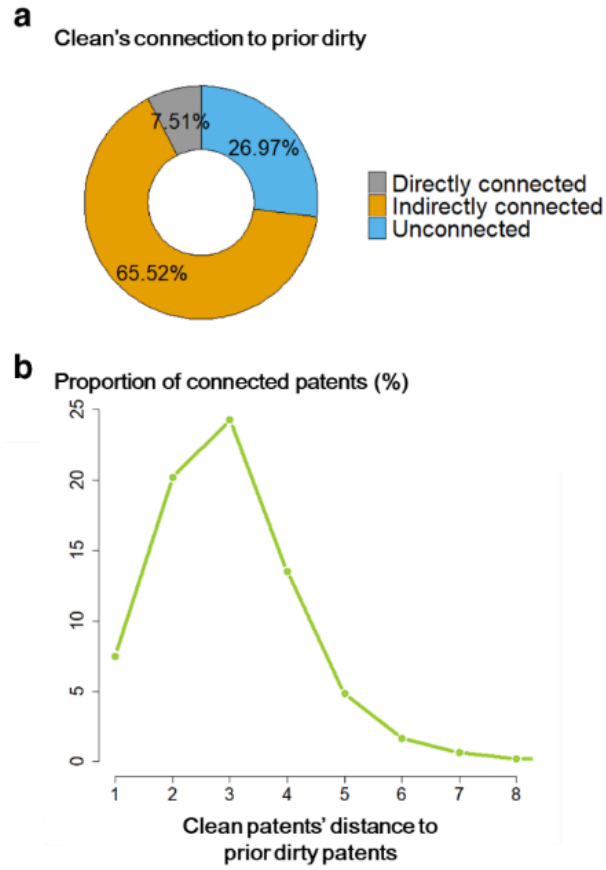


Figure 3. Connectivity from clean to prior dirty patents

Notes. Figures are made based on the directed graph of citation network from clean to previous dirty patents

The average clean patent has 9 references in its bibliography (at the DOCDB family-level). Geothermal energy, clean metals and CCS patents have the highest proportion of direct references to dirty inventions (Figure 4). Geothermal energy relies on geological surveying, drilling techniques, field development, and the construction of wells, pipelines, and other infrastructure, which requires knowledge inputs that are commonly used by fossil fuel firms. Clean innovation in metals is largely incremental in nature and consequently, still embedded

in the dirty production paradigm.[8] CCS is a complement to coal-fired power plants, gas stations and other point-sources of carbon emissions and has to be fitted to these.

Clean ICT and solar PV have negligible direct links to dirty technologies. In the case of solar PV, this may be reflective of just how different the photovoltaic paradigm is from the hydrocarbon paradigm. The former is based on the photovoltaic effect while the latter relies on spinning a coil around a magnet to generate power (i.e., turbines). This may explain why turbine-based technologies such as hydroelectric power, wind energy, and some types of marine energy have more citations to dirty technologies than solar PV.

Marine energy, for example, requires knowledge inputs that are common to dirty technologies such as offshore oil. This includes seabed engineering, constructing offshore platforms, placing under-sea cables, under-sea robots and materials that can withstand biofouling. This may explain why offshore oil companies like British Petroleum put in bids for seabed rights in the North Sea to develop offshore wind farms, as they can leverage existing knowhow (King 2021). For electric/hybrid vehicles, some elements of innovation such as car design and a more efficient internal combustion engine rely on dirty knowledge, while other elements, such as batteries are different.

[8] There are some radical strands zero-carbon innovation in metals such as zero-carbon steel made from hydrogen (e.g., the HYBRIT project). Such innovation effort is still so nascent and rare that it is not reflected in patent databases. As such, it is possible that future analyses find that clean metals rely less on dirty knowledge because radical clean innovation becomes more commonplace and better documented.

