QUANTIFYING PATTERNS OF THE POWER GENERATION SECTOR'S LOW-CARBON TRANSITION USING MACHINE LEARNING AND ASSET-LEVEL DATASETS



GALINA ALOVA-BEITNER

THESIS SUBMITTED FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

UNIVERSITY OF OXFORD

MICHAELMAS TERM 2021

HERTFORD COLLEGE

SMITH SCHOOL OF ENTERPRISE AND THE ENVIRONMENT

SCHOOL OF GEOGRAPHY AND THE ENVIRONMENT

I dedicate this DPhil dissertation to my parents Olga and Viktor, my grandmother Nadezhda, my husband Jan and son Albert.

Abstract

The past decades have seen a dramatic decline in the costs of clean power generation, driven by support policies and technology improvements, making renewable energy increasingly more cost-competitive. Yet, the share of solar and wind in global generation mix remains low, with fossil fuels continuing to dominate. This points to potential frictions in the electricity sector's transition *to* renewables and, even more so, in the sector's shift *away from* fossil fuels. Key research gaps lie in understanding and accurately capturing the pace and nature of the on-going low-carbon transition of the power sector, both at the company and country level, and across different geographies. While developing countries merit a particular research focus, given the dual challenges they face to simultaneously industrialise and decarbonise their economies, extant research tends to be often limited to the Western world and single-country studies. In this context, there is a particular need for large international analyses to examine the intricate interrelationships of different factors affecting the decarbonisation patterns of the power sector across companies and countries.

This DPhil thesis aims to contribute to closing these research gaps, by offering insights into the pace and drivers of the decarbonisation process of the global power-generation sector. In doing so, it also seeks to contribute to the methodological advancement of the field, by demonstrating the data and analytical tools that can be used to capture and examine the complexity of the sector's transition. To this end, the thesis has produced a series of three articles (Chapters 3-5) focusing on the decarbonisation of the power sector internationally, at the company and country level. Methodologically, the thesis is integrated through the application of machine-learning-based techniques, both supervised and unsupervised methods, selected on the basis of their best suitability to analyse asset-level datasets involved in addressing each research problem at hand.

The findings of the thesis point to considerable electricity system inertia. As the global analysis of utility companies suggests, this might be driven among others by the slow transition of electric utilities to renewable energy and their continued investments in fossil fuels, particularly natural gas. This could at least in part be explained by the finding that gas overall shows greater resilience to environmental policy stringency, compared to coal, as concluded by the study of the factors contributing to company technology choices. Furthermore, gas power plants have considerably higher chances of being successfully commissioned than renewable energy projects, as the analysis across African countries has shown. Utilities also tend to be less responsive to environmental policies than non-

utility actors such as independent power producers, particularly in terms of renewable energy investments. This could also contribute to explaining the fact that independent power producers own the vast majority of the currently installed global renewable energy capacity. That said, when looking across African economies, state-ownership of planned power plants does not seem to reduce their implementation chances. Overall, this work demonstrates the importance of a careful and nuanced design of electricity markets and environmental policies to promote the uptake of renewables, while simultaneously breaking the dependence on fossil fuels.

Acknowledgements

There are several people whose support has been crucial to the success of my DPhil.

First of all, I would like to thank my family: my husband Jan, who with his unwavering support has always stood by me, and my baby son Albert, who was born in the middle of my DPhil and the global pandemic, and has already given us so much happiness and joy. I am also extremely thankful to my parents, Olga and Viktor, for unconditionally believing in me and genuinely thinking that I am the best, and Ursula and Joachim, my in-laws, who have always been there for us.

I wish to express my special regards to my supervisors, Dr Ben Caldecott and Prof Cameron Hepburn, who have generously shared their invaluable expertise and advice. Particularly precious has been their encouragement to strive to achieve seemingly the most unattainable goals. I really appreciate your mentorship!

I am equally thankful to Philipp Trotter and Alex Money for their collaboration. We have been through an amazing journey with our work!

Moreover, I am very grateful to Aoife Haney, Lucas Kruitwagen, Johannes Meuer, Kelly Sims Gallagher, Daniel Tulloch, Dariusz Wójcik and other colleagues at Oxford and beyond, for taking the time to share their thoughts on my work either through informal conversations, peer-review processes or conferences. Your critique and advice have significantly improved my work!

My deepest gratitude goes to the institutions and people funding my DPhil: the ESRC Grand Union Doctoral Training Partnership, the Scatcherd European Scholarship from the University of Oxford and the 73 Scholarship Fund for Geography from Hertford College, Oxford, established through the generosity of the college's alumni, P. Newman and M. Teversham.

Finally, I extend my thanks to my friends, our DPhil and college cohort, and the general Oxford parent community – the warmth and support we have shared, albeit often virtually, has significantly brightened my journey.

Table of Contents

Abstract....5
Acknowledgements....7
Table of Contents....8
Chapter 1. Introduction....10
1.1. Context and motivation of the thesis....10
1.2. Thesis objectives....13
1.3. Summary of the methods and data selected....15
1.4. Article-based route....16
1.5. Outline of the thesis structure....17
Chapter 2. Literature Review....18
2.1. Theory: from 'creative destruction' to 'stranded assets'....18
2.1.1. Evolutionary economics: the low-carbon transition as the next technological revolution....19
2.1.2. Systems' socio-technical transitions towards sustainability....21
2.1.3. Evolutionary economic geography: spatial prism of the transition....22
2.1.4. Implications of company state versus private ownership....24
2.1.5. Corporate sustainability....26
2.1.6. Carbon lock-in and stranded assets....29
2.1.7. Uncertainty as a barrier to companies' climate action....32
2.2. State of empirical knowledge on the electricity sector's decarbonisation....34
2.2.1. Future of the electricity sector as projected by scenario-based analyses....34
2.2.2. Sources of divergence in the projections of energy and climate models....36
2.2.3. Challenges to measuring climate-related risks....41
2.2.4. Relevance of scenario modelling beyond the policy community....43
2.2.5. The impact of policies on renewable energy deployment....44
2.2.6. Pressures on electric utilities' value proposition and business models....48
2.2.7. Factors affecting company renewable energy adoption....50

2.2.8. Asset-level approaches for the energy transition research 53
2.3. Reflections on empirical literature and research gaps 55
2.3.1. The integration of predictive analytics in energy planning research 55
2.3.2. The value of company perspective in the energy transition literature 57
Chapter 3. A machine-learning approach to predicting Africa's electricity mix based on planned power plants and their chances of success 61
Chapter 4. A global analysis of the progress and failure of electric utilities to adapt their portfolios of power-generation assets to the energy transition 71
Chapter 5. A machine learning model to investigate factors contributing to the energy transition of utility and independent power producer sectors internationally 80
Chapter 6. Conclusions 99
6.1. Discussion of findings and their implications 99
6.1.1. Transition to renewables and away from fossil fuels 100
6.1.2. Gas as a driver of future carbon lock-in 101
6.1.3. Policy effectiveness 104
6.1.4. The importance of geography in energy systems' transition patterns 106
6.1.5. The role of utility companies vis-à-vis IPPs in driving the transition 108
6.1.6. Methodological contribution of this thesis 109
6.1.7. Dissemination of findings and emerging impact 110
6.2. Limitations of the thesis 111
6.3. Avenues for future research 114
Bibliography for Chapters 1, 2 and 6 119
Appendices 145
Appendix A: Supplementary Materials for Chapter 3 145
Appendix B: Supplementary Materials for Chapter 4 162
Appendix C: Supplementary Materials for Chapter 5 172
Appendix D: Overview of gradient boosted decision trees 178
Appendix E: Dissemination of DPhil research at conferences 181
Appendix F: Author contributions to Chapters 3-5 182

Chapter 1. Introduction

This DPhil thesis investigates the patterns of the global power generation sector's transition to renewable energy and away from fossil fuels. The decarbonisation of the electricity sector, as one of the largest contributors to global CO_2 emissions (IEA, 2019b), is essential if the objectives of the Paris Agreement to limit global warming are to be met (UNFCCC, 2015). The aim of my thesis is thus to expose granularity of these transition pathways and potential barriers to the sector's decarbonisation, thereby exploring the associated sources of carbon lock-in risks which would have major implications for the global efforts to combat climate change.

To produce a nuanced in-depth analysis, here I adopt a bottom-up approach, using comprehensive asset-level datasets, containing detailed information on individual power plants internationally. To these data, I apply machine-learning-based techniques best suited to each problem at hand, enabling me to uncover novel insights from the complex data. As a result, this work contributes to bridging several content and methodological gaps of the extant literature, as detailed in Chapter 2 (Section 2.3).

This introductory first chapter lays out the background for this thesis, outlining the main motivation and key objectives of this work, along with the summary of the methods and data employed to address the key research questions.

1.1. Context and motivation of the thesis

The past decade has seen a significant decline in the cost of the power generated from renewable energy sources, driven, among others, by support policies and technology improvements (Creutzig *et al.*, 2017). The cost of solar power has decreased by 80% since 2010, while wind saw depreciation of 40% (IEA, 2020d). Battery storage has also become cheaper, with lithium-ion battery pack prices falling in real terms from USD 1,100 kWh in 2010 to USD 137 kWh in 2020 (BloombergNEF, 2020). As a result of these cost

declines, global renewable energy capacity has seen dramatic expansion, driven by solar photovoltaics (PV) and wind power with an average annual growth rate since 1990 at around 37% and 23%, respectively (IEA, 2020c).

However, the share of solar and wind in total global power generation mix remains limited at 9% in 2020, with fossil fuels continuing to dominate, accounting for 60% (IEA, 2020b). Coal power plants alone contributed 30% of global carbon emissions in 2018 (IEA, 2019b). This points to potential frictions in the electricity sector's transition *to* renewables and, even more so, in the sector's shift *away from* fossil fuels. Among these barriers could be an infrastructural lock-in given long operating horizons of power plants, amplified by institutional and behavioural factors, contributing in conjunction to an inherently slow pace of energy systems' transformation – the so-called inertia (Seto *et al.*, 2016).

The extent to which these bottlenecks manifest themselves tends to vary across geographies, in view of a substantial degree of heterogeneity in the pace of the electricity sector's decarbonisation worldwide. For example, based on 2019 estimates, the share of non-hydro renewables accounted for 15.6% in Europe, compared to 8.9% in North America and 7.7% in Latin America and Caribbean. In Africa, this share stood at 3.8% and in Middle East at 0.7% (IEA, 2019c). There is also substantial variation within regions, with some countries faring well above their regional average. For example, Denmark leads the way in Europe, with its non-hydro renewables accounting for 61%, while Kenya stands out among African economies, with the share of 57.3% (IEA, 2019c).

While the transformation of the power sector could be fraught with difficulties for many countries, the energy transition presents a particularly important test for industrialising economies, such as most African countries. Besides the need to decarbonise their power, developing countries face the urgency to meet their rapidly increasing energy demand and improve development outcomes for their growing populations (Ouedraogo, 2017b). While being a challenge, it is also a unique opportunity for these countries to close energy demand through clean power, thereby avoiding a carbon lock-in that mature electricity

systems might be prone to (Bridge, Bouzarovski, Bradshaw & Eyre, 2013). Breaking countries' dependence on carbon-intensive power, however, would require a deliberate well-designed and concerted policy and private sector effort.

In this context, among the key determinants of a country's decarbonisation pace is the ability and readiness of individual power-generation companies to shift their focus to renewable energy. A well-known case is Danish Oil and Natural Gas (DONG) company that underwent a major transformation over the past decade with an ambition to become a renewable energy leader. As part of this process, the company also undertook a large-scale rebranding, including a name change to Ørsted, as DONG no longer represented its new focus on clean power. By 2021, 89% of Ørsted's heat and power generation comes from green energy (Ørsted, 2021). Another example is ScottishPower which completed its transition in 2018 becoming a 100% renewable energy company (ScottishPower, 2018).

At the same time, given that such decarbonisation of electric companies' asset base, at least in part, tends to take place through asset sell-off, this implies that there are firms willing to invest and own fossil-fuel power plants. For example, it was Drax that acquired nearly 2.6 GW generation business from ScottishPower, allowing it to complete its transition process. This included ScottishPower's last combined cycle gas turbines accounting for 78% of the 2.6 GW capacity divested (ScottishPower, 2018). Investments seem to continue also in new fossil-fuel capacity, as the global demand for coal sees a strong rebound in 2021 (IEA, 2021a), while natural gas grew even during the global COVID-19 pandemic, with 40 GW of power plants added in 2020 (IEA, 2020a).

These individual examples alone point to considerable complexity and differences in utilities' transition patterns, whilst the global landscape of electric companies is significantly more elaborate. It reaches far beyond the well-known large Western firms, comprising smaller national and municipal utilities, and increasingly non-utility actors, such as independent power producers (IPPs) (Schleicher-Tappeser, 2012). For the

objectives of the Paris Agreement (UNFCCC, 2015) to be met in a timely manner, however, a concerted push is required for decarbonisation across all countries and companies in the electricity sector (Rogelj, Shindell, *et al.*, 2018). Therefore, it is crucial to have good in-depth understanding of the progress and nature of the electricity sector's transition at both the company and country level. This in turn might help to shed light on the potential barriers that may impede the accelerated uptake of renewables and phase-out of carbon-intensive power-generation assets.

While the energy transition literature is growing, given the breadth and depth of this research topic, a considerable amount of work remains, as Section 2.3. in Chapter 2 discusses in detail. Key research gaps lie in understanding and accurately capturing the nature of the on-going energy transition and enhancing the prediction of the future decarbonisation pathways. This would help to guide current decision making which will largely predetermine whether global climate change objectives will be met. In this context, there is a particular need to examine the intricate interrelationships of different factors affecting the decarbonisation of the electricity sector.

1.2. Thesis objectives

This thesis aims to contribute to closing some of the research gaps, by offering novel insights into the pace and drivers of the decarbonisation of the global power-generation market, reflecting potential geographic disparities in the transition patterns. It also seeks to contribute to the methodological advancement of the field, by demonstrating the data and analytical tools that can be used to capture and examine the complexity of the sector's transition. To this end, I conducted a series of three studies, presented in core Chapters 3, 4 and 5, all focusing on the shift of the electricity sector internationally from fossil fuels to renewable energy, with the following three main objectives corresponding to each chapter:

Objective of Chapter 3: Advance the energy-planning literature, by developing an empirical data-driven approach to predicting where a given electricity sector is realistically heading in terms of the expansion and composition of its future capacity mix.

- Estimate the uncertainty around planned power plant commissioning chances, based on project design characteristics, and the governance and economic indicators of countries where they are located.
- Apply the approach to Africa, to explore whether the continent will live up to its potential to power its development by clean energy, and inform the energy community about potential carbon lock-in risks.

Objective of Chapter 4: Develop a systematic and comprehensive analysis of decarbonisation patterns of utility companies globally.

- Provide empirical evidence of the energy transition of the utility sector in its entirety, not limited to major international actors, using a large comprehensive sample of companies.
- Identify potential sources of inertia in utilities' transition, and associated risks of carbon lock-in for the electricity sector as a whole.

Objective of Chapter 5: Analyse the contribution of policy- and market-structure-related factors to technology choices across OECD and BRIICS economies.

- Investigate how environmental policies and market-structure-related characteristics might contribute to growth in fossil-fuelled versus renewables-based generation capacity.
- Examine the differences in response to these factors by utility company vis-à-vis IPP sectors.

1.3. Summary of the methods and data selected

Methodologically, the thesis is integrated through the application of machine-learning-based techniques, selected on the basis of their best suitability to analyse the asset-level datasets involved in addressing the research problem of each core chapter (i.e. Chapters 3-5). This section briefly summarises the methods and data used in the three articles, with more details included in the Methods sections of each Chapter and their accompanying supplementary materials (Appendices A-D).

In Chapter 3, I build a gradient boosted decision tree (GBDT) model, using the open-source algorithm LightGBM developed by Microsoft (Ke *et al.*, 2017), to address the classification problem at hand, that is to estimate the probability that a planned power plant will be successfully commissioned. GBDT is a state-of-the-art supervised machine-learning-based technique for building interpretable predictive models to analyse feature-rich, structured datasets (Hastie, Tibshirani and Friedman, 2009).

The data underlying the model are Live Data by African Energy (African Energy, 2019), containing granular information on commissioned, failed and planned power plants across 54 African countries. The asset-level dataset was coupled with additional data on countries' socio-economic and governance indicators, to explore their relative importance with project design characteristics.

Chapter 4 applies a clustering analysis, an unsupervised machine-learning-based technique, to analyse a global dataset of over 3,000 utility companies' power-generation assets, devising common energy transition patterns across the firms. The algorithm is able to systematically classify datapoints, here utility companies, into a specific group, based on predefined similarity features (i.e. growth in coal-, gas- or renewables-based capacity), so that the firms in one cluster are more similar, compared to those in the other groups. I also employed hypothesis testing, using the bootstrapping technique, to examine characteristics of the clusters identified.

The dataset for this study comprises historical releases of Utility Data Institute (UDI) World Electric Power Plants Database (WEPP) by S&P Global Market Intelligence. WEPP is considered one of the most comprehensive asset-level datasets available for the electricity sector, containing granular information on power plants globally (Gotzens *et al.*, 2019). With historical view being one of its core advantages, these data allow tracking plant ownership at the company level over time.

In Chapter 5, I again build a GBDT model, this time using CatBoost algorithm by Yandex (Yandex, 2018) that allows including multiple dependent variables in the analysis. Among the key strengths of this unified model is its ability to effectively isolate and capture synergies between the factors contributing to capacity additions by different technologies. I apply the model to the WEPP dataset, mentioned above, coupled with OECD Environmental Policy Stringency (EPS) index, as well as the data on power-generation costs, country resource endowment and electricity consumption as control variables.

At the stage of designing my research approach, I also considered qualitative techniques which could provide an additional angle to the quantitative analysis, particularly to capture some of the factors that would be more difficult to measure in numerical terms, as discussed in Chapter 6. However, given the challenges posed by the COVID-19 pandemic to social interaction and travel during the second and third year of my DPhil, I took the decision to concentrate on desk-based quantitative analysis for all the three articles. I discuss the importance of qualitative research as a potential avenue for future work on this topic in Section 6.3. of Chapter 6.

1.4. Article-based route

The thesis pursues an article route for the following reasons. First, while being thematically and methodologically coherent, the thesis falls naturally into three discrete studies, each aiming to close a distinct research gap. Second, the peer-review process preceding the publication of each article in academic journals has offered a wealth of valuable in-depth

feedback, which has significantly improved the quality of the papers and consequently the overall thesis. Third, given the fast-moving pace of the energy transition field, the article route enabled me to execute and publish my research without delay, thereby contributing to advancing the literature, before the analysis or data outdate. Finally, the publications have supported my smooth post-DPhil career transition, serving as demonstration of my analytical skills and subject expertise to prospective employers.

1.5. Outline of the thesis structure

The thesis starts with a literature review Chapter 2, comprising first an account of the relevant theoretical work to offer broad framing to the empirical analysis envisaged (Section 2.1), followed by the overview of the extant relevant empirical studies (Section 2.2). The chapter concludes with a detailed outline of the core literature gaps and the ways this thesis aims to contribute to closing them (Section 2.3). Chapter 3 constitutes the first paper of the thesis, focusing on predicting Africa's capacity mix in 2030, by estimating the chances of currently planned power plants being successfully realised this decade. Chapter 4 represents the second paper of the thesis, examining the decarbonisation patterns of utilities globally over the past nearly two decades. Building upon this work, Chapter 5, as the third paper of the dissertation, explores policy and market-structure-related factors contributing to technology choices of utility and IPP sectors. The papers are included in the thesis in the original format of the journals where they were published – *Nature Energy* and *iScience*. Supplementary materials accompanying each paper in the journal publication are enclosed as Appendices A-C. Finally, the three core content chapters are followed by Chapter 6 – the concluding chapter of the thesis, discussing the key takeaways of the analysis conducted and the implications of the findings, as well as outlining the limitations of the studies and potential further research avenues.

Chapter 2. Literature Review

This Chapter offers a review of the relevant literature that lends a theoretical (Section 2.1) and empirical (Section 2.2) framing to the research undertaken in this thesis. The Chapter concludes with reflections on this body of research highlighting the key literature gaps in the empirical analysis which this thesis seeks to contribute to closing.

2.1. Theory: from 'creative destruction' to 'stranded assets'

This first section of Chapter 2 reviews the theoretical literature that had lent useful framing to the empirical analysis conducted in this thesis, contributing to the formulation of research questions addressed in the three analytical chapters (Chapter 3-5). The aim of this section is to discuss the insights and lessons learned that the relevant strands of theoretical literature offer to better understand the on-going transition of the energy sector. Particularly pertinent to the focus of this dissertation is the role of individual companies and geographies in driving the sector's transformation.

To this end, this Section 2.1 discusses the evolution of the theoretical thinking on innovation and systems transformation in the context of corporate sustainability and the decarbonisation of the power sector. It first focuses on the angle that the literature on evolutionary economics (Section 2.1.1), systems' socio-technical transitions (Section 2.1.2) and evolutionary economic geography (Section 2.1.3) offers to understand the role of incumbent companies vis-à-vis new market entrants in driving the power sector's transformation, and the importance of their ownership type (Section 2.1.4). This Section then dwells on the evolution of corporate sustainability theories to examine the origins of firms' internal motivations for sustainability (Section 2.1.5), followed by the discussion of potential sources of inertia. Given the capital-intensive nature of power generation companies' business models, this discussion focuses on the implications of infrastructural lock-in (Section 2.1.6) and capital investment decision making under uncertainty (Section 2.1.7).

2.1.1. Evolutionary economics: the low-carbon transition as the next technological revolution

Given the pivotal role of technological progress in the low-carbon transition, evolutionary economics, starting with Kondratiev's (1925) super cycles, further evolving into Schumpeter's (1939) theory of innovation, is pertinent for understanding the nature of this phenomenon. The modern climate change and sustainable development agendas echo Schumpeter's focus on the qualitative change and structure of economic growth, rather than its pace (Fagerberg, 2018). At the centre of a Schumpeterian world is technological competition as a driving force behind capitalism – an idea, notably, borrowed from Marx and his account of mechanisation as process innovation (Fagerberg, 2003). Schumpeter introduced further types of innovation – new products, inputs, methods and markets, as well as novel modes of business organisation (Schumpeter, 1934). The latter is particularly relevant for the low-carbon transition as the electricity market faces challenges to its incumbent business models.

Building upon Schumpeter's work, Freeman and Perez (1988) introduce the concept of 'techno-economic paradigm' (TEP). Changes in TEP can be so fundamental that they could result in technological revolutions, affecting the entire economy, and requiring major social and institutional adjustments to absorb new technology. Perez (2002) distinguishes between five technological revolutions, which besides the breakthrough of new technologies are characterised by facilitating developments also in power generation and infrastructure (Perez, 2016). These major transformations started with the Industrial Revolution in the 1770s, which brought the era of mechanisation and factories, enabled by hydropower and canal infrastructure. It was followed by the rise of coal, steam and railways at the end of the1820s. In 1875, began the age of steel and heavy engineering, while the start of the twentieth century denotes the time of automobile and highways, the use of oil and the expansion of electricity access. Finally, in 1971, with the launch of Intel's

microprocessor, began the present time of information and communication technologies and the internet (Perez, 2002, 2016).

Given the scale and pace of the economic transformation required to combat climate change, scholars have started to liken the modern low-carbon transition to the technological revolutions of the past (Pearson and Foxon, 2012; Mathews, 2013; Stern, 2015). Indeed, the improved cost-competitiveness of, and innovation in, clean technologies over the previous decade have offered support to this argument. The success of the energy transition as the next technological revolution is, however, contingent on the factors not limited to the diffusion of clean energy technology. These include the electrification of production processes and transport (Fagerberg, 2018), and harnessing the synergies with the digital technologies (Pearson and Foxon, 2012), such as smart grids (Shomali and Pinkse, 2016) and electronics in automobiles[1].

Importantly, evolutionary economics also offers a micro-lens to explicate the importance of incumbents relative to new entrants in the innovation process, which is relevant to the discussion on the fate of conventional power-generation companies in a low-carbon future. In his early work, Schumpeter (1934 [1911]) emphasised the role of small new firms in driving the radical innovation, while in the later thinking (Schumpeter, 1942), he recognised the ability of large corporations thanks to their Research and Development (R&D) budgets to fuel major technological progress (Nelson and Winter, 2002).

The relationship between incumbent firms and new entrants is a prominent theme also in the research of the neo-Schumpeterians – Nelson and Winter (1982). They distinguish between the innovation originating outside the industry, and that within incumbent firms through the knowledge acquired over time. In the former, small new entrants can become more successful in recognising and acting on an opportunity to innovate. In the latter case, incumbents might have an advantage over the new actors, given their accumulated

[1] According to estimates, by 2030, electronics will constitute 50% of car's value (PwC, 2013).

knowledge (Nelson and Winter, 2002). Consequently, large incumbents tend to be better at navigating a familiar environment of their industry, rather than adapting to an external innovation shock. As a result, they are likely to exhibit a degree of path-dependency, adhering to the routines and generating only incremental innovation (Fagerberg, 2003). This discussion of evolutionary economists on the role of incumbents versus new market entrants in driving innovation has significantly contributed to shaping the focus of this thesis on the transition patterns of different electric firms, such as utilities vis-à-vis IPPs.

2.1.2. Systems' socio-technical transitions towards sustainability

Similarly to evolutionary economists, scholars working on the sustainability transitions of socio-technical systems have been concerned with the drivers of innovation, and the relative importance of incumbents and new entrants in this process (Geels, 2015; Geels & Schot, 2007; Geels, 2002; Rip & Kemp, 1998). To this end, they have adopted a 'multi-level perspective' (MLP), which distinguishes between three levels within a system: a niche, which is a hub for radical innovation; a stable incrementally changing socio-technical regime with pre-defined routines; and an exogeneous landscape, affecting both the niche and regime. The process of a system transition, characterised by technological substitution, tends to experience the opposition between the incumbents in the regime, and innovators in the niche (Geels and Schot, 2007). When considering the current low-carbon transition[2], Geels (2015) foresees significant resistance from incumbent firms in the energy and automotive sectors, and argues that an active management of the decline of fossil-fuel-based industries should be an essential part of climate change policies.

On a related issue of the effective management of system transitions, scholars (Rotmans, Kemp and van Asselt, 2001; Kemp, Loorbach and Rotmans, 2007; Loorbach, 2010) seek to understand how the sustainable development of complex systems can be guided

[2] MLP has been applied to explaining also the past economic transformations, such as the shift from sailboats to steamships (Geels, 2002), and from horse carriages to automobiles (Geels, 2005).

through participatory, iterative governance. To this end, the transition management theory combines bottom-up mutual adaptation and top-down planning processes (Kemp, Loorbach and Rotmans, 2007), and seeks to reconcile short-term and long-term development perspectives (Loorbach, 2010). An important element here is the presence of an arena – a platform where a small number of innovators with often different perspectives interact and work on integrating their ideas. Researchers have made efforts to apply this approach to devising recommendations for the development and implementation of green policies (Foxon, 2011; Kemp and Never, 2017).

Scholars working on developing economies have questioned the relevance of the theoretical framework offered by the socio-technical transitions literature for significantly different country contexts (Osunmuyiwa, Biermann and Kalfagianni, 2018; Batinge, Musango and Brent, 2019). Batinge et al. (2019) posit that an energy access gap particularly across African countries presents vast opportunities for niche innovation, while energy infrastructure deficit reduces path dependence of the incumbent regime. At the same time, Osunmuyiwa et al. (2018) suggest attributing greater attention within MLP to the notion of rent seeking between incumbents and political elite, which in countries such as Nigeria might considerably slow down the energy sector's transition. That said, the concept of rent seeking relationship is not foreign to MLP. Geels (2014) refers to it as 'relational networks' between major businesses and senior officials, arguing for incorporating the considerations of politics and power into MLP, albeit potentially without an explicit reference to developing countries.

2.1.3. Evolutionary economic geography: spatial prism of the transition

Along with the temporal perspective provided by the MLP on the systems' evolution over time, the discussion on the electricity sector's transition requires a spatial angle, which is often absent in these debates (Bridge *et al.*, 2013). Here, evolutionary economic geography can offer guidance for understanding how space shapes the transition pathways of economic systems (Boschma and Martin, 2010). It combines the economic

geography's concentration on space, with the key concepts from evolutionary economics (Boschma and Lambooy, 1999), for example, path dependency and treating firms no longer as a black box, but rather as a collection of routines that affects their competitiveness (Boschma and Frenken, 2006).

In this context, Bridge et al. (2013) provide a useful typology of the geographical factors that affect the transition of the power-generation sector. For example, they explore spatial embeddedness as a barrier to the transition, manifesting through material (e.g. sunk costs of capital investments) and cultural factors (e.g. location-specific consumption patterns). As an illustration, as also mentioned in Section 2.1.2, some developing countries with less mature, still evolving electricity systems might be less prone to carbon lock-in than OECD countries, where fossil fuels are deeply entrenched in the economy. Countries with inadequate access to electricity might also demonstrate faster uptake of off-grid decentralised renewable energy solutions (Bridge *et al.*, 2013). This thesis seeks to reflect the importance of spatial considerations in understanding companies' and countries' transition patterns, by conducting large-scale international analyses in Chapter 3, 4 and 5.

Furthermore, Bridge et al. (2013) distinguish between the location in absolute and relative terms, with the latter referring to relational proximity achieved, for example, through the development of transport infrastructure. As a result, besides the physical proximity which might drive innovation and knowledge spill-overs (Boschma, 2005; Coenen, Raven and Verbong, 2010; Stephan *et al.*, 2019; Stephan, Anadon and Hoffmann, 2021), space defined in social terms may become equally important (Raven, Schot and Berkhout, 2012; Hansen and Coenen, 2015). In this context, inter-organisational linkages, for example, between parent and subsidiary companies, could determine the commonalities in the transition of a multi-national enterprise, despite the differences in the location of its individual firms. Moreover, while extant studies tend to focus on the place-related effects on the niche, in their review, Hansen and Coenen (2015) point to the lack of theoretical

and empirical research on the impact of space on the regime. The focus of Chapter 4 of this thesis, among others, on the spatial variation in the utility companies' transition patterns might contribute to bridging this gap.

2.1.4. Implications of company state versus private ownership

In addition to the role of new market entrants vis-à-vis sector incumbents, another strand of theoretical thinking pertinent for the electricity sector's decarbonisation and this thesis concerns how company ownership, either private or public, might affect its ability to drive and adapt to technological change. The liberalisation of electricity markets that took place in many countries over the past decades has triggered the entry of new private actors into the sector as well as privatisation of the existing utility companies. As a result, although technological change was not originally part of the main rationale for liberalisation (Jamasb and Pollitt, 2011), the process created the space required for innovation (Steffen, Karplus and Schmidt, 2020), that is a niche, as described by socio-technical transition scholars (see Section 2.1.2). This in turn has raised the question on the implications of the market shift towards non-state-owned incumbents and new private actors for the transition to low-carbon power generation.

While today economists tend to agree that company private ownership results in better efficiency and innovation outcomes, this was not the case in the first half of the 20th century. In the 1930s and 1940s, there was an overall sentiment that state ownership is a required response to market failures, such as monopoly and externalities (Shleifer, 1998). As a result, the nationalisation of key industries, ranging from steel and iron, to telecommunications and automotive was advocated for. This debate often took the form of counterposing capitalism against socialism, where even the supporters of the former, such as Schumpeter, would admit, albeit reluctantly, the inevitability of its demise (Schumpeter, 1942).

However, in the 1990s with the collapse of the communist regime in the Soviet Union, the merits of state ownership were reconsidered (Shleifer, 1998). Post-soviet countries

undertook mass privatisation, whilst market economies started to question government provision of services. The “tremendous dynamic vitality of our mixed free-enterprise system” as stated by Samuelson (1948) was characterised by greater incentives to innovate and achieve efficiencies compared to state-owned companies. Theory of the firm scholars explicate this by the fact that managers in public companies might benefit less from productivity gains stemming from innovation, and thus invest less in these activities (Hart, 2003). The multiplicity and complexity of often non-measurable objectives that state-owned companies are mandated to pursue, compared to the main goal of private entities to maximise profit, could contribute to this lack of incentives for public companies to invest in productivity and innovation (Tirole, 1994). That said, Shleifer (1998) makes an interesting point on cases where this exact lack of incentives for cost savings by the government-owned enterprises might result in more efficient outcomes. Examples relevant to the current low-carbon transition include state utilities investing in water purification or state car manufacturers creating less-polluting engines. Shleifer does caution against this perspective, however, arguing that societal goals can be achieved through regulation and contracting without necessarily needing to directly rely on government ownership.

While empirical evidence supports the theoretical argument that private entities, including electric companies, can achieve higher efficiencies, in practice, the liberalisation of the power market did not lead to a complete privatisation of electric companies (Steffen, Karplus and Schmidt, 2020). Governments have tended to justify this on the grounds of, for example, avoiding risks associated with monopoly power (Goldeng, Grünfeld and Benito, 2008). The rising urgency for climate action over the past years has put an additional pressure on electric company performance, whereby the ability of private companies to achieve deep decarbonisation objectives without a state intervention has come into question (Steffen, Karplus and Schmidt, 2020). Importantly, Steffen et al. (2020) argue that the extant theoretical literature mainly focuses on the performance of public

companies relative to private entities in a specific static economic context, rather than on how company ownership could drive a socio-technical transition in dynamic terms. Chapter 5 of this thesis examines the importance of the electricity market structure, including the ownership of utility companies, for the low-carbon transition of the sector.

2.1.5. Corporate sustainability

Evolution of corporate sustainability thinking

In parallel with the literature on innovation and system transitions, theories have emerged, focusing specifically on firms' motivations for sustainability. The modern concept of corporate sustainability was first theorised by Bowen (1953), who introduced the term social responsibilities of the businessman (Chang *et al.*, 2017). However, at that time, it encountered criticism, in particular, from the neo-classical thinkers such as Friedman (1962), who contended that the key responsibility of a corporation is to create value for its shareholders.

In the 1980s, corporate sustainability reached the next stage, when Freeman (1984) developed a stakeholder theory, arguing that firms' performance depends on their response to the pressures of different actors in the society, not limited to their shareholders. This has laid the foundation to corporate social responsibility (CSR) debate. According to the stakeholder theory, firms might adopt CSR practices to avoid losing the support of stakeholders with interests that reach beyond financial considerations. As a result, while not contradicting the shareholder theory, the stakeholder theory is concerned with the interests of a much broader group of actors, focusing more on longer-term horizons.

Hart (1995) expanded the CSR discussion by incorporating Wernerfelt's (1984) resource-based-view of the firm, specifically focusing on the environmental aspect as a source of competitive advantage for firms. This has given rise to the literature examining the link

between firms' environmental sustainability and their financial performance (Russo and Fouts, 1997; Mcwilliams and Siegel, 2001).

To further highlight the interdependence of business and societal objectives when it comes to long-term economic outcomes, Porter and Kramer (2006) introduced the concept of shared value. The authors argue that when the society or business acts in their own interest without considering the interests of the others, the short-term gains would come at the cost of long-term prosperity for all. In this analysis, the authors also position CSR as a source of competitive advantage, opportunities and innovation, rather than a constraint or cost. In their later work, Porter and Kramer (2011) highlight the differences between CSR and shared value, whereby the latter is closely embedded in, rather than being considered separate from, economic benefits and profit maximisation. In this context, the authors conclude that companies are more likely to act on environmental objectives, if they regard them as a driver of their productivity, rather than a response to social pressure.

The shared value creation theory echoes the wider on-going sustainable investing debate, which besides identifying the risks associated with climate change, highlights also the opportunities that companies can unlock and impact they can achieve in their pursuit of sustainability (Kölbel *et al.*, 2020). Overall, companies that are more progressive in terms of their sustainability practices tend to incorporate sustainability-related objectives throughout their operations as a cross-cutting function, rather than consider them in a silo as a purely reporting and legal compliance issue (Beal *et al.*, 2019).

Furthermore, today, in the context of climate change and the evolution in corporate sustainability thinking, Friedman's shareholder theory could acquire a new angle and meaning. Shareholders are increasingly putting pressure on companies to disclose and mitigate physical and transition risks related to climate change, in order to preserve their value (Benz *et al.*, 2021). With climate risk now being viewed as an investment and financial risk (Fink, 2020), acting upon it is in the interests of shareholders. In this respect,

the on-going developments in how climate-related risks are considered and addressed through investment decisions connects the afore-discussed theories into the single impetus for a climate action.

As the thinking on corporate sustainability has undergone considerable development, the definitions of corporate sustainability have also evolved. In their review analysis of different definitions adopted across 33 studies, Meuer, Koelbel and Hoffmann (2020) note the ambiguity that exists around the concept of corporate sustainability. To improve the clarity, the authors distil from the existing definitions the core sources of divergence. These include the level of ambition expected from a company to be considered sustainable, the level of integration of sustainability considerations by the firm, and the specificity of sustainable development, such as economic, social, ecological or inter-generational.

Business model

A central element in corporate sustainability research is the concept of business model (Chang *et al.*, 2017), which differently from the dynamic nature of strategies is more static (Wainstein and Bumpus, 2016). Business models determine how companies achieve a competitive advantage (Bocken *et al.*, 2014), by creating and capturing value, through the products and services they offer – their value proposition (Osterwalder and Pigneur, 2010). This notion is particularly useful for the empirical discussion in Section 2.2.6 on the differences in the value propositions of incumbent electricity and new specialised renewable energy companies.

Boons and Lüdeke-Freund (2013) distinguish between three inter-related types of innovation for sustainable business models: organisational, social and technological. For the latter, the authors detail several possible scenarios. These include cases where a new business model integrates the existing technology, an existing business model absorbs new technology; technological innovation leads to the creation of new business models or vice versa. Further, Bocken et al. (2014) have also conceptualised sustainable business

models on the demand side of the energy transition. They developed an eight-element classification of value propositions, of which the most relevant to the climate change discussion are improved energy efficiency and the scaled-up use of renewables.

2.1.6. Carbon lock-in and stranded assets

The afore-discussed path dependence of incumbent actors is not the sole barrier to the decarbonisation of power generation. The global electricity market is characterised by inter-connected socio-economic, political and technological forces (Seto *et al.*, 2016), which have historically co-evolved in a manner to shape and support the current power generation system. The symbiosis of these factors may result in the so-called carbon lock-in, preventing the clean technology innovation to rapidly transform the power generation sector (Unruh, 2000, 2002; Unruh and Carrillo-Hermosilla, 2006). As an example, Kalkuhl et al. (2012) find that the electricity sector can suffer from a carbon lock-in for decades, despite the existence of more efficient alternative technologies. This is due to the concurrent presence of three phenomena: learning spill-overs, high substitutability of electricity generated from different sources, and a critical variance in the present and future costs of power generation by incumbent and new technologies (Kalkuhl, Edenhofer and Lessmann, 2012).

Carbon lock-in sources are usually associated with infrastructure and technology that contribute to CO_2 emissions (Seto *et al.*, 2016), and occur both on the demand side, that is capital assets consuming carbon-intensive electricity, and the supply side comprising the value chain from extracting and transporting, to converting fossil fuels and distributing power (Bertram *et al.*, 2015). Other sources of carbon lock-in may relate, for example, to governance and institutions that support the carbon-intensive economy; and human behaviour and habits that promote the consumption of high-carbon products and services (Seto *et al.*, 2016).

Should the transition eventually surmount the carbon lock-in, it is likely to result in the obsolesce of emission-intensive capital assets, including power plants. Consequently, the

climate change debate has increasingly raised the issue of ‘stranded assets’ (Leaton, 2011; Ansar, Caldecott and Tibury, 2013; Caldecott, Howarth and McSharry, 2013) – a phenomenon whereby capital assets suffer from “unanticipated or premature write-downs, devaluations, or conversion to liabilities” (Caldecott et al., 2013). While it was not until the 2010s that the academic debate on stranded assets gained momentum, the relevant concepts – carbon budget and unburnable carbon – emanated already in the 1980s in the work of Krause et al. (1989). However, possibly due to the lacking sense of urgency at that time to address climate change, this work did not receive deserved attention (Caldecott, 2017).

Besides innovation, which Schumpeter predicted can result in the creative destruction of incumbent technologies, asset stranding can be driven by other factors, associated with the societal response to climate change, in particular, the stringent environmental policies and regulations, as governments seek to meet the objectives of the Paris Agreement (TCFD, 2017). In this context, the Task Force on Climate-related Financial Disclosures (TCFD) distinguishes between various risks associated with the low-emission transition (TCFD, 2017). These include technological improvements and innovation, and market risks (e.g. increased price volatility of commodities, and changing consumer preferences). There are also policy and regulatory risks, as governments seek to impede actions contributing to climate change, e.g. through carbon pricing, promoting clean energy sources, energy efficiency and sustainable land-use management. Climate-related reputation risks can also be significant. For instance, public campaigns calling for divestment from fossil fuels may increase uncertainties over companies’ operating and legislative environment, and have a permanent negative impact on their valuation (Ansar, Caldecott and Tibury, 2013).The negative impacts of climate change on physical and financial capital can also create the risk of asset stranding (Dietz *et al.*, 2016).

Given the high cost and long operating horizon of power-generation assets, the investment decisions that electricity companies take today will determine the compatibility

of their portfolios with a low-carbon future. In their analysis, Pfeiffer et al. (2016) conclude that to achieve the 2°C goal, no new fossil fuel power plants can come online past 2017, unless large-scale early retirement[3] and retrofitting with carbon capture, utilisation and storage (CCUS) systems takes place. At the same time, Kefford et al. (2018) estimate the value of the power-generation assets to be retired prematurely by 2060 at USD 541 billion across the USA, EU, China and India alone. Some geographies will be particularly affected, for example, in China, two to three 500 MW plants will need to be closed at half of their lifetime every week over the next 15 years. Regarding upstream asset stranding, estimates show that limiting temperature increase to 1.5°C implies that nearly 60% of both oil and fossil methane gas, and almost 90% of coal reserves should remain unused by 2050, resulting in the so-called unburnable carbon (Welsby et al., 2021)(.

Efforts are underway to theorise the concept of stranded assets to root it in academic thinking, with economic geography suggested as a possible 'home' for the concept (Caldecott, 2017). Furthermore, environmental economists have also demonstrated interest in the phenomenon, producing useful insights. Scholars working on the supply side (Sinn, 2008, 2015; Smulders, Tsur and Zemel, 2012; Jensen *et al.*, 2015) find that in the anticipation of tightening environmental regulations, firms would in the interim aim to intensify the exploitation of their fossil fuel reserves and carbon-intensive assets – 'green paradox', which could speed up climate change, thereby effectively counteracting the intended positive effects from the policy.

At the same, studies that adopt a demand-side approach focusing on investors in, rather than suppliers of, fossil fuels (Baldwin, Cai and Kuralbayeva, 2018; Van Der Ploeg and Rezai, 2018), contest the green paradox. Assuming the irreversibility of capital investments, they conclude that it would be optimal for investors to discontinue the

[3] An average lifetime of a fossil fuel power plant varies by region and the fuel type, e.g. Caldecott et al. (2017) find that while the average retirement age of coal power plants is 40 years, the average age of the operating coal power plants in the UK is 45 years. Rode et al. (2017) estimate that the lifetime of a coal power plant can vary between 30 and 75 years, of a gas-fired power plant between 30 and 55, and of an oil-fired power plant between 25 and 55 years.

accumulation of carbon-intensive assets earlier rather than later, to avoid their stranding. As a result, this timely divestment from fossil fuels would reinforce environmental policies such as carbon tax, rather than offset them.

2.1.7. Uncertainty as a barrier to companies' climate action

The role of short-termism and uncertainty avoidance

Besides climate-related risks associated with infrastructural lock-in from continued investment in fossil-fuel-intensive power-generation assets, scholars highlight short-termism and uncertainty avoidance as a source of firms' inaction on sustainability issues, including climate change. In their theoretical multi-level framework, Slawinski et al. (2017) discuss how these two forces manifest themselves in an inter-connected manner at three layers – individual, organisational and institutional. Among the potential factors prone to short-termism and thereby contributing to firms' resistance to sustainability, the authors highlight managers' present-time perspective, focus on immediate personal goals, and biases in their reward and incentive systems. Furthermore, they argue that the uncertainty contributing to firms' inaction revolves around such considerations as the extent to which a climate action can deliver economic growth or future revenues. These are coupled with temporal incompatibility of some policies with long-term investments, and with general regulatory uncertainty. As a result, these short-term biases, combined with the avoidance of some intrinsic uncertainties around climate action, might contribute to firms' inertia in adopting sustainability practices.

Investments in power-generation assets under uncertainty

Relatedly, there is an ongoing debate on the risks associated with investments in renewable energy, under various uncertainty scenarios (Deng and Oren, 2003; Hlouskova *et al.*, 2005), and more recently, specifically exploring low-carbon power generation (Reuter, Fuss, et al., 2012; Reuter, Szolgayová, et al., 2012; Tian et al., 2017; Venetsanos et al., 2002; Zhang et al., 2016). A prominent subset of this literature examines retrofitting

power plants with CCUS (Fuss et al., 2008; Szolgayova et al., 2008; Zhang et al., 2014; Zhou et al., 2010; Zhu & Fan, 2011), and repowering coal-fuelled generators with relatively lower-carbon fuel, for example, natural gas (Shahnazari *et al.*, 2014).

While it was not until the 2000s that this discussion on uncertainty entered academic debate on the energy transition (Wang, Wei and Brown, 2017), there is currently no doubt that the on-going decarbonisation of the electricity sector holds significant uncertainty both for the continued fossil fuel-based power generation, as well as the transition to renewable energy. The uncertain factors associated with an investment into power-generation assets and determining the relative competitiveness of different technologies include, amongst others, electricity price volatility, carbon price, government support to renewable energy, and technological progress (Zhang, Zhou and Zhou, 2014, 2016).

One of the theoretical approaches to reflect these uncertainties in decision-making is the real options theory (Blyth *et al.*, 2007). It was originally developed by Black & Scholes (1973) and Merton (1973), to price financial options, with the application later extended to capital investment decisions (Blyth *et al.*, 2007). In their analysis, Dixit and Pindyck (1994) demonstrated the applicability of the real options analysis (ROA), amongst others, to planning investments in the electricity sector. This literature thereby extends the application of Markowitz portfolio theory to real assets, such as power plants, and proposes using value-at-risk and conditional value-at-risk as alternative risk measures to variance (Szolgayová *et al.*, 2011). Besides investments into individual technologies, the real options framework is also applied to portfolios, which may comprise both fossil fuel-based and low-carbon power-generation assets (Fortin *et al.*, 2007; Szolgayová *et al.*, 2011; Min and Chung, 2013; Shahnazari *et al.*, 2014). An investor would seek an optimal composition of their power generation portfolio, to ensure it remains resilient under various, including worst-case, scenarios (Fuss *et al.*, 2012).

The key advantage of ROA over the traditional appraisal methods, such as discounted cash flow and net present value analyses, is its ability to account for the value of delayed

decisions, given uncertainties, and the opportunity cost of waiting, helping estimate the optimal timing for the investor's response to these uncertainties, by eventually taking an investment decision (Shahnazari *et al.*, 2014). As an illustration, an investor considering a costly, long-term, irreversible investment, such as a renewable energy power plant, with an uncertain return due to a number of factors, may prefer delaying their decision until more information becomes available (Shahnazari *et al.*, 2014). As a result, there might be value in waiting, which does come at an opportunity cost of foregoing the income in the meantime (Blyth *et al.*, 2007). This echoes the uncertainty avoidance discussion above in relation to the sources of firms' inaction on long-term challenges such as climate change (Slawinski *et al.*, 2017).

2.2. State of empirical knowledge on the electricity sector's decarbonisation

This section continues the discussion on the changing reality of the power generation sector and its potential to decarbonise, providing a review of relevant empirical literature strands. It focuses on the ability of both individual companies within the power sector as well as of electricity systems as a whole to transition to renewables.

2.2.1. Future of the electricity sector as projected by scenario-based analyses

The potential of the electricity sector to shift to renewables and the pace of this future decarbonisation have been the central focus of a growing body of scenario-based modelling analyses. These studies tend to vary in terms of their geographic coverage[4], methodological approach, temporal scope and the authoring organisation, all of which

[4] Some have a global scope (Rogelj *et al.*, 2011; Kriegler *et al.*, 2013, 2014). Others adopt a regional focus, for example, on Europe (Van Sluisveld *et al.*, 2013), Asia (Calvin *et al.*, 2012), Latina America (Clarke *et al.*, 2016; Di Sbroiavacca *et al.*, 2016; Kober *et al.*, 2016; van der Zwaan *et al.*, 2016; van der Zwaan, Calvin and Clarke, 2016) or Africa (Sanoh *et al.*, 2014; Lucas *et al.*, 2015; Panos *et al.*, 2015; Taliotis *et al.*, 2016; Ouedraogo, 2017a; Trotter and Abdullah, 2018). Some country-level studies also exist (Van Sluisveld *et al.*, 2013; Veysey *et al.*, 2016).

might contribute to the differences in the projections they make (Jaxa-Rozen and Trutnevyte, 2021), as discussed later in this Section.

Yet, despite the heterogeneity in their design, this research has a common objective, which is to inform decision makers about the different trajectories of how the future might unravel, given specific model and scenario assumptions. To this end, this literature offers a wide spectrum of businesses-as-usual and pathways towards specific temperature targets. In doing so, these studies have the potential to support a co-ordinated government and private sector action for a timely achievement of the net-zero transition. This work is also considered important for guiding electrification efforts in the countries experiencing an energy access gap (Trotter, McManus and Maconachie, 2017).

Variations in renewable energy uptake projections

Given the aim of the scenario literature to offer a broad view of potential futures, the extant studies vary considerably in their projections of future renewable energy technology diffusion trajectories (Thimet and Mavromatidis, 2022). According to the estimates of the International Energy Agency (IEA), the shares of wind and solar in electricity generation in 2050 range from 15% to 80% across the existing IPCC scenarios (IEA, 2021b). For solar PV alone, Jaxa-Rozen and Trutnevyte (2021) find that projected generation ranges from zero to over 300 EJ yr-1 across their sample of 1,550 IPCC, non-IPCC peer-reviewed and grey literature scenarios. The divergence of the results is particularly prominent for the near-term horizon of 2030. The authors argue that such variation in projections is not unexpected, given the differences in expert stances on the role of solar PV in the future electricity systems.

Furthermore, looking across the studies predicting the generation mix of specific geographies, there is also a high degree of variation. For example, there is an over 100% spread in the projected share of non-hydro renewable energy in Africa's generation mix for a relatively proximate time horizon of 2030 (IRENA, 2015a; Lucas *et al.*, 2015; Panos *et al.*, 2015; Taliotis *et al.*, 2016; Ouedraogo, 2017a; Trotter, Maconachie and McManus,

2018; IEA, 2019a). Notably, the literature on the upper range of these projections has contributed to a prominent narrative on the continent's ability to leapfrog to renewable energy (Goldemberg, 1998; Gujba *et al.*, 2012; van der Zwaan *et al.*, 2018). This leapfrogging phenomenon is likened to the shift Africa has made to mobile phones, skipping the need to first adopt cord phones and landlines (Aker and Mbiti, 2010). Several of the studies (IRENA, 2015a; Taliotis *et al.*, 2016; Trotter, Maconachie and McManus, 2018; van der Zwaan *et al.*, 2018; IEA, 2019a) project substantial penetration of renewables into Africa's electricity mix in the coming decades, given the falling costs of clean technology (IEA, 2019a) and battery storage (BloombergNEF, 2020), coupled with the continent's abundant renewable energy resources. Yet, given the wide range of the extant projections, there is a lack of consensus on the feasibility of this accelerated transition.

2.2.2. Sources of divergence in the projections of energy and climate models

Differences in assumptions

Although the key role of scenario modelling studies is to offer a wide spectrum of possible futures, rather than a specific prediction, there is a need to better understand the underlying reasons behind such stark afore discussed discrepancies across their results (Jaxa-Rozen and Trutnevyte, 2021). The potential sources of outcome divergence are manifold. First, scenarios as stylised versions of the future (Rogelj, Popp, *et al.*, 2018) inherently rely on assumptions about how this future might unravel, including socio-economic and demographic trends, technological advancements and costs, and policy choices (McCollum *et al.*, 2018; Jaxa-Rozen and Trutnevyte, 2021). The overall timing and ambition of a climate action assumed by a scenario, and the resulting emission peaks and reductions across geographies and sectors, can vary substantially (Weber *et al.*, 2018). Critics argue that model inputs, such as the values of specific parameters, tend to be often selected on an arbitrary basis, yet they can have a dramatic effect on the results

(Pindyck, 2017). For example, scenarios could differ in the importance they attribute to specific technology solutions such as CCUS and bioenergy with carbon capture and storage (BECCS), but also the acceptability of reliance on nuclear power (Weber *et al.*, 2018; Thimet and Mavromatidis, 2022) and gas (Rogelj, Popp, *et al.*, 2018). In view of this, Thimet and Mavromatidis (2022) highlight the importance of transparency in presenting model's key assumptions.

In this context, the models that tend to focus on a long-term end-century temperature and emission targets, without imposing a medium-term cap on emissions, often over-rely on carbon dioxide removal solutions (Rogelj *et al.*, 2019). As a result, they assume the possibility of large-scale deployment of negative emission solutions post-2050, thereby potentially encouraging risky pathways characterised by reduced sense of urgency and delayed policy actions (Dyke et al., 2021). Scholars are working on offering an alternative approach, where scenario design would include an explicit global warming cap throughout the century to better manage inter-generational trade-offs (Rogelj *et al.*, 2019).

Uncertainty around the assumptions feeding into models

Second, besides the differences in the assumptions adopted by various modelling efforts, energy and climate studies are subject to deep uncertainty around the probability of the occurrence of these transition scenarios, and their underlying assumptions (Battiston and Monasterolo, 2021). These studies do tend to offer probability estimates of staying within a specific temperature target. For example, based on their model, Rogelj et al (2013) conclude that implementing a carbon price of USD 20 tCO_2e^{-1} would result in 50% probability of staying below 2°C target, while doubling this price would lead to over 66% probability. However, the estimates of the likelihood that certain model's input parameters will be realised, for example, the adoption of a concrete carbon price or technology cost decline, are not always readily available within scenario analyses (Morgan and Keith, 2008).

As a result, scenario-based studies might be considerably under- or over-forecasting the actual trends taking place in the reality (Creutzig *et al.*, 2017). As an illustration, technology diffusion might depend on a number of factors, including the decline in technology costs, which is a notoriously challenging task to predict. For example, earlier studies have largely underestimated the remarkable fall in clean technology costs and associated growth in renewable energy generation that took place over the past decades (Creutzig *et al.*, 2017). According to the analysis by Creutzig et al (2017), solar PV saw an average annual growth in cumulative installed capacity of 38% between 1998 and 2015, compared to the projections by the IEA in the range of 16% and 30% for 1998 and 2010. Such underestimation is not unique to the IEA with many historical scenarios facing a similar issue. The integrated assessment models feeding into the 2014 IPCC fifth assessment report estimated the 2015 global solar PV deployment at a half of its actual level that year (Creutzig *et al.*, 2017).

Scholars argue that the main sources of this divergence between the projections and actual renewable energy expansion is the underestimation of support policies and technological learning and resulting technology cost decline (Creutzig *et al.*, 2017). Clean technologies have become increasingly more cost-competitive compared to conventional electricity, driven among others by the improvements in efficiency and materials, economies of scale from an increasing plant size (Kavlak, McNerney and Trancik, 2018), US investments, Chinese manufacturing capabilities (Green, 2019), and stark European demand sparked by policies (Nemet, 2019).

At the same time, while in the reality, trends might be steeper than modelled by the scenarios, the real world could also exhibit barriers unaccounted for in the analyses, such as the lack of social acceptance of certain solutions, political and institutional buy-in and global co-operation (Rogelj, Popp, *et al.*, 2018). For example, the decrease in the costs and acceptance of competing technologies such as CCS (Rubin, Davison and Herzog, 2015) and nuclear power (Grubler, 2010) were often overestimated by earlier research.

Present studies aim to better identify and integrate in their projections the key factors that might continue to affect future trends, such as technology costs, over the next decades. This includes the developments in the cost of capital which are considered the key parameter in the calculation of renewable energy levelised cost of energy (LCOE) (Vartiainen *et al.*, 2020). Importantly, scholars are also examining the feasibility and challenges of shifting the global electricity sector fully to clean power over the future decades (Bogdanov *et al.*, 2019; Sinsel, Riemke and Hoffmann, 2020). In their analysis of California and Texas, Arbabzadeh et al. (2019) show that without storage, renewables are able to achieve over 70% carbon emission reductions, compared to no renewables. When some energy storage is added, 90% emission cuts are achievable. From the perspective of required cost improvements in battery storage, Ziegler et al. (2019) estimate that record low storage costs at USD 10-20/kWh would be needed to enable wind and solar power to provide baseload electricity in Massachusetts, Iowa, Texas and Arizona. That said, the authors argue that relaxing electricity availability factor requirement from 100% to 95% would raise storage cost target substantially, resulting in as much as nearly a 50% cut in the levelised cost of shaped electricity (LCOSE). LCOSE refers here to cost estimates that take into account the location, technology costs, the combination of solar and wind power in a system and output shape.

That said, the use of some of the reserved assumptions continues (Creutzig *et al.*, 2017), together with the lack of estimates of the uncertainties associated with these assumptions. The main challenge here remains the ability of scenario studies to sufficiently deviate from the past trends (Jaxa-Rozen and Trutnevyte, 2021), anticipating technological or policy disruptions. At the same time, these studies need to produce robust validated models that stay within the feasibility boundaries and account for the potential path dependency in such factors as environmental policies.

Model-related factors beyond assumptions

Third, scenario parameters aside, a concrete model, its structure and algorithm (McCollum *et al.*, 2018) used in an analysis can have an impact on the results even under similar assumptions (Pindyck, 2017). The models used in scenario studies range from recursive-dynamic partial equilibrium models to intertemporal optimisation general equilibrium models (Lucas *et al.*, 2015; McCollum *et al.*, 2018). Nevertheless, the differences stemming from the choice of a model are arguably smaller compared to the impact of using divergent values for model assumptions (Pindyck, 2017).

Finally, the type of the organisation producing a projection can also matter for the results. In their analysis, Jaxa-Rozen and Trutnevyte (2021) establish that IPCC scenarios are relatively more pessimistic in their projections of solar power adoption compared to non-IPCC work. The authors explicate that the former tend to consistently project higher capital costs and thereby lower levels of solar power penetration compared to other assessments. It is also thought that the optimism of a scenario author, for example, regarding the adoption of a certain policy or the magnitude of technology cost decline, and even the time when the analysis was conducted, might affect the assumptions and in turn the projections of the whole study (Pindyck, 2017; Jaxa-Rozen and Trutnevyte, 2021).

Along with academic research, influential international organisations also regularly release energy projections for various geographies. For example, the International Renewable Energy Agency (IRENA) has offered a number of global, regional and country-specific outlooks for renewable energy adoption (IRENA, 2015b, 2018, 2020), technology innovation (IRENA, 2016) and the energy transition more generally (IRENA, 2021). The Organisation for Economic Co-operation and Development (OECD) has also produced flagship analyses on climate-compatible economic growth (OECD, 2017). Similarly, the IEA publishes annual World Energy Outlooks (IEA, 2020d). While the IEA specifically has been found to consistently under-forecast the magnitude of renewable energy cost decline taking place over the past years as mentioned above (Creutzig *et al.*, 2017), its recent *Net Zero by 2050* report offered a radical decarbonisation pathway (IEA, 2021b). The NZE

Scenario presented in the report differs from the extant literature across multiple fronts. For example, the share of solar and wind stands at 70% of generation in 2050, compared to the 50% median across IPCC scenarios (IEA, 2021b). At the same time, the NZE Scenario's projected use of fossil fuels is lower, standing at 120 EJ compared to 155 EJ by IPCC scenarios. The reliance of the NZE Scenario on CCUS in 2050 is half of the median level of 15 Gt CO_2 across IPCC studies. Similarly, the projected use of CO_2 removal technologies is half of the lower end of the projections range of the IPCC scenarios, that is 1.9 Gt CO_2 compared to 3.5 Gt CO_2 to 16 Gt CO_2 in 2050.

Furthermore, energy models have become a widespread strategic decision tool also among major energy companies (BP, 2020; Equinor, 2020; Total, 2020; Shell Global, 2021). Being popularised in the 1970s by Shell (Heiligtag, Maurenbrecher and Niemann, 2017), these analyses help companies stress test their business models, by introducing policy and commodity or technology price shocks, and thereby plan ahead for different futures (Weber *et al.*, 2018). However, the projections by oil and gas companies have been associated with more optimistic results in terms of future fossil fuel demand and conservative projections of renewables uptake (Carrington and Stephenson, 2018). At the same time, environmental organisations, such as Greenpeace, tend to produce considerably greener scenarios, compared to fossil-fuel firms, with the projected CO_2 emissions being of several orders of magnitude lower (Carrington and Stephenson, 2018).

2.2.3. Challenges to measuring climate-related risks

One of the potential reasons for climate and energy analyses often lacking uncertainty estimates of the parameters feeding into their models, as discussed in the previous Section 2.2.2, are the challenges associated with the assessment of climate-related physical and transition risks. As a result, examining company, investor or the whole country's exposure to these risks is subject to significant difficulties. These risks tend to follow fat-tailed rather than normal probability distributions, being fraught with deep uncertainties, nonlinearity and extreme outliers (Bolton, Foxon and Hall, 2015). For

example, the assessment of a climate policy risk requires estimating the likelihood that a specific policy will be adopted, which in turn could be subject to a bias, arising from the expectations of an agent making the prediction (Battiston *et al.*, 2017). An important consideration here is also the potential path dependency of climate policies on the one hand (Bolton *et al.*, 2020), and the possibility of a rapid policy breakthrough on the other. Another challenge to assessing climate risks is the lack of historical data that would contain relevant information on the realisation of physical or transition risks (Cosemans, Hut and van Dijk, 2021). Some scholars argue that it might not even be possible to accurately estimate the uncertainties around the model parameters, given that the correct probability distributions of specific events, such as climate change-induced natural disasters, taking place might be unknown (Pindyck, 2017).

Furthermore, transition risks are characterised by endogeneity and mutually amplifying interactions between their different components. For example, climate policy can bring about or intensify technological innovation, while the response of the financial system to risks can amplify the magnitude of these risks (Chenet, Ryan-Collins and van Lerven, 2019). As a result, these factors pose a challenge to predicting the timing of these risks' occurrence and their scale. Yet, against the backdrop of these intrinsic uncertainties, one thing is rather certain. A degree of climate-related physical and transition risks will inevitably materialise in the future (NGFS, 2019).

As a result, the academic community continues seeking empirical and theoretical approaches to estimate climate risks and address the uncertainty associated with their realisation. Cosemans et al. (2021) develop a novel approach to estimating the impact of climate change on equity risk and portfolio allocation in the long term. Recognising that historical data might not contain sufficient information on the physical risks associated with climate change, the authors complement these data with a theoretical model on the impact of a temperature rise on asset prices. To this end, they make use of a Bayesian approach, where in addition to the data, investors have a prior theoretical knowledge of climate

change effects. As a result, this approach outperforms a purely data-based model, thereby providing evidence of the difficulty to measure climate risks based solely on the data, while at the same time proposing an alternative solution. Such innovative approaches help to strengthen the quality of the outputs and relevance of climate and energy models for decision makers including in the financial sector, informing their efforts to accurately anticipate and address climate risks (Section 2.2.4).

2.2.4. Relevance of scenario modelling beyond the policy community

Scenario-based climate and energy models can offer useful insights on company potential exposure to climate-related physical and transition risks. Considerations on emission trajectories are particularly important, as they could change the risk profiles of long-term capital investments, such as power plants. For instance, a delayed climate action and later emission peaks would imply a relatively lower risk associated with carbon-intensive investments in the short term (Rogelj *et al.*, 2019). However, such inaction would be fraught with a disorderly more stringent policy response later in the century when accelerated emission cuts are required to meet the temperature target (Luderer *et al.*, 2013; Rogelj, Popp, *et al.*, 2018).

Yet, deriving estimates of climate-related transition risks from the myriad of extant energy scenarios is challenging. Climate models were originally designed with the policy and planning communities in mind, and therefore might be ill-adapted to serve the needs of business use cases, such as the calculation of transition risks (Clapp and Sillmann, 2019). Key challenges include the following aspects. First, policy makers and the private sector operate at different temporal horizons. While climate scenario models project emission trajectories decades into the future (Clapp and Sillmann, 2019), thereby suiting policy cycles which tend to run over 10 to 20-year, business cycles are significantly shorter. For example, the investment horizon for some fund managers is three months (Battiston et al., 2019).

Second, the outputs of climate models might not always offer the granularity, for example, at the sector or market level, required to assess company transition risks (Weber *et al.*, 2018). Third, the assumptions that feed into the model might also not reflect the considerations that are important from a company perspective. This includes the assumptions on sector-specific policy constraints, production and capital stock additions and retirements, and technology and fuels costs (Weber *et al.*, 2018). Furthermore, the difficulty to measure the uncertainties around these parameters, such as climate-related physical and transition risks, poses a challenge to pricing in and hedging these risks (Battiston and Monasterolo, 2021). Fourth, scenario models aim to find a solution to an optimisation problem, that is meeting emission reduction goals at the lowest cost, which implies an orderly policy action. On the contrary, investors and corporates would be concerned with policy and technological shocks that are not yet priced in by the market (O'Neill *et al.*, 2020; Battiston and Monasterolo, 2021).

Finally, the afore-discussed uncertainty around the assumptions feeding into energy and climate models might impede their use among investors and corporates. Battiston and Monasterolo (2021) investigate the sensitivity of investor probability of default and expected shortfall to the probability of occurrence of different climate transition scenarios. They focus specifically on the probability of disorderly scenarios, which are most high risk and therefore need to be carefully considered in investment decisions to avoid underestimating the risk and losses involved. The authors demonstrate that the assumptions feeding into climate models and the probability of occurrence of the transition scenarios are of central importance for investor risk management.

2.2.5. The impact of policies on renewable energy deployment

The importance of policies for a successful climate action is widely recognised. Environmental policies are among key considerations of the power sector's decarbonisation both in terms of making projections of the industry's transition in the future as well as its progress to date. With the adoption of environmental policies being on a rise,

particularly across the developed world[5], literature on their effectiveness is also growing. There are ample studies examining and comparing how environmental policies support finance mobilisation and renewable energy deployment. Single-country or small-sample studies seem to prevail, with the focus being on advanced economies (Polzin *et al.*, 2019), the US, EU or OECD more broadly (Jenner, Groba and Indvik, 2013; Zhao, Tang and Wang, 2013; Polzin *et al.*, 2015; García-Álvarez, Cabeza-García and Soares, 2017). Some scholars explore policy effectiveness in developing country contexts (Surana and Anadon, 2015; Carley *et al.*, 2017).

In terms of specific policies examined, feed-in-tariffs and renewable energy quotas, such the adoption of renewable portfolio standards (RPS) across the US states (Carley, 2009; Shrimali and Kniefel, 2011), clearly dominate this literature (Polzin *et al.*, 2019). Fewer researchers have explored the impact of fossil-fuel-inhibiting policies on renewable energy uptake (Best and Burke, 2018). Policies that are aimed to disincentivise investments into fossil fuels, such as carbon pricing, tend to catch researchers' attention in terms of their effectiveness at reducing emissions rather than as part of a comprehensive climate policy mix. That said, some scholars do explicitly discuss the benefits of combining different policies (Lauber, 2004; Rogge and Reichardt, 2016; Baldwin *et al.*, 2017), including renewables-promoting and fossil-fuel-inhibiting instruments (Zhou, Wang and McCalley, 2011; Polzin *et al.*, 2015; Tvinnereim and Mehling, 2018). Zhou et al. (2011) propose a bilevel optimisation approach to designing both effective and efficient policies, positing that policy mixes combining renewable energy subsidies with carbon tax could result in higher efficiencies. Interestingly, based on the findings of a stylised model, Schmalensee (2012) concludes that over the long-term the social risk, measured as the cost of serving the fixed load, would be higher under feed-in-tariffs than RPS. The author explains this by

[5] Around 80% of high- and upper-middle-income countries had some sort of renewable energy promoting policy in place in 2018 (Polzin *et al.*, 2019).

the fact that while feed-in-tariffs remove the price fluctuation risk for an investor, the risk remains in the system being passed on to other actors who pay for this subsidy.

Yet, there is a lack of consensus in this literature on what an optimal policy environment and mix for renewable energy adoption could look like (Foxon and Pearson, 2007; del Río and Bleda, 2012; Polzin *et al.*, 2015; Rogge, Kern and Howlett, 2017). This could be partly due to the paucity of conclusive evidence on the overall effectiveness of renewable energy schemes (Polzin *et al.*, 2019), with scholars often reporting different effects depending on specific policy and technology type (Zhao, Tang and Wang, 2013). Similarly, despite the overall recognition of carbon pricing mechanisms as an integral part of a climate action, according to a recent assessment, hard evidence on their effectiveness remains sparse and is mostly limited to Europe (Green, 2021). In this context, country economic development might also be an important consideration here. Romano et al. (2017) posit that countries might need different policy interventions depending on their level of development. Furthermore, Zhao et al. (2013) find that policy impact is more pronounced in developed and emerging economies than in developing countries. Determining the most favourable policy environment for the energy transition might be further challenged by shifts in policy trends. For example, as renewable energy technologies are becoming increasingly more cost-competitive, governments are starting to reduce feed-in-tariffs, which prompts scholars to examine alternative instruments to support renewable energy deployment, such as green electricity tariffs (MacDonald and Eyre, 2018).

Implications of policy design and stringency

Besides the impact of adopting a specific policy instrument, some studies have dwelled upon the issues relating to policy design and stringency (Yin and Powers, 2010; Fischlein and Smith, 2013; Carley *et al.*, 2018). For example, Carley et al. (2018) find that more stringent RPS policies across US states do result in overall more renewable energy development, although other policy design factors might also matter. In this context, their results point to the frequency of planning activities being important for renewable energy

uptake, while the practice to count energy efficiency towards the RPS mandate could lower the effect of policy. The granularity of these findings concerning policy implementation highlights the importance of focusing research on the design rather than the mere existence of a specific policy instrument.

In this regard, particularly important is the work on policy failures to understand the reasons for slow renewable energy adoption. In their review of 50 case studies of renewable energy diffusion, Negro et al. (2012) identified as major factors the uncertainty around subsidy policies, such as delayed implementation, reduction in the pre-announced tariffs or their unexpected termination, or misalignment between policies at different government levels and across different sectors. This ambiguity can erode trust between the government and the private sector, resulting in the unwillingness of corporates and investors to take on the risks linked to renewable energy deployment. This echoes the discussion on the challenges around measuring climate-related transition risk, particularly in relation to policies (Section 2.2.3), and the debate on decision making under uncertainty and the associated benefits of delaying investment until ambiguity decreases (Section 2.1.7). Relatedly, Lanshina et al. (2018) attribute slow renewable energy deployment in Russia to drawbacks in the policy framework. They find that in Russia wind power is the second cheapest after natural gas, with the LCOE of both wind and solar PV being overall comparable to that of new conventional power generation. Yet, renewable energy adoption remains limited.

Risk-profile of renewable energy projects

Relatedly, a distinct strand of literature focuses on the impact of policies on risk-return profile of renewable energy projects as a central consideration of investment decisions (Klessmann *et al.*, 2013; Waissbein *et al.*, 2013; Schmidt, 2014; Polzin *et al.*, 2019). De-risking low-carbon investments and increasing their returns are thus two potential levers for policies to attract private investments into low-carbon projects (Schmidt, 2014). In their review of 96 empirical studies, Polzin et al. (2019) find that an effective policy would

simultaneously reduce risk while increasing returns of renewable energy projects. Particularly, policy credibility and predictability can have a considerable impact on risks.

In this context, it is important to consider the fact that renewable energy technologies have significantly different investment profiles from conventional power plants. Solar and wind projects are free from some inherent risks of fossil-fuel power plants, such as fuel fluctuations and transition risks (Awerbuch, 2000; Helms, Salm and Wüstenhagen, 2015). Operational costs are also lower, given limited maintenance requirements (Schleicher-Tappeser, 2012). The relatively smaller scale of renewable energy plants offers diversification opportunities to investors, while modularity and scalability reduces excess capacity risks (Awerbuch, 2000). Yet, these lower risks associated with renewable energy projects might not always be adequately recognised by investors, especially when a blanket company-wide cost of capital is applied (Helms, Salm and Wüstenhagen, 2015). At the same time, renewable energy technologies might face other risks. In this regard, although the risks associated with changes in policies or technological advancements have become relatively less important, research has found that price fluctuation or curtailment risks associated with grid bottlenecks have increased in their significance (Egli, 2020).

2.2.6. Pressures on electric utilities' value proposition and business models

As the power sector is undergoing transformation, the academic debate is starting to turn to considerations of whether they will be losers or winners in this transition (Kelsey and Meckling, 2018). This echoes the focus of theoretical literature on the role of different companies in driving and embracing innovation (Section 2.1). Traditional electric utilities, that are characterised by fossil-fuel-dominated asset base, face increasing competition from the new entrants into the energy market, and the technologies and business models they bring (Hannon, Foxon and Gale, 2013; Hall and Roelich, 2016; Wainstein and Bumpus, 2016; Midttun and Piccini, 2017). There is a growing academic discussion on

the potential implications the changing reality of the power sector, characterised by the rise of clean (Hall and Roelich, 2016; Pollitt and Anaya, 2016; Castaneda, Franco and Dyner, 2017) and smart technologies (Shomali and Pinkse, 2016; Midttun and Piccini, 2017) might have for the fossil fuel-based generation business. Research has found that the valuations of conventional power plants have fallen, thereby reducing equity value of the companies holding them, while debt-to-equity of utilities has seen a 6.5 percentage point increase between 2005 and 2015 (May and Neuhoff, 2021). This is possibly due to the decreasing cost of debt, write-downs of fossil fuel power plants and overall increasing competition in the market (May & Neuhoff, 2017).

Besides price competition and different risk profiles, renewable energy brings new customer-focused solutions (Midttun and Piccini, 2017), such as decentralised generation, which blur the traditional roles of electricity producers and consumers. As a result, new approaches have emerged, such as prosumer models where consumers seize the opportunity to simultaneously act as producers of electricity (Richter, 2012; Bryant, Straker and Wrigley, 2018).

Furthermore, business models are also evolving seeking, besides the decarbonisation of the power mix, to also address the need for improved energy efficiency, and the security and affordability of the energy provision (Hall and Roelich, 2016). A traditional utility model is based on the key relationship between the number of power units sold and their cost (Midttun and Piccini, 2017), whereby a competitive advantage is achieved through cost reduction with the increased scale of production. Therefore, promoting energy efficiency or decentralised power generation might not be in the best interest of these companies, given that continued consumer demand is at the core of their business model (Richter, 2012). As a result, efforts have been undertaken to decouple value propositions from the mere units of power sold, which has put the value proposition of conventional utilities at risk. For example, energy service companies that focus on the provision of a service, e.g. heating or lighting, rather than volume of energy, have the potential to achieve the triple

objective of low-carbon, efficient and low-cost energy (Hannon, Foxon and Gale, 2013). Energy efficiency in general should be thought of as an integral part of the decarbonisation of the power sector, given that the associated electrification of heating and transport will result in large energy savings (Eyre, 2021).

2.2.7. Factors affecting company renewable energy adoption

In response to these challenges, literature has emerged exploring how companies, particularly incumbent firms such as utilities, might respond to adapt (Weinhofer and Hoffmann, 2010). There is a growing body of research discussing business models and strategies for utilities to remain competitive in the context of shifting their portfolios to renewable energy (Richter, 2012, 2013; Kungl, 2015; Hall and Roelich, 2016; Löbbe and Jochum, 2016; Nillesen and Pollitt, 2016; Wainstein and Bumpus, 2016; Kungl and Geels, 2018; Patala *et al.*, 2021). In this context, scholars stress the importance of recognising and acting fast upon climate-related transition risks, particularly asset stranding. In their analysis of 29 European utilities, Hickey et al. (2020) find that immediate re-direction of cashflows to replace stranded generation capacity would have a limited effect on utility credit ratings, with a small proportion of companies affected. A delayed action, however, may lead to a speculative grade of a higher number of the utilities they examined.

The key challenge is, however, the pace at which utilities would be able to replace the existing infrastructure by new low-carbon power-generation assets to remain competitive (Richter, 2012). Emerging evidence points to electric utilities starting to integrate renewable energy into their portfolios (Frei *et al.*, 2018). Nevertheless, this process appears to be slow (Kelsey and Meckling, 2018).

Utilities' risk-return appetite

An important factor in the discussion on the speed at which a company might embrace renewables is the consideration that the risk-return profiles associated with renewable energy investments varies considerably depending on the type of investor. In their case

studies of Germany, Switzerland and Italy, Karneyeva and Wüstenhagen (2017) highlight the differences in the cost of capital incurred by various investors as one possible factor contributing to the varying appetite for renewable energy projects. The authors argue that the relatively higher cost of capital incurred by publicly listed utilities means that they are more attracted to higher-return projects than renewable energy plants. This could thereby contribute to the explanation of their limited participation in solar PV investments compared to, for example, institutional investors. Similarly, Helms et al. (2015) state that companies like utilities, that have historically been characterised by high risk and high return investments, might reject lower-return but also lower-risk renewable energy projects (Helms, Salm and Wüstenhagen, 2015). Opting for higher-risk fossil fuel projects would, however, increase the risk exposure of their overall portfolios.

In view of this, it is important to capture the complexity and heterogeneity of the renewable energy investor landscape (Bergek, Mignon and Sundberg, 2013), ranging from utility companies and independent power producers, to institutional investors and retail consumers. Notably, among these actors, the utility sector itself is also far from being homogeneous, comprising besides large international companies, also smaller national and municipal utilities (Schleicher-Tappeser, 2012). The ownership of utility companies also varies from state- to investor-owned entities, which might in turn have an effect on their ability to diversify into renewable energy (Steffen, Karplus and Schmidt, 2020).

Policy impact on companies' low-carbon transition

Relatedly, within the broader policy literature discussed in Section 2.2.5, some studies have explored technology diffusion specifically from a company angle, with the granularity of the conclusions they offer having a potentially important value for future policy design. For example, Delmas and Montes-Sancho (2011) examine the effectiveness of RPS and mandatory green power option (MGPO) for expanding renewable energy capacity in the US. The authors find that MGPO has a considerable impact on renewable energy adoption by all utilities. At the same time, investor-owned utilities tend to respond more positively

to RPS, although the overall impact of the policy instrument is negative. This highlights the importance of capturing the heterogeneity of utility landscape in the analysis, including their ownership, as mentioned above, echoing also the theoretical discussion in Section 2.1.4.

Furthermore, in the analysis of 50 vertically integrated utilities globally, Choi (2019) finds that compared to regulatory policy instruments, economic incentives are more effective at promoting utilities' investment into solar and wind power plants. On a somewhat related discussion, Yi and Feiock (2014) explore, among other factors, the impact of carbon-intensity of utility companies on renewable energy deployment across the US states, although they are not able to prove the significance of this effect.

Few researchers have also explored the interplay between policies and other factors, such as market competition, that might affect renewable energy investments by companies. For example, Weigelt and Shittu (2016) examine the interaction between RPS and competition in the context of electric firms' investments in the US. They find that while competitor's investments in renewables have a positive effect on a given firm's investment, regulatory policies tend to dampen this impact. This effect is stronger the more different the new resource is from the incumbent's existing asset base.

Shifting away from generation business

The extent to which individual utilities will be affected by the power sector's transition, besides the speed at which they could embrace renewables, would also depend on their coverage of the electricity value chain. Large multi-national electricity companies tend to be active in different parts of the value chain, while smaller companies might focus on distribution and retail (Richter, 2012). Although the challenges exist along the entire value chain (Richter, 2012; Bryant, Straker and Wrigley, 2018), changes in power generation and retail can be particularly substantial.

As a result, in addition to portfolio decarbonisation, researchers also explore the ability of utilities to participate in the low-carbon transition through activities beyond power generation, for example, through business model innovation (Richter, 2012), shifting towards service provision, the so-called servitisation (Helms, 2016). This includes, among others, electrifying heat and transport (Hall *et al.*, 2021), providing energy efficiency services (Apajalahti, Lovio and Heiskanen, 2015), facilitating decentralised and peer-to-peer prosumer solutions (Bryant, Straker and Wrigley, 2018; Hall *et al.*, 2021), and system integration and balancing (Frei *et al.*, 2018). That said, recent evidence from the UK points to consumer appetite for new utilities' business models in power provision being limited to relatively more affluent and educated homeowners' segments, posing a risk to exacerbate social inequalities (Hall *et al.*, 2021). Furthermore, research indicates that utilities might be less prone to embracing decentralised and system integration solutions (Frei *et al.*, 2018).

2.2.8. Asset-level approaches for the energy transition research

As highlighted throughout this Chapter 2, a central consideration in the debate on the energy transition of the power sector is the ability to adequately assess and respond to climate-related risks, both from the perspective of whole countries as well as individual investors and companies. A key challenge here, as touched upon in Section 2.2.3, is the availability of quality data which would allow conducting granular analyses of the sector's progress to date and projecting potential future pathways, along with the risks associated with different outcomes. In this context, scholars highlight the value of using granular datasets comprising detailed information on corporate assets, including physical capital assets, for example, power plants, mines or industrial production facilities (Caldecott, Dericks, *et al.*, 2018). Understanding where and what type of assets are located is particularly pertinent for examining both climate-related physical and transition risks associated with their ownership and operation (Carter and Christiaen, 2021).

Asset-level data have a number of advantages, offering new opportunities for research. First, such datasets allow adopting bottom-up approaches to tracking the economy's decarbonisation progress at different levels of aggregation, from a single company in a specific country and sector, to global studies (Caldecott, Dericks, *et al.*, 2018). As a result, rather than relying on aggregate company data often available at the parent company level only, asset-level datasets offer a transparent, standardised and granular lens through which to examine companies' performance. Second, built through a variety of sources, not limited to corporate disclosures, but also including third-party data collection and remote sensing, asset-level datasets help to overcome data gaps. Relatedly, asset-level data with global coverage are already available for several sectors, such as power generation, and oil and gas fields (Weber *et al.*, 2017). This allows conducting analyses on under-researched geographies, such as developing countries, including African economies, for which data are often fragmented or non-existent. Finally, detailed information on asset characteristics enables scholars to answer a multitude of research questions, both about the company's current transition progress as well as future decarbonisation pathways (Weber *et al.*, 2017). For example, particularly indicative of a company's potential for, and a commitment to, a low-carbon future are the age and technology breakdown of its assets and their operation status, such as retired or cancelled versus planned capital projects. Furthermore, quality asset-level data could also offer innovative solutions to tracking greenhouse gas (GHG) emissions, including Scope 3 which currently poses a major challenge to assessing firms' and investors' exposure to climate-related risks throughout the supply chains (Caldecott, Kruitwagen, *et al.*, 2018).

Recognising the merits of asset-level data and the contribution they can make to the energy transition research, significant efforts are under way to collect the information and improve its quality. A recent study by Kruitwagen et al. (2021) was able to capture every larger solar power plant on the planet using remote sensing and machine learning. Furthermore, also relying on machine learning techniques, the GeoAsset Project by the

Spatial Finance Initiative as part of the UK Centre for Greening Finance and Investment aims to make asset-level data for several key sectors, such as cement and iron and steel production, available as a public good (Spatial Finance Initiative, 2021).

2.3. Reflections on empirical literature and research gaps

Further to the conceptual framing to this thesis offered by the review of the theoretical literature as discussed in Section 2.1, this section highlights the central areas in the empirical energy transition research meriting further attention and how this DPhil thesis has contributed to addressing them. This discussion aims to provide a broader overview of the literature gaps beyond the condensed detail offered in the introductory sections of Chapters 3, 4 and 5, published as research articles.

2.3.1. The integration of predictive analytics in energy planning research

While the empirical literature on the electricity sector's low-carbon transition has seen substantial growth along its various strands over the past years, as discussed in Section 2.2, several gaps remain, particularly in understanding the barriers to the power sector's decarbonisation. To start with, what is still largely missing in the energy-planning research, thereby limiting the ability to better predict and prepare for the future, is an evidence-based, data-driven approach to estimating where vis-à-vis scenario-modelled futures a given electricity sector is realistically heading. As reviewed in Section 2.2.1, the results of the extant energy studies tend to vary substantially in both the scale and composition of the installed capacity and generation they project and that even for relatively proximate timeframes. While this is not a shortcoming *per se*, given that scenario literature aims to offer a perspective on a wide array of futures, this research tends to underestimate the importance of assessing the *feasibility* of certain scenarios (McCollum, 2021). This is the case particularly for the realisation likelihood of the different assumptions which feed into the analyses and can substantially affect their results, as discussed earlier in this Chapter in Section 2.2.2. As a result, critics argue that rather than offering a broad spectrum of

possible outcomes, not assigning probabilities to different scenarios might result in some potential futures being altogether overlooked (Morgan and Keith, 2008).

In this regard, one of the important considerations is the probability of a power plant currently being planned to be eventually realised, given that delays and even cancellations of planned power-generation projects are not uncommon. Possibility of such adverse events may in turn contribute to the risk profile of a planned power-generation project, which is particularly widespread in developing countries (Waissbein *et al.*, 2013; Schmidt, 2014). This is a crucial, yet largely overlooked, area in the current energy models, despite the fact that detailed project-level data with a number of crucial advantages are already available for the power-generation sector, as discussed in Section 2.2.8. There is a lack of consideration given to project-level factors also in wider energy research, including on electrification or end-user consumption, as this work tends to be mostly focused on country-level characteristics (Ahlborg et al., 2015; Trotter, 2016). Furthermore, the current energy models do not fully account for the potential frictions that energy systems are prone to in their transitions (McCollum, 2021), which is on the contrary well recognised in the theoretical literature as discussed earlier in this Chapter (Section 2.1). Critics also argue that climate models mostly serve the needs of the policy makers, with their outputs being ill-suited to the information required, for example, by the investment and financial communities, which are mostly concerned with microeconomic questions at the firm and individual project level (Section 2.2.4). It is therefore important to find granular modelling approaches that would help reconcile climate and energy scenario models with the needs of business use cases.

To contribute to bridging these research gaps in the energy transition research, this thesis develops in Chapter 3 an original empirical approach to predicting future capacity mix of a given electricity sector. The study builds a high-accuracy machine-learning-based model, to predict the probability of currently planned power plants being successfully implemented this decade. To this end, the analysis applies the model to an asset-level

dataset containing information on the characteristics of individual operating, failed and planned power plants, coupled with the socio-economic indicators of the countries where those plants are located. This study focuses specifically on African economies, given that the energy-planning literature on developing countries remains sparce, including due to data availability challenges (Ouedraogo, 2017c). At the same time, the extant analyses predominantly focused on the developed world has been subject to criticism for the applicability of these approaches to examining often unique contexts and challenges of developing countries (Ouedraogo, 2017c), also raised in the theoretical literature discussion in Section 2.1.3.

2.3.2. The value of company perspective in the energy transition literature

Conducting energy transition research through the prism of individual companies is essential. Predicting and adequately preparing for possible futures of the power-generation sector requires in-depth granular understanding of the electricity sector's ongoing energy transition patterns also from a company perspective. Recognising this, among the factors explored in the study presented in Chapter 3 is the effect of ownership on power plant realisation chances, be it, for example, state or IPP-owned projects. This is an important consideration in view of the theoretical discussion in Section 2.1.4 on the implications of company ownership for the power sector's decarbonisation.

Furthermore, Chapters 4 and 5 of this thesis dwell in detail on electric companies' transition and factors contributing to these trends. In this context, particularly important is to examine the ability of individual companies to adapt to the changing reality of the power-generation sector, assessing potential frictions they might experience in this process. As discussed earlier, the electricity sector might be subject to considerable inertia resulting, among others, from an infrastructural lock-in (Section 2.1.6). The review of the theoretical literature (Section 2.1.1. and 2.1.2) has pointed to the importance of investigating this question from the perspective of industry incumbents, such as utility companies. Specifically, innovation and systems transition scholars highlight the varying ability of

incumbent companies vis-à-vis new market entrants in adapting to and benefitting from fundamental economic transformations.

In view of this, the extant empirical research has focused on the pressures that new entrants exert on the existing electric companies. With the evidence emerging that utilities are becoming aware of these risks (Bryant, Straker and Wrigley, 2018), scholars have initiated a discussion on portfolio decarbonisation among the options for utilities to remain competitive (Richter, 2013; Frei *et al.*, 2018; Bryant, Straker and Wrigley, 2019). However, few studies have explicitly taken stock of the pace of utilities' transition and that for a limited number of companies (Frei *et al.*, 2018; Kelsey and Meckling, 2018). Again, the significant potential of asset-level datasets to answer several important research questions on companies' decarbonisation patterns, as discussed in Section 2.2.8, is largely unexploited in this strand of literature. The bulk of academic research on electric companies' transition tends to rely on qualitative data and research methods. Consequently, while offering valuable insights into the strategies of individual companies, being often narrow in sample size and geographic coverage, this research sheds limited light upon the utility sector's transition globally. Therefore, less is known about the efforts of utility companies beyond a handful of large well-known actors to shift their portfolios towards low-carbon power generation.

Against this backdrop, there is an on-going and potentially misleading discussion in the media of utilities 'leading the energy transition' (Porter, 2021), coupled with the public announcements of companies' commitments to decarbonisation (Meyer, 2020). Yet, given the lack of a comprehensive analysis of the track record and on-going progress of these companies to embrace the decarbonisation process and decisively shift away from fossil fuels, there is limited certainty about the credibility and realisation of these pledges.

Given these limitations in the current literature, there is thus a need for a comprehensive holistic analysis with a global scope which would also capture the heterogeneity of the power sector and its transition patterns, when assessing the sector's progress to date in

embracing renewable energy. This could be achieved through empirical research that would draw on large global asset-level datasets and employ quantitative advanced analytics methods to capture the complex nature of the electricity sector's transition. This would also help to identify potential disparities in the transitions of companies across different geographies, with various structures of electricity markets and level of economic development.

The energy transition literature would also benefit from further work focusing on the factors underlying electric companies' shift to renewables. Although both theoretical and empirical literature emphasise the importance of company perspective in the debate on the power sector's decarbonisation, empirical quantitative research on factors affecting electric companies' transition is not yet well established. As discussed earlier in this chapter, the bulk of the current research focuses on how individual policy instruments might affect the uptake of renewables by the power sector as a whole. A small sub-set of this work explicitly examines the ways in which individual companies, mostly utilities, respond to such drivers as environmental policies, with even fewer studies incorporating other potentially important factors, such as electricity sector's market structure (Weigelt and Shittu, 2016) and company type (Patala *et al.*, 2021). There is also paucity of studies focusing on the differences in the transition behaviours of utilities compared to IPPs (Kelsey and Meckling, 2018).

Furthermore, the energy transition research, both on companies' decarbonisation patterns and their underlying factors, should not only focus on the shift *to* renewables, but also *away from* fossil fuels. Despite the increasing penetration of renewables in the global generation mix, consumption of carbon-intensive power, including from coal, continues to grow in some geographies. After the temporary decline during 2020, the demand for coal is expected to see a rebound in 2021 outstripping its 2019 level (IEA, 2021a). This increase is driven by the power sector and the expansion of coal capacity in Asia. That said, the present literature tends to predominantly explore the uptake of renewables by

companies or electricity sectors, overlooking the importance of capturing how the same factors might affect in a similar or different ways growth also in fossil fuels.

As a result, it is important that the research approaches adopted are sufficiently flexible, enabling scholars to perform holistic, yet granular, analyses to capture the nuances and complexity of electric companies' decarbonisation. Examining the dynamic growth of companies along multiple technologies at the same time requires the use of tools able to capture this complexity. Models with a single dependent variable measuring, for example, renewable energy uptake, might not necessarily yield conclusive results when it comes to capturing the factors that might in a similar or different way affect the parallel expansion in fossil fuel capacity. Furthermore, the extant literature tends to rely on methods that are able to model mostly linear relationships, while in the reality, effects at play might be much more complex (Bolton *et al.*, 2020).

To this end, this thesis aims to contribute to bridging both content and methodological gaps in the extant literature on the energy transition of electric companies. Consequently, Chapter 4 conducts a large-scale analysis of utilities' transition worldwide over nearly two decades, applying a machine-learning-based clustering analysis to a large dataset of power plants globally. As a result, this study devises patterns of utility companies' portfolio expansion decisions offering a systematic account of the complex landscape of the global utility sector. Chapter 5 complements this work by zooming in on the factors that might affect the different patterns and pace of utilities' energy transition vis-à-vis that of IPPs. Informed by the extant literature on the drivers that might contribute to companies' transition, particularly the theoretical debate on the role of incumbents in liberalising power markets (Section 2.1.4), the study includes besides the policy instruments, such as renewable energy subsidies and fossil fuel disincentives, also market-structure-related characteristics.