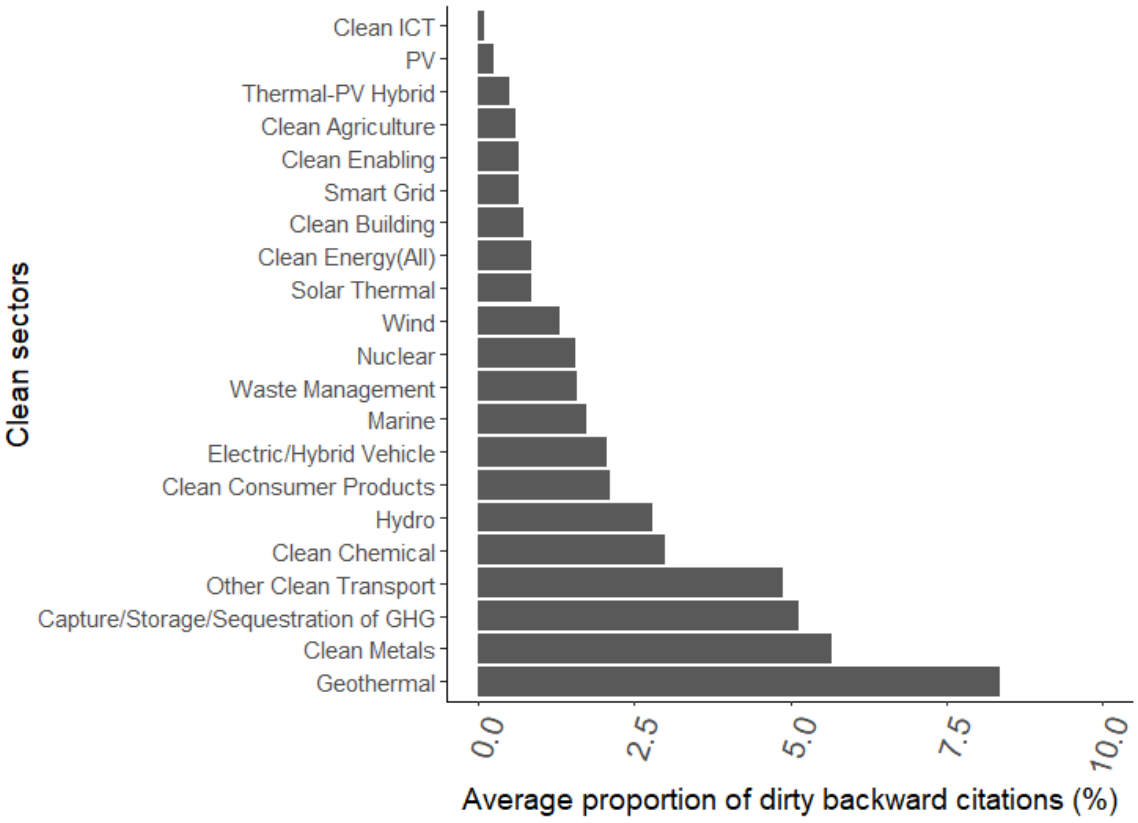


Figure 4. The average proportion of dirty backward citations by clean technology

Box 1: Offshore Oil & Offshore Wind

Firm Diversification

Offshore oil and offshore wind have significant technological similarities. Offshore oil industries possess knowledge of i) manufacturing and installation of electrical infrastructure ii) construction of seabed infrastructure, substation structures, and turbine foundations iii) mapping of ocean floors iv) installation of support services, maintenance and information services. This know-how has been leveraged by oil companies to diversify into offshore wind. Indeed, the first offshore wind structures were built based on offshore oil industry templates.

One of the most notable examples of diversification is Ørsted, which is today, one of the world's largest developers of offshore wind but was previously known as DONG Energy (Danish Oil and Natural Gas) and would manage such resources in the North Sea. DONG Energy undertook a wholesale transition around 2017 to move from offshore oil and become a leader in offshore wind.

Many traditional oil companies are following suit. Shell, British Petroleum and TotalEnergies are acquiring seabed rights to build their own offshore wind turbines.[1] Some oil companies are also engaging in offshore wind to power traditional assets. [2] For example, Equinor, a Norwegian petroleum company, is developing an 88 MW wind farm 140 km off the coast of Norway in the North Sea to supply energy to five oil & gas platforms.[3] Equinor is also expanding its operations in offshore wind significantly in Brazil.[4]

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5.2. Indirect connections and identifying the bridging technologies

The majority of the connections between clean and dirty technologies are indirect. The minimum distance at which clean patents are connected to dirty patents differs largely by technology, as plotted in Fig. 5. Nuclear has the largest share of completely disconnected patents illustrating how distinct the nuclear paradigm is from dirty technologies. Other relatively disconnected fields include solar thermal and clean agriculture, where the share of direct connections is also on the lower side.

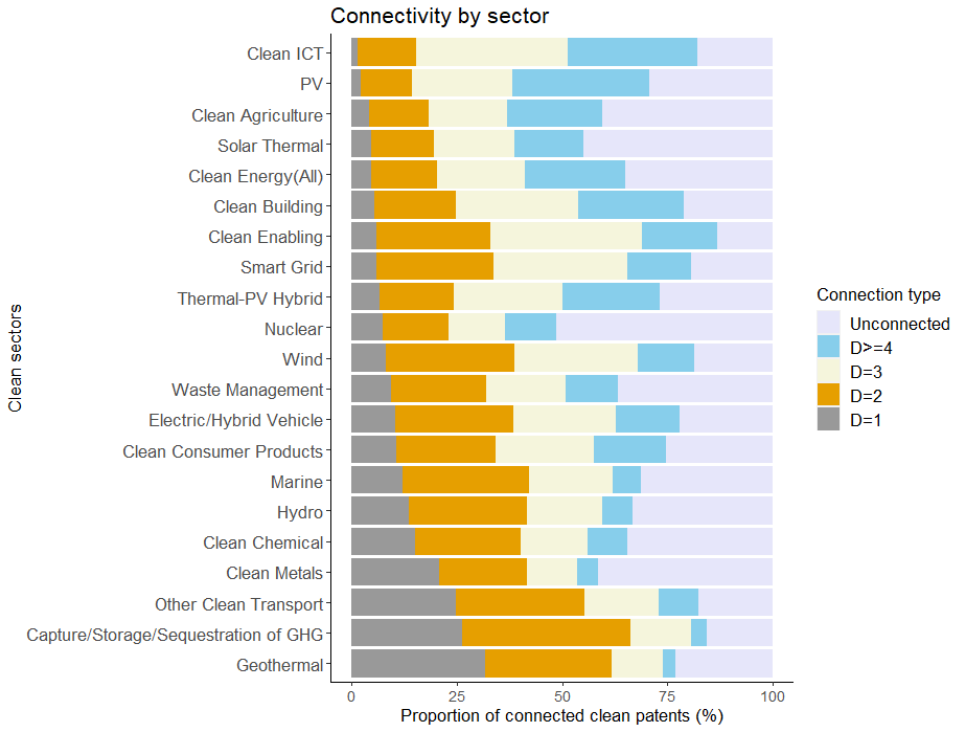


Figure 5. Sectoral details of direct and indirect connections

Notes. Each clean sector's direct and indirect connections to prior dirty technologies.