Chapter 3. A machine-learning approach to predicting Africa's electricity mix based on planned power plants and their chances of success

Reproduced with permission from Springer Nature.
This Chapter 3 was published as: Alova, G., Trotter, P.A. & Money, A. A machine-learning approach to predicting Africa's electricity mix based on planned power plants and their chances of success. *Nat Energy* **6**, 158–166 (2021). https://doi.org/10.1038/s41560-020-00755-9

ARTICLES
https://doi.org/10.1038/s41560-020-00755-9
nature energy

Check for updates

A machine-learning approach to predicting Africa's electricity mix based on planned power plants and their chances of success

Galina Alova[1]✉, Philipp A. Trotter[1,2] and Alex Money[1]

Energy scenarios, relying on wide-ranging assumptions about the future, do not always adequately reflect the lock-in risks caused by planned power-generation projects and the uncertainty around their chances of realization. In this study we built a machine-learning model that demonstrates high accuracy in predicting power-generation project failure and success using the largest dataset on historic and planned power plants available for Africa, combined with country-level characteristics. We found that the most relevant factors for successful commissioning of past projects are at plant level: capacity, fuel, ownership and connection type. We applied the trained model to predict the realization of the current project pipeline. Contrary to rapid transition scenarios, our results show that the share of non-hydro renewables in electricity generation is likely to remain below 10% in 2030, despite total generation more than doubling. These findings point to high carbon lock-in risks for Africa, unless a rapid decarbonization shock occurs leading to large-scale cancellation of the fossil fuel plants currently in the pipeline.

The development pathway that Africa's power-generation sector pursues in the next decade will be crucial in determining the pace of the continent's low-carbon transition. Nearly 80% of its present electricity generation is fossil-fuelled, with non-hydro renewable energy (RE) accounting for just over 3%[1]. At the same time, Africa's electricity demand is set to increase rapidly[2] as it seeks to industrialize and achieve improved economic development for the world's fastest growing population[3]. Its carbon emission growth rates are already among the highest globally[4], and unless new generation capacity shifts to clean energy, Africa is at risk of being locked into a carbon-intensive development trajectory with major implications for climate change globally[5].

There is little consensus in the extant literature on the future direction of Africa's electricity-generation sector[6]. The estimates of future capacity, even for the relatively proximate time frame of 2030, range from roughly 315 to 620 GW [1,6–12], a spread of nearly 100%. The upper end of this capacity range features a 7- to 12-fold increase in the share of non-hydro RE in Africa's generation mix by 2030, as projected by some of the extant energy-economic scenario modelling (Supplementary Table 1). These energy-planning analyses have contributed to a widespread narrative that Africa is able to shift to a low-carbon growth trajectory in the next decade[1,13] by leapfrogging to clean energy technologies, skipping the carbon-intensive development stage[5,14,15]. However, as these studies tend to rely on various supply, demand and policy assumptions, they might be subject to a considerable degree of uncertainty[16].

What is currently largely missing from the energy-planning literature is an evidence-based, data-driven approach to predicting where, vis-à-vis the potential future, as projected by energy-economic scenario modelling, a given electricity sector is currently heading. The literature on Africa[1,7–12] and more broadly[17] tends to overlook the need for empirical assessments of the potential commissioning successes and failures of individual planned power-generation projects, which make up the continent's medium-term capacity pipeline. The mere existence of a plant in the pipeline does not necessarily imply its eventual commissioning, given that power-generation projects tend to sometimes experience delays and even cancellation. Specifically, although Africa's present generation capacity varies substantially by such power plant characteristics as ownership, grid connection and financing[18], there is a lack of research on the implications these factors might have for a project's successful commissioning. Extant empirical research on Africa is limited to exploring country-level effects, such as economic and demographic indicators[19,20], enabling institutions[19,21] and democratic mechanisms[20–22], and that mostly in the context of end-user consumption and energy access issues. There is thus little understanding of the probability associated with the currently planned project pipeline being eventually realized. Such an analysis could therefore add considerable value to traditional energy-planning studies by helping to estimate the gap between their projections and the generation capacity based on the predicted realization of the current pipeline. Furthermore, this type of analysis would shed light on the type and magnitude of the changes required to the pipeline to achieve the outcomes of the scenario-based analyses, and the economic and policy-related developments that could bring them about.

To bridge these research gaps, in this study we set out to develop an empirical approach to predicting Africa's electricity-generation mix in 2030. We applied a machine-learning-based model to an asset-level dataset that, to the best of our knowledge, is the most complete and granular source of information on generation capacity in Africa (see Methods) and has not been used in previous studies. Combining it with historical data on countries' socio-economic and governance indicators, we assessed both project- and country-level factors for successful plant realization. We have found that project-level features have a larger impact on plant commissioning chances than country-level variables. Applying the model to the pipeline of currently planned power plants, we have predicted the continent's future capacity mix based on the probabilities of individual projects being commissioned in the next decade. The results point to a persistently small share of non-hydro RE in the

[1]Smith School of Enterprise and the Environment, School of Geography and the Environment, University of Oxford, Oxford, UK. [2]Chair of Operations Management, RWTH Aachen University, Aachen, Germany. ✉e-mail: galina.alova@ouce.ox.ac.uk

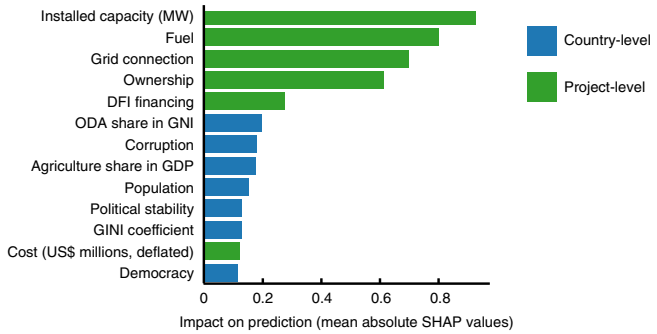


Fig. 1 | The impact of project- and country-level variables on predicting the successful commissioning of past projects. Features are compared on the basis of their individual impact on the prediction of successful power plant commissioning. The impact is expressed in mean absolute Shapley additive explanations (SHAP) values, that is, the mean absolute change in log odds (see Methods). A larger value implies a higher absolute impact of a feature on average across all projects on predicting their commissioning.

2030 capacity mix, which will continue to be dominated by fossil fuels. In addition, we have built upon our model, by integrating a set of hypothetical RE-heavier decarbonization scenarios, to make an alternative prediction and assess the changes required to the pipeline to achieve a greener capacity mix. The analysis suggests that to accelerate the RE transition, a large-scale cancellation of currently planned fossil fuel-based capacity and its replacement by equivalent RE generation is needed.

Plant- and country-level drivers of project commissioning

In our analysis, we applied gradient boosted trees (GBT), a state-of-the-art machine-learning technique for building strong predictive models[23,24], to the dataset containing granular information on power plants across 54 African countries. To build and train our GBT model, we used a sample of nearly 3,000 commissioned and failed power plant projects. Informed by the extant literature, we conducted feature selection (see Methods), with the final model including six project-level and seven country-level variables (Fig. 1).

The results reveal that the top five variables with the highest impact on our model's prediction are all plant-level, namely size (that is, plant capacity), fuel, grid connection, ownership and the participation of development finance institutions (DFI) in project financing, cumulatively accounting for 74% of the total impact of features on the prediction (Fig. 1). Power plant size is the single most important feature in our analysis. For projects below 50 MW, there is evidence for an inverse relationship between the plant's size and its impact on the predicted commissioning of this project. For larger power stations, this effect levels off (Fig. 2a).

The next three variables, namely fuel, connection and ownership, are time-dependent, in that their impact on the likelihood of a project's success appears to vary over the years. For the project's fuel, our results suggest that being powered by oil or gas has had a persistently positive impact on the chances of project commissioning, whereas being hydro-powered has substantially reduced them (Fig. 2b). At the same time, being solar-fuelled historically has had a negative impact, but in recent years these plants have seen a steep rise in their realization chances, outstripping those of gas. Conversely, being coal- or wind-powered has exerted an increasingly negative pressure on project commissioning over time. Furthermore, having off-grid or embedded generation raises project realization likelihood, whereas being on-grid reduces it considerably (Fig. 2c). In terms of plant ownership, state projects have a notably higher predicted success rate than those belonging to independent power producers (IPPs; Fig. 2d). For much of the past decade, IPPs were associated with reduced likelihood of a project being commissioned. However, recently, their realization chances have started to improve.

Other project-level features with a lower, but still material bearing on the model's output are DFI financing and project cost. The former increases plant commissioning likelihood (Supplementary Fig. 1), whereas cost has an inverse relationship with a project's implementation chances (Supplementary Fig. 2). Cheaper plants are considerably more likely to be realized. Cost-related results should, however, be treated with caution, given the sparsity and quality of these data (Supplementary Note 1).

To isolate relative effects on individual generation technologies, we calculated the interaction terms between fuel type and the other 12 variables (see Methods). These second-order effects on project success are lower than the impact of the first-order terms in the model. The results show that the impacts of plant-level variables, such as DFI financing, capacity and connection, on the commissioning success of different fuel types are generally more than three times higher than those of individual country-level indicators. The existence of DFI financing positively affects all fuel types, but is 2.5 times more important for the commissioning success of certain technologies associated with higher failure (that is, hydro, coal and wind) than it is for those with lower failure rates (that is, gas and oil). Smaller capacities are most beneficial for solar plants and, to a lesser extent, for other RE projects. Finally, the type of connection is the largest second-order effect for technologies frequently used for off-grid plants, such as solar, hydro, oil and biomass, but has a smaller impact on gas and wind.

Although the variables of countries' socio-economic development and governance have less impact than project-level features, they are nevertheless salient for the model's predictive performance, indicating that certain aspects of institutional and political stability are positively associated with plant success (Fig. 1). We observe that the features that generally improve power plant commissioning chances include a lower reliance on official development assistance (ODA), a smaller share of agriculture in gross domestic product (GDP) and limited income inequality (Fig. 2e and Supplementary Figs. 3 and 4). Furthermore, there is a clear negative relationship between a country's degree of corruption and project commissioning rate (Fig. 2f). The likelihood of plant realization also steadily increases in countries that have overcome extreme levels of political instability (Supplementary Fig. 5). Moreover, strong autocracies and, to some extent, stronger democracies are more conducive to project realization than hybrid regimes (Supplementary Fig. 6).

Spatial disparities in project pipeline realization

Upon training our model on the historic data, we applied it to nearly 2,500 planned projects currently in the pipeline (see Methods and Supplementary Note 1) to predict the probability of their commissioning, given their plant- and country-level attributes.

Having estimated the probability of the continent's current project pipeline coming online in the next decade, we observed stark inter- and intra-regional differences (Fig. 3). North Africa has a high probability (91%) of its planned capacity being commissioned by 2030. Southern and West Africa are also predicted to fare relatively well as a whole, with regional success rates of 78% and 76%, respectively. Both regions feature individual countries with an estimated plant success probability of over 90% (for example, Namibia and Lesotho in Southern Africa, Mauritania and Guinea-Bissau in West Africa), as well as under 50% (for example, Mozambique in Southern Africa, Cameroon in West Africa). For Central Africa, we predict a low 52% pipeline commissioning probability, with the Central African Republic and Gabon having a failure rate of over 80%. In East Africa, with an overall success probability of 71%, Madagascar and South Sudan have by far the poorest

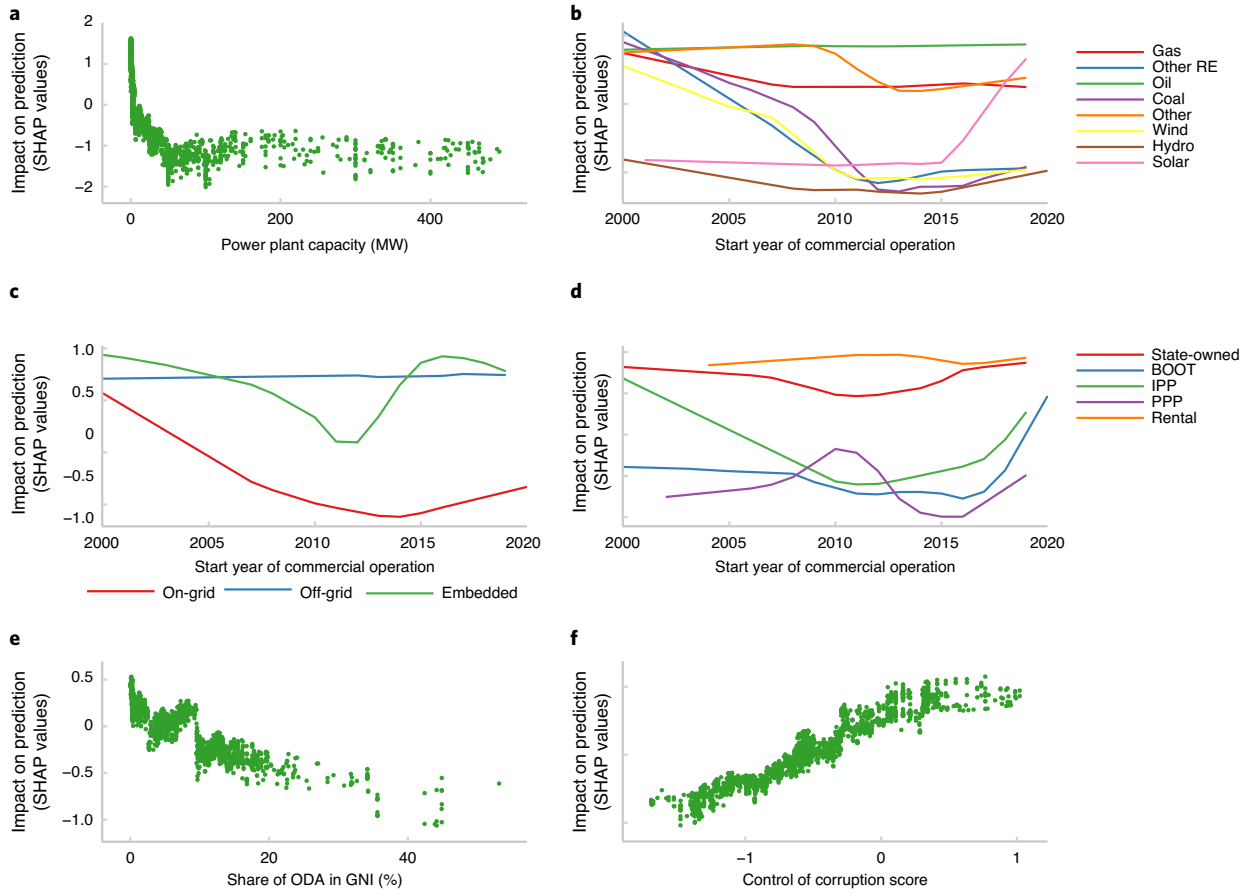


Fig. 2 | The impact of selected features on the model's prediction. a–f, The impact of a power plant's capacity (**a**), fuel type (**b**), grid connection (**c**), ownership type (**d**), share of official development assistance (ODA) in gross national income (GNI) (**e**) and control of corruption score (**f**) on the model's predictive ability. In **b**, the category 'Other' comprises nuclear- and waste-powered plants, and data points for which the information on fuel was not available (Supplementary Note 1). The category 'Other RE' includes biomass, marine and geothermal energy. Panel **d** includes plots of the following ownership types: independent power producer (IPP), build, own, operate, transfer (BOOT) and public–private partnership (PPP). The impacts of a project's fuel (**b**), connection type (**c**) and ownership type (**d**) were found to be time-dependent. Thus, **b**–**d** show plots of the impact of these features across the time span of the training set. Each feature's impact on the prediction is expressed in SHAP values, that is, the change in log odds (see Methods). The vertical distribution of the data points indicates the interaction effects of the features. In **f**, control of corruption is measured on the standard continuous and unitless World Bank's World Governance Indicator scale which ranges from −2.5 to 2.5, with a higher value indicating less corrupt regimes.

success chances, whereas Ethiopia, which comprises over 40% of the region's pipeline, has a predicted success rate of 85%.

These regional pipeline realization probabilities are driven by the varying effects that individual project- and country-level features, associated with specific planned power plants and their geographies, have on the prediction (Fig. 4). The prevalence of grid-connected capacity in the pipelines of all regions has a negative impact on their commissioning likelihood, given the results of our model, that being on-grid reduces project realization chances (Fig. 2c). At the same time, in North Africa, favourable ownership structures and fuel mix are the key drivers of its pipeline's high success probability. In total, over half of the region's planned capacity is state-owned, and over 60% is gas- or solar-powered. Moreover, our predictions point towards a conducive country-level environment (Fig. 4), further improving North Africa's pipeline implementation chances.

In West and Southern Africa, IPPs own 60% of the pipeline. In the former, this is driven by Nigeria and Ghana, and in the latter, by Botswana, Zimbabwe, Malawi and South Africa, which all have pipelines with at least 60% IPP ownership. In both regions, the fuel mix has a negative effect on commissioning success overall, especially in Southern Africa, where, despite considerable solar additions, coal and hydro still account for nearly half of the pipeline's planned capacity. In Mozambique specifically, this reliance on coal and hydro, combined with predominantly public–private partnership ownership structures, lowers the country's predicted commissioning probability (Fig. 3). Furthermore, nearly all country-level features, except for the limited reliance on ODA by most countries, reduce both regions' chances of pipeline success. Particularly noteworthy is the high inequality in Southern Africa.

In East and Central Africa, high reliance on hydro projects negatively affects their pipeline success probabilities. This is driven by Ethiopia, Tanzania and Uganda dominating planned hydropower capacity in East Africa, whereas in Central Africa 90% of the planned hydro belongs to the Democratic Republic of Congo and Cameroon. At the same time, ownership structures in East Africa are predicted to have a positive effect on its pipeline realization, with nearly 44% being state-owned and IPPs contributing a further 22%. In Central Africa, however, specifically driven by the Democratic Republic of Congo's Inga III dam, most of the planned capacity is public–private partnership, which has reduced plant success chances in the past (Fig. 2d). Notably, in both regions, DFI participation is relatively high, which increases project implementation likelihood. Furthermore, country-level features overall have a negative impact in both regions, however, noteworthy intra-regional

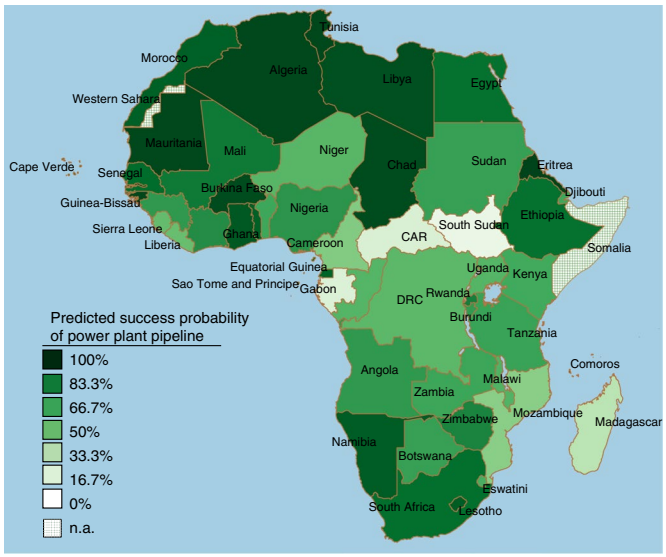


Fig. 3 | The predicted success probabilities of African countries' planned project pipelines. The depicted success probabilities are calculated as country-wide averages weighted by plant capacities. CAR, Central African Republic; DRC, Democratic Republic of Congo.

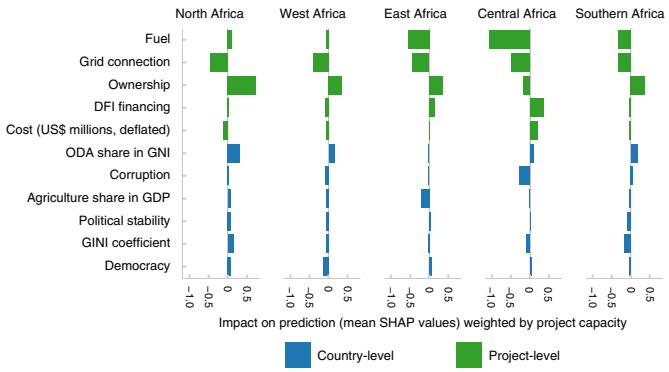


Fig. 4 | The contribution of individual features to the predicted realization of regional planned project pipelines. Project- and country-level features are weighted by plant capacities.

differences exist. In Ethiopia, a favourable combination of comparably low income inequality and corruption results in a higher probability of its pipeline being commissioned than in the Democratic Republic of Congo or Madagascar, where nearly all project- and country-level features negatively affect these chances.

Africa's predicted future electricity mix

Based on the probability estimates of individual planned projects being commissioned, we predict that 269 GW or 77% of the pipeline will be successfully realized by 2030 (Fig. 5). This would result in a doubling of Africa's 2019 generation capacity, bringing the total to 472 GW (net of 28 GW capacity, which is assumed to be retired by then). Taking into account the fuels' average capacity factors, this translates into 1,877 TWh generation (Supplementary Tables 5 and 6), lying within the range of 1,600–2,150 TWh projected by the extant energy-planning literature for 2030[1,5–12].

At the same time, our model predicts a persistently fossil fuel-intensive technology mix. Non-hydro RE will account for 17.4% of the total installed capacity and 9.6% of generation, with the latter being between a third and a fifth of prominent RE-heavy scenarios[1,8–10] (Supplementary Table 1). Fossil fuels will continue to dominate generation capacity, accounting for 62% of the total and half of all newly commissioned capacity. This is despite the 34% predicted failure rate of planned coal-fired capacity. For hydropower, our model predicts a 61% success rate, the lowest of any fuel, leading to its capacity and generation shares staying largely constant (Supplementary Table 6).

The spatial disparities in pipeline commissioning probabilities, discussed above, also translate into the capacity mix (Supplementary Fig. 7). In North Africa, we predict capacity to increase by 60% between 2019 and 2030, with natural gas remaining the dominant fuel (70%) and non-hydro RE rising from 4% to 13%. In West, Central and East Africa, installed capacity is predicted to roughly triple by 2030. In West Africa, over two-thirds of capacity continues to be fossil-fuelled, whereas in Central Africa, the reliance on hydropower further increases to 77%. In these two regions, non-hydro RE capacity shares are predicted to remain at low levels, 11% and 4%, respectively, whereas East and Southern Africa both increase their non-hydro RE capacity share to roughly a quarter. For the latter, this constitutes an almost fourfold increase relative to the current level, driven by South Africa, which is forecast to transition towards RE, with coal's capacity share falling from 75% to 49% and solar rising from 4% to 24%. Indeed, of the 49 GW of predicted additional solar capacity across Africa, 39% will be in South Africa alone.

It is also noteworthy that our results on total generation for individual countries point to potential gaps between the demand projections by the extant studies and the future generation we predict on the basis of the pipeline. For example, although our predicted total 420 TWh generation for South Africa is closely aligned with previous research[25], we estimate roughly 25% lower generation for Kenya and 20% higher generation for Egypt relative to the existing demand projections[26,27].

Need for a rapid policy shift towards decarbonization

We expect the pipeline for the next decade, as we currently know it based on our data, to remain largely unchanged and persistently dominated by fossil fuels, unless an abrupt shock takes place in the immediate future triggering effects not yet reflected in the projects already planned (Supplementary Note 2). To prompt a decisive low-carbon transition, akin to the projections offered by some of the extant decarbonization scenarios (Supplementary Table 1), besides promoting RE expansion, continued investment in fossil fuel plants should be disincentivized. Common policy mechanisms to foster this include the removal of fossil fuel subsidies, the introduction of a sufficiently high carbon price and the exit of DFIs, both national and international, from fossil fuel projects[28].

We ran a series of scenarios assuming such policy action takes place in the near future in a concerted manner across Africa (see Supplementary Note 3 for the scenario design), leading to a large-scale transformation of the current pipeline away from fossil fuels and towards RE. In the first 'decarbonization' scenario, we assumed the cancellation of half of all planned coal- and oil-fired and a third of gas-fuelled capacity taking place from 2025 onwards. The lost generation is replaced by equivalent new non-hydro RE generation with favourable characteristics to improve their commissioning chances. In this scenario, non-hydro RE would constitute a higher share than in our original prediction, 26% of capacity and 14% of generation. Nevertheless, their importance still falls short of the existing projections, with fossil fuels continuing to dominate the mix (Fig. 6). For non-hydro RE to achieve a share in capacity comparable to the projections of existing studies, the cancellation of all planned coal- and oil-fired and a third of gas-fired capacity should take place immediately, that is, a 'rapid decarbonization' scenario in our analysis. Reaching this outcome implies nearly doubling the RE capacity in 2030 compared with the first scenario. The third scenario adds an earlier than usual retirement of

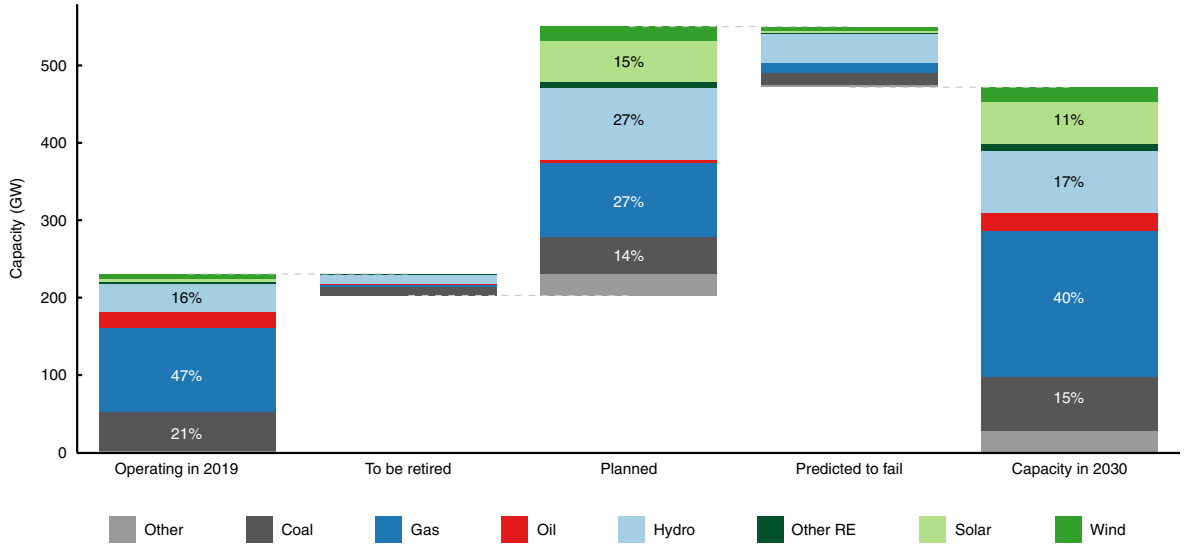


Fig. 5 | Africa's current and predicted 2030 electricity capacity mix by fuel type. The 'Operating in 2019' bar refers to the operating capacity, as of October 2019, when the data were retrieved, 'To be retired' is the capacity that in 2030 will be older than 50 years and under a conservative assumption will be retired by then, 'Planned' denotes the projects currently in the pipeline, 'Predicted to fail' is the planned capacity predicted not to be commissioned and 'Capacity in 2030' is the predicted overall capacity mix in 2030.

coal and oil plants and their replacement by low-carbon generation, leading to non-hydro RE representing over 50% of the capacity by 2030 (Supplementary Table 7).

Discussion

In this study we have found that plant-level features have been the dominant drivers of project successful commissioning compared to country-level circumstances. Our results suggest steep learning curves for recent solar projects as both the number of planned plants and their commissioning success have sharply increased. Small project size appears to have had the single most positive effect on plant commissioning chances. Packaging envisaged capacity into smaller lower-cost projects, an approach followed by South Africa's Renewable Energy Independent Power Producer Procurement Programme, especially for solar plants, can spread financial risks, attract new entrants, creating competition-induced efficiency gains[29], and reduce implementation complexities of megaprojects[30,31]. Conversely, those non-hydro RE technologies that have lower success rates (for example, wind, geothermal and biomass) tend to be associated with limited prior usage, especially in West and Central Africa. For example, although wind power has experienced a remarkable cost decline in recent years globally, its contribution to Africa's pipeline and commissioning success remains limited. Our results show the role of DFIs to be particularly important for the successful realization of these types of projects. DFIs are key to securing concessional finance and de-risking investments[32], thereby helping to overcome first-mover risks and kick-start new generation technologies[33]. As for hydropower projects, there do not seem to be substantive learning curve effects, despite the long history of implementation. Hydropower projects are associated with unique implementation challenges, such as siting constraints, limited modularity[34], considerable ecological impact, citizen resettlement and complex multilateral geopolitics[35].

Despite the operational inefficiencies associated with public utilities in Africa[36], we found consistently positive effects of state ownership on plant commissioning chances. Contrary to the private sector, governments command substantial non-project-related revenue streams that enable them to absorb economic losses and delays during project development. Empirical evidence also suggests that governments have potential to lead technological change in the energy sector[37,38]. At the same time, the number of IPP-owned plants, especially in West and Southern Africa, has risen sharply since 2010, with our results of their increasing commissioning success pointing to considerable learning curve effects associated with these projects.

Our findings also show that a project being off-grid contributes positively to its commissioning chances, which can potentially be explained by the majority of off-grid capacity being directly linked to a commercial offtaker[39], providing a clear route to market without relying on costly transmission line expansion[40]. By contrast, we found that connection to a grid is associated with higher plant failure rates, likely due to land access issues and poorly financed transmission infrastructure, which can lead to grid-connected plants being delayed or proving infeasible[41].

Finally, albeit of lower importance for the prediction, our findings point to a positive effect of country-level indicators on project commissioning. Government financial independence from ODA, an economic shift away from agricultural to more electricity-intensive industrial activities and lower income inequality suggest the merits of a strong electricity customer base, a crucial feature of a conducive power offtake environment[36]. Where country-specific challenges exist, for example, in parts of West, East and Central Africa, a focus on plant-level factors is important, as they might be easier to influence.

Our prediction of Africa's capacity mix in 2030 points to a risk of missing an opportunity for a rapid low-carbon transition. Despite the continent's vast untapped RE resources[42], improved cost competitiveness of low-carbon technologies vis-à-vis fossil-fuelled power plants and our finding that over half of Africa's total predicted capacity by 2030 is yet to be commissioned, we estimate the share of non-hydro RE in overall generation capacity to remain modest. It is predicted to be just over 17% of capacity in 2030, corresponding to less than 10% of generation. At the same time, fossil fuels are predicted to continue to dominate, particularly in North, West and Southern Africa. This creates a considerable risk of carbon lock-in for Africa's power sector. Generally, carbon-intensive technologies have a tendency to hinder low-carbon alternatives due to institutional capture and system inertia[43,44]. In West and Southern

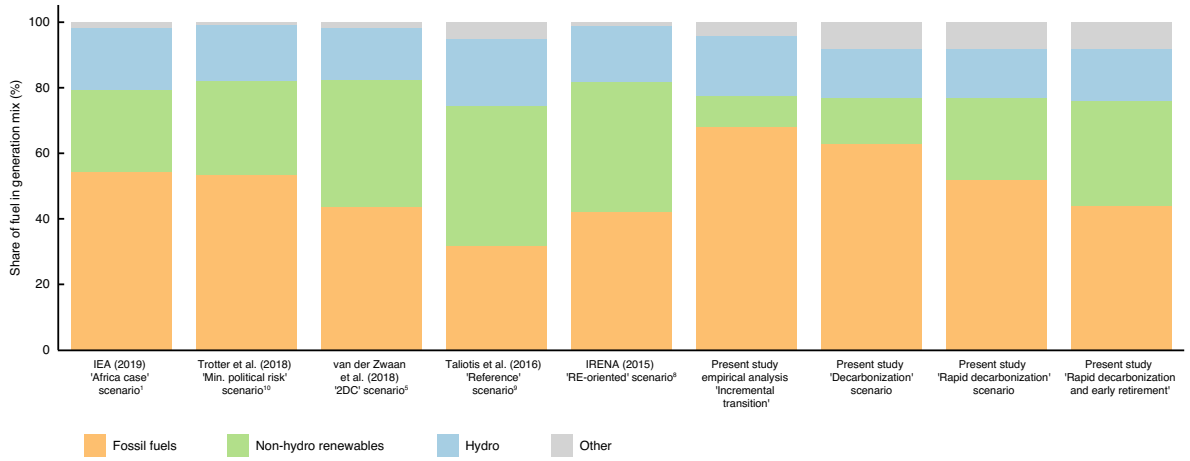


Fig. 6 | Comparison of the 2030 generation mix, as projected by extant RE-heavy scenarios and predicted by the present study. The data are taken from existing studies and compared with the results of the predicted generation mix and three different decarbonization scenarios presented in this study. The studies cited here are described on the *x* axis (see also Supplementary Table 1 for more details). The 2DC in the scenario by van der Zwaan et al. (2018) stands for 2 °C, and refers to their scenario in which future global warming is likely to be capped at 2 °C.

Africa, this is exacerbated by large electricity access gaps and budgetary constraints to replace fossil fuel infrastructure before the end of its lifetime[45]. Moreover, most of Central Africa and the countries around the Nile and Zambezi river basins[46] will continue to rely on hydropower. This is likely to render them vulnerable to the effects of climate change[47]. Notably, Chinese investors are involved in financing over half of the contracted hydropower plants in Africa[48], thus having a substantial role in managing associated climate risk exposure.

Our analysis reveals the fundamental changes to the current pipeline composition required to achieve Africa's rapid transition to RE by 2030. To minimize carbon lock-in and physical climate risks while meeting growing electricity demand, a rapid shift of the continent's pipeline composition should take place towards non-hydro RE with favourable project characteristics to ensure higher realization chances, coupled with a large-scale cancellation of planned and the early retirement of the existing fossil fuel capacity. This is likely to require a decisive concerted effort from the public and private sectors as well as the development finance community.

Moreover, our analysis complements traditional energy-planning studies in several ways. The probabilities of individual projects being commissioned, as predicted by our model, could serve as a useful input into scenario-based analyses, indicating the plant- and country-level risks associated with the capacity that is assumed will be built in the future. These risks would affect financing conditions and the cost of capital, an important[49], yet largely neglected, aspect of Africa's energy-planning research[1,7–10]. Furthermore, the predicted probabilities of project success can be used to calculate the expected supply and reserve margin associated with different scenarios, thereby testing their respective expected ability to meet future demand. Low chances of pipeline success in specific countries may also warrant governments to aim for an increased planned reserve margin to minimize the risk of future blackouts.

Methods

Data. *Plant-level data.* As the core dataset for this study on power-generation plants, we used Live Data, a living proprietary, commercial product supplied by African Energy[50]. Amongst the information included in Live Data are plant name, capacity, fuel, location, grid connection, ownership type (for example, government, IPP, public–private), cost and DFI financing. The dataset also allows the evolution of plant status to be tracked over time, containing, where available, the dates of the signing of a power purchase agreement, the start of construction and commercial operations, and retirement. Although these factors have not previously been analysed in combination, there is increasing qualitative evidence that plant-level variables, for example, ownership structures[36], development finance[32], plant size[31], connection type[51] and location[52], play an important role in shaping Africa's future power sector.

Live Data is, to the best of our knowledge, the most complete dataset on power-generation assets for Africa currently available, containing information on operating, retired and planned power plants, as well as unsuccessful projects that never reached their commissioning. As of October 2019, it comprised a total of 6,414 projects across 54 African countries, with their overall capacity totalling nearly 713 GW. Of this, operating capacity constitutes 231 GW (representing over 95% of the 2018 installed capacity, as estimated by the International Energy Agency)[1]. Furthermore, Live Data has a particularly good coverage of planned and failed projects, even compared with historical asset-level datasets, such as the S&P Market Intelligence UDI World Electric Power Plants (WEPP) Database, considered amongst the most comprehensive of datasets[53]. As an illustration, although in 2018, WEPP contained data on 225 GW of the operating capacity in Africa, close to that of Live Data, it only had 56 GW of failed (delayed, cancelled or deferred) and 200 GW of capacity under planning or construction, compared with 108 and 347 GW in Live Data, respectively.

It is worth noting that although African Energy has good coverage, some particularly small off-grid power plants may have been omitted. Specifically, we considered the coverage of the failed off-grid plants, given that their failure rate is relatively modest and lower than that of on-grid projects. This could in part be due to the difficulty of tracking unsuccessful off-grid projects, resulting in data limitation, or off-grid plants being generally associated with higher realization chances. The arguments presented in Supplementary Note 4 give us confidence to conclude that the latter is more likely to be the case for the majority of off-grid plants.

Country-level data. Furthermore, we retrieved country-specific information, such as a range of economic, demographic, institutional and governance indicators, to capture the development of nations over time. The economic and demographic data come from the World Bank's World Development Indicators[45]. The source of the institutional variables is the World Bank's World Governance Indicators database[54]. We also integrated data from the Polity IV Project of the Center for Systemic Peace, which tracks countries' regime type characteristics between 1800 and 2017[55,56]. This choice of country-level features was informed by the extant literature, which argues that strong and diversified economies, high population density, institutionally conducive environments and democratic regimes are positively associated with electricity access and consumption in Africa[19–22,31] (there is a lack of literature on plant realization success).

Before building and training our model, we prepared the data on plant- and country-level features following the steps outlined in Supplementary Note 1. We split our obtained dataset into a training set (2,969 plants) of commissioned or failed plants, and an application set of 2,479 planned plants (see Supplementary Note 1 for details).

Model for predicting plant commissioning. *Gradient boosted trees.* To predict the probability of individual power plants going online in the next decade, we used GBT for our classification problem, a state-of-the-art machine-learning-based technique for building non-parametric and interpretable predictive models[23,24]. A high quality of prediction was achieved by training individual decision trees in an additive and sequential manner, optimizing arbitrary differentiable loss functions, to

produce a strong prediction from the ensemble of shallow trees. The interpretability of the model's inner workings is an essential characteristic of GBT, enabling us to understand the relationship between the input variables and the prediction[57].

We built our GBT model using the free open-source algorithm LightGBM, developed by Microsoft. Compared with other GBT algorithms, its key advantages include higher training speed and efficiency, and lower memory consumption[58], by splitting trees leaf- or depth-wise rather than breadth-wise. As a result, it performs well on large datasets. LightGBM also tends to achieve high prediction accuracies[59] and is a winner of numerous machine-learning competitions[60].

GBT models have become the de facto standard in machine learning for analysing feature-rich, structured datasets such as ours[58]. In addition to their ability to capture non-linear relationships, GBT models deal well with both numerical and categorical variables, and are robust to such issues as feature multi-collinearity, imbalanced datasets and the existence of outliers and missing values[57]. For example, in the case of patchy data, LightGBM ignores the missing values when determining the next best split of a tree, thereafter allocating them to the side that minimizes the loss. These GBT attributes are particularly valuable given the characteristics of our dataset, discussed below.

As a result, our model achieved good predictive performance. The area under the receiver operating characteristic curve (roc-auc) score was 0.97 for the training set, and 0.93 for the test set. Roc-auc, a common and important performance indicator for machine-learning models, is equivalent to the probability that the model will rank a randomly chosen positive instance higher than a randomly chosen negative instance[61] (see Supplementary Table 2 for a list of other performance metrics). The performance of our model was also superior to that of a logistic regression (with a 0.89 roc-auc score for the training set and a 0.88 score for the test set) run on the same data to illustrate the advantages of the approach selected for this study (see Supplementary Tables 2 and 3 for metrics on the GBT model and logistic regression, respectively). Even after regularization of the logistic regression and power transforming the highly skewed features (for example, capacity and cost), its performance was considerably lower than that of the GBT model.

Machine-learning-based predictive techniques, such as our GBT model, require substantial technical expertise to enable them to achieve the strong performance they are capable of. To this end, building and training our model involved several steps: hyperparameter tuning, data preparation, feature selection, model validation, calibration and interpretation. This process allowed us to ensure the robustness and reproducibility of the model's results and develop a reliable and rigorous approach that can be effectively applied to other settings and datasets. Some of the steps, such as hyperparameter tuning, feature selection and model validation, were performed iteratively. These steps were particularly important to ensure that the model achieved good predictive performance and did not overfit, that is, that it performed well beyond the training set, on new, previously unseen data. To reduce the training time, we automated some of the steps, for example, hyperparameter tuning, and trained the model using a remote Linux cluster, which resulted in the training time taking a matter of minutes. Even on a common laptop, the training time should not be an issue, given that GBT models are greedy algorithms designed to scale to datasets as large as a million data points. Once trained, the model can be easily applied to future data to make a prediction. Below, we discuss each of the steps of the training process.

Hyperparameter tuning. To ensure the model's high predictive performance, as measured by the metrics discussed above and in Supplementary Table 2, and address the potential risk of overfitting (that is, a model performing well in-sample, but poorly out-of-sample)[62], we tuned the model's hyperparameters. This resulted in the model being regularized, gearing it to exclude the patterns that are not important for the prediction and that are not generalizing beyond the training set. These hyperparameters included core parameters (for example, learning rate and the number of trees and leaves) and learning control parameters (for example, maximum tree depth and L1 and L2 regularization; see Supplementary Table 8 for all hyperparameters tuned). The values of the hyperparameters should be chosen so as to maximize the prediction accuracy (that is, minimize cross-entropy), given that the model is being trained on a training set. The best set of parameters enables the model to generalize from the training set to the test set while maintaining the highest possible accuracy.

To perform the tuning, we used the derivative-free maxLIPO+TR optimization method[63], which, to find a global maximum of the hyperparameter space, alternates between the non-parametric global optimization of Lipschitz functions (LIPO)[64] and the local Powell's quadratic trust region (TR) method[65]. Both methods estimate a lower bound of the cross-entropy and choose its minimum as the next point for evaluation. The LIPO method approximates the lower bound using the Lipschitz constant, ensuring that the global optimum is found. The TR method locally approximates the cross-entropy using a quadratic function around the current global minimum, leading to a fast local convergence of the algorithm. This approach has been proven to substantially outperform random search[64] and is often preferred to Bayesian optimization, given its fast convergence of hyperparameter values to an optimum[63]. We confirmed the convergence of the tuned hyperparameters to an optimum through a visual inspection of the tuning results. We automated the process of hyperparameter tuning to expedite it and reduce the training time.

Feature selection. Before confirming the final list of features to be included in the model, we performed feature subset selection[66], identifying the variables most relevant to the prediction and removing those that do not contribute to, or reduce, the predictive power of the model. The latter comprises, for example, plant location and country's GDP per capita, likely due to the incorporation of other socio-economic variables into the model, which capture more relevant country-specific differences, having a higher impact on the prediction. Informed by the extant literature, as discussed above in the Data section, we selected 12 project-level and 21 country-level features and tested their impact on the model's prediction of a plant being successfully commissioned.

This feature selection process involved several steps, being part of the model training process. First, we tuned the hyperparameters of the model (see above) and then excluded the variables that have an impact on the prediction close to zero. Second, we investigated a potential domain shift of the variables, that is, whether they perform differently in the future compared with in the past. This means that for the data ordered in time, these variables behave differently when the model is run on the different splits of these data. To this end, we trained a sequence of three models with multiple splits on our training set for robustness checks, and calculated the average of the mean absolute impact of a feature on the predictions of the three models, and the average of the correlations between these impacts (Supplementary Fig. 8). This matrix informed our decision to exclude the features that, along with a low mean absolute impact, have a negative average correlation, which implies that the model learns something completely different across the various splits of the training set, and that a feature's individual impacts on the prediction are not stable (that is, do not generalize beyond the training set). Finally, we explored potentially related features as groups, such as governance and macroeconomic indicators, to analyse their cumulative importance relative to their individual impacts on the prediction, and identified the features that could be excluded without substantially reducing the group's overall importance for the prediction.

This rigorous multiphase feature selection process ensured that the 13 variables included in the final model were all stable and important for the prediction. The six plant-level features comprised power plant fuel, capacity, ownership, grid connection, cost and DFI financing (taking a value of one if there is participation from a bilateral and/or multilateral DFI, and zero otherwise). Power plant fuel, ownership and connection type were found to be time-dependent, in that we observed a trend in their actual success rate over time (Supplementary Fig. 9). For example, there was an increase over time in the success rate of solar power plants and those owned by IPPs. To account for this trend and capture the temporal evolution of the impact these variables might have on the prediction, they were target-encoded using a simple exponential average. The model's predictive performance improved as a result of the transformation of these variables. The seven country-level features included in the model were the share of agriculture in GDP, the share of ODA in GNI, population, GINI coefficient, political stability, corruption and democracy score. We also applied monotonicity constraints as a regularization technique to the variables exhibiting a strong trend in one direction, that is, corruption, fuel, connection and ownership type.

Model validation. To ensure that our results are robust and reproducible, we validated the model, a process to test the performance of the tuned (see the Hyperparameter tuning section above) and trained model on data different from the training set, that is, a validation set. The aim of a machine-learning model is to ensure that it does not overfit, that is, that it performs well not only on the training set, but also out-of-sample, and, in the case of our time series data, out-of-time. To this end, we used out-of-time validation for time series with multiple splits of the data ordered in time to stabilize the error estimate. This approach is a variation of the original k-fold cross-validation, in which the data are split into k folds and the model is fitted k times, each time with a different fold chosen as a test set with the rest performing as a training set. If used in this traditional form, k-fold cross-validation would result in overfitting of the time series data. Conversely, the out-of-time validation orders the folds in time, and returns in each kth split the first k folds as a training set and the $(k+1)$th fold as a test set, that is, it always validates the model on the data in the future end of the training set. We performed the process using sixfold validation, with at least three folds available for training. This resulted in three consecutive splits: (1) the first three folds for training, the fourth fold for test, (2) the first four folds for training, the fifth fold for test and (3) the first five folds for training, the sixth fold for test. As mentioned above, our trained, tuned and validated model performed well both on the training set and the test set (Supplementary Table 2).

Model calibration. Finally, we calibrated the probabilistic prediction made by our model using the sigmoid approach or Platt scaling[67–69]. Calibration is essential for retrieving unbiased probability estimates from the model. The output of a well-calibrated model can be directly interpreted as an estimate of probability[70].

Model interpretation. As highlighted above, an important attribute of GBT models is their interpretability. For this purpose, we used SHAP values to assign each feature under consideration its importance for the model's prediction (here, plant commissioning)[71]. Thus, the SHAP value of a feature, expressed in log odds,

denotes how much this feature changes the prediction in one or the other direction. A positive SHAP value assigned to a feature for a given power plant implies that this feature increases the power plant's realization chances, whereas a negative value would decrease their chances.

SHAP values are both a consistent and locally accurate method of model interpretation, combining the characteristics of several previously existing approaches[71]. Consistency refers here to the case in which the importance of a feature does not decrease as a result of the model being changed to rely more on this feature. At the same time, local accuracy signifies that the importance associated with individual features adds up to the total prediction of the model[72].

In addition to the first-order SHAP values (that is, the effect of a feature on the prediction), we also calculated second-order SHAP values for the fuel variable (that is, the interaction terms of fuel with the remaining 12 features). We analysed the relative and absolute importance of these interaction effects in mean absolute and mean terms to determine the magnitude and direction of their impact, respectively. The sum of a feature's interaction effects with all the other features and its direct effect on the prediction yields the total SHAP value.

Decarbonization policy shock. Although we expect the project pipeline, as we currently know it, to remain largely stable in the next decade, as discussed in Supplementary Note 2, our approach allows incorporation into the analysis scenarios of abrupt pipeline decarbonization that would involve a large-scale cancellation of planned fossil fuel projects and their replacement by equivalent RE generation with favourable characteristics to improve their commissioning chances (see Supplementary Note 3 for the design of the scenarios).

Future capacity mix. We calculated the capacity mix for Africa in 2030 by summing the current installed capacity (the net of the plants assumed to be retired being over 50 years by 2030) and the capacity currently in the pipeline and predicted to be realized over the next decade, based on the estimated probabilities of individual plants being successfully commissioned. This method is plausible to the problem at hand, allowing us to capture nuances between different plant success probabilities and account for potential project downscaling, which has occurred in Africa in the past[73]. There is an alternative approach to converting probabilities, as predicted by the model, into the presence or absence of a specific event (in our case plant realization) that is based on a predefined probability threshold (for example, 50%)[74]. We therefore also calculated the predicted installed capacity mix using the cut-off point of 50%, which yielded a very similar outcome to our original results.

Data availability

The data on power-generation assets from LiveData were obtained under licence from African Energy (https://www.africa-energy.com/live-data). The country-level data on macroeconomic variables were retrieved from the World Bank World Development Indicators (http://datatopics.worldbank.org/world-development-indicators/), on institutional variables from the World Bank World Governance Indicators (https://info.worldbank.org/governance/wgi/) and on countries' regime types from the Polity IV Project of the Center for Systemic Peace (https://www.systemicpeace.org/polityproject.html). The data on feed-in-tariff introduction dates were retrieved from RE21 annual Global Status Reports and are publicly available from https://www.ren21.net/reports/global-status-report/. The data on fossil fuel subsidies were retrieved from the International Monetary Fund and are publicly available from https://www.imf.org/en/Topics/Environment/energy-subsidies. The data that support the figures and other findings of the study are available from the corresponding author upon reasonable request.

Code availability

In this study a gradient boosted tree model was built using LightGBM, which is an open-source free algorithm developed by Microsoft. This code is available from the corresponding author upon reasonable request.

Received: 3 March 2020; Accepted: 30 November 2020;
Published online: 11 January 2021

References

1. *Africa Energy Outlook 2019* (IEA/OECD, 2019).
2. Ouedraogo, N. S. Modeling sustainable long-term electricity supply-demand in Africa. *Appl. Energy* **190**, 1047–1067 (2017).
3. *World Population Prospects 2019 - Volume I: Comprehensive Tables* (United Nations, 2019).
4. Steckel, J. C., Hilaire, J., Jakob, M. & Ottmar, E. Coal and carbonization in sub-Saharan Africa. *Nat. Clim. Chang.* **10**, 83–88 (2020).
5. van der Zwaan, B., Kober, T., Longa, F. D., van der Laan, A. & Jan Kramer, G. An integrated assessment of pathways for low-carbon development in Africa. *Energy Policy* **117**, 387–395 (2018).
6. Lucas, P. L. et al. Future energy system challenges for Africa: insights from integrated assessment models. *Energy Policy* **86**, 705–717 (2015).
7. Sanoh, A., Kocaman, A. S., Kocal, S., Sherpa, S. & Modi, V. The economics of clean energy resource development and grid interconnection in Africa. *Renew. Energy* **62**, 598–609 (2014).
8. *Africa Power Sector: Planning and Prospects for Renewable Energy* (IRENA, 2015).
9. Taliotis, C. et al. An indicative analysis of investment opportunities in the African electricity supply sector — using TEMBA (The Electricity Model Base for Africa). *Energy Sustain. Dev.* **31**, 50–66 (2016).
10. Trotter, P. A., Maconachie, R. & McManus, M. C. Solar energy's potential to mitigate political risks: the case of an optimised Africa-wide network. *Energy Policy* **117**, 108–126 (2018).
11. Panos, E., Turton, H., Densing, M. & Volkart, K. Powering the growth of sub-Saharan Africa: the jazz and symphony scenarios of world energy council. *Energy Sustain. Dev.* **26**, 14–33 (2015).
12. Ouedraogo, N. S. Africa energy future: alternative scenarios and their implications for sustainable development strategies. *Energy Policy* **106**, 457–471 (2017).
13. *Scenarios for Sustainable Energy, SDG 7 Outlook for Africa* (IISD, 2019).
14. Goldemberg, J. Leapfrog energy technologies. *Energy Policy* **26**, 729–741 (1998).
15. Gujba, H., Thorne, S., Mulugetta, Y., Rai, K. & Sokona, Y. Financing low carbon energy access in Africa. *Energy Policy* **47**, 71–78 (2012).
16. Trutnevyte, E., Guivarch, C., Lempert, R. & Strachan, N. Reinvigorating the scenario technique to expand uncertainty consideration. *Clim. Change* **135**, 373–379 (2016).
17. Collins, S. et al. Planning the European power sector transformation: the REmap modelling framework and its insights. *Energy Strategy Rev.* **22**, 147–165 (2018).
18. Eberhard, A., Gratwick, K., Morello, E. & Antmann, P. Accelerating investments in power in sub-Saharan Africa. *Nat. Energy* **2**, 17005 (2017).
19. Onyeji, I., Bazilian, M. & Nussbaumer, P. Contextualizing electricity access in sub-Saharan Africa. *Energy Sustain. Dev.* **16**, 520–527 (2012).
20. Trotter, P. A. Rural electrification, electrification inequality and democratic institutions in sub-Saharan Africa. *Energy Sustain. Dev.* **34**, 111–129 (2016).
21. Ahlborg, H., Boräng, F., Jagers, S. C. & Söderholm, P. Provision of electricity to African households: the importance of democracy and institutional quality. *Energy Policy* **87**, 125–135 (2015).
22. Brown, D. S. & Mobarak, A. M. The transforming power of democracy: regime type and the distribution of electricity. *Am. Polit. Sci. Rev*. https://doi.org/10.1017/S0003055409090200 (2009).
23. Friedman, J. H. Stochastic gradient boosting. *Comput. Stat. Data Anal.* **38**, 367–378 (2002).
24. Friedman, J. H. Greedy function approximation: a gradient boosting machine. *Ann. Stat.* **29**, 1189–1232 (2001).
25. Arndt, C. et al. A sequential approach to integrated energy modeling in South Africa. *Appl. Energy* **161**, 591–599 (2016).
26. Rady, Y. Y., Rocco, M. V., Serag-Eldin, M. A. & Colombo, E. Modelling for power generation sector in developing countries: case of Egypt. *Energy* **165**, 198–209 (2018).
27. Moksnes, N., Korkovelos, A., Mentis, D. & Howells, M. Electrification pathways for Kenya–linking spatial electrification analysis and medium to long term energy planning. *Environ. Res. Lett.* **12**, 095008 (2017).
28. Pfeiffer, A., Hepburn, C., Vogt-Schilb, A. & Caldecott, B. Committed emissions from existing and planned power plants and asset stranding required to meet the Paris Agreement. *Environ. Res. Lett.* **13**, 054019 (2018).
29. Eberhard, A. & Naude, R. The South African renewable energy independent power producer procurement programme: a review and lessons learned. *J. Energy South. Afr.* **27**, 1–14 (2016).
30. Khobai, H., Mugano, G. & Le Roux, P. The impact of electricity price on economic growth in South Africa. *Int. J. Energy Econ. Policy* **7**, 108–116 (2017).
31. Green, N., Sovacool, B. K. & Hancock, K. Grand designs: assessing the African energy security implications of the Grand Inga Dam. *Afr. Stud. Rev.* **58**, 133–158 (2015).
32. Steffen, B. & Schmidt, T. S. A quantitative analysis of 10 multilateral development banks' investment in conventional and renewable power-generation technologies from 2006 to 2015. *Nat. Energy* **4**, 75–82 (2019).
33. Steffen, B., Matsuo, T., Steinemann, D. & Schmidt, T. S. Opening new markets for clean energy: the role of project developers in the global diffusion of renewable energy technologies. *Bus. Polit.* **20**, 553–587 (2018).
34. Ansar, A., Flyvbjerg, B., Budzier, A. & Lunn, D. Should we build more large dams? The actual costs of hydropower megaproject development. *Energy Policy* **69**, 43–56 (2014).
35. *State of the River Nile Basin 2012* (Nile Basin Initiative, 2013).
36. Eberhard, A., Gratwick, K., Morella, E. & Antmann, P. *Independent Power Projects in Sub-Saharan Africa: Lessons from Five Key Countries* (World Bank, 2016); https://doi.org/10.1596/978-1-4648-0800-5

37. Power, M. et al. The political economy of energy transitions in Mozambique and South Africa: the role of the rising powers. *Energy Res. Soc. Sci.* **17**, 10–19 (2016).
38. Mah, D. N., Wu, Y.-Y., Ip, J. C. & Hills, P. R. The role of the state in sustainable energy transitions: a case study of large smart grid demonstration projects in Japan. *Energy Policy* **63**, 726–737 (2013).
39. *Off-Grid Renewable Energy Solutions: Global and Regional Status and Trends* (IRENA, 2018).
40. Kemausuor, F., Adkins, E., Adu-Poku, I., Brew-Hammond, A. & Modi, V. Electrification planning using Network Planner tool: the case of Ghana. *Energy Sustain. Dev.* https://doi.org/10.1016/j.esd.2013.12.009 (2014).
41. *GET FiT Uganda Annual Report 2019* (KFW, 2020).
42. Huld, T., Müller, R. & Gambardella, A. A new solar radiation database for estimating PV performance in Europe and Africa. *Sol. Energy* **86**, 1803–1815 (2012).
43. Unruh, G. C. Understanding carbon lock-in. *Energy Policy* **28**, 817–830 (2000).
44. Seto, K. C. et al. Carbon lock-in: types, causes, and policy implications. *Annu. Rev. Environ. Resour.* **41**, 425–452 (2016).
45. *World Development Indicators* (World Bank, accessed 1 September 2019); http://datatopics.worldbank.org/world-development-indicators/
46. Conway, D., Dalin, C., Landman, W. A. & Osborn, T. J. Hydropower plans in eastern and southern Africa increase risk of concurrent climate-related electricity supply disruption. *Nat. Energy* **2**, 946–953 (2017).
47. Thomas, N. & Nigam, S. Twentieth-century climate change over Africa: seasonal hydroclimate trends and Sahara desert expansion. *J. Clim.* **31**, 3349–3370 (2018).
48. China continues to build much-needed power capacity in Africa. *Power Technology* https://www.power-technology.com/comment/chinese-investment-in-africa-2019/ (2019).
49. Labordena, M., Patt, A., Bazilian, M., Howells, M. & Lilliestam, J. Impact of political and economical barriers for concentrating solar power in sub-Saharan Africa. *Energy Policy* **102**, 52–72 (2017).
50. *About the Data Tool* (African Energy, accessed 21 December 2019); https://www.africa-energy.com/live-data/about-the-data-tool
51. Peters, J., Sievert, M. & Toman, M. A. Rural electrification through mini-grids: challenges ahead. *Energy Policy* **132**, 27–31 (2019).
52. Kruger, W., Stritzke, S. & Trotter, P. A. De-risking solar auctions in sub-Saharan Africa – a comparison of site selection strategies in South Africa and Zambia. *Renew. Sustain. Energy Rev.* **104**, 429–438 (2019).
53. Gotzens, F., Heinrichs, H., Hörsch, J. & Hofmann, F. Performing energy modelling exercises in a transparent way - the issue of data quality in power plant databases. *Energy Strategy Rev.* **23**, 1–12 (2019).
54. *World Governance Indicators* (World Bank, accessed 1 October 2019); https://info.worldbank.org/governance/wgi/
55. *Polity IV Project* (Center for Systemic Peace, accessed 1 October 2019); https://www.systemicpeace.org/polityproject.html
56. Marshall, M. G., Gurr, T. R. & Jaggers, K. *Polity IV Project: Political Regime Characteristics and Transitions, 1800–2017. Dataset Users' Manual* (Center for Systemic Peace, 2018).
57. Hastie, T., Tibshirani, R. & Friedman, J. H. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (Springer, 2009).
58. Ke, G. et al. LightGBM: a highly efficient gradient boosting decision tree. In *Proc. Advances in Neural Information Processing Systems* (Eds. Guyon, I. et al.) 3147–3155 (NIPS, 2017).
59. *Welcome to LightGBM's Documentation!* (Microsoft, accessed 2 January 2020); https://lightgbm.readthedocs.io/en/latest/
60. *LightGBM: Light Gradient Boosting Machine* (Microsoft, accessed 6 January 2020); https://github.com/microsoft/LightGBM
61. Fawcett, T. An introduction to ROC analysis. *Pattern Recognit. Lett.* **27**, 861–874 (2006).
62. Varian, H. R. Big data: new tricks for econometrics. *J. Econ. Perspect.* **28**, 3–28 (2014).
63. King, D. A Global Optimization Algorithm Worth Using. *dlib C++ Library* http://blog.dlib.net/2017/12/a-global-optimization-algorithm-worth.html (2017, accessed 19 December 2019).
64. Malherbe, C. & Vayatis, N. Global optimization of Lipschitz functions. In *Proceedings of the 34th International Conference on Machine Learning* (Eds. Precup, D., Teh, Y.W.) 3592–3601 (PMLR, 2017).
65. Powell, M. J. D. On the global convergence of trust region algorithms for unconstrained mimimization. *Math. Program.* **29**, 297–303 (1984).
66. Unler, A. & Murat, A. A discrete particle swarm optimization method for feature selection in binary classification problems. *Eur. J. Oper. Res.* **206**, 528–539 (2010).
67. Niculescu-Mizil, A. & Caruana, R. Obtaining calibrated probabilities from boosting. In *Proceedings of the 21st Conference on Uncertainty in Artificial Intelligence* (Eds. Bacchus, F. & Jaakkola, T.) 413–420 (AUAI Press, 2005).
68. Niculescu-Mizil, A. & Caruana, R. Predicting good probabilities with supervised learning. In *Proceedings of the 22nd International Conference on Machine Learning* (Eds. Dzeroski, S. et al.) 625–632 (ACM, 2005)
69. sklearn.calibration.CalibratedClassifierCV (Scikit-learn, accessed 1 November 2019); https://scikit-learn.org/stable/modules/generated/sklearn.calibration.CalibratedClassifierCV.html
70. Probability calibration (Scikit-learn, accessed 20 December 2019); https://scikit-learn.org/stable/modules/calibration.html
71. Lundberg, S. M. & Lee, S. I. A unified approach to interpreting model predictions. In *Proc. Advances in Neural Information Processing Systems* (Eds. Guyon, I. et al.) 4766–4775 (NIPS, 2017).
72. Lundberg, S. M., Erion, G. G. & Lee, S.-I. Consistent individualized feature attribution for tree ensembles. Preprint at http://arxiv.org/abs/1802.03888 (2018).
73. Scholvin, S. *A New Scramble for Africa? The Rush for Energy Resources in Sub-Saharan Africa* (Routledge, 2016).
74. Freeman, E. A. & Moisen, G. G. A comparison of the performance of threshold criteria for binary classification in terms of predicted prevalence and kappa. *Ecol. Modell.* **217**, 48–58 (2008).

Acknowledgements

We thank B. Caldecott, A. Haney, C. Hepburn, W. Kruger and D. Tulloch for comments on the manuscript. G.A. is grateful for the financial support of her doctoral research offered by the ESRC Grand Union Doctoral Training Partnership, the Scatcherd European Scholarship from the University of Oxford and the 73 Scholarship Fund for Geography from Hertford College, Oxford, established through the generosity of the college's alumni, P. Newman and M. Teversham. A.M. acknowledges the support received from the British Academy's Sustainable Development Programme, specifically, award GF160016 - *Making Light Work*, which was key to conceiving the research idea.

Author contributions

A.M. conceived the original research idea and sourced the asset-level data. G.A. and P.A.T. designed the research approach and merged asset- and country-level data. G.A. built, validated and interpreted the machine-learning-based model and produced the visuals of its results. P.A.T. developed the map. A.M. provided an early draft. G.A. and P.A.T. wrote the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is available for this paper at https://doi.org/10.1038/s41560-020-00755-9.

Correspondence and requests for materials should be addressed to G.A.

Peer review information *Nature Energy* thanks Dan Marks and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

© The Author(s), under exclusive licence to Springer Nature Limited 2021

Chapter 4. A global analysis of the progress and failure of electric utilities to adapt their portfolios of power-generation assets to the energy transition

Reproduced with permission from Springer Nature.
This Chapter 4 was published as: Alova, G. A global analysis of the progress and failure of electric utilities to adapt their portfolios of power-generation assets to the energy transition. *Nat Energy* **5**, 920–927 (2020). https://doi.org/10.1038/s41560-020-00686-5

ANALYSIS
https://doi.org/10.1038/s41560-020-00686-5
nature energy

Check for updates

A global analysis of the progress and failure of electric utilities to adapt their portfolios of power-generation assets to the energy transition

Galina Alova

The penetration of low-carbon technologies in power generation has challenged fossil-fuel-focused electric utilities. While the extant, predominantly qualitative, literature highlights diversification into renewables among possible adaptation strategies, comprehensive quantitative understanding of utilities' portfolio decarbonization has been missing. This study bridges this gap, systematically quantifying the transitions of over 3,000 utilities worldwide from fossil-fuelled capacity to renewables over the past two decades. It applies a machine-learning-based clustering algorithm to a historical global asset-level dataset, distilling four macro-behaviours and sub-patterns within them. Three-quarters of the utilities did not expand their portfolios. Of the remaining companies, a handful grew coal ahead of other assets, while half favoured gas and the rest prioritized renewables growth. Strikingly, 60% of the renewables-prioritizing utilities had not ceased concurrently expanding their fossil-fuel portfolio, compared to 15% reducing it. These findings point to electricity system inertia and the utility-driven risk of carbon lock-in and asset stranding.

Recent years have seen remarkable penetration of renewable energy (RE) into the global electricity mix[1]. This is driven by independent power producers (IPPs)[2,3], which according to estimates owned in 2018 three-quarters of the global non-hydro RE capacity, while utilities accounted for 19% (ref. [4]). This development, coupled with decentralized generation and smart technology solutions, could potentially undermine the value proposition of the sector's incumbents—conventional power utilities focused on fossil-fuel-based (FF-based) generation[5–16]. The extant literature highlights that along with the shift into alternative business models, the decarbonization of portfolios of the utilities that decide to remain in electricity generation is a plausible strategy to stay competitive vis-à-vis the new technologies and market entrants[10,17–22].

However, a systematic quantitative global account of how power utilities are developing their asset portfolios over time, in the context of the low-carbon transition, has been missing. The existing research tends to be limited to case studies and/or to focus on major electricity companies, often from a handful of geographies, mostly the United States (US) or Europe[9,12,14,19,23–27]. It largely overlooks the more complex global utility landscape, which also includes smaller national and local actors, potentially important for the pace of the transition[28].

Here, I conduct a quantitative global analysis encompassing the utility sector in its entirety, examining whether companies' portfolio decisions over the years have been aligned with, or indeed hindered, the global shift to RE. To this end, I quantify and compare the dynamics of utilities' portfolio composition over time, to distill common patterns. I rely on a large global dataset of power-generation assets, and apply as a core analytical tool a clustering algorithm, an unsupervised machine-learning-based method, capable of identifying patterns in large, complex datasets (see Methods). This work offers a potentially useful demonstration to future studies of the suitable methodology and data to analyse the intricate landscape of the global utility sector's transition. I show that utilities' decarbonization remains slow. While a considerable share of the companies prioritized growth of RE capacity, the majority of them continued to simultaneously increase, albeit at a slower rate, their FF asset base, particularly gas. Furthermore, while only a handful continued to favour the expansion of their coal portfolios over gas and RE, a substantial number grew gas-fired capacity ahead of other assets. My results also suggest a potential link between utilities' behaviour patterns and a RE-enabling policy environment, as well as the structure of the market where the companies operate.

Utilities' typology based on capacity growth patterns

I perform the analysis on 3,311 electric companies identified as utilities, that is, regulated (including those owned by national or local governments), investor-owned and cooperative utilities, existing at some point between 2001 and 2018, with gas- and/or coal-based generation assets in their portfolio. To this end, I retrieved historical releases of a global asset-level dataset, which offers a unique opportunity to capture changes of plant ownership over time. While having several limitations, including the less-than-complete coverage of specific technologies of certain capacity in some geographies, the dataset is considered to be among the most comprehensive asset-level databases available for the electricity-generation sector (see Methods). I adopt a bottom-up approach, examining the portfolio developments of the utilities that directly own the power-generation assets, rather than of their parent companies, should they have one. Conducting the analysis at the parent company level could mask the granularity of individual companies' behaviours, particularly those operating in a different geography and having a divergent portfolio expansion strategy from their parent (see Supplementary Note 1).

I cluster the utilities based on their average growth of three fuel types over the past two decades: non-hydro RE- (hereinafter simply referred to as RE), gas- and coal-based capacity (see Methods). The analysis identifies four macro-behaviours and additional granular sub-patterns (Fig. 1). The first and by far the largest cluster (over 75% of all utilities, and nearly 50% of their capacity) comprises the

Smith School of Enterprise and the Environment, School of Geography and the Environment, University of Oxford, Oxford, England.
e-mail: galina.alova@ouce.ox.ac.uk

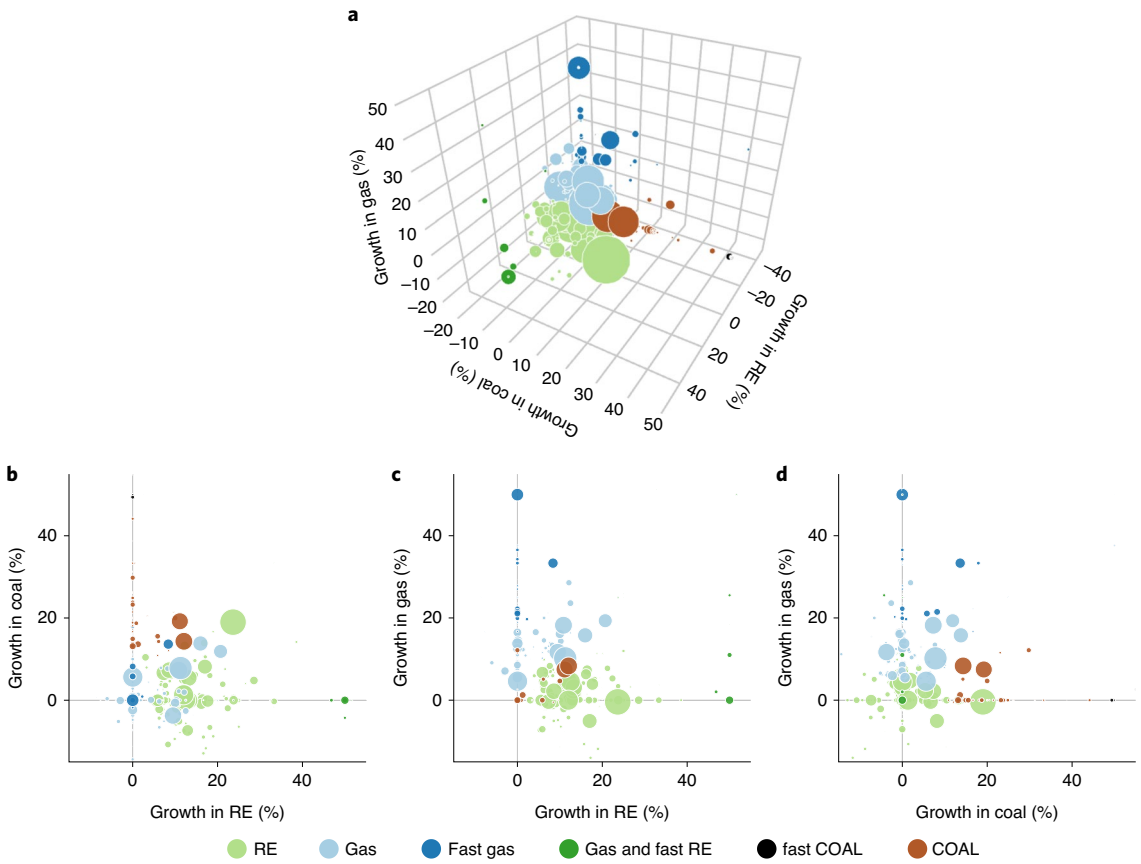


Fig. 1 | Utilities' portfolio growth patterns by fuel type. a–d, A three-dimensional representation of the clusters and their sub-clusters (**a**), which is complemented by two-dimensional projections (**b–d**). Utilities here are those considered active, having grown their capacity in at least one of the fuel types under consideration. The bubble size refers to the total generation capacity of a utility. The 'fast gas' category incorporates both the sub-cluster within the main gas-prioritizing cohort, as well as the small distinct cluster identified separately by the algorithm (see Supplementary Table 1).

so-called passive companies, which did not actively grow RE but also did not expand their FF portfolios (Supplementary Table 1). The cluster is dominated by European (42%), followed by North American and Asian utilities (both 20%). Over half of the companies come from four countries: the US, China, Germany and Denmark; and over 70% are state owned, including smaller regional and municipal utilities, the highest share compared to the other clusters. Furthermore, the utilities here are FF-intensive, with on average 85% of their portfolios containing gas and/or coal capacity. As the hypotheses testing shows (see H1–H3, Supplementary Table 2), these utilities are substantially smaller in their capacity size and own a somewhat more modest market share in the countries in which they operate, compared to the companies in the other clusters. Expectedly, the average growth of their capacity is also dramatically lower.

The second distinct utility behaviour is to prioritize growth of RE (on average 14% across the cluster) over the other assets (Fig. 1 and Supplementary Table 1). Companies in this cluster added nearly 55 GW of RE to the global capacity since the 2000s, with wind accounting for 77%, solar for 14% and biomass for nearly 7%. This cluster contributes 10% of all or 43% of active utilities (26% of all capacity), and is dominated by Europe and North America, cumulatively accounting for over two-thirds of companies. The individual leading countries are the US (29% of the cluster), followed by Germany and China, with 13% and 10%, respectively.

Although the utilities in this cluster clearly prioritize RE growth, the vast majority are still at the very beginning of their transition (Fig. 2). In 2018, over half of them had less than 3% of RE in their

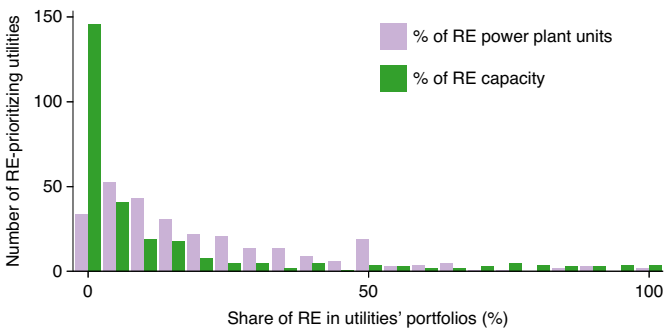


Fig. 2 | The share of RE in the RE-prioritizing utilities' portfolios, 2018. RE refers to non-hydro renewable energy. Companies here come from the RE-prioritizing cluster.

portfolios, while only 13% had over half. At the same time, virtually all of them saw on average an increase in the share of their RE capacity over time. As an example, ENGIE Brasil in Brazil demonstrated considerable growth in RE, mostly wind power, with the share in its portfolio increasing from zero at the beginning of the 2000s to nearly 6% by 2018 (Fig. 3b).

Strikingly, 57% of the utilities in this cluster continued to grow either their gas or coal portfolio, or both. Nearly 80% of these FF-growing companies expanded their gas portfolio at an average 5%,

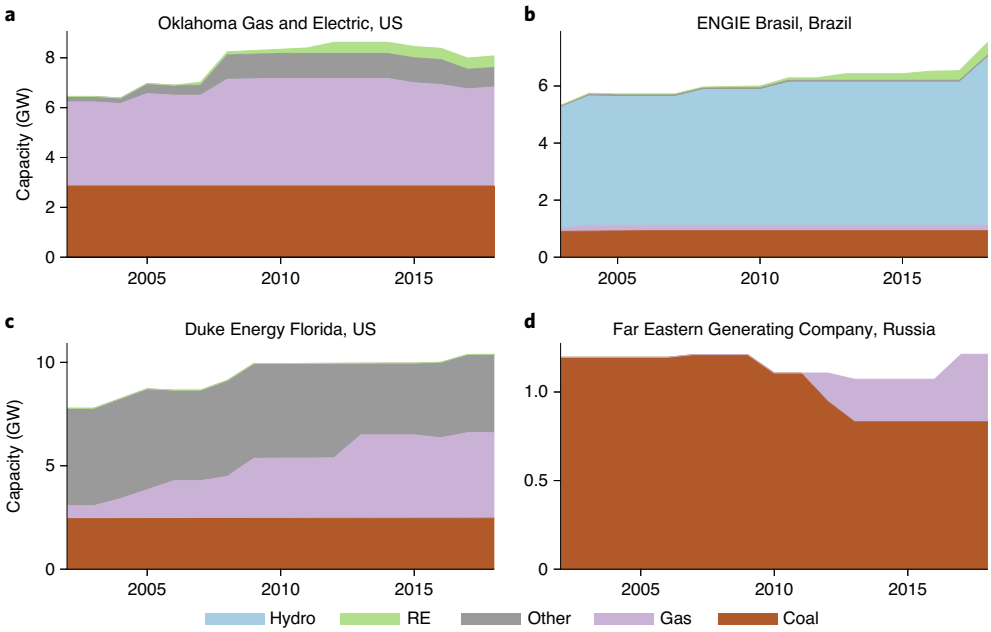


Fig. 3 | Portfolio composition of select companies. a–d, Companies constitute examples of the RE-prioritizing cluster (**a**,**b**) and gas-prioritizing cluster (**c**,**d**).

compared to 35% increasing coal capacity at a slower 1% rate. Middle Eastern utilities had on average the highest accompanying growth in gas. For example, Dubai Electricity and Water Authority (DEWA) in the United Arab Emirates has been expanding into RE, which still accounts for a fraction of its gas-dominated portfolio. Moreover, DEWA has a 2.4 GW Hassyan coal power station under construction that, once completed, will further grow its FF asset base. That said, it also has nearly 3 GW of further solar capacity in the pipeline. In terms of coal, Asian companies had the highest growth. For example, China Guodian Group Corporation grew its wind portfolio while also expanding coal-fired capacity. Furthermore, over 16% of the companies in this cluster have new gas capacity, and nearly 7% have new coal capacity, in the pipeline, totalling 46 GW and 36.5 GW, respectively (based on the information currently available in the dataset).

Generally, the transition to RE often goes hand-in-hand with growth in gas capacity. For example, within the RE-prioritizing cluster, a distinct subgroup was identified, totalling 7% of the companies, characterized by particularly fast growth of RE (49% on average), coupled with on average 19% growth in gas (Fig. 1). As an illustration, Oklahoma Gas & Electric Company in the US increased the share of RE through wind power from zero at the start of the dataset to roughly 6% in 2018 (Fig. 3a). Gas, which it also grew, albeit at a slower rate, accounted for half of the portfolio, while coal capacity, which it did not expand, still contributed a third.

By comparison, 34% of the utilities in the RE-prioritizing cluster had on average negative growth in either their coal or gas capacity, with 15% reducing both. European companies account for over 40% of the latter. For example, Ørsted, formerly a Danish oil and gas company, and currently an electricity company, in its effort to phase out coal by 2023 (ref. [29]), has substantially reduced its capacity along with natural-gas-fired generation, while expanding its RE portfolio. Similarly, Stadtwerke München, a communal company owned by the city of Munich in Germany, has been expanding into wind, including acquiring projects in France, while reducing the share of its gas capacity.

Hypotheses were tested (see H4–H8, Supplementary Table 2) to understand the market-structure-related features of the cluster. Results suggest that utilities in this cluster are larger and own a higher market share in their respective countries' capacity than the companies in the other cohorts. The findings also point to these utilities being in the jurisdictions with higher shares of non-utility-owned RE capacity, compared to the other clusters.

The correlations between the measures of RE capacity owned by IPPs and utilities were also examined, to explore whether their respective roles are complementary, or if utilities might be crowded out from the RE sector (Supplementary Fig. 1). I observe a very small positive correlation (0.04) between the countries' share of IPP-owned RE and growth of utilities' RE capacity, and a small negative correlation (−0.09) between the share of utility-owned and growth of IPP-owned RE capacity. At the same time, there are considerable positive links between the growth of utilities' and IPPs' RE (0.19), IPP-owned RE capacity and growth of utilities' RE capacity (0.30) and vice versa (0.28), as well as a strong positive correlation (0.73) between utility- and IPP-owned RE.

The composition of the cluster was also examined in terms of the shares of the companies in the countries with enabling policies in place either at the national or sub-national level, which could potentially affect utilities' behaviour[24,25,28,30–34]. These include feed-in-tariffs (FIT), renewable portfolio standards (RPS), carbon taxes (CT) and emission trading systems (ETS; Supplementary Fig. 2). Of the RE-prioritizing utilities, 60% were in jurisdictions with FIT, and nearly half with RPS. This cluster also had a relatively higher share of companies in the countries with carbon pricing policies (21% with CT and 15% with ETS), compared to the other groups. The testing of related hypotheses (H9–H13, Supplementary Table 2) yielded similar conclusions: the jurisdictions with either one or all of these policies had substantially higher utility-owned RE capacity than the countries without any of the policy instruments.

Third, there are companies (10% of all utilities and 19% of their capacity) that favoured the expansion of gas capacity (on average 13% growth across the cluster) over that of coal or RE (Supplementary Table 1). This third cluster is dominated by the US, which alone contributes 29% of the companies, followed by Russia and Germany, with 8% and 7%, respectively. In terms of regional distribution, the utilities from North America (30%) and Europe (26%) prevail, followed by Asia (13%) and the Commonwealth of Independent States (12%). As an illustration, Duke Energy Florida

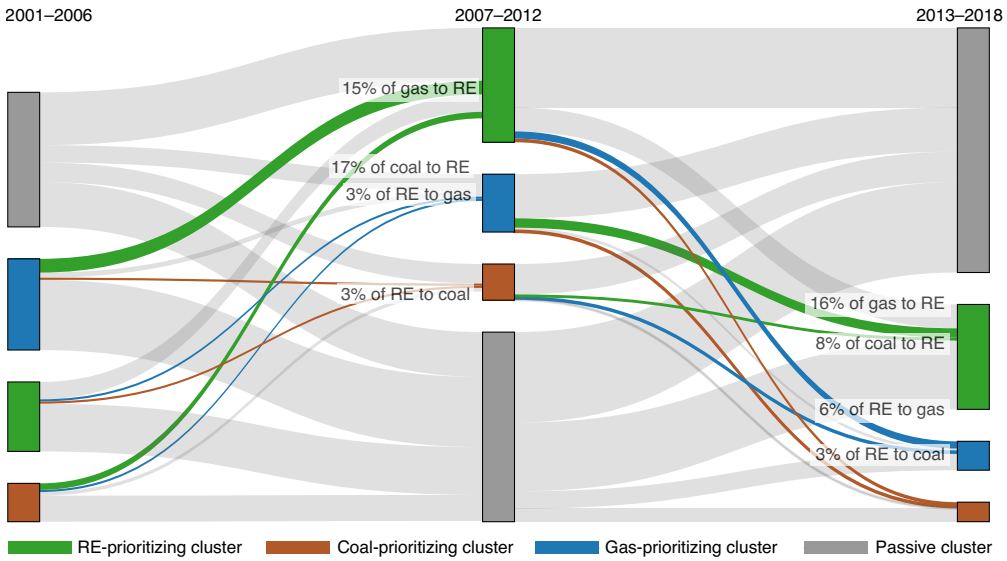


Fig. 4 | Utilities' transition between clusters. Companies here exclude those that stayed in the passive cluster (that is, those that did not grow RE- or FF-based capacity) throughout the three periods. The high number of these excluded passive companies would obscure the graph. Also, the companies that existed in only one time period cannot be displayed.

in the US has considerably grown its gas portfolio over the past two decades from 7% to nearly 40% by 2018 (Fig. 3c). Another example is a smaller regional utility, Far Eastern Generating Company, in Russia that started its efforts to transition from coal to gas (Fig. 3d), completing in 2013 the conversion of the three units of the Vladivastok-2 power plant, which resulted in a tenfold reduction in greenhouse gas emissions and particulate matter[35].

Furthermore, several sub-behaviours exist within this cluster. First, not all companies grew gas at the same rate. One-fifth exhibited particularly fast growth, on average 26%. For example, Basin Electric Power Cooperative in the US grew the share of its gas capacity from just over 1% in 2002 to 20% in 2018. Similarly, Shenergy Group Company in China expanded gas as a share of overall capacity from 0% in 2009 to 19% in 2018. Notably, the clustering analysis also identified a separate, distinct, albeit tiny, cluster with 78% average growth in gas (Supplementary Table 1).

While prioritizing gas, some companies also expanded, although to a lesser extent, their coal- or RE-based capacity, accounting for nearly 18% and 17% of the utilities in this cluster, respectively. This was, for example, the case for Tuas Power in Singapore, which along with more than doubling its gas portfolio, started to build coal-fired power plants. At the same time, Basin Electric Power Cooperative in the US, despite its fast transition to gas, mentioned above, remains dominated by coal, which it also grew, although at a much slower rate.

Finally, in the fourth, relatively smaller (2% of all companies and 5% of capacity) and less heterogeneous cluster, there are companies prioritizing the expansion of coal-based capacity (on average 27% growth across the cluster; Supplementary Table 1). This cluster is dominated by China, which alone contributed over 60% of the companies, followed by India (9%) and Vietnam (5%), with Asia overall accounting for over 82% of the cluster. Over 70% of the utilities here are coal focused with no RE or gas in their portfolios. Furthermore, 83% of the plants here are subcritical, with only 5% being ultra-supercritical and the rest being supercritical. Examples include Guangdong Electric Power Development Company in China, which saw regular growth of its largely coal-based portfolio, and Haryana Power Generation Corporation in India, which grew its coal assets, particularly, in the first half of the period under consideration.

Moreover, the coal-prioritizing cohort demonstrated the lowest share of companies in the jurisdictions that had CT or ETS (6% and 3% of the companies, respectively) in place. Further, fewer than a third of the utilities were in the jurisdictions with FIT or RPS, the lowest share compared to the other clusters (Supplementary Fig. 2).

Utilities shifting clusters over time

As shown by my analysis, besides a dominant portfolio growth pattern, which characterizes a utility over time, the company might in parallel exhibit a sub-behaviour, growing another fuel, albeit at a lower rate. If in a certain time period this sub-behaviour is particularly strong, the utility might be clustered into a different cohort from its dominant pattern, while still preserving its macro-identify over the whole 18 years under consideration (see Methods). To offer such temporal granularity and detect utilities' potential shift towards RE-prioritizing behaviour, I perform three additional clustering analyses over separate six-year spans (Fig. 4; see Methods).

The results point to a considerable degree of companies transitioning to the RE-prioritizing cluster, while the coal- and gas-favouring cohorts shrank in size over time. This trend generally coincides with the overall increase in the share of global operating capacity being covered by at least one of the RE-promoting or FF-inhibiting policies, from 18% in 2001 to over 85% in 2018 (Supplementary Fig. 3). This might signal a link between companies' changing behaviour patterns and the gradual shift of policies towards RE. Between the first and second period, 15% of the companies in the gas cluster and 17% in the coal cluster moved to the RE-prioritizing group. Between the second and third period, such companies accounted for 16% of the gas-prioritizing and 8% of the coal-prioritizing cohorts. The US and China contributed nearly half of such companies. For example, PacifiCorp Energy in the US, being dominated by gas growth over the two decades studied, was assigned to a gas-prioritizing cohort as its prevailing behaviour. Given its incipient expansion into low-carbon assets, in line with its plan to phase out most of its coal fleet by 2038 and replace it by solar and wind capacity[36], it exhibited a substantial RE-growing sub-behaviour in some years, and was therefore classified as a RE-prioritizing utility in the second time span of the three-period clustering. This shift took place in parallel with the increase in the share of PacifiCorp's capacity being covered by subnational RPS, from 13% in 2001 to 18% by 2018, as the different states where the company operates were rolling out the policy over time. Similarly, as mentioned above, China Guodian Group

Corporation, being clustered into the RE-prioritizing cohort as a dominant behaviour throughout the 18 years studied, also showed substantial growth in coal, which prevailed in the earlier years of the dataset over growth in RE. Therefore, it was characterized by the three-period clustering as a coal-prioritizing company in the first time span, transitioning to the RE cohort in the subsequent two periods. This behaviour coincided with the increase in the share of the company's capacity covered by subnational ETS, from 0% at the start of the dataset to 14% by 2018, given the provinces where it has assets. These include, for example, Tianjin, Hubei and Guangdong, where ETS covers, among others, the power-generation sector[37].

There is also an opposite, although markedly smaller, movement away from the RE-prioritizing cluster (Fig. 4). While it does not necessarily imply that these companies reversed their RE-growing strategy altogether, they did prioritize it to a lesser extent than coal or gas over recent years. In line with the macro-clustering analysis, this suggests that even the companies growing RE capacity might aim to balance it with FF expansion, rather than transition entirely to low-carbon generation.

Finally, a considerable movement can be noted between the three active clusters and the passive cohort, signifying iterations between the periods of portfolio expansion and no asset growth. For example, Stadtwerke München, mentioned above, classified as a RE-prioritizing company by the one-period clustering, had no growth in RE or FF in the early 2000s. It was therefore assigned by the three-period clustering to the passive cohort in the first time span and to the RE-prioritizing cluster for the two subsequent periods.

Discussion

The analysis in this paper points to power utilities lagging behind, and even hindering, the global transition to RE. Although a minority continued to invest in coal-fired capacity ahead of other assets in the last two decades, gas was prioritized by a substantial share of the companies. Furthermore, while a considerable and increasing number of utilities were prioritizing RE, their transition remained slow. This was driven by the majority still growing in parallel, albeit to a lesser extent, their FF portfolios. Coupled with the finding that the RE-prioritizing companies tend to be larger and own a higher market share than the other utilities, the results imply that these companies might not necessarily aim to replace their FF capacity with RE, but rather add low-carbon assets to their growing core business. Essentially, they have started to explore new technologies while continuing to exploit the incumbent technologies[38], without sufficiently disrupting their conventional business. Notably, the clustering did not identify a distinct group of utilities with a considerable reduction of FF capacity. Only a small share of the utilities in the RE-prioritizing cluster were concurrently reducing both their coal and gas capacities, driven by European companies. This might in part be attributed to relatively higher carbon prices[39] and RE support policies in some European countries, improving the cost competitiveness of low-carbon technologies[40]. Furthermore, while a utility might be transitioning to RE in terms of its capacity, this may not directly translate into its electricity generation, given that wind and solar photovoltaics as variable energy sources have on average relatively lower capacity factors than FF, particularly coal[1].

In view of these findings, it is unsurprising that the utilities continue to dominate global FF-based electricity generation, holding over 70% of operating coal and gas capacity in 2018 (ref. [4]). A large share of these assets is far from its retirement age, with a third being added in the last ten years[4]; and unless retired early and resulting in asset stranding[41], these power plants are here to stay for decades, leading to carbon lock-in. It is worth noting, however, that at least part of the increase in utilities' gas capacity might be due to its role as a transition fuel, providing load-balancing services to intermittent RE generation[42]. Further, with China dominating the coal-prioritizing cluster, the goal to cap China's coal consumption[43] and the plans to reform its FF subsidies (the world's highest)[44] in the near to long term[45], if implemented, could reduce the number of coal-prioritizing companies in the future. Nevertheless, there are signs that China recently returned to expanding its coal-fired fleet, after the government's 2017 move to cancel over 120 GW of new capacity[46]. Similarly, in India, another notable contributor to the coal-prioritizing cluster, with uncertainty around coal phase-out plans, coal demand is forecasted to grow to fuel the expanding economy[47]. Should countries and their utilities fail to overcome electricity system inertia[48], the transition will be inevitably slowed down, no matter how fast global RE capacity expands. Continued growth of FF capacity beyond the support to low-carbon electricity systems will likely lead to more severe carbon lock-in and asset stranding in the future, unless the present use of carbon capture, utilization and storage is substantially scaled up.

Notably, companies whose portfolio expansion decisions towards RE or FF can largely predetermine the speed of the electricity sector's transition only constituted a quarter of the utilities examined in this study, while they own half of the global capacity. The majority of the utilities did not grow their RE and FF at all, implying that while they did not diversify into clean generation, they did not aggravate their carbon lock-in either. These companies tend to be smaller, with a limited market share compared to the other utilities. As one possible explanation, they could be financially constrained from undertaking costly portfolio expansion and, instead, could potentially act as power off-takers from IPPs (ref. [3]).

Relatedly, utilities might participate in the low-carbon transition through business activities not limited to generation, for example, enabling energy efficiency, decentralized generation and system integration and balancing[11,17,18,27,49]. Their long-term expertise and customer base could grant them a comparative advantage[27] in these decarbonization pathways, which may merit further analysis.

In terms of the market-structure-related attributes of the clusters, I observe that RE-prioritizing utilities are generally located in the countries with higher participation from non-utility actors. These findings point to the roles of the utilities that have already started their decarbonization and non-utility actors in driving RE transition being complementary rather than mutually exclusive. This could imply that diversification into RE could be one of the potential survival strategies for utilities seeking to stay in the generation business, despite the changing reality of the sector.

Furthermore, my results on the policies characterizing the clusters serve as a preliminary indication that an enabling framework promoting the uptake of RE may have a link to utilities' portfolio growth patterns. This relationship between policies and companies' transitions could benefit from further analysis. The effectiveness of a policy often depends on its design and complementarity with other instruments, rather than its mere existence.

Finally, other factors deserving future research attention to explain the phenomena in the utilities' transitions identified here include, among others, the relative prices of technologies and financial performance of utilities. These are likely to affect their decisions to invest into certain generation assets[50], and whether to invest at all.