For a lot of sectors, there are a substantial proportion of patents that are connected at D=2. For geothermal, an investigation of the raw data reveals that many geothermal patents draw on intermediary patents related to heat exchange or compression which in turn cite patents in the sub-field of upstream fossil fuels, such as bore-holing. Similarly, wind patents cite technologies related to controlling electric motors which connect back to dirty technologies

that also rely on the turning of a motor.

On aggregate, we find that for clean transport, patents related to arranging automobile parts, engine apparatus, gearing, circuitry and chemical processes most often serve as the bridge between clean and dirty patents. For clean energy, patents linked to batteries, circuitry, chemical processes, and motors are often the bridge. This highlights how for dirty sectors where there is no direct link to a clean technology, there may still be indirect pathways for diversification. Literature has emphasized the importance of these indirect routes or "weak ties", which have been shown to be promising as they are different enough to be novel yet close enough to still be accessible (Noteboom 2000).

We also extract case studies from the data to show how connections at D=2 can represent meaningful indirect learning.

- Clean patent #36933371 which is about solar cells using high transmission glass, does not directly cite any dirty patent but cites intermediate patent #22076423 which is about infrared absorbing glass, which in turn cites dirty patent #24632438, which is about inductively heating molten glass.
- Clean patent #49382706 which is related to programmable electrical devices (used in clean buildings & smart grids) cites intermediary patent #11418031 related to monitoring technologies, which in turn builds upon technologies used in patent #23474906 which is about automatic safety checks in thermal powerplants.
- Clean patent #72944505, which is about software to determine the orientation of a wind turbine nacelle, cites intermediary patent #36694399 which about model-based, multi-objective asset optimization, which in turn cites dirty patent #29272616 which is about models to detect heat exchanger tube failures to optimize the operations of a thermal powerplant.
- Clean patent #50731728 which is about reducing indoor air pollution cites intermediate patent #36590829 which is about filtration/removing contaminants,

which in turn cites dirty patent #23777699 which is about particulate traps used in the exhaust system of a diesel engine.

5.3. Grey Technologies

Grey technologies can either be a steppingstone towards decarbonisation or can lock-in emissions. For example, in areas where clean energy is available, building new gas infrastructure may simply exacerbate carbon lock-in even though it is less polluting than coal. On the other hand, if no radically clean technologies are available, or if they are imperfect substitutes, grey technologies may help incrementally reduce emissions while more radical solutions are being developed (Stern and Valero 2021). We find that 23% of all grey patents have at least one reference to dirty patents (D=1). This is substantially higher than the 7.5% of clean patents that have at least one reference to dirty patents. Additionally, on average, 7% of all backward citations in grey patents relate to dirty patents. This indicates, perhaps intuitively, that pivoting from dirty to grey R&D is relatively more accessible than dirty to clean R&D.

5.4. Cross Technology Linkages

Which dirty technologies do clean technologies draw on? Supplementary Fig. 8 maps clean technologies to connected dirty technologies in a disaggregated manner. Electric vehicles, smart grids, enabling technologies in manufacturing, clean buildings, and clean ICT are connected to dirty transportation but at increasing levels of indirectness.[9] Clean technologies in hard-to-decarbonise sectors, such as chemicals, metals and long-distance transportation share connections with dirty manufacturing and downstream fossil fuel technologies.[10] Firms

[9] See star dots in Supplementary Fig. 8a

[10] See triangle and diamond dots in Supplementary Fig. 8a

that specialize in innovating in mining, drilling and processing may be in a relatively better position to pivot into clean innovation which also relies on some of these engineering processes (e.g. geothermal). This may provide a way of partially ameliorating the transitional costs since some proportion of existing knowhow will find gainful employment in "adjacent" clean sectors (e.g. Hausmann et al. 2014).

6. Robustness checks

Patent bibliography lengths are growing over time (Supplementary Fig. 5), which could theoretically increase the chance of citing old hydrocarbon knowledge and consequently, decrease D_i mechanically. However, this does not happen. We see the opposite: values of D_i rise over time as the composition of clean innovation shifts towards technologies that are more distant from the hydrocarbon paradigm (supplementary Fig. 6).

From the 1970s to the present day, the composition of clean patenting has changed, with the share of patenting in electric/hybrid vehicles, clean ICT and solar PV rising, and the share of patenting in nuclear energy declining (Supplementary Fig. 6)

7. Discussion

Economic activity has an imperative to transition to a low-carbon paradigm to limit the impacts of climate change. Innovation will be critical in achieving the net-zero pledges that now cover 90% of global GDP (Net Zero Tracker, 2022). For carbon-intensive ("dirty") firms, the pivot towards clean industries is not only a matter of honoring climate pledges but also of mitigating transitional risks since regulation is expected to move in the direction of higher carbon prices, mandatory disclosure of climate-related risks, and border carbon adjustments (Roddan, 2021).

As the fracking revolution revealed, the overall direction of innovation is still uncertain and can move in directions that do not support the clean energy transition. The target of net-zero emissions by 2050 necessitates control over the amount, direction and speed of innovation

(Stern and Valero 2021), and in this regard, it is important to understand areas where dirty knowledge spills over into clean technologies.

To what extent does society's large history of dirty R&D lock it into further dirty R&D? Models of directed technical change argue that there is hysteresis in the innovation system (Acemoglu et al., 2012; Aghion, et al., 2016). This in turn, informs views on diversification. Yet, such models arrive at this conclusion by implicitly assuming that clean and dirty technologies do not learn from each other.

We test this assumption empirically and find that only 7.5% of clean patents have a direct connection to dirty technologies. Around 27% of clean patents cannot be connected to dirty patents at any distance in the citation network. The remaining are indirectly linked, with the mode of connection being 3 degrees. We interpret this as indicative that the pivot from dirty to clean, in many cases, will not be straightforward.

However, aggregate results conceal areas of relative proximity. In reality, the degree to which clean technology learns from dirty technology is nuanced, sector-specific and sometimes indirect. Clean sectors that draw from the hydrocarbon knowledge paradigm include geothermal, clean metals, CCS, long-haul transport and clean chemicals. Others include marine and wind energy where the learning largely is indirect rather than direct. These areas of relative proximity may offer dirty R&D incumbents some opportunities to recycle their knowhow.

In terms of limitations, we are constrained, to a large extent, by existing classifications of clean and dirty patents. Future work could use machine learning to better discern categories using information contained within patents' abstract, title and claims. Additionally, while patents represent a well-codified and accessible dataset for researchers, not all forms of technological knowledge are captured in patents. Some knowledge remains undisclosed, such as trade secrets and tacit knowledge of within-firm expertise (Roach and Wesley 2013). One could use data on scientific publications, categorise them as clean, dirty or grey, and measure spillovers using this dataset, and compare it to the results of this paper.

An avenue for future research is to explore knowledge flows between clean technologies and other general sectors of the economy. Furthermore, it would be interesting to more systematically test if knowledge spillovers, as measured by patent citations, are positively correlated with the use of similar types of capital and labour (e.g., seabed engineers, floating platforms, robots that work at sea, etc.). While this is likely to be the case from the contents of the patents, formal proof would be useful.

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VII Appendix

Supplementary Table 1. Patent search strategy

	Sector	Sub-sector	CPC	IPC
Clean[1]	Clean Building		Y02B	
	Capture/Storage/Sequestration of GHG (CCS)		Y02C	
	Clean Energy	Geothermal	Y02E 10/10	
		Hydro	Y02E 10/20	
		Nuclear	Y02E 30	
		Photovoltaic	Y02E 10/50	
		Sea	Y02E 10/30	
		Solar thermal	Y02E 10/40	
		Thermal-PV hybrids	Y02E 10/60	
		Wind	Y02E 10/70	
		Others	Y02E 40, Y02E 50, Y02E 60, Y02E 70	
	Clean ICT		Y02D	
	Clean Manufacturing	Agriculture	Y02P 60	

		Chemical	Y02P 20, Y02P 30, Y02P 40	
		Consumer products	Y02P 70, Y02P 80	
		Enabling	Y02P 90	
		Metal	Y02P 10	
	Smart Grid		Y04S	
	Clean Transport[3]	Electric/Hybrid vehicle	Y02T 10, Y02T 90	see Aghion et al. (2016)'
		Aero, waterways, or railways	Y02T 30, Y02T 50, Y02T 70	
	Waste Management		Y02W	
Dirty	Energy	Upstream	see IEA (2021)[5]	
		Processing and downstream		
		Transmission and distribution		
	Transport	Internal combustion engine		see Aghion et al. (2016)
	General (Manufacturing)			see Dechezleprêtre et al. (2021)
Grey[8]	Energy[6]	Combustion technologies with mitigation potential	Y02E 20	

Manufacturing[7]	Technologies related to metal processing/Recycling	Y02P 10/20
	Technologies related to metal processing/Process efficiency	Y02P 10/25
	Technologies relating to chemical industry/Process efficiency/Energy recovery, e.g., by cogeneration, H2recovery or pressure recovery turbines	Y02P 20/129
	Technologies relating to chemical industry/Feedstock/the feedstock being recycled material, e.g., plastics	Y02P 20/143
	Technologies relating to chemical industry/Reduction of greenhouse gas [GHG] emissions, e.g., CO2	Y02P 20/151/low
	Technologies relating to chemical industry/Improvements relating to chlorine production	Y02P 20/20/low
	Technologies relating to chemical industry/Improvements relating to adipic acid or caprolactam production	Y02P 20/30/low
	Technologies relating to chemical industry/Improvements relating to fluorochloro hydrocarbon, e.g., chlorodifluoromethane [HCFC-22] production	Y02P 20/40/low
	Technologies relating to chemical industry/Improvements relating to the production of bulk chemicals	Y02P 20/50/low

Technologies relating to oil refining and petrochemical industry/Ethylene production	Y02P 30/40
Technologies relating to the processing of minerals/Production of cement, e.g., improving or optimising the production methods; Cement grinding/Energy efficiency measures, e.g., improving or optimising the production methods	Y02P 40/121
Technologies relating to the processing of minerals/Glass production, e.g., reusing waste heat during processing or shaping/Improving the yield, e-g- reduction of reject rates	Y02P 40/50, Y02P 40/57
Technologies relating to the processing of minerals/Production of ceramic materials or ceramic elements, e.g., substitution of clay or shale by alternative raw materials, e.g., ashes	Y02P 40/60
Climate change mitigation technologies in the production process for final industrial or consumer products/Manufacturing or production processes characterised by the final manufactured product	Y02P 70/50/low