Methods

Asset-level dataset. The Utility Data Institute (UDI) World Electric Power Plants Database (WEPP) by S&P Global Market Intelligence serves as a main dataset for this study. WEPP is considered one of the most comprehensive asset-level databases for the electricity sector, recording global generation capacity on a quarterly basis at the power plant unit level[51]. This is particularly valuable, given that different units of the same power plant can sometimes run on different fuels and come into operation or be retired at different times. Aggregation to plant level would reduce the granularity of the data. As of 2018, WEPP contained information on over 6 TW of currently operating and nearly 800 GW of retired capacity. Its coverage, while generally adequate, may vary across geographies, technologies and plant capacity. According to the WEPP documentation[52], the database is considered comprehensive (>75%) for large- and medium-sized power plants of all types of fuel and technology. For several technologies and capacities, coverage is complete

(>95%), for example, for thermal steam electric power plants of over 50 MW (except for in China, where it is comprehensive) or for gas turbines of over 25 MW. On the other hand, for some smaller assets, select countries, company types or technologies, the coverage might be representative (>50%); for example, this is the case for onshore wind power plants below 1 MW. Rarely, and only for small plants of specific technologies (for example, hydroelectric plants of below 5 MW in China, or onshore wind turbines below 0.1 MW), the coverage might fall below the majority[52]. While the contribution of such plants to the overall capacity might be limited, their incomplete coverage might, to some extent, affect the portfolios of smaller companies specializing in small-scale projects. That said, nearly a quarter of the dataset in 2018 constituted power plants below 1 MW. In 2018, the number of overall power-generating units of different operating status recorded in the dataset was nearly 219,500, which can be aggregated to roughly 109,500 power plants, and operated by over 42,700 companies.

WEPP has some further limitations, besides coverage, in terms of how information is being recorded, as identified in the course of the analysis and by other researchers[53]. First, there might be inconsistencies in capacity ratings, as featured in the dataset, given that there is a lack of standardization in the definitions and use of different terms, such as gross, net, nominal or nameplate capacity. This might lead to errors in plant capacity data. WEPP preferentially reports plant gross capacity[54]. However, when this information is unavailable, WEPP might include whatever other type of capacity rating is presented in power plant documentation. Second, there may also be discrepancies and delays in accounting for power plant upgrading or downgrading, which could potentially result in a deviation from reality in plant capacities as recorded by WEPP. Third, there might be inaccuracies in the details of power plants besides their capacity, for example, lags in recording their construction, completion or retirement and imprecisions in these dates. Finally, while WEPP is a unit-based dataset, there might be cases when it, either erroneously or due to a lack of information, records data on a power-plant basis, rather than on its individual units, which could reduce granularity in tracking changes to these power stations.

In view of these limitations, I considered using WEPP in conjunction with other asset-level databases to reconcile some of the potential discrepancies. Studies concerned with the present state of the power-generation sector sometimes merge WEPP data with other datasets, such as CoalSwarm or CarbonMonitoring for Action (CARMA)[41,55], to further improve the coverage and accuracy. However, these additional datasets do not tend to offer historical releases of the data, required for tracking assets and their ownership over time, which is a unique feature of WEPP. Moreover, other datasets also sometimes deviate from reality in the accuracy of their data, and therefore might introduce further inaccuracies. As another alternative, I also explored retrieving information on individual companies' assets from their annual reports. However, given the lack of standardized disclosure requirements, the completeness of information reported might vary substantially across utilities and geographies[56]. As a result, despite its potential limitations, WEPP was considered the most suitable dataset for the purpose of this study, and the most complete currently available global historical database. Therefore, the decision was made to use it; when occasional discrepancies were detected, I updated or corrected the information. If some inaccuracies remained unidentified, they might have impacted the results, if they led to considerable differences in plant capacity compared to reality.

Historical WEPP releases for the period between 2001 and 2018 were obtained and merged into a time-series dataset. The aim was to capture the critical time period when the transition of the global electricity system towards RE gained momentum[57] and therefore could offer useful insights into the potential shift of utilities as the sector's incumbents. While several studies[2,27,41,58,59] have used single, usually most-up-to-date releases of WEPP data to address a variety of research questions, few studies[53,56,60] have collected historical data to construct a time-series dataset. Here, an 18-year time-series has been built to address the research problem.

Besides the unit size and fuel, WEPP records a substantial number of other useful features, for example, the power-generating unit's location, status and year of entry into operation and retirement. Importantly, WEPP has information on the operating company, that is, the facility operator and/or sole or majority owner of each unit. This allows aggregating data to the company level for the analysis of portfolio composition and the change in plant ownership over time. If a unit or plant is co-owned, only the company with a majority stake in it would feature in the dataset, which would not allow tracking the changes in minority owners, introducing a potential limitation. Furthermore, the company operating a plant might in turn be owned by a parent company; however, this information is only available for later WEPP releases. Sourcing additional data, to complement WEPP, that would track the historical ownership of both listed and unlisted utilities worldwide proved to be a challenge. A decision was made against merging incomplete data into the WEPP dataset, which could introduce a bias and would not add substantial value to the analysis. In my analysis, I adopted a bottom-up approach, examining the portfolio developments of the companies that immediately own the power-generation assets, rather than of their parent companies, for the reasons (other than the aforementioned data availability) outlined in Supplementary Note 1. I also conducted an additional analysis at the parent-company level to compare to the results of the clustering at the subsidiary level (see Supplementary Note 1 for results).

Focus on utilities. WEPP also includes data on the operating company's business type (for example, energy, manufacturing, commercial or government entity) and the electricity production type (for example, utility, private power producer, or commercial and industrial autoproducer), allowing a number of possible company type combinations. I combined the information from the business type and electricity production type categories to engineer a company type feature, marking entities either as a utility (which includes both government- and investor-owned utilities), an IPP or an autoproducer. Given the focus of this study on utilities' transition as incumbents of the energy sector, the sample comprises the companies with non-zero gas and/or coal capacity, identified as utilities, such as regulated utilities (including those owned by national or local governments), investor-owned utilities and cooperative utilities, existing at some point between 2001 and 2018. Autoproducers were not included in the main clustering analysis given that they are most likely to be industrial or commercial enterprises generating their own electricity, typically without off-site energy sales. IPPs were not included for the following reasons. First, the focus of this paper is on electric utilities as incumbents of the power-generation sector, and their ability to embrace new RE technologies and disrupt the use of conventional FF technologies. Second, IPPs tend to be substantially more advanced in their transition away from FF towards RE, than utilities. Over 75% of IPPs in 2018 that also owned FF had over half of their capacity in RE, compared to 23% of utilities. Furthermore, IPPs accounted for 22% of global FF capacity in 2018, compared to over 70% owned by utilities. At the same time, IPPs owned over three-quarters of the global RE capacity, while utilities only contributed 19%. Therefore, the inclusion of IPPs together with utilities would likely result in a more positive overall picture, distorting the results for utilities.

The obtained dataset was cleaned, to remove possible discrepancies in the recordings of the same company's name across different data releases, which could introduce inaccuracies in tracking a power plant's ownership over time. To this end, a string similarity algorithm, the Jaro–Winkler distance, was employed to detect closely related company names. These were then manually reviewed, to identify and amend the name variations of the same company. Furthermore, 2.7% of the company-year data points, constituting extreme outliers, were removed (that is, the companies that had over 100% positive or negative growth in either of the three asset types, resulting from such events as company liquidation and/or transfer of all assets to a new company, or erroneous entries in WEPP). The final sample size used in this study was 3,311 utilities. The number of utilities in individual years can vary, given that over the 18 years under consideration, some companies might have emerged, undertaken restructuring or ceased operations.

While the core clustering analysis focuses on utilities, the study also draws on information about non-utility actors (IPPs and autoproducers) to analyse, through hypothesis testing (see below), the market-structure-related characteristics of the utility clusters identified.

Policy data. The dataset was extended to include historical information on the RE-promoting and carbon pricing policies in place at the national or subnational level, retrieved from annual REN21 Renewables Global Status Reports[61] and the World Bank's Carbon Pricing Dashboard[62], respectively. These policy instruments include FIT, RPS, ETS and CT.

Clustering for unsupervised problems. Clustering, a machine-learning-based method, was selected as a core analytical tool for the study. It allows gaining insights by letting the algorithm classify data points (in this case, utility companies) into a specific group, based on predefined features, so that the firms in one cluster have shorter distances between each other (that is, they are more similar) than to those in the other groups[63,64]. Clustering as an unsupervised technique is particularly useful for identifying patterns in large data. This is the case here, where the study aims to uncover different behaviours that utilities exhibit in growing or reducing their power-generation portfolios, with the shape of this landscape a priori unknown. The chosen method has thus enabled me to capture the transition behaviours of the utilities worldwide, something that alternative approaches, be it case studies, descriptive statistics or manual categorization of companies, would not be able to achieve in a rigorous and consistent manner, given the size and heterogeneity of the dataset. Clustering has been previously applied in several studies on climate-related corporate issues[65–68].

I performed the analysis, using an agglomerative hierarchical technique, with Euclidean distances and ward linkage, which aims to minimize the variance within the clusters. To this end, I applied a clustering algorithm, provided by the open-source SciPy library in Python. Notably, the hierarchical clustering enables one to track the split between larger clusters into new smaller ones—a property important for identifying sub-patterns within the utilities' macro-behaviours. Furthermore, a pertinent use case of the hierarchical clustering includes detecting unevenly sized clusters, which is in line with the expectation that utilities might cluster into groups of considerably different size, depending on the assets they have chosen to grow.

Feature engineering. As the crucial first step in the analysis, I constructed appropriate features, based on which the algorithm could perform clustering; that is, I defined what exactly it means, for the purpose of this study, that utilities are similar. As I focus here on the utilities' asset growth patterns, the features representing fuel-class-related growth measures were selected. These include

companies' growth in operating non-hydro RE-, gas- and coal-based generation capacity over the period of 18 years. An average for each of the three features was taken across the years a company existed in the dataset. Hydropower has been excluded from the analysis, given its maturity as a low-carbon technology as opposed to the learning technologies, such as solar and wind power[69]. Furthermore, the reliance on hydropower in some parts of the world, particularly eastern and southern Africa, might expose those regions to physical climate risks[70]. Clustering by the growth in the number of RE-, coal- and gas-based power-generation units was also considered. However, the capacity-based features were selected, because they are more meaningful in tracking utilities' behaviour, allowing better comparability across asset types and companies, as opposed to the mere number of generation assets.

Furthermore, alternative clustering based on additional features was considered, including (besides the growth in capacity) relative measures, to capture the different stages of utilities' transition to one or another asset. These measures include the share of RE-, coal- and gas-based assets in the companies' portfolios, and/or the growth in these shares. However, a decision was made to discard these additional features for two reasons. The first reason was to avoid the curse of dimensionality[71,72]. The inclusion of the additional features reduced cluster distinctness, in that the companies' behaviour patterns as captured by the clusters became less clear. This was also the case when, in addition to capacity-based features, growth in the number of units was considered for inclusion in the clustering. The second reason was to maintain the homogeneity of the features and the interpretability of the distances between the companies. Features of the same type (for example, growth in capacity) yield more meaningful distances (here Euclidean) between the data points, than do the combination of features of different types (for example, growth in capacity and share of assets in portfolio). As a result, the three core features—growth in non-hydro RE-, gas- and coal-based generation capacity—were selected for the final analysis. To obtain meaningful Euclidean distances between the companies growing at different speeds, I log-transformed the features selected, which converted growth measures and distances from multiplicative into additive.

It is important to highlight that I rely on utilities' capacity data by fuels, which might not directly translate into generation, given different capacity factors across technologies and geographies. Accounting for these is, however, challenging, given the limited data availability on generation by individual plants and variations across companies and geographies; hence, the focus of this study is on the trends in utilities' capacity.

Clustering evaluation metrics. Finally, I applied clustering evaluation metrics—Silhouette[73], Calinski Harabasz[74] and Davies Bouldin[75,76] scores—to identify an optimal number of clusters. The validation techniques suggested a range between two and six clusters (Supplementary Fig. 4). The decision was made to select five clusters, since they best captured the macro-behaviours of the companies, yielding the clearest results, followed by exploring more granular sub-patterns by tracking cluster splitting up to eight clusters.

Three-period clustering. Besides a dominant portfolio growth pattern, as identified by the main clustering in the whole 18 years under consideration, companies might in parallel exhibit a sub-behaviour, growing another fuel, albeit at a lower rate. This sub-behaviour could accompany the company in moderate terms throughout the two decades, or emerge more strongly in a certain time period. If this sub-behaviour outstrips the growth of the utility's main fuel in a given set of years, the company may be clustered into a different cohort from its dominant pattern for this period in time. This shift would not undermine the results of the aggregate clustering, as the utility would still preserve its macro-identity, measured over the whole 18-year time span. Instead, it would indicate that, should this sub-behaviour continue to intensify, the company might be on the path of transition in the next decades. For example, a gas-prioritizing utility might have started to diversify its portfolio into RE in the mid-2010s, and therefore could be considered a RE-favouring company for that particular period, while remaining a gas-prioritizing utility for the whole two decades under consideration.

To capture this temporal granularity and companies' potential movements towards RE-prioritizing behaviour, I performed, in addition to the aggregate clustering over 18 years, separate clustering analyses for three time spans. To this end, the dataset was divided into three periods of equal six-year lengths—2001 to 2006, 2007 to 2012 and 2013 to 2018—whereby the same company in different time periods was treated as a different company. The averages of the three growth features (RE, coal and gas) were calculated for each time period. Again, the hierarchical clustering algorithm was applied to the dataset. Once clustered, I tracked companies' allocation to the clusters in different time periods to explore their transitions, and presented the results in a Sankey graph for visual clarity (Fig. 4).

Hypothesis testing. The clustering analysis was complemented by hypothesis testing to validate true-or-false claims (Supplementary Table 2) using bootstrapping—a resampling technique based on a random iterative sampling of a dataset with replacement. Bootstrapping with 10,000 samples was performed[77–79]. In bootstrapping, a hypothesis on two populations is tested by comparing the means of the differences between the resampled subsets drawn from the two populations, and the actual difference of the means between the two populations, to determine whether the latter could have happened by chance. The advantage of the bootstrapping method is that it does not imply a normal distribution of data, and therefore can be applied to non-normal distributions, such as the populations in my hypothesis testing.

Data availability

The data on power-generation assets from the UDI WEPP database were received under licence from S&P Global Market Intelligence and could be obtained under similar arrangements from www.spglobal.com/marketintelligence. The historical data on the countries' policies were retrieved from the annual REN21 Renewables Global Status Reports publicly available at https://www.ren21.net/reports/global-status-report and from the World Bank's Carbon Pricing Dashboard publicly available at https://carbonpricingdashboard.worldbank.org. The data that support the graphs within this article and other findings of the study are available from the author upon reasonable request.

Code availability

The study employs a hierarchical clustering algorithm by the free open-source SciPy library in Python. The code is available from the author upon reasonable request.

Received: 16 December 2019; Accepted: 4 August 2020;
Published online: 31 August 2020

References

1. *World Energy Outlook 2018: The Future is Electrifying* (IEA/OECD, 2018).
2. Kelsey, N. & Meckling, J. Who wins in renewable energy? Evidence from Europe and the United States. *Energy Res. Soc. Sci.* **37**, 65–73 (2018).
3. Eberhard, A., Gratwick, K., Morella, E. & Antmann, P. Accelerating investments in power in sub-Saharan Africa. *Nat. Energy* **2**, 17005 (2017).
4. S&P Global Market Intelligence World Electric Power Plants Database (S&P Global, 2018); www.spglobal.com/marketintelligence
5. Castaneda, M., Franco, C. J. & Dyner, I. Evaluating the effect of technology transformation on the electricity utility industry. *Renew. Sustain. Energy Rev.* **80**, 341–351 (2017).
6. Hannon, M. J., Foxon, T. J. & Gale, W. F. The co-evolutionary relationship between energy service companies and the UK energy system: implications for a low-carbon transition. *Energy Policy* **61**, 1031–1045 (2013).
7. Pollitt, M. G. & Anaya, K. L. Can current electricity markets cope with high shares of renewables? A comparison of approaches in Germany, the UK and the State of New York. *Energy J.* **37**, 69–88 (2016).
8. Shomali, A. & Pinkse, J. The consequences of smart grids for the business model of electricity firms. *J. Clean. Prod.* **112**, 3830–3841 (2016).
9. Wainstein, M. E. & Bumpus, A. G. Business models as drivers of the low carbon power system transition: a multi-level perspective. *J. Clean. Prod.* **126**, 572–585 (2016).
10. Hall, S. & Roelich, K. Business model innovation in electricity supply markets: the role of complex value in the United Kingdom. *Energy Policy* **92**, 286–298 (2016).
11. Midttun, A. & Piccini, P. B. Facing the climate and digital challenge: European energy industry from boom to crisis and transformation. *Energy Policy* **108**, 330–343 (2017).
12. Kungl, G. Stewards or sticklers for change? Incumbent energy providers and the politics of the German energy transition. *Energy Res. Soc. Sci.* **8**, 13–23 (2015).
13. Mitchell, C. Momentum is increasing towards a flexible electricity system based on renewables. *Nat. Energy* **1**, 15030 (2016).
14. Kungl, G. & Geels, F. W. Sequence and alignment of external pressures in industry destabilisation: understanding the downfall of incumbent utilities in the German energy transition (1998–2015). *Environ. Innov. Soc. Transit.* **26**, 78–100 (2018).
15. Markard, J. The next phase of the energy transition and its implications for research and policy. *Nat. Energy* **3**, 628–633 (2018).
16. Parag, Y. & Sovacool, B. K. Electricity market design for the prosumer era. *Nat. Energy* **1**, 16032 (2016).
17. Richter, M. Utilities' business models for renewable energy: a review. *Renew. Sustain. Energy Rev.* **16**, 2483–2493 (2012).
18. Bryant, S. T., Straker, K. & Wrigley, C. The typologies of power: energy utility business models in an increasingly renewable sector. *J. Clean. Prod.* **195**, 1032–1046 (2018).
19. Richter, M. Business model innovation for sustainable energy: German utilities and renewable energy. *Energy Policy* **62**, 1226–1237 (2013).
20. Yi, H. & Feiock, R. C. Renewable energy politics: policy typologies, policy tools, and state deployment of renewables. *Policy Stud. J.* **42**, 391–415 (2014).
21. Löbbe, S. & Jochum, G. in *Future of Utilities—Utilities of the Future: How Technological Innovations in Distributed Energy Resources Will Reshape the Electric Power Sector* (ed. Sioshansi, F. P.) 323–341 (Elsevier, 2016).

22. Nillesen, P. & Pollitt, M. in *Future of Utilities—Utilities of the Future: How Technological Innovations in Distributed Energy Resources Will Reshape the Electric Power Sector* (ed. Sioshansi, F. P.) 283–301 (Elsevier, 2016).
23. Carley, S., Davies, L. L., Spence, D. B. & Zirogiannis, N. Empirical evaluation of the stringency and design of renewable portfolio standards. *Nat. Energy* **3**, 754–763 (2018).
24. Delmas, M. A. & Montes-Sancho, M. J. U.S. state policies for renewable energy: context and effectiveness. *Energy Policy* **39**, 2273–2288 (2011).
25. Yin, H. & Powers, N. Do state renewable portfolio standards promote in-state renewable generation? *Energy Policy* **38**, 1140–1149 (2010).
26. Ma, C. & He, L. From state monopoly to renewable portfolio: restructuring China's electric utility. *Energy Policy* **36**, 1697–1711 (2008).
27. Frei, F., Sinsel, S. R., Hanafy, A. & Hoppmann, J. Leaders or laggards? The evolution of electric utilities' business portfolios during the energy transition. *Energy Policy* **120**, 655–665 (2018).
28. Schleicher-Tappeser, R. How renewables will change electricity markets in the next five years. *Energy Policy* **48**, 64–75 (2012).
29. *Annual Report 2018* (Ørsted, 2019).
30. Carley, S. State renewable energy electricity policies: an empirical evaluation of effectiveness. *Energy Policy* **37**, 3071–3081 (2009).
31. Polzin, F., Migendt, M., Täube, F. A. & von Flotow, P. Public policy influence on renewable energy investments—a panel data study across OECD countries. *Energy Policy* **80**, 98–111 (2015).
32. Solangi, K. H., Islam, M. R., Saidur, R., Rahim, N. A. & Fayaz, H. A review on global solar energy policy. *Renew. Sustain. Energy Rev.* **15**, 2149–2163 (2011).
33. Best, R. & Burke, P. J. Adoption of solar and wind energy: the roles of carbon pricing and aggregate policy support. *Energy Policy* **118**, 404–417 (2018).
34. Jotzo, F. Australia's carbon price. *Nat. Clim. Change* **2**, 475–476 (2012).
35. During the ten-year transition to gas, the power-generation assets of Far Eastern Generating Company have seen a three-fold reduction in their greenhouse gas emissions (in English). *PrimaMedia* https://primamedia.ru/news/573854/ (2017).
36. *Bringing the Best of the West to Our Customer's Door* (PacifiCorp, 2019).
37. *Climate Change Mitigation: Policies and Progress* (OECD, 2015).
38. Ossenbrink, J., Hoppmann, J. & Hoffmann, V. H. Hybrid ambidexterity: how the environment shapes incumbents' use of structural and contextual approaches. *Organ. Sci.* **30**, 1319–1348 (2019).
39. *Effective Carbon Rates 2018: Pricing Carbon Emissions Through Taxes and Emissions Trading* (OECD, 2018).
40. *Energy Prices and Costs in Europe* (European Commission, 2019).
41. Pfeiffer, A., Millar, R., Hepburn, C. & Beinhocker, E. The '2°C capital stock' for electricity generation: committed cumulative carbon emissions from the electricity generation sector and the transition to a green economy. *Appl. Energy* **179**, 1395–1408 (2016).
42. Mac Kinnon, M. A., Brouwer, J. & Samuelsen, S. The role of natural gas and its infrastructure in mitigating greenhouse gas emissions, improving regional air quality, and renewable resource integration. *Prog. Energy Combust. Sci.* **64**, 62–92 (2018).
43. Fei, T. *Coal Transition in China. Options to Move from Coal Cap to Managed Decline under an Early Emissions Peaking Scenario* (IDDRI and Climate Strategies, 2018).
44. Coady, D., Parry, I., Le, N.-P. & Shang, B. Global Fossil Fuel Subsidies Remain Large: an Update Based on Country-Level Estimates Working paper no. 19/89 (International Monetary Fund, 2019).
45. *China's Efforts To Phase Out and Rationalise Its Inefficient Fossil-Fuel Subsidies: a Report on the G20 Peer Review of Inefficient Fossil-Fuel Subsidies that Encourage Wasteful Consumption in China* (G20 Peer Review Team, 2016).
46. Shih, G. China is back to building coal power plants, sparking fears over climate change. *Washington Post* (20 November 2019).
47. *Coal 2019* (IEA/OECD, 2019).
48. Seto, K. C. et al. Carbon lock-in: types, causes, and policy implications. *Annu. Rev. Environ. Resour.* **41**, 425–452 (2016).
49. Apajalahti, E. L., Lovio, R. & Heiskanen, E. From demand side management (DSM) to energy efficiency services: a Finnish case study. *Energy Policy* **81**, 76–85 (2015).
50. Adams, R. & Jamasb, T. Optimal power generation portfolios with renewables: an application to the UK. *Cambridge Working Papers in Economics* 1646 (2016).
51. Gotzens, F., Heinrichs, H., Hörsch, J. & Hofmann, F. Performing energy modelling exercises in a transparent way—the issue of data quality in power plant databases. *Energy Strateg. Rev.* **23**, 1–12 (2019).
52. *Data Base Description and Research Methodology: UDI World Electric Power Plants Data Base* (S&P Global, 2015).
53. Smouse, S. M., Jones, A., Fapohunda, B. O., Render, M. & Hindman, J. W. Coal- and gas-fired power construction and cancellation trends in countries with the most new coal power capacity since 2003. In *Proc. ASME 2018 Power & Energy Conference & Exhibition* 7466 (ASME, 2018).
54. *Data Base Description and Research Methodology: World Electric Power Plants Data Base* (S&P Global, 2018).
55. Liao, X., Chai, L., Jiang, Y., Ji, J. & Zhao, X. Inter-provincial electricity transmissions' co-benefit of national water savings in China. *J. Clean. Prod.* **229**, 350–357 (2019).
56. Reinartz, S. J. & Schmid, T. Production flexibility, product markets, and capital structure decisions. *Rev. Financ. Stud.* **29**, 1501–1548 (2016).
57. IRENA releases world's most comprehensive renewable energy capacity figures. *IRENA* (14 June 2015); https://www.irena.org/newsroom/articles/2015/Jun/IRENA-Releases-Worlds-Most-Comprehensive-Renewable-Energy-Capacity-Figures
58. Aboumahboub, T., Schaber, K., Wagner, U. & Hamacher, T. On the CO_2 emissions of the global electricity supply sector and the influence of renewable power-modeling and optimization. *Energy Policy* **42**, 297–314 (2012).
59. Peter, J. How does climate change affect electricity system planning and optimal allocation of variable renewable energy? *Appl. Energy* **252**, 113397 (2019).
60. Mayer, K. & Trück, S. Electricity markets around the world. *J. Commod. Mark.* **9**, 77–100 (2018).
61. *Global Status Reports* (REN21, 2005–2019).
62. *Carbon Pricing Dashboard* (World Bank, accessed 1 July 2019); https://carbonpricingdashboard.worldbank.org/
63. Maimon, O. & Rokach, L. *Data Mining and Knowledge Discovery Handbook* (Springer, 2010); https://doi.org/10.1007/978-0-387-09823-4
64. Hastie, T., Tibshirani, R. & Friedman, J. H. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (Springer, 2009).
65. Backman, C. A., Verbeke, A. & Schulz, R. A. The drivers of corporate climate change strategies and public policy: a new resource-based view perspective. *Bus. Soc.* **56**, 545–575 (2017).
66. Gasbarro, F., Iraldo, F. & Daddi, T. The drivers of multinational enterprises' climate change strategies: a quantitative study on climate-related risks and opportunities. *J. Clean. Prod.* **160**, 8–26 (2017).
67. Haney, A. B. Threat interpretation and innovation in the context of climate change: an ethical perspective. *J. Bus. Ethics* **143**, 261–276 (2017).
68. Weinhofer, G. & Busch, T. Corporate strategies for managing climate risks. *Bus. Strateg. Environ.* **22**, 121–144 (2013).
69. Kalkuhl, M., Edenhofer, O. & Lessmann, K. Learning or lock-in: optimal technology policies to support mitigation. *Resour. Energy Econ.* **34**, 1–23 (2012).
70. Conway, D., Dalin, C., Landman, W. A. & Osborn, T. J. Hydropower plans in eastern and southern Africa increase risk of concurrent climate-related electricity supply disruption. *Nat. Energy* **2**, 946–953 (2017).
71. Bellman, R. *Dynamic Programming* (Princeton Univ. Press, 1957).
72. Bellman, R. *Adaptive Control Processes: a Guided Tour* (Princeton Univ. Press, 1961).
73. Rousseeuw, P. J. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *J. Comput. Appl. Math.* **20**, 53–65 (1987).
74. Caliński, T., Harabasz, J. & Caliliski, T. A dendrite method for cluster analysis. *Commun. Stat.* **3**, 1–27 (1974).
75. Davies, D. L. & Bouldin, D. W. A cluster separation measure. *IEEE Trans. Pattern Anal. Mach. Intell.* **PAMI-1**, 224–227 (1979).
76. Halkidi, M. On clustering validation techniques. *J. Intell. Inf. Syst.* **17**, 107–145 (2001).
77. Efron, B. Computers and the theory of statistics: thinking the unthinkable. *SIAM Rev.* **21**, 460–480 (1979).
78. Efron, B. & Tibshirani, R. *An Introduction to the Bootstrap* (Chapman & Hall, 1993).
79. Buckland, S. T., Davison, A. C. & Hinkley, D. V. *Bootstrap Methods and Their Application* (Cambridge Univ. Press, 1997); https://doi.org/10.2307/3109789

Acknowledgements

I thank B. Caldecott, A. Haney, C. Hepburn and D. Tulloch for comments on the manuscript. I am also thankful for the financial support to my doctoral research offered by the ESRC Grand Union Doctoral Training Partnership, a Scatcherd European Scholarship by the University of Oxford and the 73 Scholarship Fund for Geography by Hertford College, Oxford, established through the generosity of the college's alumni—P. Newman and M. Teversham.

Competing interests

The author declares no competing interests.

Additional information

Supplementary information is available for this paper at https://doi.org/10.1038/s41560-020-00686-5.

Correspondence and requests for materials should be addressed to G.A.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

© The Author(s), under exclusive licence to Springer Nature Limited 2020

Chapter 5. A machine learning model to investigate factors contributing to the energy transition of utility and independent power producer sectors internationally

This Chapter 5 was published as: Alova and Caldecott, A machine learning model to investigate factors contributing to the energy transition of utility and independent power producer sectors internationally, *iScience* (2021), https://doi.org/10.1016/j.isci.2021.102929

iScience

CellPress
OPEN ACCESS

Article

A machine learning model to investigate factors contributing to the energy transition of utility and independent power producer sectors internationally

Key take-aways

The study examines the contribution of 5 environmental policy instruments and 5 market structure characteristics to technology choices of utility and independent power producer (IPP) sectors across 33 countries over 20 years.

The study builds a machine-learning-based model with multiple dependent variables to conduct a holistic, yet granular, analysis of factors affecting in a similar or different ways IPP and utility sectors' investments in various technologies.

The relationship between environmental policies and company technology choices is often non-linear.

Gas portfolios show resilience to environmental policy stringency.

IPP ⟷ Utility

Compared to utilities, IPP sectors are more responsive to environmental policies in terms of renewables growth, particularly wind power.

Compared to policies, market structure characteristics appear more salient for fossil fuel growth.

Different market structures might be conducive to curbing fossil fuel growth compared to promoting renewable energy uptake.

Galina Alova, Ben Caldecott

galina.alova@ouce.ox.ac.uk

Highlights

The study examines factors contributing to electric companies' technology choices

Policy effectiveness is more pronounced for curbing coal than gas capacity growth

Independent power producers appear more responsive to policies than utilities

Market characteristics matter particularly for renewables uptake by utilities

Alova & Caldecott, iScience 24, 102929
September 24, 2021 © 2021 The Author(s).
https://doi.org/10.1016/j.isci.2021.102929

iScience

CellPress
OPEN ACCESS

Article

A machine learning model to investigate factors contributing to the energy transition of utility and independent power producer sectors internationally

Galina Alova[1,2,*] and Ben Caldecott[1]

SUMMARY

There is evidence of independent power producers dominating the electricity sector's uptake of renewable energy, with utilities lagging behind. Here, we build a machine-learning-based model with multiple dependent variables to simultaneously explore environmental policy and market structure contributions to investment patterns in different technologies by utility and independent producer sectors across 33 countries over 20 years. With the analysis enabling the capture of non-linear relationships, our findings suggest substantial resistance of gas capacity to even strict carbon pricing policies, while coal appears more responsive. There is also an indication of policy pricing in effects. The positive link of renewables subsidies and fossil fuel disincentives to renewables expansion, particularly wind, is more prominent for independent power producers than utilities. Regarding market structures, different characteristics tend to matter for renewables growth compared to fossil fuel reductions. The results also suggest considerable differences in policy and market factor contributions to technology choices of Organisation for Economic Co-operation and Development vis-à-vis emerging economies.

INTRODUCTION

The past years have seen substantial additions of renewable energy to global installed capacity (IEA, 2020) and falling carbon intensity of the power generated (IEA, 2019). Despite the electricity sector's good potential for uptake of renewables, compared to transport and industry sectors that might be more difficult to decarbonize (Sharmina et al., 2020; Thiel and Stark, 2021), the sector is yet to undergo decisive transformation. Solar and wind constituted 9% in global generation in 2020, with fossil fuels still representing 60% (IEA, 2020) and coal-fired generation alone accounting for 30% of global CO_2 emissions in 2018 (IEA, 2019).

Against this backdrop of a limited, albeit growing, share of renewables in the global electricity mix, there is considerable variation in the contribution of different power-generating actors to decarbonization. While independent power producers (IPPs) accounted for over 80% of non-hydro renewable energy capacity in 2020 (WEPP, 2020), electric utility companies that historically dominated power generation have tended to lag behind. The pace of their decarbonization remains slow, hindered by continued investment in fossil-fuel-based capacity (Alova, 2020). There are ample studies discussing the risks that new market entrants and power generation solutions may pose to the value proposition of traditional utilities and their carbon-intensive business models (Bryant et al., 2018; Castaneda et al., 2017; Frei et al., 2018; Geels et al., 2017; Kungl and Geels, 2018; Markard, 2018; Mitchell, 2016; Nillesen and Pollitt, 2016; Parag and Sovacool, 2016; Richter, 2013; Shomali and Pinkse, 2016; Wainstein and Bumpus, 2016). However, several research gaps exist in relation to understanding the underlying reasons for the varying pace of electric companies' transition.

Present studies tend to examine the impact the deployment of renewables-promoting policy instruments has on the adoption of clean energy by the electricity sector as a whole, with few studies focusing on the company level (Choi, 2019; Delmas and Montes-Sancho, 2011). The effect of policy stringency is also rarely assessed (Polzin et al., 2019). Furthermore, the extant literature tends to be limited in scope: the geographies, policies, and the number of companies it covers. The bulk of research dwells on select policy

[1]Smith School of Enterprise and the Environment, School of Geography and the Environment, University of Oxford, Oxfordshire OX1 3QY, UK

[2]Lead contact

*Correspondence: galina.alova@ouce.ox.ac.uk

https://doi.org/10.1016/j.isci.2021.102929

This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

instruments, such as the impact of renewable portfolio standards on mostly US utilities (Carley, 2009; Shrimali and Kniefel, 2011), less frequently extending the focus to major international companies (Patala et al., 2021) or beyond. There is thus a paucity of studies with comprehensive samples, encompassing smaller national actors, whose decarbonization is nevertheless important for the sector's overall energy transition (Schleicher-Tappeser, 2012). Notably, the current literature also overlooks the need to simultaneously examine the drivers of continued growth in fossil-fuel-based capacity. The increasing uptake of renewables alone does not necessarily reduce companies' carbon intensity. Moreover, analyses focusing on policies combined with other factors, for example, related to market structures (Weigelt and Shittu, 2016), could merit further attention. Finally, and equally importantly, there is a lack of research with a comparative lens on the utilities' transition vis-à-vis that of IPPs (Kelsey and Meckling, 2018).

To address these research gaps, we built a model that enables us to conduct a holistic analysis of the potential contributions environmental policies and market structures might have to technology choices by the utility and IPP sectors in 33 economies over the past 20 years (see STAR Methods). We focus on utility and IPP sectors' annual capacity growth by different technologies to capture the dynamics of their response to the factors examined. To this end, we used gradient boosted decision trees (GBDTs), a state-of-the-art machine-learning-based technique for predictive analytics. We built the model using CatBoost algorithm by Yandex (Yandex, 2021) that allows including multiple dependent variables—an original approach which, to the best of our knowledge, has not been previously employed in the extant energy transition literature. As a result, we were able to simultaneously examine the potential factors behind both renewable energy and fossil fuel capacity growth. Among the key strengths of this unified model, besides its ability to capture non-linear relationships, is to effectively isolate effects and identify synergies between different features and their contributions to the prediction, here capacity additions by different technologies. Some factors might be linked to the overall expansion of generation capacity, regardless of specific technology, while others could be associated with the uptake of specific technology. These effects could be prone to conflation in traditional single-target models that prevail in the current literature and explore changes in one specific technology.

We apply the model to one of the most comprehensive historical asset-level datasets available for the electricity sector, containing granular information on power plants and their ownership globally over the past two decades. These data are coupled with environmental policy stringency indices by policy instrument type and data on power generation costs, country renewable energy resource endowment, and development indicators as control features (see STAR Methods and Table S1).

RESULTS

The study explores the energy transition response by the electricity sector to policy- and market-structure-related features in terms of annual generation capacity growth distinguished by technology type (that is, solar, wind, coal, and gas) and ownership (country's utility and IPP sectors). The sample includes electricity sectors across 27 member countries of the Organisation for Economic Co-operation and Development (OECD) and 6 emerging economies (Brazil, Russia, Indonesia, India, China, and South Africa [BRIICS]) over the past 20 years (see STAR Methods for more information).

Policy effectiveness is more pronounced for curbing coal than gas capacity growth

Findings show that while the overall policy environment can have a considerable contribution to curbing fossil-fuel-based capacity growth, the effect varies remarkably by the sub-sector, being of larger amplitude for IPPs than utilities. This is clearly visible in the differences in y axis scales which denote the impact of a feature on the prediction in Figures 1A and 1C, compared to Figures 1B and 1D. There are also discrepancies in the response of different technologies within these sub-sectors. Among utilities, the negative policy impact is particularly strong for growth in coal, while for gas, it is of smaller prominence.

The analysis of individual policy instruments offers further insights, particularly into non-linearity of policy contribution to generation capacity growth (Figure S1). The push mechanisms, such as emission taxes, trading schemes, and standards, which are aimed to disincentivize investments in fossil fuels, have an overall distinct negative impact on the growth of coal capacity across the utility and IPP sectors. Noteworthy is how this relationship might vary with policy stringency. For example, for taxes and trading schemes (Figures S1A and S1C), their negative association with utilities' coal intensifies once the policy reaches higher stringency, while in case of emission standards, the relationship is the steepest for medium stringency, flattening out under stricter policies (Figure S1E). This effect is observable also for IPPs, with, for example,

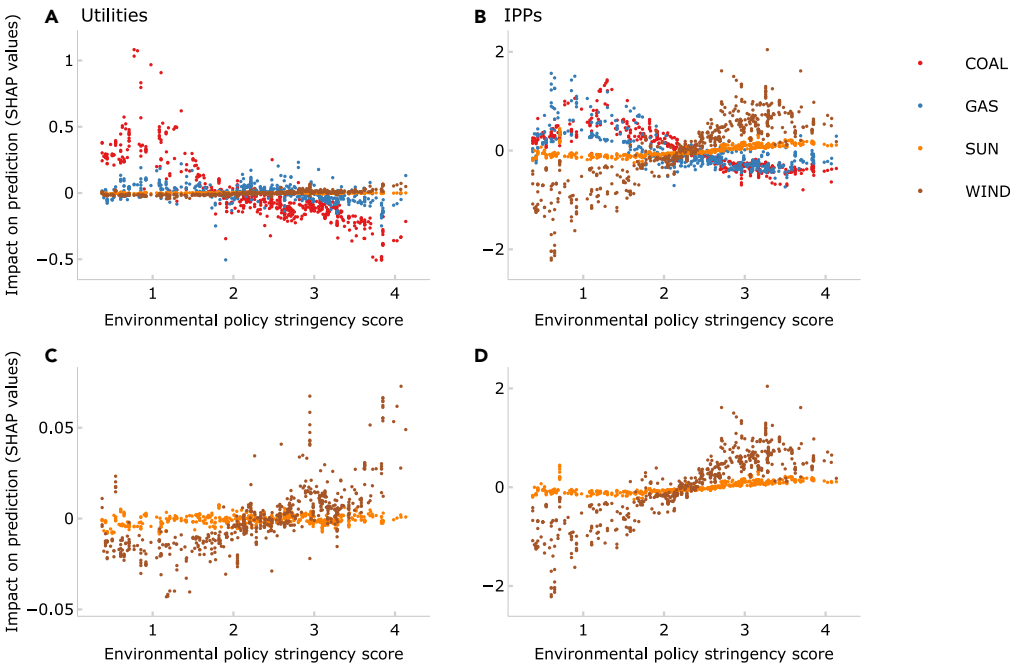


Figure 1. Contributions of environmental policy stringency to capacity growth differentiated by fuel type and ownership

The figure depicts the relationship between the overall aggregate environmental policy stringency and generation capacity growth, differentiated by technology and company type, that is, utility (A and B) and IPP companies (B and D). X axis represents environmental policy stringency scores. According to the OECD methodology, the stringency scores of environmental policy range between 0 and 6 (Botta and Koźluk, 2014). Y axis shows feature's contribution to the prediction, measured in SHapley Additive exPlanations (SHAP) values and expressed as change in log odds (see STAR Methods). A larger positive SHAP value implies a higher positive contribution of a feature to the prediction associated with a data point, that is, capacity growth in a given technology by utility or IPP sector in a given year and country. (A) and (B) show this relationship between policy stringency and capacity growth differentiated by four technology types, that is, coal, gas, solar, and wind, for comparison purposes. For better clarity, (C) and (D) re-depict the relationship between policy stringency and growth in solar and wind capacity without fossil fuels.

the inverse association of emission taxes with coal growth leveling off for higher policy stringencies. Pull instruments, such as feed-in-tariffs and research and development (R&D) subsidies aimed to promote the uptake of clean technologies, might also have a displacing effect on coal capacity (Figures S1D–S1J).

At the same time, gas tends to show relatively greater resistance to policies observable for both utilities and IPPs. Among the countries' utility sectors, emission standards see nearly no bearing (Figure S1E), while tax and trading schemes have a moderately positive effect (Figures S1A and S1C), with the former seeing a slight downward trend when the policy reaches higher stringency scores. For IPPs, emission standards seem to be most effective in limiting gas expansion (Figure S1F). Taxes tend to positively affect gas growth (Figure S1B), and the impact of trading schemes sees an upward trend for lower stringency scores, declining somewhat as the policy gets stricter (Figure S1D). Notable is the observation that when comparing mean absolute impacts of features, emission standards have the highest effect for fossil fuel growth, with other policy instruments having a relatively smaller bearing across both the IPP- and utility-owned capacity (Figures 2A and 2C).

Policies could contribute to renewables uptake among IPPs but less so for utilities

The contribution of environmental policies to boosting renewable energy adoption appears to be less pronounced for the utility than the IPP sector (Figures 1C and 1D). Individual policy instruments are among the top five features determining renewable energy growth of IPPs (Figure 2D), with IPP-owned wind capacity showing a particularly pronounced response, visible also across the contributions of individual policy instruments to the prediction (Figure S1). For utilities' renewable energy capacity, policies including feed-in-tariffs appear of relatively lower importance compared to some of the market characteristics (Figure 2B).

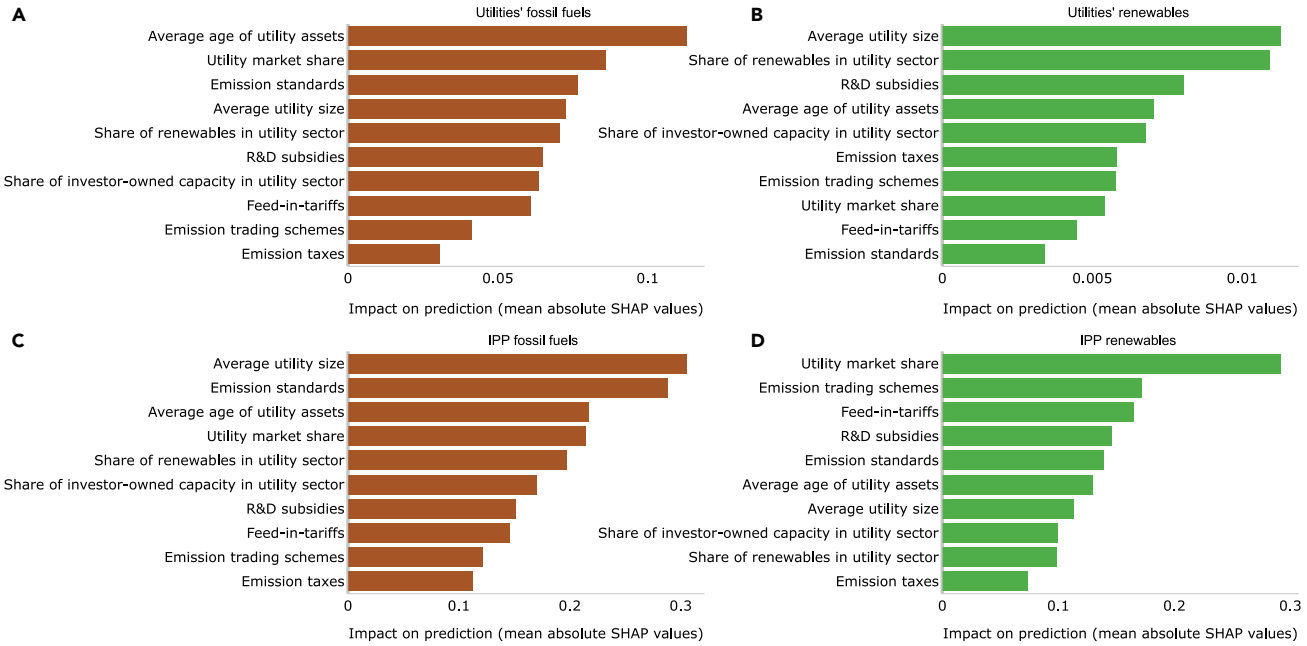


Figure 2. Comparison of feature contributions to generation capacity growth in fossil fuels versus renewables

(A) depicts the contributions of different features to growth in utility-owned fossil fuel capacity, (B) depicts feature contributions to growth in utility-owned renewable energy capacity, (C) depicts feature contributions to growth in IPP-owned fossil fuel capacity, and (D) depicts feature contributions to growth in IPP-owned renewable energy capacity. Features are compared on the basis of their individual impact on the prediction. The impact is expressed in mean absolute SHAP values, that is, the mean absolute change in log odds (see STAR Methods). A larger value implies a higher absolute impact of a feature on average across all data points.

Noteworthy are also the observations relating to policy interaction effects. The results point to emission taxes augmenting the uplifting impact of feed-in-tariffs on solar capacity of IPPs (Figure S2A). Feed-in-tariffs, on the other hand, which seem to have a limited impact on utility-owned renewables, appear to amplify the negative impact that emission trading schemes (Figure S2B) and taxes (Figure S2C) can have on utility-owned coal capacity.

Important nuances exist in contributions of market characteristics to technology choices

The analysis of market-structure-related features identifies several factors that could contribute to the shift of the power sector away from fossil fuels (Figure 3). Overall, with the exception of emission standards, market characteristics appear relatively more salient for fossil fuel growth, compared to policies, both for utilities and IPPs (Figures 2A and 2C). The market share of the utility sector has a distinct positive effect on utilities' growth in coal, while the link with gas growth seems to be negative, albeit weaker, manifesting most clearly for particularly high market shares (Figure 3A). There appears to be also a relationship between the size of utility companies and their fossil fuel capacity, in that markets with on average larger utilities see more active expansion in utilities' carbon-intensive portfolios (Figure 3G). The results indicate that a smaller utility size may also dampen the positive impact of utility market share on coal (Figure S2D). Interestingly, the share of renewable energy in utility sector tends to be positively associated with fossil fuel growth when renewables penetration is still low and negatively when renewables gain higher presence in utility portfolios (Figure 3I). At the same time, the share of investor-owned capacity in the utility sector is associated with a somewhat positive impact on growth in utility-owned coal when investor presence is still low, with the impact becoming negative for higher investor participation (Figure 3C). This link to the growth in gas is limited. Similarly, for IPPs, the utility sectors conducive to competition characterized by a relatively lower market share, higher investor ownership, and a smaller company size appear favorable to the transition away from fossil fuels (Figures 3B, 3D, and 3H).

Market structures tend to be important also for the uptake of renewables particularly among utilities (Figure 4), against the backdrop of the aforementioned limited response of utilities to policies. The characteristics of a market that is conducive to renewables expansion might differ from the market structures associated with fossil fuel reduction (Figures 2, 3, and 4). As a proxy for utilities' technological endowment and strategic direction toward

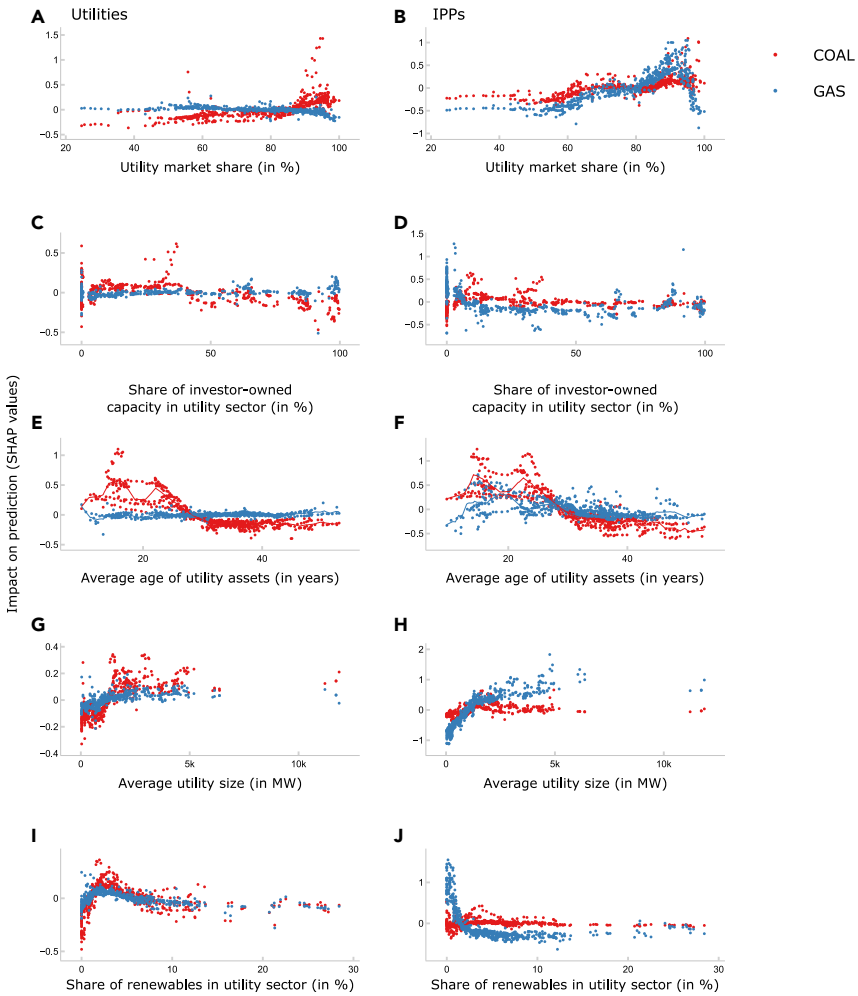


Figure 3. Contribution of market-structure-related features to fossil fuel capacity growth by company sector type

(A–J) (A), (C), (E), (G), and (I) denote the relationship between each feature and growth in utility-owned coal and gas capacity.

(B), (D), (F), (H), and (J) denote these relationships for IPP-owned coal and gas capacity. Each feature's impact on the prediction is expressed in SHAP values, that is, the change in log odds. The vertical distribution of the data points indicates the interaction effects of the features. These results are based on the model that includes individual policy instruments as features (see STAR Methods and Table S1).

renewables, the share of solar and wind power plants in their portfolios in a preceding year appears to have the second strongest link to growth in utilities' renewables, after the utility size (Figures 2B and 4I). This is most prominent for wind capacity. The share of renewable energy plants in utility portfolios seems to also have a positive, albeit weaker, association with IPP-owned renewables growth (Figure 4J), with the effect eventually leveling off for the latter. Smaller utility size and on average younger power plant fleets tend to be positively associated with growth in wind (Figures 4E and 4G). Yet, older portfolios of above 35 years might be linked to a moderate positive impact on solar growth (Figure 4E). The age of the utility-owned fleet could also have implications for IPPs, having a positive impact on growth in their renewable energy capacity (Figure 4F). At the same time, high utility market share seems to be somewhat positively linked to growth in utility-owned wind capacity. On the solar capacity, this link is inverse for less utility-dominated markets, becoming positive for higher market shares (Figure 4A). Market characteristics are important also for IPP-owned renewable energy expansion, with utility market share being the top feature by its importance to the prediction (Figure 2D). Electricity sectors where utilities own a higher share appear to have a positive relationship with growth in IPP wind, and to a smaller extent, in solar capacity (Figure 4B). Furthermore, investor ownership of utilities is positively linked to the growth in utility-owned

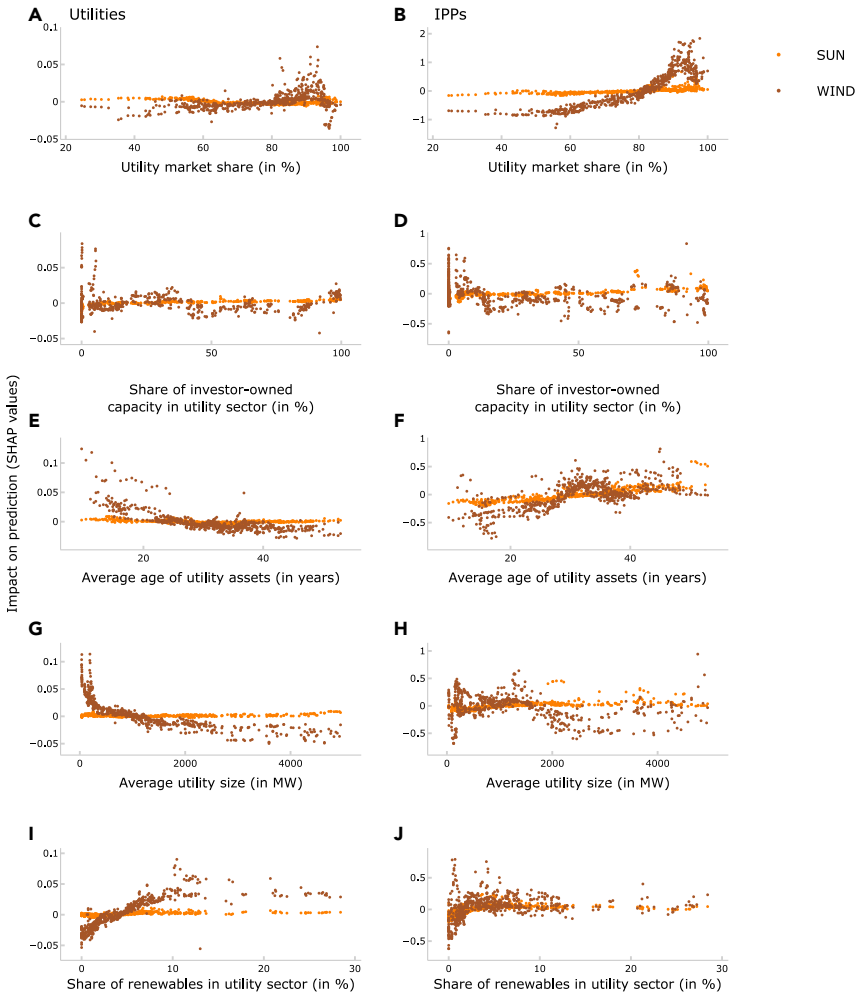


Figure 4. Contribution of market-structure-related features on renewable energy capacity growth by company sector type

(A–J) (A), (C), (E), (G), and (I) denote the relationship between each feature and growth in utility-owned solar and wind capacity.

(B), (D), (F), (H), and (J) denote these relationships for IPP-owned solar and wind capacity. Each feature's impact on the prediction is expressed in SHAP values, that is, the change in log odds. The vertical distribution of the data points indicates the interaction effects of the features. These results are based on the model that includes individual policy instruments as features (see STAR Methods and Table S1).

solar capacity (Figure 4C), with the impact on utilities' wind and IPP renewables being less distinct (Figures 4C and 4D).

Inter-country variations exist in feature contributions to technology choices

We observe considerable differences between OECD and BRIICS economies in the contributions of policy- and market-structure-related features, associated with these countries, to technology choices over the time period under consideration (Figure 5). For BRIICS, most features, with the exception of emission taxes and trading schemes, have shown a positive association with fossil fuel growth. This positive relationship is particularly distinct for emission standards (Figure 5A). On the contrary, for the OECD countries, most features have a negative link to fossil fuel growth (Figure 5C), particularly emission standards which on average show considerably higher stringencies than across BRIICS. This echoes the aforementioned finding that emission standards are among the top features by their importance to the prediction of fossil fuel growth by both utility and IPP sectors.

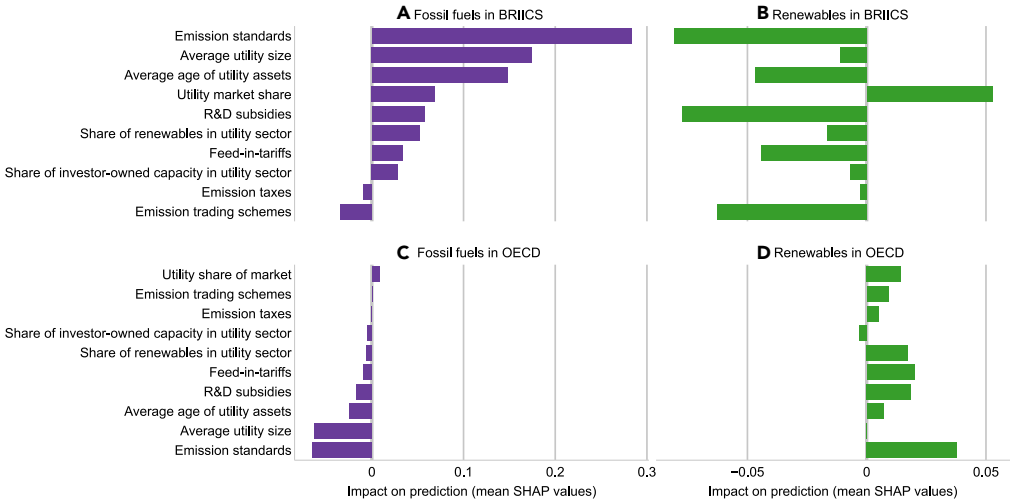


Figure 5. The contributions of policy- and market-structure-related features fossil fuel and renewables growth across BRIICS and OECD countries

(A) depicts the contributions of different features to growth in fossil fuel capacity across BRIICS countries over the 20 years under consideration, (B) depicts feature contributions to growth in BRIICS renewable energy capacity, (C) depicts feature contributions to growth in OECD fossil fuel capacity, and (D) depicts feature contributions to growth in OECD renewable energy capacity. Each feature's impact on the prediction is expressed in mean SHAP values, that is, the average change in log odds (see STAR Methods on model interpretation).

At the same time, when exploring the transition to renewables, most features for the OECD countries have a positive link to capacity growth (Figure 5D), while for BRIICS, these relationships are predominantly negative (Figure 5B). The exception is utility market share, which demonstrates a positive association with renewable energy growth. In this context, noteworthy is also the observation that, while most features have opposite effects on fossil fuels relative to renewables, this is not the case for utility market shares across both OECD and BRIICS economies. This echoes the previously discussed findings that markets characterized by high shares of utility-owned generation capacity tend to be associated with higher fossil fuel but also, to some extent, higher renewable energy growth.

At the aggregate level of the general policy environment, there are also considerable inter-country differences in the effect the policy environment stringency has on growth of fossil fuels vis-à-vis renewables (Figure 6). The overall lax policy stringency across the emerging economies in our sample over the 20 years under consideration tends to be associated with higher fossil fuel and reduced renewable energy growth. At the same time, an enabling policy environment in countries with on average the highest environmental policy stringencies, for example, in Denmark, the Netherlands, and Finland, can result in relatively more favorable outcomes for their energy transition, that is, higher renewable energy and reduced fossil fuel energy growth.

Interestingly, similar policy stringencies might yield different results on technology choices, depending on the strength of specific instruments and their interactions with each other (Figure 6). For example, France and Finland have on average an overall similarly stringent environmental policy framework. Yet, for France, its policy stringency is linked to a higher positive effect on both wind and solar and to a higher negative effect on fossil fuels, particularly coal. This could be due to the fact that France has more stringent trading schemes and taxes, coupled with stringent feed-in-tariffs which, as discussed above, could amplify the effectiveness of carbon pricing. For Finland, the overall policy environment is driven by stringent R&D subsidies.

DISCUSSION

Different market characteristics matter for fossil fuel reduction compared to renewables uptake

Our study finds that electricity market structures can be of considerable importance for the power sector's decarbonization, although different features might matter more for reducing growth in fossil fuels

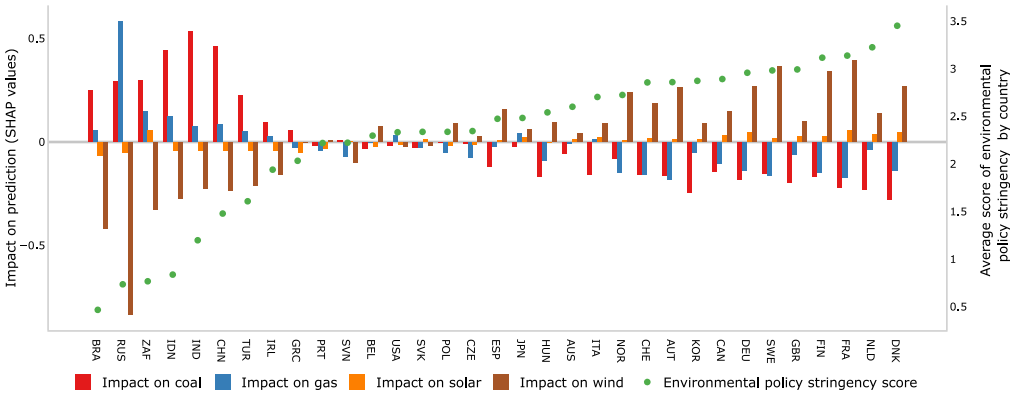


Figure 6. Inter-country differences in environmental policy stringency and implications for technology choices by the electricity sector

The environmental policy stringency and its impact on capacity growth of different technologies is expressed in average terms for the 20 years studied (that is, average stringency score and average SHAP values across countries' electricity sectors). According to the OECD methodology, the stringency scores of environmental policy range between 0 and 6 (Botta and Koźluk, 2014).

vis-à-vis promoting renewables uptake. The results suggest that smaller average utility company sizes and market shares and thereby potentially higher competition in the market tend to be negatively linked to growth in most fossil fuel capacity across the power sector. Notable exception is the inverse link between utility market share and utility-owned gas capacity, signaling that utility sectors in generally more liberalized electricity markets might be replacing their coal capacity with gas. This is generally in line with an expectation that market openness to the actors from outside the utility sector could be conducive to innovation and the shift away from relatively more polluting technologies (Markard and Truffer, 2006).

When it comes to the transition to renewables, however, evidence points to high utility market shares not necessarily impeding and potentially supporting growth in renewable energy capacity by both utilities and IPPs. This could in part be due to the argument that state companies, such as utilities, can unlock capital for innovative projects (Tõnurist and Karo, 2016), for example, renewable energy plants that are known to be relatively more capital intensive than fossil fuel power plants (Schmidt, 2014). Yet, this might be less relevant for countries, such as Germany, where renewable energy investments often take place through project finance, with less dependence on the financial strength of a sponsor (Steffen, 2018). Another reasoning could involve non-utility actors as innovators being particularly important at the outset of the energy transition. When renewable energy sectors mature, utility companies re-gain their role in scaling up clean power adoption (Steffen et al., 2020). This echoes our results that the share of solar and wind plants in utility portfolio as a proxy for the companies' strategic orientation and technological endowment is positively linked to growth particularly in wind capacity. Scandinavian countries and the Netherlands offer such an example, where utilities tend to dominate renewable-based power generation (Kelsey and Meckling, 2018). Notable is also the observation that the share of renewables in utilities' portfolios does not appear to negatively affect growth in IPP renewables capacity. Higher shares of renewables in utility-owned capacity also have a pronounced negative impact on IPP gas growth. All in all, these findings suggest potential complementarity, rather than mutual exclusion, of IPP and utilities' efforts in driving the sector's transition to clean power.

There are also signs that investor ownership is associated with moderate growth in utilities' renewables, mostly solar. This could be the result of increasing pressure from investors and lenders, including shareholders and banks, for utilities to disclose and mitigate exposure to climate-related transition risks associated with carbon-intensive assets (Benz et al., 2021). This highlights the potential role of active ownership efforts through, for example, shareholder resolutions, stewardship meetings, and co-ordinated shareholder engagement strategies such as Climate Action 100+, to encourage utilities to reduce the carbon intensity of their asset base. As the currently still relatively nascent active ownership and engagement activities in the power sector mature, tracking and measuring the impact of these efforts on investor-owned utilities' capital expenditure decisions could merit future research attention.

Utilities' muted response to policies could be a signal of inertia or changing business models

Our results suggest that environmental policies are more effective at driving renewable energy growth among IPPs than for utilities, both in terms of their absolute impact and compared to other features. This is the case not only for feed-in-tariffs which are sometimes thought of as an IPP-targeting instrument (Carley et al., 2017) but also for fossil-fuel-inhibiting instruments, such as emission trading schemes and standards. These policies are among the top features affecting IPP renewable energy growth, having a relatively lower effect on utility sectors for which market structures tend to have more bearing on the expansion of their clean power assets. This observation that policies beyond feed-in-tariffs can have positive implications for IPP renewable energy growth is important given that support schemes might see reduction or phase-out in the future as a result of the increasing cost competitiveness of renewables (Sinsel et al., 2019). Emission-related policies and regulations are, on the other hand, likely to remain and become more stringent as the world seeks to achieve the net zero objective over the next decades.

While utilities' more muted response to policies could point to their potential path dependence and resistance to embracing new technologies even under relatively strict environmental policies, these results could also serve as an indication of changing utility business models. Utilities might be shifting away from directly owning power generation assets toward off-taking power generated by IPPs. This shift could also occur due to the challenges utilities might face in accessing capital, both in terms of liquidity and cost (Eberhard et al., 2017). We find that in the markets where utilities delay renewing their portfolios, IPPs have responded by expanding renewable energy capacity, suggesting that balance sheet and financing constraints among utilities might be preventing their expansion and a shift to renewables. That said, our findings also indicate a positive, albeit considerably weaker, relationship between on average higher age of power plants in the utility sector and growth in utilities' solar capacity. Older power plant fleets could possibly make it easier for utilities to justify investments in new assets (Delmas et al., 2007). Our analysis also highlights the importance of striking the right policy mix and embracing synergies between policy instruments. For example, IPP solar capacity, which shows a relatively weaker response to policies compared to wind, tends to benefit from an amplified positive impact when feed-in-tariffs are complemented with emission taxes.

The link of policy stringency to fossil fuel capacity growth is non-linear

Our study suggests that there is clearly value in focusing research on policy stringency and potential non-linearity of policy contributions to generation capacity growth, differentiated by company type and technology, if we are to achieve intended decarbonization outcomes in the most efficient manner. Specifically, our results show that the relationship between policies and generation capacity growth is often non-linear, in that it might alternate between increasing and leveling off for different stringencies, depending on the policy instrument, company type, and technology. For example, emission trading schemes are inversely linked to utility coal capacity growth for low and high stringencies leveling off for medium scores. At the same time, low and medium stringency of emission standards is negatively associated with utilities' coal capacity, with the effect flattening out thereafter. This could be due to the expected impact of policies being eventually priced in either indefinitely or until they reach even higher stringency levels. This is an important consideration particularly for future forward-looking analyses discussed below.

The importance of understanding how different electricity sub-sectors respond to policies in terms of investments in specific technologies is also crucial. We observe that gas capacity shows stronger resistance compared to coal to both to the overall policy environment and individual policy instruments. While this notion is stronger for utilities, it is present also for IPPs. This is concerning, given that although in the short term gas might contribute to the uptake of renewables through its grid-balancing role (Mac Kinnon et al., 2018), expanding gas capacity is fraught with carbon lock-in and asset stranding risks (Pfeiffer et al., 2018). In this context, the results highlight the importance of policy stringency, not only the mere adoption of policy instruments. We find, for example, that emission standards start reducing growth in the IPP-owned gas capacity growth once they reach medium levels of stringency. Introducing policies in a timely fashion and of sufficient stringency could help avoid higher economic costs associated with delayed policy action (Daniel et al., 2019).

From the perspective of individual countries, while our results also clearly point to the importance of ensuring sufficient stringency of the policy regimes as shown by the comparative analysis of OECD versus BRIICS economies, similar stringencies in countries' overall policy frameworks could lead to different

outcomes. The extent to which policies would shape investment decisions from the perspective of specific technologies and company types would depend on the individual instruments adopted and their complementarity with other policies. For example, results on interaction effects point to feed-in-tariffs enhancing the negative association of carbon pricing policies with the expansion of utilities' coal capacity.

Contribution of this study

While the bulk of the extant research focuses on renewable energy adoption by the electricity sector as a whole, our study highlights the importance of examining the sector's decarbonization also from a company and specific technology perspective. Our findings point to considerable differences in IPP and utility sector responses to policy- and market-structure-related factors in terms of their technology choices. Exploring the contribution of these factors to investments in different technologies in a concurrent unified manner is crucial for capturing potential synergies between the effects identified. For example, our findings suggest that some features might have a positive link to both renewables and fossil fuel expansion. As the sector's decarbonization would involve its simultaneous transition to renewables and away from fossil fuels, which might not always go hand-in-hand at least for utilities (Alova, 2020), understanding the factors contributing to the changes in fossil-fuel-based capacity is equally important as examining the uptake of renewables. Moreover, adopting modeling approaches that enable to capture non-linear relationships between factors can shed further light on the electricity sector's transition, as this study has demonstrated. As a result, future research, including forward-looking studies aiming to project the decarbonization trajectories of the global power sector for the next decades could benefit from integrating such granularity into their analyses. This would help better model how the actors in the electricity sector will respond to different factors and manage and price in the expectations relating to the impacts associated with these factors. This would also enhance the relevance of energy systems modeling for use cases and actors beyond the policy community, including for the financial and corporate sectors concerned with company and investment portfolio exposure to climate-related policy risks (O'Neill et al., 2020; Weber et al., 2018).

Limitations of the study and future research avenues

While our study contributes to the extant literature by both offering valuable insights into the power sector's transformation over the past decades and a methodological advancement to the energy transition analysis, there are some limitations worth considering. First, while the use of SHapley Additive exPlanations values (see STAR Methods) enables interpretability of the model in terms of the contribution of different features to the prediction, caution should be exercised when interpreting these results from the causality perspective. We have informed feature selection by domain knowledge and the extant literature on the drivers of technology diffusion in the power sector. We cannot, however, rule out the possibility that some of the relationships detected are not necessarily causal in nature. This could be the case if, despite our best effort to include potential key drivers, some of the relevant confounders remain uncaptured or spurious relationships between variables exist, which is a common issue not limited to machine-learning-based models. For example, in terms of uncaptured confounders, these might be the factors that have in the first place affected the adoption of a specific policy or led to the creation of a market structure, which could be the focus of future research. That said, while offering some valuable insights, our results are not counterintuitive, with explanations existing in the academic literature and industry practice, as we summarize in the discussion section. This lends us confidence that our results on specific variables can be interpreted in terms of their causal impact on capacity growth, albeit with a degree of caution. Second, our study focuses on understanding the factors that have contributed to electric companies' investment decisions to date. Forward-looking analyses seeking to identify pathways for the future development of the power sector would complement our empirical study, particularly if they integrate some of the methodological elements of our approach, as discussed above. Finally, future work could extend the geographic scope of our analysis beyond the 33 OECD and BRIICS economies and sector focus to industries other than the power sector.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- RESOURCE AVAILABILITY

- Lead contact
- Materials availability
- Data and code availability
- METHOD DETAILS
  - Data
- MODEL
  - Gradient boosted decision trees
  - Target variable and model granularity
  - Feature engineering and selection
  - Hyperparameter tuning
  - Model validation
  - Model interpretation

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2021.102929.

ACKNOWLEDGMENTS

G.A. is grateful for the financial support of her doctoral research offered by the ESRC Grand Union Doctoral Training Partnership, the Scatcherd European Scholarship from the University of Oxford and the 73 Scholarship Fund for Geography from Hertford College, Oxford, established through the generosity of the college's alumni, P. Newman and M. Teversham. The authors thank T. R. Fetter for comments on the manuscript.

AUTHOR CONTRIBUTIONS

G.A. conceived the research idea; sourced the data; built, validated, and interpreted the machine learning model; produced the visuals of the results; and wrote the paper. B.C. contributed to conceptualizing and writing the paper and reviewed the drafts.

DECLARATION OF INTERESTS

The authors declare no competing interests.

Received: April 29, 2021
Revised: July 7, 2021
Accepted: July 23, 2021
Published: August 18, 2021

REFERENCES

Alova, G. (2020). A global analysis of the progress and failure of electric utilities to adapt their portfolios of power-generation assets to the energy transition. Nat. Energy *5*, 920–927. https://doi.org/10.1038/s41560-020-00686-5.

Alova, G., Trotter, P.A., and Money, A. (2021). A machine-learning approach to predicting Africa's electricity mix based on planned power plants and their chances of success. Nat. Energy, 1–9. https://doi.org/10.1038/s41560-020-00755-9.

Benz, L., Paulus, S., Scherer, J., Syryca, J., and Trück, S. (2021). Investors' carbon risk exposure and their potential for shareholder engagement. Bus. Strateg. Environ. *30*, 282–301. https://doi.org/10.1002/bse.2621.

Botta, E., and Koźluk, T. (2014). Measuring Environmental Policy Stringency in OECD Countries (OECD Economics Department Working). https://doi.org/10.1787/5jxrjnc45gvg-en.

Bryant, S.T., Straker, K., and Wrigley, C. (2018). The typologies of power: energy utility business models in an increasingly renewable sector. J. Clean. Prod. *195*, 1032–1046. https://doi.org/10.1016/j.jclepro.2018.05.233.

Carley, S. (2009). State renewable energy electricity policies: an empirical evaluation of effectiveness. Energy Policy *37*, 3071–3081. https://doi.org/10.1016/J.ENPOL.2009.03.062.

Carley, S., Baldwin, E., MacLean, L.M., and Brass, J.N. (2017). Global expansion of renewable energy generation: an analysis of policy instruments. Environ. Resource Econ. *68*, 397–440. https://doi.org/10.1007/s10640-016-0025-3.

Castaneda, M., Franco, C.J., and Dyner, I. (2017). Evaluating the effect of technology transformation on the electricity utility industry. Renew. Sustain. Energy Rev. *80*, 341–351. https://doi.org/10.1016/J.RSER.2017.05.179.

Choi, H. (2019). Incumbents' response to demand-side policies: the case of solar and wind power sectors. Sci. Public Policy, 1–13. https://doi.org/10.1093/scipol/scz017.

Daniel, K.D., Litterman, R.B., and Wagner, G. (2019). Declining CO2 price paths. Proc. Natl. Acad. Sci. U S A *116*, 20886–20891. https://doi.org/10.1073/pnas.1817444116.

Delmas, M.A., and Montes-Sancho, M.J. (2011). U.S. state policies for renewable energy: context and effectiveness. Energy Policy *39*, 2273–2288. https://doi.org/10.1016/j.enpol.2011.01.034.

Delmas, M., Russo, M.V., and Montes-Sancho, M.J. (2007). Deregulation and environmental differentiation in the electric utility industry. Strateg. Manage. J. *28*, 189–209. https://doi.org/10.1002/smj.578.

Eberhard, A., Gratwick, K., Morella, E., and Antmann, P. (2017). Accelerating investments in power in sub-Saharan Africa. Nat. Energy *2*, 17005. https://doi.org/10.1038/nenergy.2017.5.

EIA, (2021), Installed Electricity Capacity Worldwide in 2019, https://www.statista.com/statistics/267358/world-installed-power-capacity/

Frei, F., Sinsel, S.R., Hanafy, A., and Hoppmann, J. (2018). Leaders or laggards? The evolution of electric utilities' business portfolios during the energy transition. Energy Policy *120*, 655–665. https://doi.org/10.1016/j.enpol.2018.04.043.

Friedman, J.H. (2001). Greedy function approximation: a gradient boosting machine. Ann. Stat. *29*, 1189–1232. https://doi.org/10.2307/2699986.

Friedman, J.H. (2002). Stochastic gradient boosting. Comput. Stat. Data Anal. *38*, 367–378. https://doi.org/10.1016/S0167-9473(01)00065-2.

Geels, F.W., Sovacool, B.K., Schwanen, T., and Sorrell, S. (2017). The socio-technical dynamics of low-carbon transitions. Joule *1*, 463–479. https://doi.org/10.1016/j.joule.2017.09.018.

Gotzens, F., Heinrichs, H., Hörsch, J., and Hofmann, F. (2019). Performing energy modelling exercises in a transparent way - the issue of data quality in power plant databases. Energy Strategy Rev. *23*, 1–12. https://doi.org/10.1016/j.esr.2018.11.004.

Hastie, T., Tibshirani, R., and Friedman, J.H. (2009). The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second edi (Springer).

IEA, (2019), Global Energy & CO2 Status Report 2019. https://www.iea.org/reports/global-energy-co2-status-report-2019/emissions

IEA (2020). Global Energy Review 2020. https://doi.org/10.1787/a60abbf2-en.

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., and Liu, T.Y. (2017). LightGBM: a highly efficient gradient boosting decision tree. Advances in Neural Information Processing Systems, *Vol. 2017*, pp. 3147–3155. https://github.com/Microsoft/LightGBM.

Kelsey, N., and Meckling, J. (2018). Who wins in renewable energy? Evidence from Europe and the United States. Energy Res. Soc. Sci. *37*, 65–73. https://doi.org/10.1016/J.ERSS.2017.08.003.

King, D. (2017). A Global Optimization Algorithm Worth Using. http://blog.dlib.net/2017/12/a-global-optimization-algorithm-worth.html.

Kungl, G., and Geels, F.W. (2018). Sequence and alignment of external pressures in industry destabilisation: understanding the downfall of incumbent utilities in the German energy transition (1998–2015). Environ. Innovat. Soc. Trans. *26*, 78–100. https://doi.org/10.1016/j.eist.2017.05.003.

Lazard. (2020). Levelized Cost of Energy and Levelized Cost of Storage – Version 14.0. https://www.lazard.com/perspective/levelized-cost-of-energy-and-levelized-cost-of-storage-2020/.

Lundberg, S.M., Erion, G.G., and Lee, S.-I. (2018). Consistent Individualized Feature Attribution for Tree Ensembles. http://arxiv.org/abs/1802.03888.

Lundberg, S.M., and Lee, S.I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, *Vol. 2017*, pp. 4766–4775. https://github.com/slundberg/shap.

Mac Kinnon, M.A., Brouwer, J., and Samuelsen, S. (2018). The role of natural gas and its infrastructure in mitigating greenhouse gas emissions, improving regional air quality, and renewable resource integration. Prog. Energy Combust. Sci. *64*, 62–92. https://doi.org/10.1016/j.pecs.2017.10.002.

Malherbe, C., & Vayatis, N., (2017), Global optimization of Lipschitz functions, In 34th International Conference on Machine Learning, ICML 2017 (Vol. 5, pp. 3592–3601).

Markard, J. (2018). The next phase of the energy transition and its implications for research and policy. Nat. Energy. https://doi.org/10.1038/s41560-018-0171-7.

Markard, J., and Truffer, B. (2006). Innovation processes in large technical systems: market liberalization as a driver for radical change? Res. Policy *35*, 609–625. https://doi.org/10.1016/j.respol.2006.02.008.

Mitchell, C. (2016). Momentum is increasing towards a flexible electricity system based on renewables. Nat. Energy *1*. https://doi.org/10.1038/nenergy.2015.30.

Nguyen, Q., Diaz-Rainey, I., and Kuruppuarachchi, D. (2021). Predicting corporate carbon footprints for climate finance risk analyses: a machine learning approach. Energy Econ. *95*, 105129. https://doi.org/10.1016/j.eneco.2021.105129.

Nillesen, P., and Pollitt, M. (2016). New business models for utilities to meet the challenge of the energy transition. In Future of Utilities - Utilities of the Future: How Technological Innovations in Distributed Energy Resources Will Reshape the Electric Power Sector, F.P. Sioshansi, ed. (Elsevier), pp. 283–301.

NREL (2014). Global CFDDA-Based Onshore and Offshore Wind Potential Supply Curves by Country, Class, and Depth (Quantities in GW and PWh). https://data.openei.org/submissions/273.

O'Neill, B.C., Carter, T.R., Ebi, K., Harrison, P.A., Kemp-Benedict, E., Kok, K., et al. (2020). Achievements and needs for the climate change scenario framework. Nat. Clim. Change *10*, 1074–1084. https://doi.org/10.1038/s41558-020-00952-0.

Parag, Y., and Sovacool, B.K. (2016). Electricity market design for the prosumer era. Nat. Energy *1*. https://doi.org/10.1038/nenergy.2016.32.

Patala, S., Juntunen, J.K., Lundan, S., and Ritvala, T. (2021). Multinational energy utilities in the energy transition: a configurational study of the drivers of FDI in renewables. J. Int. Business Stud. 1–21. https://doi.org/10.1057/s41267-020-00387-x.

Pfeiffer, A., Hepburn, C., Vogt-Schilb, A., and Caldecott, B. (2018). Committed emissions from existing and planned power plants and asset stranding required to meet the Paris Agreement. Environ. Res. Lett. *13*. https://doi.org/10.1088/1748-9326/aabc5f.

Polzin, F., Egli, F., Steffen, B., and Schmidt, T.S. (2019). How do policies mobilize private finance for renewable energy?—a systematic review with an investor perspective. Appl. Energy *236*, 1249–1268. https://doi.org/10.1016/j.apenergy.2018.11.098.

Powell, M.J.D. (1984). On the global convergence of trust region algorithms for unconstrained mimimization. Math. Programming *29*, 297–303.

Richter, M. (2013). Business model innovation for sustainable energy: German utilities and renewable energy. Energy Policy *62*, 1226–1237. https://doi.org/10.1016/j.enpol.2013.05.038.

Schleicher-Tappeser, R. (2012). How renewables will change electricity markets in the next five years. Energy Policy *48*, 64–75. https://doi.org/10.1016/J.ENPOL.2012.04.042.

Schmidt, T.S. (2014). March 26), Low-carbon investment risks and de-risking. Nat. Clim. Change. https://doi.org/10.1038/nclimate2112.

Sharmina, M., et al. (2020). Decarbonising the critical sectors of aviation, shipping, road freight and industry to limit warming to 1.5–2°C. Clim. Policy, 1–20. https://doi.org/10.1080/14693062.2020.1831430.

Shomali, A., and Pinkse, J. (2016). The consequences of smart grids for the business model of electricity firms. J. Clean. Prod. *112*, 3830–3841. https://doi.org/10.1016/j.jclepro.2015.07.078.

Shrimali, G., and Kniefel, J. (2011). Are government policies effective in promoting deployment of renewable electricity resources? Energy Policy *39*, 4726–4741. https://doi.org/10.1016/J.ENPOL.2011.06.055.

Sinsel, S.R., Yan, X., and Stephan, A. (2019). Building resilient renewable power generation portfolios: the impact of diversification on investors' risk and return. Appl. Energy *254*, 113348. https://doi.org/10.1016/j.apenergy.2019.113348.

Solargis. (2020). Global Photovoltaic Power Potential by Country. https://datacatalog.worldbank.org/dataset/global-photovoltaic-power-potential-country.

S&P Global (2015). Data base description and research methodology: UDI World Electric Power Plants Data Base (S&P Global).

Steffen, B. (2018). The importance of project finance for renewable energy projects. Energy Econ. *69*, 280–294. https://doi.org/10.1016/j.eneco.2017.11.006.

Steffen, B., Karplus, V.J., and Schmidt, T.S. (2020). State Ownership and Technology Adoption: The Case of Electric Utilities and Renewable Energy (MIT CEEPR).

Thiel, G.P., and Stark, A.K. (2021). To decarbonize industry, we must decarbonize heat. Joule. https://doi.org/10.1016/j.joule.2020.12.007.

Tõnurist, P., and Karo, E. (2016). State owned enterprises as instruments of innovation policy. Ann. Public Coop. Econ. *87*, 623–648. https://doi.org/10.1111/apce.12126.

Varian, H.R. (2014). Big data: new tricks for econometrics. J. Econ. Perspect. *28*, 3–28. https://doi.org/10.1257/jep.28.2.3.

Wainstein, M.E., and Bumpus, A.G. (2016). Business models as drivers of the low carbon power system transition: a multi-level perspective. J. Clean. Prod. *126*, 572–585. https://doi.org/10.1016/j.jclepro.2016.02.095.

Weber, C., McCollum, D.L., Edmonds, J., Faria, P., Pyanet, A., Rogelj, J., et al. (2018). October 1), Mitigation scenarios must cater to new users. Nat. Clim. Change. https://doi.org/10.1038/s41558-018-0293-8.

Weigelt, C., and Shittu, E. (2016). Competition, regulatory policy, and firms' resource investments: the case of renewable energy technologies. Acad. Manage. J. *59*, 678–704. https://doi.org/10.5465/amj.2013.0661.

Welch, E.W., Mazur, A., and Bretschneider, S. (2000). Voluntary behavior by electric utilities: levels of adoption and contribution of the Climate Challenge Program to the reduction of carbon dioxide. J. Policy Anal. Manage. *19*, 407–425. https://doi.org/10.1002/1520-6688(200022)19:3<407::AID-PAM3>3.0.CO;2-7.

WEPP, (2020), S&P Global Market Intelligency World Electric Power Plnats Data Base.

World Bank. (2020). World Development Indicators. https://datatopics.worldbank.org/world-development-indicators/.

Yandex. (2018). CatBoost GitHub: GBDT Speed Benchmarks. https://github.com/catboost/benchmarks/blob/master/training_speed/README.md.

Yandex. (2021). CatBoost Is a High-Performance Open Source Library for Gradient Boosting on Decision Trees. https://catboost.ai/.

STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
All the data sources used in the study have been reported in the Supplemental Information (Table S2)		N/A
Software and algorithms		
Python programming language, version 3.7.4	Python Software Foundation	https://www.python.org/
CatBoost open-source gradient boosting library	Yandex	Documentation available at https://catboost.ai/docs

RESOURCE AVAILABILITY

Lead contact

Further information requests should be directed to the lead contact Galina Alova at galina.alova@ouce.ox.ac.uk.

Materials availability

This study did not use or generate reagents.

Data and code availability

All data sources used in this study have been reported in the Supplemental Information (Table S2) and methods are discussed in the Method details section below.

METHOD DETAILS

Data

The data on installed generation capacity used in this study come from the Utility Data Institute (UDI) World Electric Power Plants Data Base (WEPP) by S&P Global Market Intelligence. Amongst its key advantages is that it offers quarterly historical releases of the data on power plants globally between 2001 and 2020. Amongst the granular information recorded for individual power plants, WEPP includes data on a company owning the asset (operator and/or sole or majority owner of each power plant unit). It also offers information on the company business and electricity production type (for example, utility or private power producer). This allows distinguishing between utility and IPP companies and aggregating the data on individual power plant units to the utility and IPP segments of a given electricity sector. Utility companies include regulated utilities (such as those owned by national or local governments), investor-owned utilities and cooperative utilities. IPPs include non-utility actors that also generate power for sale.

WEPP is considered one of the most comprehensive global asset-level datasets available for the electricity sector (Gotzens et al., 2019), although its coverage might vary by geography, technology or plant size, being less inclusive for smaller power stations in select countries, such as onshore wind power below 0.1 MW in China (Alova, 2020; S&P Global, 2015). Such limitations are not expected to have a substantial impact on the data coverage. As of 2020, WEPP contained information on over 6.6 TW of currently operating capacity, which accounts for over 98% of global estimated capacity mix (EIA, 2021), in addition to 910 GW of previously retired capacity (WEPP, 2020).

We combined the WEPP data with the OECD Environmental Policy Stringency (EPS) Index – the data on the aggregate index as an indicator of a country's overall environmental policy stringency and its components, that is the stringency indices of three fossil-fuel-inhibiting policy groups, such as emission-related taxes, trading schemes and standards, and two renewables-promoting instrument groups, such as feed-in-tariffs and R&D subsidies. We built two models, the first one using the individual policy instrument groups, and

the second one using the aggregate index. The EPS Index is focused predominantly on the policy instruments common for the energy sector (Botta and Koźluk, 2014), which makes these data particularly suitable for the study at hand.

The EPS data are currently available between 1990 and 2015 for 27 OECD and 6 BRIICS economies, i.e. Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, South Korea, the Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom, the United States, Brazil, China, India, Indonesia, Russia and South Africa. The missing data points up to 2020 were filled with values from the last available year, which was deemed an adequate approach, given the slow-moving nature of the policy environment. Furthermore, the results demonstrated robustness to an alternative approach, when the missing policy values were filled by using forecasted data, instead of the latest available data points.

Data on electricity consumption per capita were obtained from the World Bank World Development Indicators database (World Bank, 2020), on country solar resource endowment from the World Bank Energy Sector Management Assistance Program (Solargis, 2020), on country wind resource endowment from National Renewable Energy Laboratory (NREL, 2014), and on levelised cost of electricity from Lazard (Lazard, 2020) (see Table S2).

MODEL

Gradient boosted decision trees

To explore the potential contribution of policy- and market-related factors to generation capacity growth of different technologies by the utility and IPP sectors, we used gradient boosted decision trees (GBDT), which is a state-of-the-art machine-learning-based technique for non-parametric and interpretable predictive analytics(Friedman, 2001, 2002). The high quality of prediction is achieved by training individual decision trees in an additive and sequential manner, optimizing arbitrary differentiable loss functions, in order to produce a strong prediction from the ensemble of shallow trees. While still nascent, machine-learning-based models are starting to see an increasing application in the research focusing on the low-carbon transition (Nguyen et al., 2021).

GBDT models have become the *de facto* standard in machine learning for analyzing feature-rich, structured datasets (Ke et al., 2017). Efficient interpretability of models inner workings, through the use of SHAP values (see below), is an essential characteristic of the GBDT, enabling to understand the relationship between the input variables and the prediction (Hastie et al., 2009). This is of particular importance for this study which focuses on examining the factors behind electricity companies' decarbonization choices. Furthermore, besides capturing non-linear relationships and dealing well with both numerical and categorical variables, the GBDT models are robust to such data issues as feature multi-collinearity, imbalanced datasets and outliers(Hastie et al., 2009).

We built our GBDT model using CatBoost – a free open-source algorithm by Yandex (Yandex, 2021). The key advantage of CatBoost for us is the possibility to conduct a multi-regression analysis with multiple dependent variables. We have employed this feature to explore the relationship between different variables and capacity growth distinguished by technology and sector type. CatBoost also has a training speed comparable to other leading GBDT algorithms, such as LightGBM or XGBoost (Yandex, 2018), being a matter of minutes for the dataset used in this study.

Building and training of our model comprised several steps: target formulation, feature engineering and selection, hyperparameter tuning, model validation and interpretation. As a result of this rigorous process, the model is appropriately specified, demonstrating good performance with a low error on the prediction both on the training and test set (see Table S3 for evaluation metrics), producing robust and reproducible results, and offering a reliable approach that can be applied to other settings and datasets. Below, we discuss each of the steps involved in building the model.

Target variable and model granularity

The analysis examines the relationship between policy or market-structure-related features and capacity growth, distinguished by technology and company type across 33 countries over 2001-2020. Growth is measured as the change in the operating capacity of certain technology owned by a country's utility or

IPP sector in a given year compared to the previous year, divided by the total capacity owned by this sector in the previous year, as follows: $\frac{MW_{y,\ t,\ c,s} - MW_{y-1,\ t,\ c,s}}{MW_{\ y-1,\ c,s}}$, where MW stands for capacity; y for a year; t for technology, that is either solar, wind, gas, coal, oil, hydro, or other; s for a sector, that is utility or IPP; and c for a country. Growth is modeled at the country's aggregate IPP and utility sector level, to capture the sector's response to policies and market structures, which is the primary focus of the study. Relevant individual company-level characteristics were included as part of the market-structure related features (see below). Annual IPP or utility sector's absolute growth in a given technology was capped at 20% to treat extreme outliers (which accounted for 1.7% of the data points), which has resulted in the model's better performance and generalization.

Feature engineering and selection

Along with the impact of policy variables (emission-related taxes, standards and trading schemes, feed-in-tariffs and R&D subsidies) which are particularly relevant for the electricity sector as mentioned above, the analysis examines the importance of market-structure-related factors. Informed by the extant studies (M. A. Delmas and Montes-Sancho, 2011; Markard and Truffer, 2006; Weigelt and Shittu, 2016; Welch et al., 2000) that focus on other factors besides policies, the following features were included at the country level for each year under consideration: utility market share (utility-owned generation capacity as % of overall installed capacity), share of investor-owned utilities (% of the overall utility-owned capacity owned by investor-owned utilities), average size of a utility in a given utility sector (in MW), average age of operating power plant units in a given utility sector, and share of renewables-based power plant units, that is solar and wind, in the utility sector's asset base. These variables were lagged by one year, to avoid reverse causality, where the target, that is growth, for example, in utility-owned gas capacity in a given year, would affect one of the features, for example, the utility sector's market share or average company size in that year.

The analysis also controls for solar and wind resource endowment of a country, the improved cost-competitiveness of renewables vis-à-vis fossil fuels (that is the difference between the levelised costs of electricity generation from solar and coal in USD per MWh) and country's overall level of development (measured by electricity consumption in kWh per capita in the previous year) (see also Table S1).

These features included in the final model were determined through a multi-step feature selection process, to ensure that they are all salient and stable for the prediction. First, we investigated the predictive power of features to exclude those with an impact close to zero, as measured by SHAP values (see below). Second, we examined a potential domain shift of features, that is, whether they perform differently on different splits of the data. To this end, we trained a sequence of three models with multiple splits on the training set for robustness checks, and calculated the average of the mean absolute impact of a feature on the predictions of the three models, and the average of the correlations between these impacts (see Figure S3). A negative average correlation would imply that the model learns something different about the feature across the various splits of the training set. The process helped to ensure that only the features with a stable impact on the prediction were included in the model. Finally, an important consideration was to avoid including distinctly inter-related features (e.g. the share of renewable energy power plant units in both utility sector and the IPP sector; or electricity consumption per capita and country Gross Domestic Product).