	Climate change mitigation technologies for sector-wide applications/Reducing waste in manufacturing processes; Calculations of released waste quantities	Y02P 80/30	
	Climate change mitigation technologies for sector-wide applications/Minimising material used in manufacturing processes	Y02P 80/40	
Transport	Fuel efficiency of internal combustion engine-based vehicles	Y02T 10/10	see Aghion et al. (2016)

Notes. 1. We refer to Haščič and Migotto (2015), Popp et al. (2020) and Aghion et al. (2016) to collect clean patents; 2. Grey manufacturing patents are excluded from the list of clean manufacturing patents; 3. Grey transport patents are excluded from the list of clean transport patents; 4. B06L 11 is transferred to B60L 50/00 - B60L 58/40 (see IPC ver. 2019); 5. Search strategy of IEA (2021) combines both CPC and keyword based search; 6. Authors' interpretation; 7. Authors' interpretation; 8. Grey patents are excluded from the final list of clean and dirty patents. Patents classified as both clean and dirty patents are excluded from our main analysis (see Supplementary Fig. 1).

Supplementary Table 2. Top 10 countries of creating clean, dirty and grey patents

	Clean patents		Dirty patents		Grey patents	
	Country	Patent counts (Family)	Country	Patent counts (Family)	Country	Patent counts (Family)
1	US	122,515	US	88,319	US	39,660
2	Japan	56,632	Japan	19,377	Japan	28,462
3	Germany	22,622	Germany	13,344	Germany	13,930
4	South Korea	18,755	UK	6,546	South Korea	3,530
5	France	9,230	France	6,465	France	3,422
6	China	8,172	Canada	5,675	UK	3,394
7	Taiwan	7,312	Switzerland	2,177	Canada	2,084
8	UK	6,914	Netherlands	2,081	Italy	1,704
9	Canada	6,472	Sweden	1,669	Switzerland	1,477
10	Switzerland	3,327	Norway	1,529	China	1,244

Notes. Patents issued by USPTO during 1976-2020

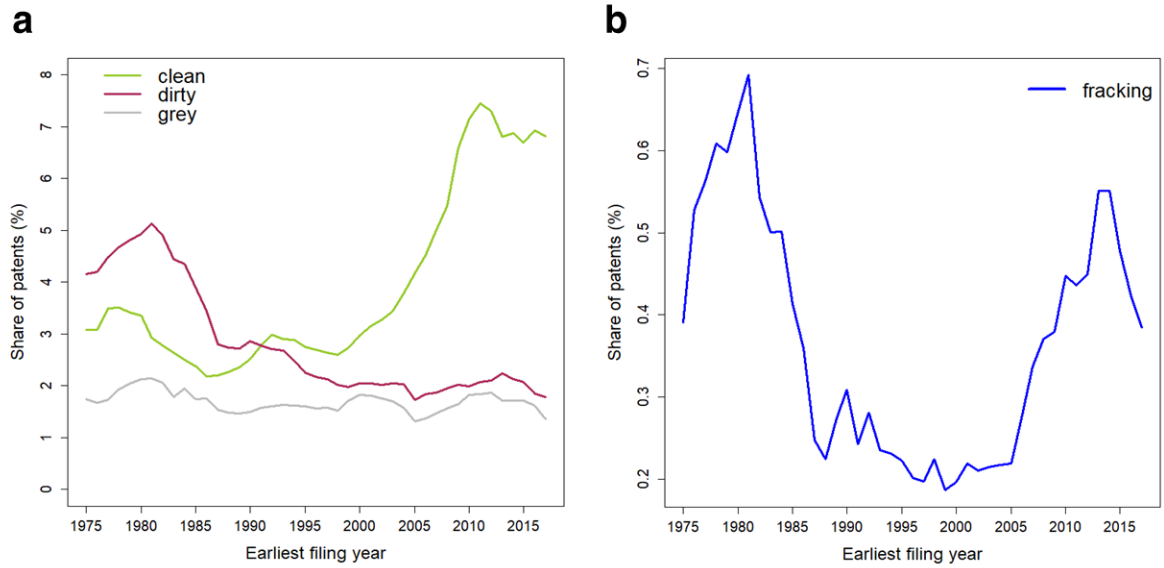
Supplementary Figures

Supplementary Figure 1. Venn diagram for clean, dirty and grey patents



Notes. We regard clean or dirty patents that are also classified grey patents as grey patents. Patents classified as both clean and dirty patents are excluded from our main analysis.

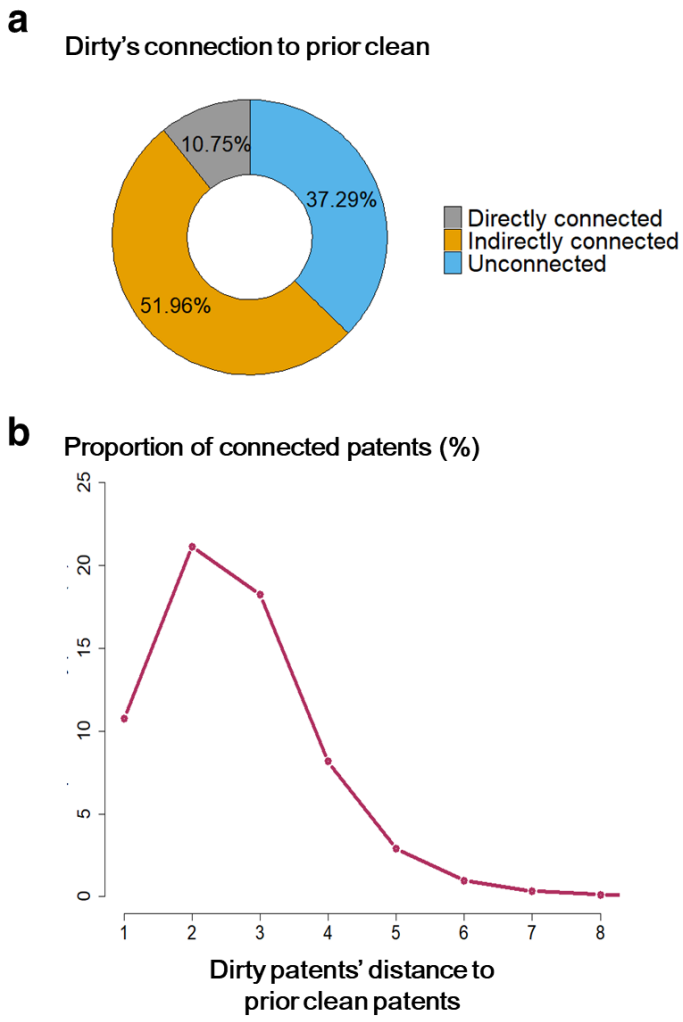
Supplementary Figure 2. Number of patents as a share of all patents



Notes. (a) The number of clean, dirty and grey patents as a share of all the US patents by year, (b) The number of fracking related patents as a share of all US patents by year. To search fracking related patents, we combine the search strategy for unconventional fossil fuel patents in IEA (2021) and for hydrofracturing patents

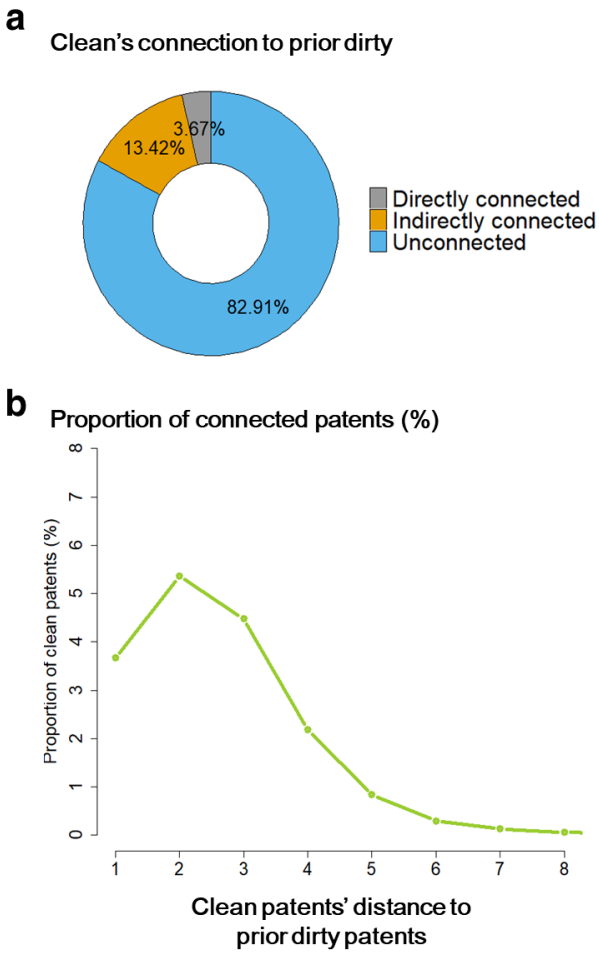
in Popp et al. (2020). Patents are sorted by priority year (i.e., earliest filing year) and counted at DOCDB family-level.

Supplementary Figure 3. Connectivity from dirty to prior clean patents



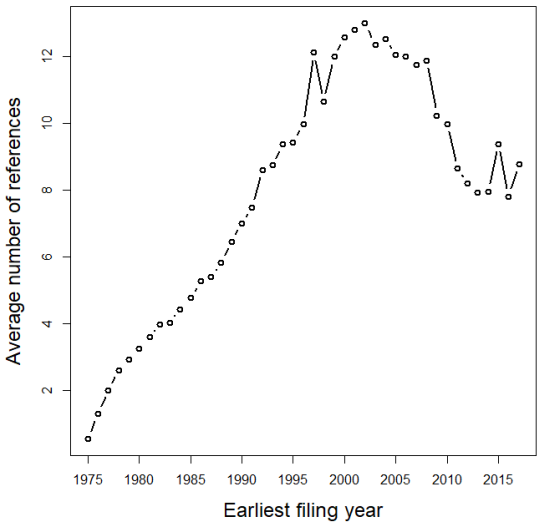
Notes. Figures are made based on the directed graph of citation network from dirty to previous clean patents.