Hyperparameter tuning

To ensure that the model does not overfit (that is, performs well in- and out-of-sample) (Varian, 2014), we tuned the model's hyperparameters, which determine the optimal structure of the ensemble of the decision trees and the training process. These include, for example, the number of trees, maximum depth of each tree, or the minimum number of training samples in a leaf. Finding the best set of parameters results in a regularized model geared to exclude patterns that are not important for the prediction, thereby generalizing from the training to the test set, while maintaining the best possible accuracy (see Table S4 for the list of hyperparameter values).

To tune the model, we used the derivative-free maxLIPO+TR optimization method(King, 2017), proven to outperform random parameter search (Malherbe and Vayatis, 2017), and often preferred to Bayesian optimization for its faster convergence to an optimum (King, 2017). The method finds a global maximum of the hyperparameter space, by alternating between the non-parametric global optimization of Lipschitz functions (LIPO) (Malherbe and Vayatis, 2017) and the local Powell's quadratic trust region (TR) method (Powell,

1984) (see Alova et al. (2021) for more detail on this approach). We confirmed the convergence of the tuned hyperparameters to an optimum through a visual inspection of the tuning results.

Model validation

Upon training and tuning the model, we also validated it, that is tested its performance on the data different from the training set. To this end, we used out-of-time validation with multiple splits of the data with folds ordered in time. This approach enables us to ensure that the model is always validated on the future sub-set of the dataset, preventing it from overfitting by learning future information that would not be available at the point of its training.

We performed out-of-time validation using three consecutive splits of the data in time: training on 2001-2011 and validating on 2012-2014; ii) training on 2001-2014 and validating on 2015-2017; and iii) training on 2001-2017 and validation on 2018-2020.

Model interpretation

To interpret the model, we made use of SHAP values which were assigned to each feature in relation to a given data point. A SHAP value of a feature, expressed in log odds, denotes how much a given feature changes the prediction in one or another direction (Lundberg and Lee, 2017). A positive SHAP value assigned to a feature for given capacity growth in certain technology and company type (e.g. growth in solar capacity by the utility sector in France in 2005) would mean that the feature has a positive impact on this growth, whereas a negative value would reduce this growth. The total SHAP value constitutes the sum of a direct effect of a feature on the prediction and the interaction effects with all other features.

SHAP values have been proven to be the only solution to satisfy three important conditions: consistency, missingness and local accuracy, combining the characteristics of several previously existing approaches (Lundberg and Lee, 2017). Consistency refers here to the case in which the importance of a feature does not decrease as a result of the model being changed to rely more on this feature. Missingness means that a missing feature, that is a feature that is not used by the model, gets a SHAP value of zero. Local accuracy signifies that the impacts associated with individual features add up to the total prediction of the model (Lundberg et al., 2018).

Chapter 6. Conclusions

6.1. Discussion of findings and their implications

This DPhil thesis has aimed to examine the pace and nuanced patterns of the power-generation sector's transition to renewable energy and away from fossil fuels. While there is a growing body of literature on renewable energy adoption trends, few studies have to date conducted in-depth analyses on the key barriers to breaking the sector's dependence on fossil fuels, and that on an international, rather than a single country, scale (see Section 2.3 of Chapter 2).

In this regard, the key contribution of this thesis is its cross-country focus on capturing the detailed dynamics of the power sector's decarbonisation at the company and country level, and by examining both the sector's past and predicting its future performance. The adoption of machine-learning-based techniques has allowed to effectively interrogate granular data on power plants internationally. As a result, this thesis offers empirical evidence to the theoretical discussion in Chapter 2 on the carbon lock-in risks that electricity systems tend to be prone to (Section 2.1.6).

This section provides a synthesis of the key findings, discussing the narrative emerging from the results, and highlights the contributions of this DPhil thesis to the extant empirical literature on the energy transition. The section starts by discussing the findings pointing to the sector's shift to renewable energy and away from fossil fuels not taking place in tandem (Section 6.1.1), with the opaque role of gas in the energy transition being among the contributing factors (Section 6.1.2). It then continues to explore the findings around environmental policy effectiveness both in the context of growth in renewable energy and fossil fuels (Section 6.1.3). The section then zooms in on the importance of individual geographies, discussing the chances of developing countries skipping the carbon-intensive development pathway (Section 6.1.4), and the role of companies, such as utilities vis-à-vis IPPs in driving the transition (Section 6.1.5). It concludes by highlighting

the methodological contribution of the thesis to the literature on the energy transition (Section 6.1.6) and the emerging impact of the publications conducted as part of this research (Section 6.1.7).

6.1.1. Transition to renewables and away from fossil fuels

One of the cross-cutting conclusions emerging from the findings of the three studies conducted in this thesis is that the transition to renewable energy and away from fossil fuels does not always happen hand-in-hand. First, the fast addition of renewable energy to the global installed capacity does not necessarily imply ceased growth in fossil-fuel-based power generation. For example, when looking at utility companies' energy transition, the analysis suggests that the majority of even those companies that have prioritised renewable energy growth over gas or coal in their portfolios have in tandem expanded their fossil fuel capacity.

Second, the predictive analysis of the future capacity mix in Africa has shown that while the installed capacity of the continent will more than double this decade and renewables will account for a considerably higher share than at present, fossil fuels will continue to dominate the mix. This again points to a complex nature of the transition, which does not necessarily break the dependence on carbon-intensive electricity, even when renewables-based generation capacity is growing.

Third, the findings of the study on the factors contributing to company technology choices have highlighted that the same factors might have a different effect on boosting renewables compared to curbing fossil fuel growth. For example, for utility companies, the environmental policy framework as a whole seems to have a more pronounced contribution to reducing fossil fuel growth, particularly that of coal, than promoting renewables expansion. When comparing to IPPs, utilities are overall less responsive to environmental policy instruments in their uptake of renewable energy. At the same time, while a low utility-owned share of the electricity market tends to have a distinct negative contribution to growth in coal, this link is not as clear-cut for renewables, pointing to the

high utility presence in the market potentially also supporting renewable energy expansion. This suggests that achieving the dual objectives of shifting the sector to renewables and away from fossil fuels would require a careful design of both policies and market structures. Importantly, this would need to take into account the potential granularity in the effects that different factors might have on the transition outcomes of both specific companies and the sector as a whole.

6.1.2. Gas as a driver of future carbon lock-in

The findings of this DPhil also point to gas likely to be the key source of carbon lock-in in the future. As the analysis on the transition of Africa's electricity sector over the next decade has shown, fossil fuels, particularly gas, tend to dominate the pipeline of the currently planned power plants. This implies that investments in fossil fuel power plants continue, despite the falling clean technology prices, abundance of African economies in renewable energy and potential high future climate-related transition risks associated with carbon-intensive investments. Furthermore, the study also concludes that when looking at already planned power plants, fossil fuel projects, such as gas and oil, have on average had higher commissioning chances than most renewable energy plants.

These findings also resonate in the global analysis of utilities' investment patterns, which finds that a considerable share of the companies under consideration still prioritised fossil fuel growth over renewable energy adoption. Moreover, as mentioned above, a high share of these utilities that did favour renewables in their portfolios, have in parallel still expanded their fossil fuel capacity, although that at a lower speed.

Among the potential explanations for the continued important role of gas in global power generation could be the finding that gas portfolios of electric companies, both utilities and IPPs, in general tend to be considerably more resilient to factors such as environmental policy stringency. Among the policy instruments examined, only emission standards seem to have a pronounced contribution to reducing growth in gas capacity of IPPs throughout the different policy stringencies. Furthermore, market liberalisation might not necessarily

lead to the shift away from the reliance on gas. While such market characteristics as lower utility market shares tend to be conducive to curbing growth in coal capacity, there appears to be an inverse, albeit less prominent, link with gas expansion. This could suggest that utilities in relatively more liberalised markets might be substituting their coal assets for gas.

Ambiguity on the role of gas in a low-carbon future

In the context of the findings of this thesis on the gas-driven inertia in the electricity sector's decarbonisation, it is useful to consider the general lack of consensus on the extent to which the continued use of natural gas is compatible with net zero objectives. While gas tends to be generally considered less polluting than coal, in terms of the carbon dioxide emissions from its combustion (Stephenson, Doukas and Shaw, 2012), methane emission leakage from natural gas systems has raised significant concerns (de Gouw *et al.*, 2020). At the same time, many still believe that gas will have an integral part in the energy transition for its load-balancing services as a potential near-term solution to the intermittency of renewable energy sources (Gürsan and de Gooyert, 2021). This is under an assumption that battery storage still needs to see significant cost depreciation to make fully renewable energy systems financially feasible (Ziegler *et al.*, 2019).

Against this backdrop, the future use of natural gas in the electricity sector is an area of policy ambiguity. Climate scenarios vary extensively in their assumptions of the acceptability of natural gas in a low-carbon future. The IEA's recent Net Zero scenario argues for a much lower role of gas in achieving decarbonisation objectives, compared to the existing IPCC models (IEA, 2021b). Yet, at present, the EU Taxonomy neither explicitly excludes nor includes natural gas on its list of green activities (European Commission, 2021). World Bank's new Climate Change Action Plan 2021-2025 also allows some flexibility for continued investments in gas infrastructure in countries "where there are urgent energy demands and no short-term renewable alternatives" (World Bank, 2021). This has sparked a debate on whether the strategy is sufficiently ambitious (Larsen

et al., 2021), particularly given the importance of channelling development finance towards renewable energy to de-risk these projects (Matthäus and Mehling, 2020), thereby boosting their competitiveness.

The lack of clear policy signal on the role of gas in the energy transition contributes, among others, to the uncertainty around climate-related transition risks, which several strands of the theoretical literature, as discussed in Chapter 2 (Section 2.1.7), highlight as one of the underlying reasons for firms' delayed climate action. As a result, this policy ambiguity could serve as a useful prism through which to interpret the results of this thesis relating to the gas-driven inertia of the electricity system. A decisive and co-ordinated government position on gas with clarity on the timing and stringency of policy actions would be needed to help to quantify and price in climate-related transition risks, thereby better assessing the financial viability of continued investments in gas power plants.

Importance of action on coal

While the findings of this thesis point to gas being among the key areas of uncertainty in the future low-carbon transition, the challenge of breaking dependence on coal is not yet resolved either. As the results of this analysis suggest, still a considerable number of utility companies, albeit the smallest cluster identified, continue to prioritise coal over gas and renewable energy capacity. Coal also maintains a substantial share in the predicted capacity mix across the African continent, particularly in Southern Africa.

Moreover, against the backdrop of the finding that coal appears to be more responsive to environmental policies than gas capacity, policy stringency across emerging economies has been considerably lower than in the OECD countries. This could potentially contribute to explaining the fact that demand for coal continues to grow in many parts of the developing world (IEA, 2021a). While advanced economies have on average seen a gradual decline in coal consumption over the past decades, across developing countries growth persists, with 2021 seeing a particularly strong rebound in demand for coal (IEA, 2021a).

In this context, COP26 in Glasgow has achieved mixed success of ensuring Parties' commitment to breaking the dependence on coal. While the pledge to accelerate the transition away from unabated coal power was made by over 40 countries (UNFCCC, 2021b), major coal consumers such as China, India and the US did not sign up to this commitment (C. Taylor, 2021). Furthermore, the accord offers two speeds of the transition, first, in the 2030s for major economies, and second, in the 2040s for all the others. This might slow the overall shift away from coal to clean energy, given that, for example, Poland a major consumer of coal power in Europe highlighted that it considers itself belonging to the second cohort of countries. As a result, it aims to phase out coal by 2049 (K. Taylor, 2021). Moreover, although the Glasgow Pact signed by the Parties at COP26 did for the first time explicitly mention the importance of taking action on the use of coal and fossil fuel subsidies (UNFCCC, 2021a), this language was weakened in the final draft to secure the agreement from India and China (Hook, Hodgson and Pickard).

6.1.3. Policy effectiveness

This thesis has also sought to contribute to the literature on environmental policy effectiveness at both supporting renewable energy uptake and reducing fossil fuel investments, with the following key conclusions. First, among the key findings is the divergence in responsiveness of utilities compared to IPPs to different policy instruments, which could contribute to the explanation on the slow transition of utility companies to renewable energy. For example, across IPPs sectors, four out of five policy instruments examined (that is, emission trading schemes, feed-in-tariffs, R&D subsidies and emission standards) are all among top features affecting their renewable energy growth, while for utility companies, environmental policies tend to be of lower salience, with market structure characteristics mattering more. The interplay of different policy instruments, such as fossil fuel disincentives and renewable energy subsidies, appears also to be of considerable relevance for breaking the companies' path dependence. For example, the

existence of feed-in-tariffs might amplify the effect of carbon pricing policies on reducing growth in utility-owned coal capacity.

Second, the effect of policy stringency on specific technology choices of companies appears to be often non-linear. For example, the contribution of emission standards to growth in utilities' coal capacity or of emission taxes to growth in IPP-owned coal capacity levels off as the policies become more stringent. This could be due to companies already being at a certain maximum possible level of reduction of their fossil fuel capacity growth for a specific policy stringency, given that it is costly and might take time to disinvest their capital assets. In this case, increasing policy stringency might not necessarily trigger faster shift away from fossil fuels. Alternatively, these findings could also suggest that the effect of a policy has already been priced in at the point of its announcement, in that businesses have adjusted their portfolio expansion in anticipation of a stricter policy. In this case, delivering on the promised policy stringency is all-important for the government to preserve the trust of the companies, and ensure future effectiveness of these policies.

At the same time, some policies might show alternation between a stagnation period in their effect and a new heightened impact, as the instrument becomes even stricter. This seems to be the case, for example, for the effect of emission trading schemes on reducing growth in utility-owned coal capacity. This could imply that for a certain set of policy stringencies, companies decide to curb their fossil fuel growth at a certain level, and it takes a considerably stronger policy shock to induce even greater reductions.

Finally, besides domestic policies, the findings of this thesis have implications also for international co-operation, particularly when it comes to improving the success chances of renewable energy projects. As the analysis on African economies has shown, renewable energy projects tend to have considerably lower commissioning rates than some fossil fuel plants. Among the underlying reasons could be the lack of experience in these technologies, given a relatively lower number of projects implemented to date, which in turn might drive continued investments in fossil fuels power plants to meet growing

energy demand. There is evidence, for example, that cumulative production experience can reduce technology cost (Louwen, Schreiber and Junginger, 2020). Similarly, gaining experience in implementing and maintaining renewable energy power plants can further reduce the cost and risks associated with these investments (Steffen *et al.*, 2020).

Against this backdrop, the participation of development finance institutions in project financing was one of the top features contributing to the successful commissioning of power plants. Directing development co-operation efforts to de-risking renewable energy investments and mobilising private finance could, therefore, help to deliver more of these projects, thereby building an associated technical expertise. In this regard, the pledge of advanced economies to annually mobilise USD 100 billion a year in climate finance for developing economies by 2020 is particularly important. However, according to the estimates, the commitment will be met with a delay of several years (Pickard and Hook, 2021). At the same time, COP26 saw 20 countries make a commitment to end public financing of international projects in the unabated fossil fuel energy sector by 2022 (UNFCCC, 2021c). This is the first such an agreement to include, besides coal, also oil and gas (Kottasová *et al.*, 2021).

6.1.4. The importance of geography in energy systems' transition patterns

The analysis has captured several manifestations of spatial differences in how companies and countries embrace the energy transition process. To begin with, at the company level, there is clear regional dominance in some of the utility transition patterns. For example, there are predominantly Asian companies, particularly from China, in the coal-prioritising cluster, while renewable-energy favouring companies come mostly from Europe and the US. Furthermore, geography also tends to matter when examining the response of the electricity sectors to policy and market-structure-related factors across OECD vis-à-vis BRIICS economies. Over the two decades under consideration, developed countries overall seem to have had on average conducive policy environments and market structures for their transition to renewable energy. This becomes clear in most features

contributing positively to renewable energy uptake, while reducing fossil fuel growth. On the contrary, emerging economies on average have seen policy- and market-structure-related features taking values that have had an opposite effect, that is contributed positively to fossil fuel growth and negatively to the expansion of renewable energy.

This question on whether developing countries have greater potential to achieve rapid decarbonisation is subject to an on-going debate. On the one hand, the low-carbon transition is one of pressing priorities that developing countries face, such as poverty eradication, inequality reduction and industrialisation (Wieczorek, 2018). On the other hand, the infrastructure gap that many countries tend to experience eliminates the need to replace the existing assets, offering an opportunity to skip the carbon-intensive development trajectory, leapfrogging directly to a low-carbon economic model (Bridge *et al.*, 2013; Wieczorek, 2018). As discussed in Section 2.2.1, this has been the narrative underpinning some of the extant optimistic projections of Africa meeting its growing energy demand increasingly through renewable energy in the coming years. However, as the analysis in Chapter 3 has predicted, this transition might not necessarily take place at the speed implied by these scenarios, given the emerging carbon lock-ins stemming from the project pipelines and the commissioning chances of planned power plants. As a result, the inherent inertia that electricity systems are fraught with seems to be present not only in the mature electricity systems of developed countries, but also emerging in developing economies that are often considered less at risk of path dependence, given their still expanding power-generation systems.

In this context, the study has also found that there are stark inter- and intra-regional differences also in the estimated realisation chances of planned project pipelines when looking across the African continent, varying as much as from 52% in Central Africa to 91% in North Africa. The combination of the pipeline composition and project realisation chances result also in differences in the predicted 2030 capacity mixes across the regions, with gas playing an important role in North and West Africa, whilst East and Central Africa

demonstrating high reliance on hydropower. At the same time, Southern Africa is likely to see the highest share of non-hydro renewable energy in its capacity mix, compared to other regions, with coal also still playing a considerable role.

Finally, noteworthy is also the finding that while several country-specific socio-economic and governance indicators are important for the prediction of project realisation chances, these features are relatively less salient than power plant characteristics. This could be a potentially useful observation, in that it might be arguably easier to change specifications of a planned project to increase its commissioning chances than to improve the development outcomes of an entire country.

6.1.5. The role of utility companies vis-à-vis IPPs in driving the transition

The DPhil thesis has also offered several granular insights into the roles of utilities compared to IPPs in driving the transition of the power generation sector to renewable energy. When exploring the utility sector globally, the analysis points to utility companies being slow at decarbonising their portfolios, with the majority of renewable energy installed capacity owned by non-utility actors such as IPPs. At the same time, when looking at the success rates of already planned projects, IPP ownership does not necessarily imply their better commissioning chances. As an example, across African economies, IPPs only recently reached the success rates comparable to those of state-owned projects. This could be due to some of the arguments for state ownership of renewable energy projects, discussed in Chapter 2 Section 2.1.4.

Overall, several findings across the three chapters point to the roles of utilities and IPPs in driving the transition not necessarily needing to be mutually exclusive, but being potentially reinforcing. The analysis on the factors contributing to company technology investments suggests that while liberalised electricity markets tend to be conducive to the shift away from most fossil fuels, as mentioned above, high utility presence in the power sector does not always impede the penetration of renewable energy. Findings also point to renewables-prioritising utilities tending to be in the jurisdictions with high shares of non-

utility-owned renewables. There are also overall considerable correlations between IPP-owned renewable energy capacity and utilities' growth in renewables and vice versa. Relatedly, the analysis has also shown that the share of renewables in utilities' portfolios seems to have a positive contribution to IPP-owned renewable energy growth, which does level off for higher shares.

6.1.6. Methodological contribution of this thesis

In addition to generating potentially useful insights into the power sector's decarbonisation, the aim of this thesis is also to demonstrate the data and tools that could be used to capture the complexity of the electricity systems' transition. As a result, this DPhil has made some contributions to advancing the academic debate on the methodologies underlying the energy transition.

First, Chapter 3 has re-opened the discussion on the use of predictions versus projections in the energy transition literature. The analyses that aim to demonstrate possible future development trajectories of the energy sector, particularly in the long-term, are inevitably subject to considerable uncertainty, as highlighted in the literature review in the Section 2.2.2. Therefore, climate and energy modelling studies tend to seek to project the whole breadth of possible outcomes, to inform decision making under uncertainty, rather than producing a specific prediction. To offer such projections, researchers use assumptions-based scenarios rather than predictive models.

That said, predictive models such as in the study of Chapter 3 do have their *raison d'être*. As McCollum highlights in his review of this study, predictive analytics can be a powerful tool in energy research when used for near-term analyses (McCollum, 2021). Studies that rely on the data and approaches that are able to offer both an assessment of the past and a glimpse into the future, such as capital expenditure projects under way and their associated realisation chances, can serve as an early warning of how the near-term future could realistically unravel. As a result, predictive studies could be particularly important for demonstrating what needs to be done to align the likely future with the outcomes

desired, given some of the emerging lock-ins. In this context, Chapter 3 highlights several potential levers to improve the commissioning rates of renewable energy projects, while also shifting the composition of the pipeline away from fossil fuels.

Relatedly, this study also offers a perspective on how predictive and scenario-based approaches could be merged. To this end, it runs several scenarios with assumptions that alter the composition of the pipeline as known at the moment of the analysis, to demonstrate the gap between the likely reality and the projections of Africa's low-carbon futures. This discussion on potential avenues for future work on reconciling prediction- and projection-based approaches continues below in Section 6.3. of this Chapter.

Second, this thesis has aimed to highlight the importance of selecting the appropriate tools for the problems at hand, to effectively interrogate the datasets enabling them to reveal valuable insights. As an example, Chapter 4 provides a systematic global analysis of investment patterns across a large sample of utility companies in an encompassing and robust manner, which case studies or descriptive statistics might not have been able to achieve to the same extent. To this end, the study applies a clustering analysis that is able to effectively devise broad conclusions from a large granular power-plant-level dataset, containing information on assets of a heterogeneous set of companies. The study in Chapter 5 has also taken a non-trivial approach, by building a model that includes multiple dependent variables and allows capturing the nuances in how the same policy or market factors could contribute differently to company portfolio expansion, given the technology and the type of firm at play. As a result, this analysis can isolate effects and capture synergies between different factors, producing nuanced results, as discussed above.

6.1.7. Dissemination of findings and emerging impact

Recognising that dissemination is an important part of a research project, I have made a deliberate effort to engage with diverse sets of audiences to help the key messages of my work to reach decision makers. This section presents some of the key outputs, with this dissemination work still on-going.

To date, I have presented my research at ten academic and practitioner conferences (see Appendix E) to share the findings and engage with the energy transition debate. The highlights include the presentation at the workshop on Tackling Climate Change with Machine Learning at the Conference on Neural Information Processing Systems (NeurIPS) 2020, one of the most prestigious machine learning conferences in the world. Another achievement is the Best Paper Prize on Emerging Market Actors at the 3rd annual conference of the Global Research Alliance for Sustainable Finance and Investment (GRASFI 2020). I also held several workshops dedicated to my research, for example, for Credit Suisse and the multi-stakeholder Financial Big Data Cluster project, led by FS-UNEP Centre. Moreover, I wrote a number of op-eds based on my work, among others, for The Conversation (Alova and Trotter, 2021), the OECD Development Matters (Alova, 2021), and Behavioural and Social Sciences at Nature Research (Alova, 2020).

The publication of the papers has also attracted significant attention, including from major news outlets, among others, by BBC, The Guardian and The New York Times, and leading academics in this field. The contribution of Chapter 3 to advancing the energy-planning literature was recognised by Dr David McCollum in an expert piece for *Nature Energy* (McCollum, 2021) and by Prof Destenie Nock in her review for *Joule* (Nock, 2021). Finally, equally valuable from the potential impact perspective is the mentioning of my research in practitioners' reports, such as the work of the TCFD Portfolio Alignment Team (Blood and Levina, 2020).

6.2. Limitations of the thesis

Besides the contributions this thesis has aimed to make to the current energy transition literature, there are some limitations worth considering, which could also give rise to future research strands in this domain (see Section 6.3). This section highlights some of the key points, in addition to the discussion of constraints relating, for example, to the data structure or interpretation of the findings, already outlined in the individual Methods and Conclusions sections of Chapters 3-5 as well as the accompanying Appendices A-C.

First, there is a question on the extent to which advancing the understanding of the past could be useful for informing how the future of electricity systems might look like. The ability to sufficiently deviate from historical trends to foresee abrupt policy and technology advancements, while still learning from the past where it is beneficial, has been a long-standing challenge for energy and climate modellers (Jaxa-Rozen and Trutnevyte, 2021). This is a particularly important consideration for studies aiming to model the development of an economic system far into the future.

Being aware of this issue, Chapter 3 focuses the analysis on a ten-year, rather than a longer, time horizon, as the relationships between the features devised from the past data could be of lower predictive power for more distant futures. This, for example, has also become apparent when constructing the training set for the model. The final model was trained on the past two decades only, as extending the training set further back into the past proved to undermine the predictive power of the model. As a result, while the near-term focus of the study is one of its limitations, as this research does not offer a longer-term perspective of the future, this approach ensures the robustness of the results. Furthermore, as discussed in Supplementary Note 2 (Appendix A), limiting the time horizon of the study to the near term lends also confidence in the quality of the data on the planned project pipeline, as known at the moment of the analysis.

Second, while the analysis conducted in this DPhil has aimed to capture the key features that might affect electricity systems' transition patterns, thereby also extending the factors considered by the extant literature, some of the considerations might still have been missed. Among these possibly omitted variables could be the factors which are more challenging to capture in quantitative terms for a large set of companies and geographies, such as firms' organisational structure or senior management's support for a climate action.

In this regard, the focus of this DPhil on quantitative empirical research methods could also be considered an additional limitation. On the one hand, quantitative analyses allow

examining large datasets in a systematic robust manner and drawing conclusions that are potentially applicable to different electricity systems and their actors. On the other hand, working with large data inevitably implies that some granular case-specific information might not be reflected. Therefore, complementing such an analysis with qualitative work could shed additional light on the narrative emerging from the quantitative analysis. In view of this, the thesis had originally aimed to complement the quantitative studies with data collection through interviews with key stakeholders, to unpack some of the issues that might be more qualitative in nature. However, given the restrictions imposed by the global pandemic in 2020 and 2021 on social interaction, I had to adjust this plan. Instead, this thesis has focused primarily on desktop research, whilst tapping into the extant large qualitative empirical, but also theoretical, literature to offer additional framing to the research and the interpretation of the findings.

Further to the challenge of collecting primary qualitative data, I discovered the difficulties to incorporate companies' financial metrics in the analysis. Although this information could have offered an additional angle to the narrative, retrieving historical financial data for a large sample of companies and that at a sufficiently granular level of an individual subsidiary has proven challenging. This is particularly the case for non-listed entities and the firms operating outside the developed world, for example, utility companies in Africa. Conducting such an analysis would have required a significant primary data collection effort which was beyond the scope of my thesis. However, bridging this data gap, thereby opening new research avenues including on developing countries, could present an opportunity for future work, as discussed in Section 6.3.

Third, another data-related limitation stems from the fact that the analysis of company investments in technologies is based on the data on nameplate capacities of power plants, rather than their use. Data availability is the key challenge here. Future efforts could target bridging this gap by improving data availability on the use of installed capacity, although

there might be temporal limitations as collecting such historical data ex-post and on a global scale is a significant challenge.

Finally, this thesis focuses on understanding how utility companies and sectors embrace renewables and shift away from fossil fuels compared to IPPs. Although the analysis does aim to capture how these companies might interact and affect each other's roles in the transition, it does not focus on the transition dynamics stemming, for example, from their common ownership by one parent. As I argue in Appendix B in relation to the approach selected for Chapter 4, the focus of the analysis on the subsidiary level directly owning power generation assets, rather than parent companies, is one of the key strengths of this study. That said, it could also be considered a limitation, in that it might not reflect utilities creating or acquiring non-utility entities as a transition strategy on its own. Future studies might wish to focus on research questions around how utilities structure their renewable energy businesses in the context of their core conventional operations, as proposed in further detail in Section 6.3.

6.3. Avenues for future research

Stemming from both limitations but also contributions of the thesis to the field, there are several areas that future research could focus on. First, the conclusions of this thesis could contribute to improving the granularity of energy modelling. As McCollum argues, predictive analyses, such as Chapter 3, could complement the extant energy transition literature "to tune the parametric and structural assumptions of integrated assessment and energy-economic models so that the near-term projections of those models — not only for the power sector — do a better job of incorporating relevant aspects of socio-technical realism" (McCollum, 2021). To begin with, on the discussion of the use of projections vis-à-vis predictions when assessing the future trajectories of the electricity and other sectors, there is potential to reconcile these two approaches, which could be beneficial to both. This can be done by integrating, among others, planned power plant information and probabilities of their implementation chances into scenario-based projections. In light of

the findings of this thesis, another lever would be to account for the potentially non-linear effects of policies on technology choices by companies. Relatedly, work could be done to reflect the observation regarding the differences in company technology choices in response to market and policy-related factors, depending on the firm type. Finally, as discussed in Section 6.2, there remains a methodological challenge of finding a way to make high-accuracy predictions of more distant futures, beyond the ten-year horizon adopted in Chapter 3. Future research focusing on integrating predictive and projections-based approaches could also aim to address this research limitation.

Second, there are opportunities to extend the geographic and sector scope of the analysis I conducted in the three core chapters. As highlighted above, among the aims of this thesis is to demonstrate how granular project-level data and machine-learning-based techniques can be used to assess a sector's transition pathways at the company and country level. It is important to continue these efforts to further develop asset-level research. For example, the predictive approach to energy modelling presented in Chapter 3 could be used for other regions and countries besides Africa, provided granular asset-level data are available on planned, failed and commissioned power plants. Similarly, Chapter 5 could be extended to other economies, particularly to include more developing countries in the sample, again subject to the data availability, for example, on policy stringency. Relatedly, future research could extend the current analysis, by modelling other potentially relevant features that could contribute to the transition patterns of companies and countries. While doing so, it is important to be mindful that there would always be more factors to include, while not all of them might have strong predictive power, especially in combination with the existing variables. Data limitations could also constrain the choice of variables for the analysis. Finally, the modelling and clustering approaches adopted in this thesis could also be successfully applied to other infrastructure-heavy sectors for which data on capital assets exist, to conduct the analysis at both the company and country level.

In this context, continued efforts to improve the availability and quality of asset-level data for different geographies and sectors is crucial. Complementing and verifying the existing corporate asset-level data through the information provided with satellite imagery and remote sensing is an important development in this field that can significantly enhance data quality and coverage (Kruitwagen *et al.*, 2021). Improved asset-level data would in turn advance our ability to assess countries' and companies' decarbonisation patterns, project their future transition pathways and estimate climate-related risks associated with different futures (Weber *et al.*, 2017).

Third, overcoming the challenges of integrating the information on company financial performance into asset-level datasets, mentioned in Section 6.2, would open a multitude of areas for future research. One of these opportunities is to examine how companies' different transition patterns to renewables might affect their financial performance – an area which remains sparsely researched. Ruggiero and Lehkonen (2017) find a negative relationship between utilities' financial performance (measured as returns on equity and on assets), and renewable energy penetration into their asset mix. The authors, however, note limitations in their analysis, including a relatively small sample, skewed towards developed countries. Further research, with larger samples, and using additional financial performance measures, would be beneficial to test this conclusion.

Furthermore, Ruggiero and Lehkonen (2017) also suggest the existence of an equilibrium point for renewable energy penetration at which companies' financial performance is maximised and beyond which it starts to decline. In this case, companies would seek to balance their conventional assets with renewable energy, rather than complete the transition. Examining where this point might be for different companies, and the underlying factors affecting it, could help also explain the finding of this thesis regarding companies' continued expansion of fossil fuel capacity in parallel with investments in renewable energy.

Fourth, improving the understanding of how the transitioning utilities manage their renewable energy assets either by integrating them into the existing business or separating them into a subsidiary company is another important area for future research. There could be strong underlying motivation for either strategy. For example, integrating new assets into the existing conventional business could result in a more balanced portfolio. At the same time, the choice to split renewable energy assets into a separate company might be driven by the aim to capture the positive momentum created around clean power generation, and benefit from associated regulated contracts to hedge against the risk of fluctuating electricity prices (Caldecott *et al.*, 2017).

The restructuring and asset swap of RWE and E.ON that took place in the past years have offered a wealth of examples in this regard. In 2016, RWE split its business, keeping the conventional assets under the old brand, while segregating its renewable energy portfolio into a subsidiary Innogy, which also includes the network and retailing business (Midttun and Piccini, 2017). At the same time, in its restructuring, E.ON separated the existing hydro, natural gas, coal and global energy trading into a new company Uniper. Under its established brand, E.ON retained energy distribution, customer-oriented, solutions, renewable and nuclear power[6] (Chazan, 2016; Midttun and Piccini, 2017). Yet, RWE and E.ON did not stop there. In 2018, they announced a complex asset swap, completed in 2020, which involved the split of Innogy (Rack, 2020). While E.ON overtook Innogy's networks and supply businesses, RWE integrated Innogy's and E.ON's renewable energy assets, in addition to their coal and gas power plants. RWE's goal was to establish itself as a renewable energy utility with a sufficiently diversified asset base, to ensure the security of supply, while E.ON aimed for the stable returns of the distribution grid business and end-consumer solutions (Buck, 2019). In view of the examples offered by these individual companies, conducting a large-scale global analysis would be useful to

[6] Originally, the plan was for Uniper to assume also E.ON's nuclear business. However, government concerns over shifting the liability over atomic waste forced E.ON to retain its nuclear assets (Chazan, 2016).

understand the behaviour patterns of the transitioning utilities worldwide, regarding the management of their renewable energy businesses.

Furthermore, future work could examine how the financial performance of the transitioning companies might be linked to the way they manage their renewable energy assets, either keeping them as an integral part of their core business, or dividing them into a separate company. In their analysis, Midttun and Piccini (2017) conclude that the renewable energy subsidiaries of ENEL and EDP demonstrated better performance in terms of their share value than their parent companies. It would be interesting to examine these issues at scale across a large sample of companies.

Finally, in light of the findings of this thesis, there could be value in focusing academic debate specifically on how the transitioning companies manage the decline of their core businesses, such as fossil-fuel-based power generation. While there is growing research on carbon lock-in and asset stranding risks (Section 2.1.6), the extant literature on the electricity sector has not yet extensively considered why some power generation assets are being retired, while others are sold. Companies buying mature fossil-fuel assets are likely to expect them to generate income, betting on continued demand for electricity from fossil fuels, capacity payment mechanisms or other factors increasing the attractiveness of these investments. Research is required to shed light on whether some companies' disinvestment from fossil-fuel-based power plants contributes to the overall sector's transition or, indeed, prolongs it, if these assets are not phased out but rather sold on.

Bibliography for Chapters 1, 2 and 6

African Energy (2019) *Live Data: Evaluate power sector trends and identify gaps in the market*. Available at: https://www.africa-energy.com/live-data/about-the-data-tool (Accessed: 21 December 2019).

Aker, J. C. and Mbiti, I. M. (2010) 'Mobile phones and economic development in Africa', *Journal of Economic Perspectives*, 24(3), pp. 207–232. doi: 10.1257/jep.24.3.207.

Alova, G. (2020) *Are electric utilities greening their business?*, *Behavioural and Social Sciences at Nature Research*. Available at: https://socialsciences.nature.com/posts/are-electric-utilities-greening-their-business (Accessed: 20 September 2021).

Alova, G. (2021) *Are African countries heading for a carbon lock-in or leapfrogging to renewables?*, *OECD Development Matters*. Available at: https://oecd-development-matters.org/2021/03/19/are-african-countries-heading-for-a-carbon-lock-in-or-leapfrogging-to-renewables/ (Accessed: 20 September 2021).

Alova, G. and Trotter, P. A. (2021) *Africa looks likely to continue relying on power from fossil fuels for some time*, *The Conversation*. Available at: https://theconversation.com/africa-looks-likely-to-continue-relying-on-power-from-fossil-fuels-for-some-time-155404 (Accessed: 20 September 2021).

Ansar, A., Caldecott, B. and Tibury, J. (2013) *Stranded assets and the fossil fuel divestment campaign: what does divestment mean for the valuation of fossil fuel assets?* Oxford Sustainable Finance Programme, Smith School of Enterprise and the Environment, University of Oxford.

Apajalahti, E. L., Lovio, R. and Heiskanen, E. (2015) 'From demand side management (DSM) to energy efficiency services: A Finnish case study', *Energy Policy*, 81, pp. 76–85. doi: 10.1016/j.enpol.2015.02.013.

Arbabzadeh, M. *et al.* (2019) 'The role of energy storage in deep decarbonization of electricity production', *Nature Communications*, 10(1), pp. 1–11. doi: 10.1038/s41467-019-11161-5.

Awerbuch, S. (2000) 'Investing in photovoltaics: Risk, accounting and the value of new technology', *Energy Policy*, 28(14), pp. 1023–1035. doi: 10.1016/S0301-4215(00)00089-6.

Baldwin, E. *et al.* (2017) 'Global Renewable Electricity Policy: A Comparative Policy

Analysis of Countries by Income Status', *Journal of Comparative Policy Analysis: Research and Practice*, 19(3), pp. 277–298. doi: 10.1080/13876988.2016.1166866.

Baldwin, E., Cai, Y. and Kuralbayeva, K. (2018) *To build or not to build? Capital stocks and climate policy*. Munich Society for the Promotion of Economic Research - CESifo GmbH.

Batinge, B., Musango, J. K. and Brent, A. C. (2019) 'Sustainable energy transition framework for unmet electricity markets', *Energy Policy*, 129, pp. 1090–1099. doi: 10.1016/j.enpol.2019.03.016.

Battiston, S. *et al.* (2017) 'A climate stress-test of the financial system', *Nature Climate Change*, 7(4), pp. 283–288. doi: 10.1038/nclimate3255.

Battiston, S. and Monasterolo, I. (2021) 'On the Dependence of Investor's Probability of Default on Climate Transition Scenarios', *SSRN Electronic Journal*. doi: 10.2139/ssrn.3743647.

Beal, D. *et al.* (2019) *What Companies Can Learn from World Leaders in Societal Impact*. Boston Consulting Group.

Benz, L. *et al.* (2021) 'Investors' carbon risk exposure and their potential for shareholder engagement', *Business Strategy and the Environment*, 30(1), pp. 282–301. doi: 10.1002/bse.2621.

Bergek, A., Mignon, I. and Sundberg, G. (2013) 'Who invests in renewable electricity production? Empirical evidence and suggestions for further research', *Energy Policy*, 56, pp. 568–581. doi: 10.1016/j.enpol.2013.01.038.

Bertram, C. *et al.* (2015) 'Carbon lock-in through capital stock inertia associated with weak near-term climate policies', *Technological Forecasting and Social Change*, 90, pp. 62–72. doi: 10.1016/J.TECHFORE.2013.10.001.

Best, R. and Burke, P. J. (2018) 'Adoption of solar and wind energy: The roles of carbon pricing and aggregate policy support', *Energy Policy*, 118, pp. 404–417. doi: 10.1016/J.ENPOL.2018.03.050.

Black, F. and Scholes, M. (1973) 'The Pricing of Options and Corporate Liabilities', *Journal of Political Economy*, 81(3), pp. 637–654. doi: 10.1086/260062.

Blood, D. and Levina, I. (2020) *Measuring Portfolio Alignment*. TCFD Portfolio Alignment Team.

BloombergNEF (2020) 'Battery Pack Prices Cited Below $100/kWh for the First Time in

2020, While Market Average Sits at $137/kWh', *BloombergNEF*, 16 December. Available at: https://about.bnef.com/blog/battery-pack-prices-cited-below-100-kwh-for-the-first-time-in-2020-while-market-average-sits-at-137-kwh/ (Accessed: 9 March 2021).

Blyth, W. *et al.* (2007) 'Investment risks under uncertain climate change policy', *Energy Policy*, 35(11), pp. 5766–5773. doi: 10.1016/J.ENPOL.2007.05.030.

Bocken, N. M. P. *et al.* (2014) 'A literature and practice review to develop sustainable business model archetypes', *Journal of Cleaner Poduction Production*, 65, pp. 42–56. doi: 10.1016/j.jclepro.2013.11.039.

Bogdanov, D. *et al.* (2019) 'Radical transformation pathway towards sustainable electricity via evolutionary steps', *Nature Communications*, 10(1), pp. 1–16. doi: 10.1038/s41467-019-08855-1.

Bolton, P. *et al.* (2020) *The green swan: Central banking and financial stability in the age of climate change*. Bank for International Settlements.

Bolton, R., Foxon, T. J. and Hall, S. (2015) 'Energy transitions and uncertainty: Creating low carbon investment opportunities in the UK electricity sector', *Environment and Planning C: Government and Policy*, 34(8), pp. 1387–1403. doi: 10.1177/0263774X15619628.

Boons, F. and Lüdeke-Freund, F. (2013) 'Business models for sustainable innovation: state-of-the-art and steps towards a research agenda', *Journal of Cleaner Poduction*, 45, pp. 9–19. doi: 10.1016/j.jclepro.2012.07.007.

Boschma, R. A. (2005) 'Proximity and Innovation: A Critical Assessment', *Regional Studies*, 39(1), pp. 61–74. doi: 10.1080/0034340052000320887.

Boschma, R. A. and Frenken, K. (2006) 'Why is economic geography not an evolutionary science? Towards an evolutionary economic geography', *Journal of Economic Geography*, 6(3), pp. 273–302. doi: 10.1093/jeg/lbi022.

Boschma, R. A. and Lambooy, J. G. (1999) 'Evolutionary economics and economic geography', *Journal of Evolutionary Economics*, 9, pp. 411–429. doi: 10.4337/9781847205391.

Boschma, R. A. and Martin, R. (2010) 'The aims and scope of evolutionary economic geography', in Boschma, R. A. and Martin, R. (eds) *The Handbook of Evolutionary Economic Geography*. Edward Elgar.

Bowen, H. R. (1953) *Social Responsibilities of the Businessman*. New York: Harper .

BP (2020) *Energy Outlook 2020*. BP.

Bridge, G. *et al.* (2013) 'Geographies of energy transition: Space, place and the low-carbon economy', *Energy Policy*, 53, pp. 331–340. doi: 10.1016/j.enpol.2012.10.066.

Bryant, S. T., Straker, K. and Wrigley, C. (2018) 'The typologies of power: Energy utility business models in an increasingly renewable sector', *Journal of Cleaner Production*, 195, pp. 1032–1046. doi: 10.1016/j.jclepro.2018.05.233.

Bryant, S. T., Straker, K. and Wrigley, C. (2019) 'The discourses of power-governmental approaches to business models in the renewable energy transition'. doi: 10.1016/j.enpol.2019.03.050.

Buck, T. (2019) 'Winds of change: Eon and RWE race to adapt to climate demands', *Financial Times*, 24 October. Available at: https://www.ft.com/content/303d7dec-e4e9-11e9-9743-db5a370481bc (Accessed: 4 October 2021).

Caldecott, B. (2017) 'Introduction to special issue: stranded assets and the environment', *Journal of Sustainable Finance and Investment*, 7(1), pp. 1–13. doi: 10.1080/20430795.2016.1266748.

Caldecott, B. *et al.* (2017) *The fate of European coal-fired power stations planned in the mid-2000s: Insights for policymakers, companies, and investors considering new coal*. Oxford: Oxford Sustainable Finance Programme, Smith School of Enterprise and the Environment, University of Oxford.

Caldecott, B., Dericks, G., *et al.* (2018) *Asset-level data and the Energy Transition: Findings from ET Risk Work Package 2*. Oxford Sustainable Finance Programme, Smith School of Enterprise and the Environment, University of Oxford.

Caldecott, B., Kruitwagen, L., *et al.* (2018) *Climate risk analysis from space: remote sensing, machine learning, and the future of measuring climate-related risk*. Sustainable Finance Programme, Smith School of Enterprise and the Environment, University of Oxford.

Caldecott, B., Howarth, N. and McSharry, P. (2013) *Stranded Assets in Agriculture: Protecting Value from Environment-Related Risks*. Sustainable Finance Programme, Smith School of Enterprise and the Environment, University of Oxford.

Calvin, K. *et al.* (2012) 'The role of Asia in mitigating climate change: Results from the Asia modeling exercise', *Energy Economics*, 34(SUPPL. 3), pp. S251–S260. doi: 10.1016/J.ENECO.2012.09.003.

Carley, S. (2009) ‘State renewable energy electricity policies: An empirical evaluation of effectiveness’, *Energy Policy*, 37(8), pp. 3071–3081. doi: 10.1016/J.ENPOL.2009.03.062.

Carley, S. *et al.* (2017) ‘Global Expansion of Renewable Energy Generation: An Analysis of Policy Instruments’, *Environmental and Resource Economics*, 68(2), pp. 397–440. doi: 10.1007/s10640-016-0025-3.

Carley, S. *et al.* (2018) ‘Empirical evaluation of the stringency and design of renewable portfolio standards’, *Nature Energy*, 3(9), pp. 754–763. doi: 10.1038/s41560-018-0202-4.

Carrington, G. and Stephenson, J. (2018) ‘The politics of energy scenarios: Are International Energy Agency and other conservative projections hampering the renewable energy transition?’, *Energy Research and Social Science*, 46, pp. 103–113. doi: 10.1016/j.erss.2018.07.011.

Carter, M. and Christiaen, C. (2021) *Asset-level Data and Spatial Finance Use Cases for the Cement and Steel Sectors*.

Castaneda, M., Franco, C. J. and Dyner, I. (2017) ‘Evaluating the effect of technology transformation on the electricity utility industry’, *Renewable and Sustainable Energy Reviews*, 80, pp. 341–351. doi: 10.1016/J.RSER.2017.05.179.

Chang, R. D. *et al.* (2017) ‘Evolving theories of sustainability and firms: History, future directions and implications for renewable energy research’, *Renewable and Sustainable Energy Reviews*, 72, pp. 48–56. doi: 10.1016/j.rser.2017.01.029.

Chazan, G. (2016) ‘Eon and RWE pursue radical restructurings’, *Financial Times*, 18 May. Available at: https://www.ft.com/content/316ce884-1cdc-11e6-a7bc-ee846770ec15 (Accessed: 11 April 2021).

Chenet, H., Ryan-Collins, J. and van Lerven, F. (2019) *Climate-related financial policy in a world of radical uncertainty: Towards a precautionary approach*. Available at: https://www.ucl.ac.uk/bartlett/public-purpose/wp2019-13 (Accessed: 10 June 2021).

Choi, H. (2019) ‘Incumbents’ response to demand-side policies: The case of solar and wind power sectors’, *Science and Public Policy*, 46(5), pp. 648–660. doi: 10.1093/scipol/scz017.

Clapp, C. and Sillmann, J. (2019) ‘Facilitating Climate-Smart Investments’, *One Earth*, 1(1), pp. 57–61. doi: 10.1016/j.oneear.2019.08.009.

Clarke, L. *et al.* (2016) ‘Long-term abatement potential and current policy trajectories in Latin American countries’, *Energy Economics*, 56, pp. 513–525. doi: 10.1016/J.ENECO.2016.01.011.