Supplementary Figure 4. Connectivity from clean to prior dirty patents (Applicant citation only)

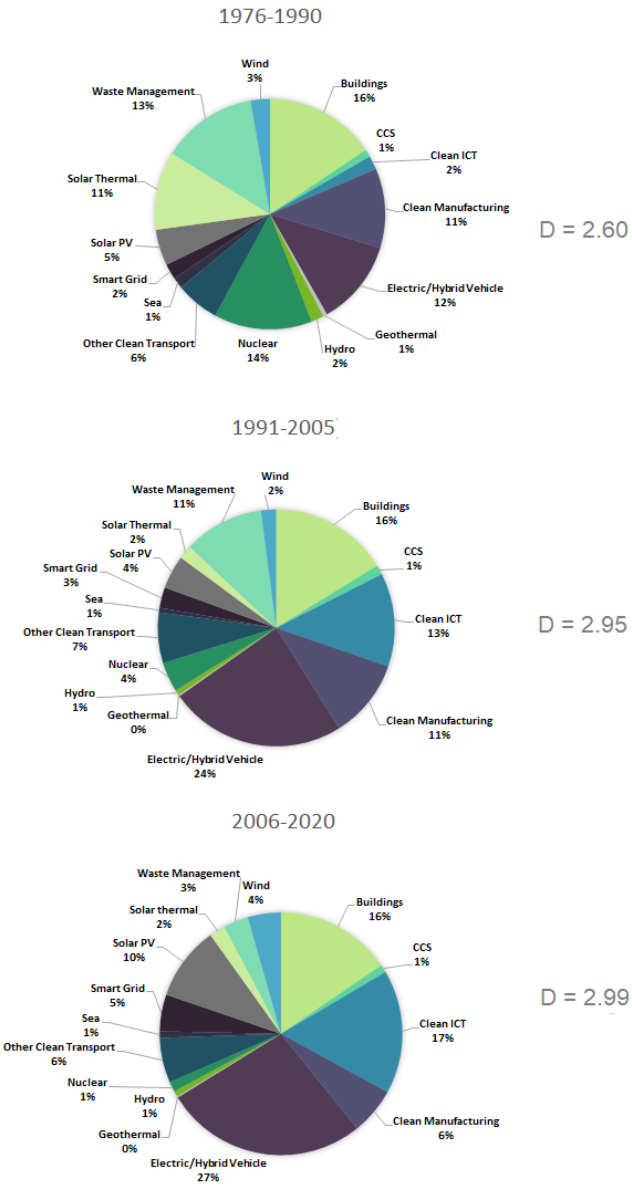


Notes. Figures are made based on the directed graph of citation network from clean to previous dirty patents.

Supplementary Figure 5. Bibliography length of clean patents

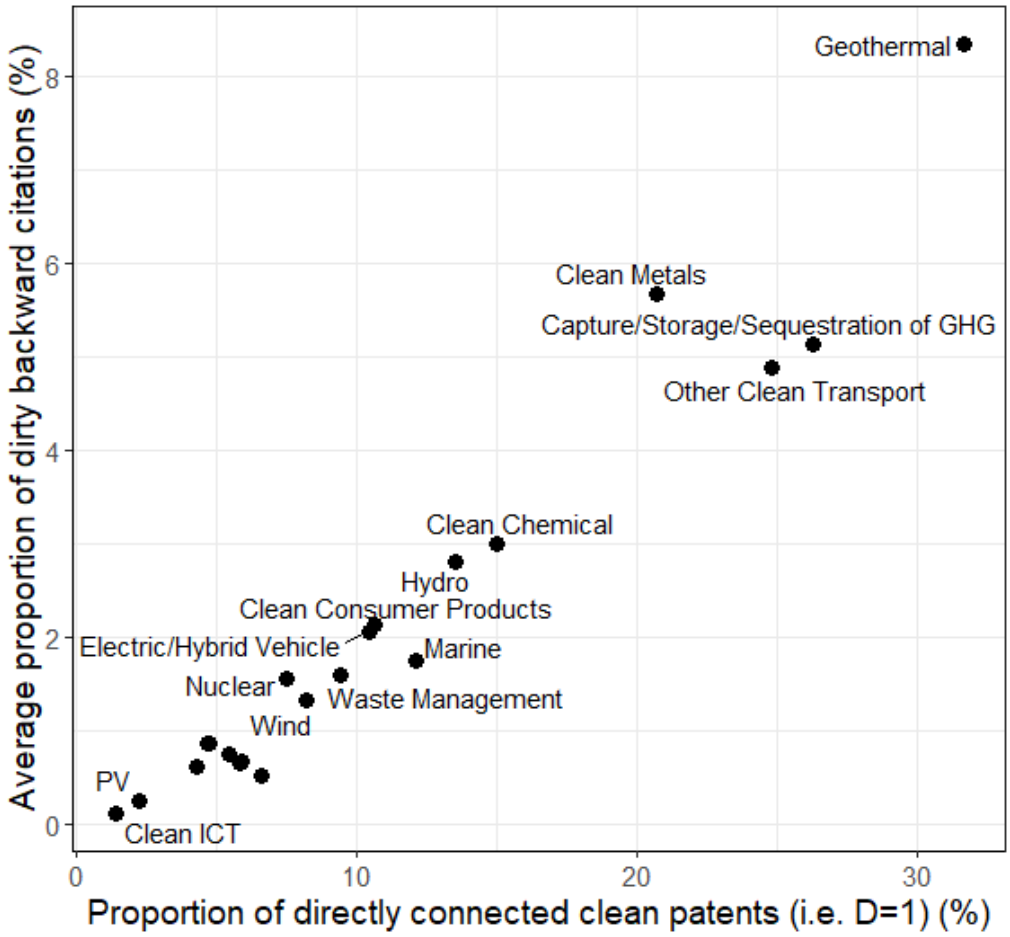


Supplementary Figure 6. The Composition of Clean Patenting over Time



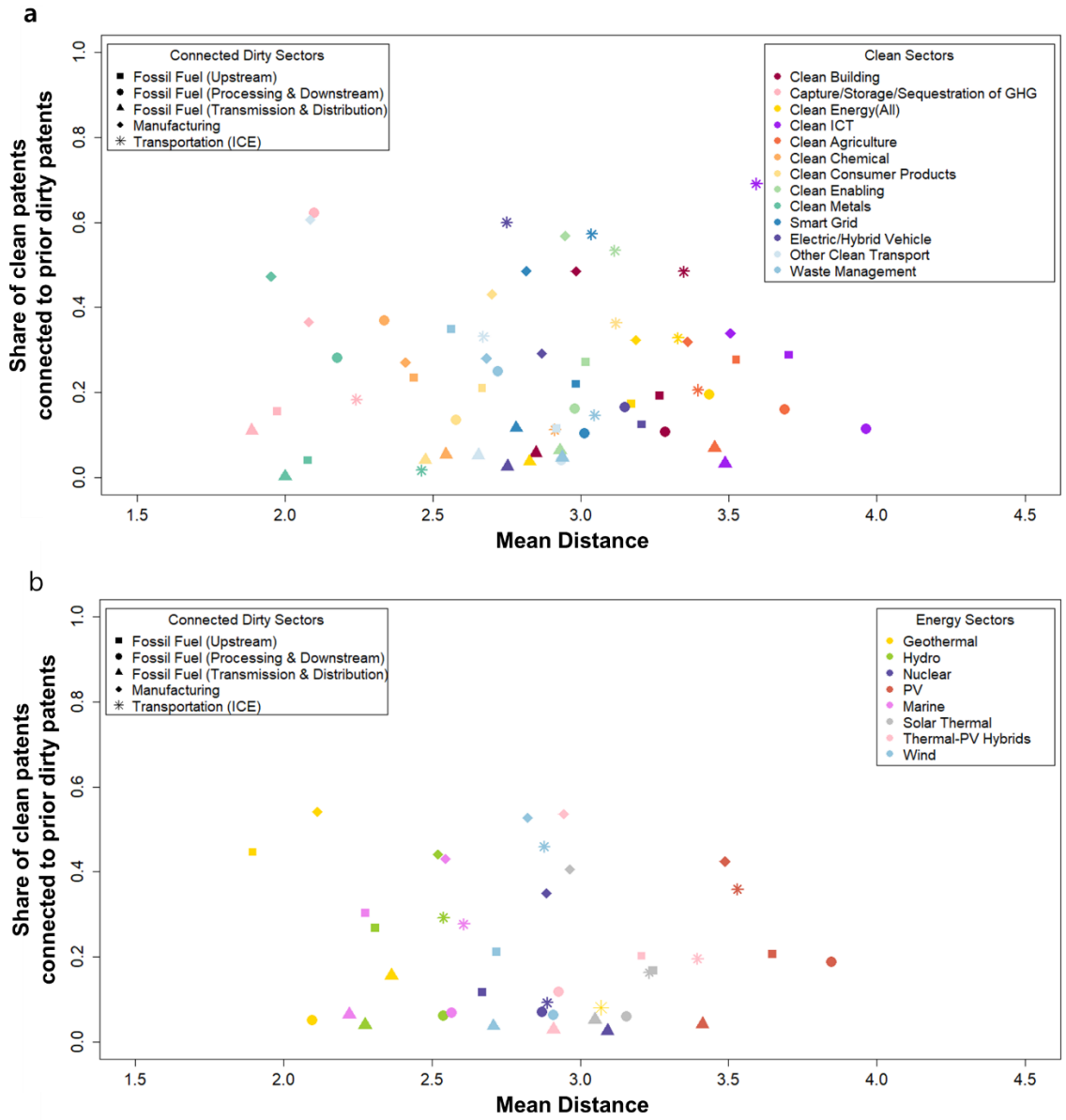
Notes. Graph shows share of granted patents in each time period. Total count for first, second and third time period is respectively, 28,000, 60,000, and 140,000 (reported to two significant figures). Patents can be tagged as relevant to multiple clean sectors.

Supplementary Figure 7. Sectoral mapping of range and intensity of direct connections



Notes. X-axis indicates the proportion of clean patents that are directly connected to prior dirty patents among the clean patents in each sector (Range of direct connection). Y-axis is the average of the proportion of dirty backward citations among the total backward citations (Sectoral average of intensity metric). Overall, the figure shows that the range and intensity of direct connection tend to be positively correlated, confirming that our D metric well represents the connectivity between clean and dirty technologies.

Supplementary Figure 8. The pattern of sectoral connections from clean patents to prior dirty patents



Notes. X-axis presents the mean of distances from patents in a certain clean sector (indicated by color of dots) to patents in a certain prior dirty sector (indicated by shape of dots). Y-axis presents the share of connected patents in a certain clean sector to patents in a certain prior dirty sector. (a) For all clean sectors. (b) For clean energy sub sectors only.