Coenen, L., Raven, R. and Verbong, G. (2010) ‘Local niche experimentation in energy transitions: A theoretical and empirical exploration of proximity advantages and disadvantages’, *Technology in Society*, 32(4), pp. 295–302. doi: 10.1016/J.TECHSOC.2010.10.006.

Cosemans, M., Hut, X. and van Dijk, M. (2021) ‘The Impact of Climate Change on Optimal Asset Allocation for Long-Term Investors’, *Network for Studies on Pensions, Aging and Retirement*.

Creutzig, F. *et al.* (2017) ‘The underestimated potential of solar energy to mitigate climate change’, *Nature Energy*, 2(9), p. 17140. doi: 10.1038/nenergy.2017.140.

Delmas, M. A. and Montes-Sancho, M. J. (2011) ‘U.S. state policies for renewable energy: Context and effectiveness’, *Energy Policy*, 39(5), pp. 2273–2288. doi: 10.1016/j.enpol.2011.01.034.

Deng, S.-J. and Oren, S. S. (2003) ‘Incorporating operational characteristics and start-up costs in option-based valuation of power generation capacity’, *Probability in the Engineering and Informational Sciences*, 17, pp. 155–181. doi: 10.1017/S0269964803172014.

Dietz, S. *et al.* (2016) ‘Climate value at risk’ of global financial assets’, *Nature Climate Change*, 6(7), pp. 676–679. doi: 10.1038/nclimate2972.

Dixit, A. K. and Pindyck, R. S. (1994) *Investment under uncertainty*. Princeton University Press.

Egli, F. (2020) ‘Renewable energy investment risk: An investigation of changes over time and the underlying drivers’, *Energy Policy*, 140, p. 111428. doi: 10.1016/J.ENPOL.2020.111428.

Equinor (2020) *Energy Perspectives 2020: A time of great uncertainty*. Available at: https://www.equinor.com/en/sustainability/energy-perspectives.html (Accessed: 11 May 2021).

European Commission (2021) *Questions and Answers: Taxonomy Climate Delegated Act and Amendments to Delegated Acts on fiduciary duties, investment and insurance advice*. Available at:

https://ec.europa.eu/commission/presscorner/detail/en/qanda_21_1805.

Eyre, N. (2021) ‘From using heat to using work: reconceptualising the zero carbon energy transition’, *Energy Efficiency 2021 14:7*, 14(7), pp. 1–20. doi: 10.1007/S12053-021-09982-9.

Fagerberg, J. (2003) ‘Schumpeter and the revival of evolutionary econo’, *Journal of Evolutionary Economics*, 13(2), pp. 125–159. Available at: https://link.springer.com/content/pdf/10.1007%2Fs00191-003-0144-1.pdf (Accessed: 15 January 2019).

Fagerberg, J. (2018) ‘Mobilizing innovation for sustainability transitions: A comment on transformative innovation policy’, *Research Policy*, 47(9), pp. 1568–1576. doi: 10.1016/j.respol.2018.08.012.

Fink, L. (2020) *A Fundamental Reshaping of Finance: Larry Fink’s 2020 Letter to CEOs*, *BlackRock*. Available at: https://www.blackrock.com/us/individual/larry-fink-ceo-letter (Accessed: 26 August 2021).

Fischlein, M. and Smith, T. M. (2013) ‘Revisiting renewable portfolio standard effectiveness: Policy design and outcome specification matter’, *Policy Sciences*, 46(3), pp. 277–310. doi: 10.1007/s11077-013-9175-0.

Fortin, I. *et al.* (2007) *An integrated CVaR and real options approach to investments in the energy sector*. 209. Vienna. Available at: http://hdl.handle.net/10419/72703www.econstor.eu (Accessed: 18 February 2019).

Foxon, T. J. (2011) ‘A coevolutionary framework for analysing a transition to a sustainable low carbon economy’, *Ecological Economics*, 70. doi: 10.1016/j.ecolecon.2011.07.014.

Foxon, T. J. and Pearson, P. J. G. (2007) ‘Towards improved policy processes for promoting innovation in renewable electricity technologies in the UK’, *Energy Policy*, 35(3), pp. 1539–1550. doi: 10.1016/j.enpol.2006.04.009.

Freeman, C. and Perez, C. (1988) ‘Structural Crises of Adjustment, Business Cycles and Investment Behaviour’, in Dosi, G., Freeman, C., Nelson, R.R., Silverberg, G., Soete, L. G. (ed.) *Technical Change and Economic Theory*. London: Francis Pinter, pp. 38–66.

Freeman, R. E. (1984) *Strategic management : a stakeholder approach*. Cambridge, UK: Cambridge University Press.

Frei, F. *et al.* (2018) ‘Leaders or laggards? The evolution of electric utilities’ business portfolios during the energy transition’, *Energy Policy*, 120, pp. 655–665. doi: 10.1016/j.enpol.2018.04.043.

Friedman, M. (1962) *Capitalism and freedom*. Chicago and London: The University of Chicago Press.

Fuss, S. *et al.* (2008) ‘Investment under market and climate policy uncertainty’, *Applied Energy*, 85(8), pp. 708–721. doi: 10.1016/J.APENERGY.2008.01.005.

Fuss, S. *et al.* (2012) ‘Renewables and climate change mitigation: Irreversible energy investment under uncertainty and portfolio effects’, *Energy Policy*, 40, pp. 59–68. doi: 10.1016/J.ENPOL.2010.06.061.

García-Álvarez, M. T., Cabeza-García, L. and Soares, I. (2017) ‘Analysis of the promotion of onshore wind energy in the EU: Feed-in tariff or renewable portfolio standard?’, *Renewable Energy*, 111, pp. 256–264. doi: 10.1016/j.renene.2017.03.067.

Geels, F. W. (2002) ‘Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and a case-study’, *Research Policy*, 31, pp. 1257–1274. doi: 10.1016/S0048-7333(02)00062-8.

Geels, F. W. (2014) ‘Regime Resistance against Low-Carbon Transitions: Introducing Politics and Power into the Multi-Level Perspective’, *Theory, Culture & Society*, 31(5), pp. 21–40. doi: 10.1177/0263276414531627.

Geels, F. W. (2015) ‘The arduous transition to low-carbon energy: a multi-level analysis of renewable electricity niches and resilient regimes’, in Fagerberg, J., Laestadius, S., and Martin, B. R. (eds) *The Triple Challenge for Europe Economic Development, Climate Change and Governance*. Oxford, UK: Oxford University Press, pp. 91–118. doi: 10.1093/acprof:oso/9780198747413.001.0001.

Geels, F. W. and Schot, J. (2007) ‘Typology of sociotechnical transition pathways’, *Research Policy*, 36(3), pp. 399–417. doi: 10.1016/J.RESPOL.2007.01.003.

Geels, I. F. W. (2005) ‘The dynamics of transitions in socio-technical systems: A multi-level analysis of the transition pathway from horse-drawn carriages to automobiles (1860-1930)’, *Technology Analysis and Strategic Management*, 17(4), pp. 445–476. doi: 10.1080/09537320500357319.

Goldemberg, J. (1998) ‘Leapfrog energy technologies’, *Energy Policy*. Elsevier Sci Ltd, pp. 729–741. doi: 10.1016/S0301-4215(98)00025-1.

Goldeng, E., Grünfeld, L. A. and Benito, G. R. G. (2008) 'The Performance Differential between Private and State Owned Enterprises: The Roles of Ownership, Management and Market Structure', *Journal of Management Studies*, 45(7), pp. 1244–1273. doi: 10.1111/J.1467-6486.2008.00790.X.

Gotzens, F. *et al.* (2019) 'Performing energy modelling exercises in a transparent way - The issue of data quality in power plant databases', *Energy Strategy Reviews*, 23, pp. 1–12. doi: 10.1016/j.esr.2018.11.004.

de Gouw, J. A. *et al.* (2020) 'Daily Satellite Observations of Methane from Oil and Gas Production Regions in the United States', *Scientific Reports 2020 10:1*, 10(1), pp. 1–10. doi: 10.1038/s41598-020-57678-4.

Green, J. F. (2021) 'Does carbon pricing reduce emissions? A review of ex-post analyses', *Environmental Research Letters*, 16(4), p. 043004. doi: 10.1088/1748-9326/abdae9.

Green, M. A. (2019) 'How Did Solar Cells Get So Cheap?', *Joule*. Cell Press, pp. 631–633. doi: 10.1016/j.joule.2019.02.010.

Grubler, A. (2010) 'The costs of the French nuclear scale-up: A case of negative learning by doing', *Energy Policy*, 38(9), pp. 5174–5188. doi: 10.1016/j.enpol.2010.05.003.

Gujba, H. *et al.* (2012) 'Financing low carbon energy access in Africa', *Energy Policy*, 47(SUPPL.1), pp. 71–78. doi: 10.1016/j.enpol.2012.03.071.

Gürsan, C. and de Gooyert, V. (2021) 'The systemic impact of a transition fuel: Does natural gas help or hinder the energy transition?', *Renewable and Sustainable Energy Reviews*, 138, p. 110552. doi: 10.1016/J.RSER.2020.110552.

Hall, S. *et al.* (2021) 'Matching consumer segments to innovative utility business models', *Nature Energy*, 6(4), pp. 349–361. doi: 10.1038/s41560-021-00781-1.

Hall, S. and Roelich, K. (2016) 'Business model innovation in electricity supply markets: The role of complex value in the United Kingdom', *Energy Policy*, 92, pp. 286–298. doi: 10.1016/j.enpol.2016.02.019.

Hannon, M. J., Foxon, T. J. and Gale, W. F. (2013) 'The co-evolutionary relationship between energy service companies and the UK energy system: Implications for a low-carbon transition', *Energy Policy*, 61, pp. 1031–1045. doi: 10.1016/j.enpol.2013.06.009.

Hansen, T. and Coenen, L. (2015) 'The geography of sustainability transitions: Review,

synthesis and reflections on an emergent research field', *Environmental Innovation and Societal Transitions*, 17, pp. 92–109. doi: 10.1016/J.EIST.2014.11.001.

Hart, O. (2003) 'Incomplete contracts and public ownership: Remarks, and an application to public-private partnerships', *Economic Journal*, 113(486), pp. 69–76. doi: 10.1111/1468-0297.00119.

Hart, S. L. (1995) 'A Natural-Resource-Based View of the Firm', *The Academy of Management Review*, 20(4), pp. 986–1014.

Hastie, T., Tibshirani, R. and Friedman, J. H. (2009) *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. New York: Springer.

Heiligtag, S., Maurenbrecher, S. and Niemann, N. (2017) *From scenario planning to stress testing: The next step for energy companies*, *McKinsey & Company*.

Helms, T. (2016) 'Asset transformation and the challenges to servitize a utility business model', *Energy Policy*, 91, pp. 98–112. doi: 10.1016/j.enpol.2015.12.046.

Helms, T., Salm, S. and Wüstenhagen, R. (2015) 'Investor-specific cost of capital and renewable energy investment decisions', in *Renewable Energy Finance: Powering the Future*. Imperial College Press, pp. 77–101. doi: 10.1142/9781783267774_0004.

Hickey, C. *et al.* (2020) 'Can European Electric Utilities Manage Asset Impairments Arising From Net Zero Carbon Targets?', *European Finance eJournal*. doi: 10.2139/ssrn.3531724.

Hlouskova, J. *et al.* (2005) 'Real options and the value of generation capacity in the German electricity market'. doi: 10.1016/j.rfe.2004.12.001.

Hook, L., Hodgson, C. and Pickard, J. 'COP26 agrees new climate rules but India and China weaken coal pledge', *Financial Times*, November. Available at: https://www.ft.com/content/c891d4af-f80b-48f0-8b6f-a8763655c936 (Accessed: 16 November 2021).

IEA (2019a) *Africa Energy Outlook 2019*. Paris: IEA.

IEA (2019b) *Global Energy & CO2 Status Report 2019*. Paris: IEA.

IEA (2020a) *Electricity Market Report*. Paris: IEA.

IEA (2020b) *Global Energy Review 2020*. Paris: IEA.

IEA (2020c) *Renewables Information: Overview*. Paris: IEA.

IEA (2020d) *World Energy Outlook 2020*. Paris: IEA.

IEA (2021a) *Global Energy Review 2021*. Paris: IEA.

IEA (2021b) *Net Zero by 2050: A Roadmap for the Global Energy Sector*. Paris: IEA.

IRENA (2015a) *Africa Power Sector: Planning and Prospects for Renewable Energy*. Abu Dhabi.

IRENA (2015b) *Africa Power Sector: Planning and Prospects for Renewable Energy*. Abu Dhabi: IRENA.

IRENA (2016) *Innovation Outlook: Offshore Wind*. Abu Dhabi: IRENA.

IRENA (2018) *Renewable Energy Outlook: Egypt*. Abu Dhabi: IRENA.

IRENA (2020) *Global Renewables Outlook: Energy transformation 2050*. Abu Dhabi: IRENA.

IRENA (2021) *World Energy Transitions Outlook: 1.5°C Pathway*. Abu Dhabi: IRENA.

Jamasb, T. and Pollitt, M. G. (2011) 'Electricity sector liberalisation and innovation: An analysis of the UK's patenting activities', *Research Policy*, 40(2), pp. 309–324. doi: 10.1016/j.respol.2010.10.010.

Jaxa-Rozen, M. and Trutnevyte, E. (2021) 'Sources of uncertainty in long-term global scenarios of solar photovoltaic technology', *Nature Climate Change*, 11(3), pp. 266–273. doi: 10.1038/s41558-021-00998-8.

Jenner, S., Groba, F. and Indvik, J. (2013) 'Assessing the strength and effectiveness of renewable electricity feed-in tariffs in European Union countries', *Energy Policy*, 52, pp. 385–401. doi: 10.1016/j.enpol.2012.09.046.

Jensen, S. *et al.* (2015) 'An Introduction to the Green Paradox: The Unintended Consequences of Climate Policies', *Review of Environmental Economics and Policy*, 9(2), pp. 246–265. doi: 10.1093/reep/rev010.

Kalkuhl, M., Edenhofer, O. and Lessmann, K. (2012) 'Learning or lock-in: Optimal technology policies to support mitigation', *Resource and Energy Economics*, 34(1), pp. 1–23. doi: 10.1016/J.RESENEECO.2011.08.001.

Karneyeva, Y. and Wüstenhagen, R. (2017) 'Solar feed-in tariffs in a post-grid parity world: The role of risk, investor diversity and business models', *Energy Policy*, 106, pp. 445–456. doi: 10.1016/j.enpol.2017.04.005.

Kavlak, G., McNerney, J. and Trancik, J. E. (2018) ‘Evaluating the causes of cost reduction in photovoltaic modules’, *Energy Policy*, 123, pp. 700–710. doi: 10.1016/j.enpol.2018.08.015.

Ke, G. *et al.* (2017) ‘LightGBM: A highly efficient gradient boosting decision tree’, in *Advances in Neural Information Processing Systems*, pp. 3147–3155. Available at: https://github.com/Microsoft/LightGBM. (Accessed: 19 December 2019).

Kefford, B. M. *et al.* (2018) ‘The early retirement challenge for fossil fuel power plants in deep decarbonisation scenarios’, *Energy Policy*, 119, pp. 294–306. doi: 10.1016/J.ENPOL.2018.04.018.

Kelsey, N. and Meckling, J. (2018) ‘Who wins in renewable energy? Evidence from Europe and the United States’, *Energy Research & Social Science*, 37, pp. 65–73. doi: 10.1016/J.ERSS.2017.08.003.

Kemp, R., Loorbach, D. and Rotmans, J. (2007) ‘Transition management as a model for managing processes of co-evolution towards sustainable development’, *International Journal of Sustainable Development and World Ecology*, 14(1), pp. 78–91. doi: 10.1080/13504500709469709.

Kemp, R. and Never, B. (2017) ‘Green transition, industrial policy, and economic development’, *Oxford Review of Economic Policy*, 33(1), pp. 66–84. doi: 10.1093/oxrep/grw037.

Klessmann, C. *et al.* (2013) ‘Policy options for reducing the costs of reaching the European renewables target’, *Renewable Energy*, 57, pp. 390–403. doi: 10.1016/j.renene.2013.01.041.

Kober, T. *et al.* (2016) ‘A multi-model study of energy supply investments in Latin America under climate control policy’, *Energy Economics*, 56, pp. 543–551. doi: 10.1016/J.ENECO.2016.01.005.

Kölbel, J. F. *et al.* (2020) ‘Can Sustainable Investing Save the World? Reviewing the Mechanisms of Investor Impact’:, *https://doi.org/10.1177/1086026620919202*, 33(4), pp. 554–574. doi: 10.1177/1086026620919202.

Kottasová, I. *et al.* (2021) ‘Countries at COP26 commit to ending financing for fossil fuel projects abroad - CNN’, *CNN*, 4 November. Available at: https://edition.cnn.com/2021/11/03/world/countries-agree-to-end-fossil-fuel-financing-abroad-cop26-climate/index.html (Accessed: 11 November 2021).

Krause, F., Bach, W. and Koomey, J. (1989) *Energy policy in the greenhouse: From warming fate to warming limit*. El Cerrito, CA: International Project for Sustainable Energy Paths.

Kriegler, E. *et al.* (2013) 'What does the 2 °C target imply for a global climate agreement in 2020? The LIMITS study on Durban Platform scenarios', *Climate Change Economics*, 4(4), p. 1340008. doi: 10.1142/S2010007813400083.

Kriegler, E. *et al.* (2014) 'The role of technology for achieving climate policy objectives: Overview of the EMF 27 study on global technology and climate policy strategies', *Climatic Change*, 123(3–4), pp. 353–367. doi: 10.1007/s10584-013-0953-7.

Kruitwagen, L. *et al.* (2021) 'A global inventory of photovoltaic solar energy generating units', *Nature*, 598(7882), pp. 604–610. doi: 10.1038/s41586-021-03957-7.

Kungl, G. (2015) 'Stewards or sticklers for change? Incumbent energy providers and the politics of the German energy transition', *Energy Research and Social Science*, 8, pp. 13–23. doi: 10.1016/j.erss.2015.04.009.

Kungl, G. and Geels, F. W. (2018) 'Sequence and alignment of external pressures in industry destabilisation: Understanding the downfall of incumbent utilities in the German energy transition (1998–2015)', *Environmental Innovation and Societal Transitions*, 26, pp. 78–100. doi: 10.1016/j.eist.2017.05.003.

Lanshina, T. A. *et al.* (2018) 'The slow expansion of renewable energy in Russia: Competitiveness and regulation issues', *Energy Policy*, 120, pp. 600–609. doi: 10.1016/j.enpol.2018.05.052.

Larsen, G. *et al.* (2021) '5 Ways the World Bank's Climate Action Plan Could Go Further', *WRI Insights*. Available at: https://www.wri.org/insights/5-ways-world-banks-climate-action-plan-could-go-further (Accessed: 28 September 2021).

Lauber, V. (2004) 'REFIT and RPS: Options for a harmonised Community framework', *Energy Policy*, 32(12), pp. 1405–1414. doi: 10.1016/S0301-4215(03)00108-3.

Leaton, J. (2011) *Unburnable Carbon - Are the world' s financial markets carrying a carbon bubble?*, *Carbon Tracker Initiative*.

Löbbe, S. and Jochum, G. (2016) 'Thriving Despite Disruptive Technologies: A German Utilities' Case Study', in Sioshansi, F. P. (ed.) *Future of Utilities - Utilities of the Future: How Technological Innovations in Distributed Energy Resources Will Reshape the Electric Power Sector*. Walnut Creek, CA: Elsevier.

Loorbach, D. A. (2010) ‘Transition management for sustainable development: A prescriptive, complexity-based governance framework’, *Governance: An International Journal of Policy, Administration, and Institutions*, 23(1), pp. 161–183. doi: 10.1111/j.1468-0491.2009.01471.x.

Louwen, A., Schreiber, S. and Junginger, M. (2020) ‘Implementation of experience curves in energy-system models’, *Technological Learning in the Transition to a Low-Carbon Energy System: Conceptual Issues, Empirical Findings, and Use, in Energy Modeling*, pp. 33–47. doi: 10.1016/B978-0-12-818762-3.00003-0.

Lucas, P. L. *et al.* (2015) ‘Future energy system challenges for Africa: Insights from Integrated Assessment Models’, *Energy Policy*, 86, pp. 705–717. doi: 10.1016/j.enpol.2015.08.017.

Luderer, G. *et al.* (2013) ‘Economic mitigation challenges: how further delay closes the door for achieving climate targets’, *Environmental Research Letters*, 8(3), p. 034033. doi: 10.1088/1748-9326/8/3/034033.

MacDonald, S. and Eyre, N. (2018) ‘An international review of markets for voluntary green electricity tariffs’, *Renewable and Sustainable Energy Reviews*, 91, pp. 180–192. doi: 10.1016/J.RSER.2018.03.028.

Mathews, J. A. (2013) ‘The renewable energies technology surge: A new techno-economic paradigm in the making?’, *Futures*, 46, pp. 10–22. doi: 10.1016/j.futures.2012.12.001.

Matthäus, D. and Mehling, M. (2020) ‘De-risking Renewable Energy Investments in Developing Countries: A Multilateral Guarantee Mechanism’, *Joule*, 4(12), pp. 2627–2645. doi: 10.1016/J.JOULE.2020.10.011.

May, N. and Neuhoff, K. (2021) ‘Financing power: Impacts of energy policies in changing regulatory environments’, *Energy Journal*, 42(4), pp. 131–151. doi: 10.5547/01956574.42.4.NMAY.

McCollum, D. L. *et al.* (2018) ‘Energy investment needs for fulfilling the Paris Agreement and achieving the Sustainable Development Goals’, *Nature Energy*, 3(7), pp. 589–599. doi: 10.1038/s41560-018-0179-z.

McCollum, D. L. (2021) ‘Machine learning for energy projections’, *Nature Energy*, 6(2), pp. 121–122. doi: 10.1038/s41560-021-00779-9.

Mcwilliams, A. and Siegel, D. (2001) ‘Corporate Social Responsibility: A Theory of the

Firm Perspective', *Source: The Academy of Management Review*, 26(1), pp. 117–127. Available at: https://about.jstor.org/terms (Accessed: 6 September 2021).

Merton, R. C. (1973) 'Theory of Rational Option Pricing', *The Bell Journal of Economics and Management Science*, 4(1), pp. 141–183. doi: 10.2307/3003143.

Meuer, J., Koelbel, J. and Hoffmann, V. H. (2020) 'On the Nature of Corporate Sustainability', *Organization and Environment*, 33(3), pp. 319–341. doi: 10.1177/1086026619850180.

Meyer, G. (2020) 'Do US power companies' carbon pledges add up?', *Financial Times*, 9 November. Available at: https://www.ft.com/content/e5ef25f0-ae43-42c2-a1b3-74ce1992c516 (Accessed: 5 November 2021).

Midttun, A. and Piccini, P. B. (2017) 'Facing the climate and digital challenge: European energy industry from boom to crisis and transformation', *Energy Policy*, 108, pp. 330–343. doi: 10.1016/j.enpol.2017.05.046.

Min, D. and Chung, J. (2013) 'Evaluation of the long-term power generation mix: The case study of South Korea's energy policy', *Energy Policy*, 62, pp. 1544–1552. doi: 10.1016/j.enpol.2013.07.104.

Morgan, M. G. and Keith, D. W. (2008) 'Improving the way we think about projecting future energy use and emissions of carbon dioxide', *Climatic Change*, 90(3), pp. 189–215. doi: 10.1007/s10584-008-9458-1.

Negro, S. O., Alkemade, F. and Hekkert, M. P. (2012) 'Why does renewable energy diffuse so slowly? A review of innovation system problems', *Renewable and Sustainable Energy Reviews*. Pergamon, pp. 3836–3846. doi: 10.1016/j.rser.2012.03.043.

Nelson, R. R. and Winter, S. G. (2002) 'Evolutionary Theorizing in Economics', *Journal of Economic Perspectives*, 16(2), pp. 23–46. doi: 10.1257/0895330027247.

Nemet, G. (2019) *How Solar Energy Became Cheap: A Model for Low-Carbon Innovation*. Abingdon and New York: Routledge.

NGFS (2019) *Network for Greening the Financial System First comprehensive report A call for action Climate change as a source of financial risk*. NGFS.

Nillesen, P. and Pollitt, M. (2016) 'New Business Models for Utilities to Meet the Challenge of the Energy Transition', in Sioshansi, F. P. (ed.) *Future of Utilities - Utilities of the Future: How Technological Innovations in Distributed Energy Resources Will Reshape the Electric Power Sector*. Walnut Creek, CA: Elsevier, pp. 283–301.

Nock, D. (2021) ‘Closing the void in energy planning modeling: Integrating local realities’, *Joule*, 5(5), pp. 1031–1033. doi: 10.1016/J.JOULE.2021.04.013.

O’Neill, B. C. *et al.* (2020) ‘Achievements and needs for the climate change scenario framework’, *Nature Climate Change*, 10(12), pp. 1074–1084. doi: 10.1038/s41558-020-00952-0.

OECD (2017) *Investing in Climate, Investing in Growth*. Paris: OECD.

Ørsted (2021) *Interim financial report: First half year 2021*. Ørsted.

Osterwalder, A. and Pigneur, Y. (2010) *Business model generation : a handbook for visionaries, game changers, and challengers*. Hoboken, New Jersey: Wiley.

Osunmuyiwa, O., Biermann, F. and Kalfagianni, A. (2018) ‘Applying the multi-level perspective on socio-technical transitions to rentier states: the case of renewable energy transitions in Nigeria’, *Journal of Environmental Policy and Planning*, 20(2), pp. 143–156. doi: 10.1080/1523908X.2017.1343134.

Ouedraogo, N. S. (2017a) ‘Africa energy future : Alternative scenarios and their implications for sustainable development strategies’, *Energy Policy*, 106(February), pp. 457–471. doi: 10.1016/j.enpol.2017.03.021.

Ouedraogo, N. S. (2017b) ‘Modeling sustainable long-term electricity supply-demand in Africa’, *Applied Energy*, 190, pp. 1047–1067. doi: 10.1016/j.apenergy.2016.12.162.

Ouedraogo, N. S. (2017c) ‘Modeling sustainable long-term electricity supply-demand in Africa’, *Applied Energy*, 190, pp. 1047–1067. doi: 10.1016/j.apenergy.2016.12.162.

Panos, E. *et al.* (2015) ‘Powering the growth of sub-saharan africa: The jazz and symphony scenarios of world energy council’, *Energy for Sustainable Development*, 26, pp. 14–33. doi: 10.1016/j.esd.2015.01.004.

Patala, S. *et al.* (2021) ‘Multinational energy utilities in the energy transition: A configurational study of the drivers of FDI in renewables’, *Journal of International Business Studies*, pp. 1–21. doi: 10.1057/s41267-020-00387-x.

Pearson, P. J. G. and Foxon, T. J. (2012) ‘A low carbon industrial revolution? Insights and challenges from past technological and economic transformations’, *Energy Policy*, 50, pp. 117–127. doi: 10.1016/j.enpol.2012.07.061.

Perez, C. (2002) *Technological revolutions and financial capital : The dynamics of bubbles and golden ages.* Cheltenham: Elgar.

Perez, C. (2016) ‘Capitalism, Technology and a Green Global Golden Age: The Role of History in Helping to Shape the Future’, in Jacobs, M., & Mazzucato, M. (ed.) *Rethinking capitalism: economics and policy for sustainable and inclusive growth*. New York: John Wiley & Sons, pp. 204–229.

Pfeiffer, A. *et al.* (2016) ‘The “2°C capital stock” for electricity generation: Committed cumulative carbon emissions from the electricity generation sector and the transition to a green economy’, *Applied Energy*, 179, pp. 1395–1408. doi: 10.1016/j.apenergy.2016.02.093.

Pickard, J. and Hook, L. (2021) ‘Rich countries scramble to hit $100bn climate finance target’, *Financial Times*, 8 November. Available at: https://www.ft.com/content/2fc0398d-c982-4214-b534-1ee3205cde97 (Accessed: 11 November 2021).

Pindyck, R. S. (2017) ‘The use and misuse of models for climate policy’, *Review of Environmental Economics and Policy*, 11(1), pp. 100–114. doi: 10.1093/reep/rew012.

Van Der Ploeg, F. and Rezai, A. (2018) ‘Climate Policy and Stranded Carbon Assets: a Financial Perspective’, *Oxford Centre for the Analysis of Resource Rich Economies*.

Pollitt, M. G. and Anaya, K. L. (2016) ‘Can current electricity markets cope with high shares of renewables? A comparison of approaches in Germany, the UK and the state of New York’, *Energy Journal*, 37(Special Issue 2), pp. 69–88. doi: 10.5547/01956574.37.SI2.mpol.

Polzin, F. *et al.* (2015) ‘Public policy influence on renewable energy investments—A panel data study across OECD countries’, *Energy Policy*, 80, pp. 98–111. doi: 10.1016/J.ENPOL.2015.01.026.

Polzin, F. *et al.* (2019) ‘How do policies mobilize private finance for renewable energy?—A systematic review with an investor perspective’, *Applied Energy*, 236, pp. 1249–1268. doi: 10.1016/j.apenergy.2018.11.098.

Porter, M. E. and Kramer, M. R. (2006) ‘Strategy and Society: The Link Between Competitive Advantage and Corporate Social Responsibility’, *Harvard Business Review*, December, pp. 78–93.

Porter, M. E. and Kramer, M. R. (2011) ‘Creating shared value’, *Harvard Business Review*, January-Fe. Available at: http://www.hks.harvard.edu/m-rcbg/fellows/N_Lovegrove_Study_Group/Session_1/Michael_Porter_Creating_Shared_Value.pdf.

Porter, S. (2021) ‘The Future Of Energy: Decarbonization In Power And Utilities’, *Forbes*, 21 June. Available at: https://www.forbes.com/sites/deloitte/2021/06/21/the-future-of-energy-decarbonization-in-power-and-utilities/?sh=ff0a2b469e07 (Accessed: 3 September 2021).

PwC (2013) *Spotlight on Automotive: PwC Semiconductor Report*. Technology Institute, PwC.

Rack, Y. (2020) ‘RWE closes asset swap with E.ON in final step of German power sector revamp’, *S&P Global Market Intelligence*, 1 July. Available at: https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/rwe-closes-asset-swap-with-e-on-in-final-step-of-german-power-sector-revamp-59275234 (Accessed: 4 October 2021).

Raven, R., Schot, J. and Berkhout, F. (2012) ‘Space and scale in socio-technical transitions’, *Environmental Innovation and Societal Transitions*, 4, pp. 63–78. doi: 10.1016/J.EIST.2012.08.001.

Reuter, W. H., Fuss, S., *et al.* (2012) ‘Investment in wind power and pumped storage in a real options model’, *Renewable and Sustainable Energy Reviews*, 16(4), pp. 2242–2248. doi: 10.1016/J.RSER.2012.01.025.

Reuter, W. H., Szolgayová, J., *et al.* (2012) ‘Renewable energy investment: Policy and market impacts’, *Applied Energy*, 97, pp. 249–254. doi: 10.1016/j.apenergy.2012.01.021.

Richter, M. (2012) ‘Utilities’ business models for renewable energy: A review’, *Renewable and Sustainable Energy Reviews*, 16(5), pp. 2483–2493. doi: 10.1016/j.rser.2012.01.072.

Richter, M. (2013) ‘Business model innovation for sustainable energy: German utilities and renewable energy’, *Energy Policy*, 62, pp. 1226–1237. doi: 10.1016/j.enpol.2013.05.038.

del Río, P. and Bleda, M. (2012) ‘Comparing the innovation effects of support schemes for renewable electricity technologies: A function of innovation approach’, *Energy Policy*, 50, pp. 272–282. doi: 10.1016/j.enpol.2012.07.014.

Rip, A. and Kemp, R. (1998) ‘Technological change’, in Rayner, S. and Malone, E. L. (eds) *Human Choice and Climate Change Vol. II, Resources and Technology*. Columbus, Ohio: Battelle Press, pp. 327–399.

Rode, D. C., Fischbeck, P. S. and Páez, A. R. (2017) 'The retirement cliff: Power plant lives and their policy implications', *Energy Policy*, 106, pp. 222–232. doi: 10.1016/j.enpol.2017.03.058.

Rogelj, J. *et al.* (2011) 'Emission pathways consistent with a 2 °C global temperature limit', *Nature Climate Change 2011 1:8*, 1(8), pp. 413–418. doi: 10.1038/nclimate1258.

Rogelj, J. *et al.* (2013) 'Probabilistic cost estimates for climate change mitigation', *Nature*, 493(7430), pp. 79–83. doi: 10.1038/nature11787.

Rogelj, J., Shindell, D., *et al.* (2018) 'Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable Development', in Masson-Delmotte V. et al. (eds) *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change*. UNFCCC.

Rogelj, J., Popp, A., *et al.* (2018) 'Scenarios towards limiting global mean temperature increase below 1.5 °c', *Nature Climate Change*, 8(4), pp. 325–332. doi: 10.1038/s41558-018-0091-3.

Rogelj, J. *et al.* (2019) 'A new scenario logic for the Paris Agreement long-term temperature goal', *Nature*, 573(7774), pp. 357–363. doi: 10.1038/s41586-019-1541-4.

Rogge, K. S., Kern, F. and Howlett, M. (2017) 'Conceptual and empirical advances in analysing policy mixes for energy transitions', *Energy Research and Social Science*, 33, pp. 1–10. doi: 10.1016/J.ERSS.2017.09.025.

Rogge, K. S. and Reichardt, K. (2016) 'Policy mixes for sustainability transitions: An extended concept and framework for analysis', *Research Policy*, 45(8), pp. 1620–1635. doi: 10.1016/J.RESPOL.2016.04.004.

Romano, A. A. *et al.* (2017) 'Renewable investments: The impact of green policies in developing and developed countries', *Renewable and Sustainable Energy Reviews*, 68, pp. 738–747. doi: 10.1016/j.rser.2016.10.024.

Rotmans, J., Kemp, R. and van Asselt, M. (2001) 'More evolution than revolution: transition management in public policy', *Foresight*, 3(1), pp. 15–31. doi: 10.1108/14636680110803003.

Rubin, E. S., Davison, J. E. and Herzog, H. J. (2015) 'The cost of CO2 capture and storage', *International Journal of Greenhouse Gas Control*, 40, pp. 378–400. doi: 10.1016/j.ijggc.2015.05.018.

Ruggiero, S. and Lehkonen, H. (2017) ‘Renewable energy growth and the financial performance of electric utilities: A panel data study’, *Journal of Cleaner Production*, 142, pp. 3676–3688. doi: 10.1016/j.jclepro.2016.10.100.

Russo, M. V and Fouts, P. A. (1997) ‘A resource-based perspective on corporate environmental performance and profitability’, *Academy of Management Journal*, 40(3), pp. 534–559. doi: 10.2307/257052.

Samuelson, P. A. (1948) *Economics*. New Yor: McGraw-Hill, Inc.

Sanoh, A. *et al.* (2014) ‘The economics of clean energy resource development and grid interconnection in Africa’, *Renewable Energy*, 62, pp. 598–609.

Di Sbroiavacca, N. *et al.* (2016) ‘Emissions reduction scenarios in the Argentinean Energy Sector’, *Energy Economics*, 56, pp. 552–563. doi: 10.1016/J.ENECO.2015.03.021.

Schleicher-Tappeser, R. (2012) ‘How renewables will change electricity markets in the next five years’, *Energy Policy*, 48, pp. 64–75. doi: 10.1016/J.ENPOL.2012.04.042.

Schmalensee, R. (2012) ‘Evaluating policies to increase electricity generation from renewable energy’, *Review of Environmental Economics and Policy*, 6(1), pp. 45–64. doi: 10.1093/reep/rer020.

Schmidt, T. S. (2014) ‘Low-carbon investment risks and de-risking’, *Nature Climate Change*. Nature Publishing Group, pp. 237–239. doi: 10.1038/nclimate2112.

Schumpeter, J. A. (1934) *The theory of economic development : an inquiry into profits, capital, credit, interest, and the business cycle*. Cambridge, Massachusetts: Harvard University Press.

Schumpeter, J. A. (1939) *Business cycles: a theoretical, historical, and statistical analysis of the capitalist process*. New York; London: McGraw-Hill.

Schumpeter, J. A. (1942) *Capitalism, Socialism and Democracy*. New York: Harper & Brothers.

ScottishPower (2018) ‘100% green generation for ScottishPower with sale of remaining gas plant’, *ScottishPower, Press release*, 16 October. Available at: www.scottishpower.com/news/pages/100percent_green_generation_for_scottishpower_with_sale_of_remaining_gas_plant.aspx (Accessed: 14 February 2019).

Seto, K. C. *et al.* (2016) ‘Carbon Lock-In: Types, Causes, and Policy Implications’, *Annual Review of Environment and Resources*, 41, pp. 425–452. doi: 10.1146/annurev-

environ-110615-085934.

Shahnazari, M. *et al.* (2014) ‘Evaluation of power investment decisions under uncertain carbon policy: A case study for converting coal fired steam turbine to combined cycle gas turbine plants in Australia’, *Applied Energy*, 118, pp. 271–279. doi: 10.1016/J.APENERGY.2013.12.050.

Shell Global (2021) *Shell Scenarios energy models*. Available at: https://www.shell.com/energy-and-innovation/the-energy-future/scenarios/shell-scenarios-energy-models.html (Accessed: 11 May 2021).

Shleifer, A. (1998) ‘State versus Private Ownership’, *Journal of Economic Perspectives*, 12(4), pp. 133–150. doi: 10.1257/jep.12.4.133.

Shomali, A. and Pinkse, J. (2016) ‘The consequences of smart grids for the business model of electricity firms’, *Journal of Cleaner Production*, 112, pp. 3830–3841. doi: 10.1016/j.jclepro.2015.07.078.

Shrimali, G. and Kniefel, J. (2011) ‘Are government policies effective in promoting deployment of renewable electricity resources?’, *Energy Policy*, 39(9), pp. 4726–4741. doi: 10.1016/J.ENPOL.2011.06.055.

Sinn, H.-W. (2015) ‘Introductory Comment - The Green Paradox: A Supply-Side View of the Climate Problem’, *Review of Environmental Economics and Policy*, 9(2), pp. 239–245. doi: 10.1093/reep/rev011.

Sinn, H. W. (2008) ‘Public policies against global warming: A supply side approach’, *International Tax and Public Finance*, 15, pp. 360–394. doi: 10.1007/s10797-008-9082-z.

Sinsel, S. R., Riemke, R. L. and Hoffmann, V. H. (2020) ‘Challenges and solution technologies for the integration of variable renewable energy sources—a review’, *Renewable Energy*, 145, pp. 2271–2285. doi: 10.1016/J.RENENE.2019.06.147.

Slawinski, N. *et al.* (2017) ‘The Role of Short-Termism and Uncertainty Avoidance in Organizational Inaction on Climate Change: A Multi-Level Framework’, *Business & Society*, 56(2), pp. 253–282. doi: 10.1177/0007650315576136.

Van Sluisveld, M. A. E. *et al.* (2013) ‘A multi-model analysis of post-2020 mitigation efforts of five major economies’, *Climate Change Economics*, 4(4), p. 1340012. doi: 10.1142/S2010007813400125.

Smulders, S., Tsur, Y. and Zemel, A. (2012) ‘Announcing climate policy: Can a green

paradox arise without scarcity?', *Journal of Environmental Economics and Management*, 64, pp. 364–376. doi: 10.1016/j.jeem.2012.02.007.

Spatial Finance Initiative (2021) 'GeoAsset Project - Greening Finance and Investment', *UK Centre for Greening Finance and Investment*. Available at: https://www.cgfi.ac.uk/spatial-finance-initiative/geoasset-project/ (Accessed: 4 November 2021).

Steffen, B. *et al.* (2020) 'Experience Curves for Operations and Maintenance Costs of Renewable Energy Technologies', *Joule*, 4(2), pp. 359–375. doi: 10.1016/J.JOULE.2019.11.012.

Steffen, B., Karplus, V. and Schmidt, T. (2020) 'State Ownership and Technology Adoption: The Case of Electric Utilities and Renewable Energy', *MIT CEEPR, Working Paper Series*.

Stephan, A. *et al.* (2019) 'The role of inter-sectoral knowledge spillovers in technological innovations: The case of lithium-ion batteries', *Technological Forecasting and Social Change*, 148, p. 119718. doi: 10.1016/J.TECHFORE.2019.119718.

Stephan, A., Anadon, L. D. and Hoffmann, V. H. (2021) 'How has external knowledge contributed to lithium-ion batteries for the energy transition?', *iScience*, 24(1), p. 101995. doi: 10.1016/J.ISCI.2020.101995.

Stephenson, E., Doukas, A. and Shaw, K. (2012) '"Greenwashing gas: Might a 'transition fuel' label legitimize carbon-intensive natural gas development?"', *Energy Policy*, 46, pp. 452–459. doi: 10.1016/J.ENPOL.2012.04.010.

Stern, N. H. (2015) *Why are we waiting? : The logic, urgency, and promise of tackling climate change*. Cambridge, Massachusetts; London, UK: The MIT Press.

Surana, K. and Anadon, L. D. (2015) 'Public policy and financial resource mobilization for wind energy in developing countries: A comparison of approaches and outcomes in China and India', *Global Environmental Change*, 35, pp. 340–359. doi: 10.1016/j.gloenvcha.2015.10.001.

Szolgayová, J. *et al.* (2011) 'A dynamic CVaR-portfolio approach using real options: an application to energy investments', *European Transactions on Electrical Power*, 21(6), pp. 1825–1841. doi: 10.1002/etep.429.

Szolgayova, J., Fuss, S. and Obersteiner, M. (2008) 'Assessing the effects of CO2 price caps on electricity investments—A real options analysis', *Energy Policy*, 36(10), pp.

3974–3981. doi: 10.1016/J.ENPOL.2008.07.006.

Taliotis, C. *et al.* (2016) ‘An indicative analysis of investment opportunities in the African electricity supply sector - Using TEMBA (The Electricity Model Base for Africa)’, *Energy for Sustainable Development*, 31, pp. 50–66. doi: 10.1016/j.esd.2015.12.001.

Taylor, C. (2021) ‘COP26: Countries pledge to phase out coal — but the U.S., China and India are missing’, *CNBC*, 4 November. Available at: https://www.cnbc.com/2021/11/04/seo-cop26-165-countries-pledge-to-phase-out-coal.html (Accessed: 11 November 2021).

Taylor, K. (2021) ‘Poland clarifies position on coal phase-out, it is still 2049’, *Euroactiv*, 5 November. Available at: https://www.euractiv.com/section/energy/news/poland-clarifies-position-on-coal-phase-out-it-is-still-2049/ (Accessed: 11 November 2021).

TCFD (2017) *Recommendations of the Task Force on Climate-related Financial Disclosures*. Task Force on Climate-Related Financial Disclosures.

Thimet, P. J. and Mavromatidis, G. (2022) ‘Review of model-based electricity system transition scenarios: An analysis for Switzerland, Germany, France, and Italy’, *Renewable and Sustainable Energy Reviews*, 159, p. 112102. doi: 10.1016/j.rser.2022.112102.

Tian, L. *et al.* (2017) ‘The valuation of photovoltaic power generation under carbon market linkage based on real options’, *Applied Energy*, 201, pp. 354–362. doi: 10.1016/J.APENERGY.2016.12.092.

Tirole, J. (1994) ‘The internal organization of government’, *Oxford Economic Papers*, 46(1), pp. 1–29. doi: 10.1093/oxfordjournals.oep.a042114.

Total (2020) *Total Energy Outlook 2020*. Total.

Trotter, P. A. and Abdullah, S. (2018) ‘Re-focusing foreign involvement in sub-Saharan Africa’s power sector on sustainable development’, *Energy for Sustainable Development*, 44, pp. 139–146. doi: 10.1016/j.esd.2018.03.003.

Trotter, P. A., Maconachie, R. and McManus, M. C. (2018) ‘Solar energy’s potential to mitigate political risks: The case of an optimised Africa-wide network’, *Energy Policy*, 117. doi: 10.1016/j.enpol.2018.02.013.

Trotter, P. A., McManus, M. C. and Maconachie, R. (2017) ‘Electricity planning and implementation in sub-Saharan Africa: A systematic review’, *Renewable and Sustainable Energy Reviews*, 74(June 2016), pp. 1189–1209. doi:

10.1016/j.rser.2017.03.001.

Tvinnereim, E. and Mehling, M. (2018) ‘Carbon pricing and deep decarbonisation’, *Energy Policy*, 121, pp. 185–189. doi: 10.1016/J.ENPOL.2018.06.020.

UNFCCC (2015) *Paris Agreement*. UNFCCC.

UNFCCC (2021a) *Decision-/CP.26 Glasgow Climate Pact*. UNFCCC, COP26.

UNFCCC (2021b) *Global Coal to Clean Power Transition Statement*. UNFCCC, COP26.

UNFCCC (2021c) *Statement on International Public Support for the Clean Energy Transition*. UNFCCC, COP26.

Unruh, G. C. (2000) ‘Understanding carbon lock-in’, *Energy Policy*, 28(12), pp. 817–830. doi: 10.1016/S0301-4215(00)00070-7.

Unruh, G. C. (2002) ‘Escaping carbon lock-in’, *Energy Policy*, 30(4), pp. 317–325. doi: 10.1016/S0301-4215(01)00098-2.

Unruh, G. C. and Carrillo-Hermosilla, J. (2006) ‘Globalizing carbon lock-in’, *Energy Policy*, 34(10), pp. 1185–1197. doi: 10.1016/J.ENPOL.2004.10.013.

Vartiainen, E. *et al.* (2020) ‘Impact of weighted average cost of capital, capital expenditure, and other parameters on future utility-scale PV levelised cost of electricity’, *Progress in Photovoltaics: Research and Applications*, 28(6), pp. 439–453. doi: 10.1002/pip.3189.

Venetsanos, K., Angelopoulou, P. and Tsoutsos, T. (2002) ‘Renewable energy sources project appraisal under uncertainty: The case of wind energy exploitation within a changing energy market environment’, *Energy Policy*, 30(4), pp. 293–307. doi: 10.1016/S0301-4215(01)00096-9.

Veysey, J. *et al.* (2016) ‘Pathways to Mexico’s climate change mitigation targets: A multi-model analysis’, *Energy Economics*, 56, pp. 587–599. doi: 10.1016/J.ENECO.2015.04.011.

Wainstein, M. E. and Bumpus, A. G. (2016) ‘Business models as drivers of the low carbon power system transition: a multi-level perspective’, *Journal of Cleaner Production*, 126, pp. 572–585. doi: 10.1016/j.jclepro.2016.02.095.

Waissbein, O. *et al.* (2013) ‘Derisking Renewable Energy Investment’, *United Nations Development Programme*.

Wang, L., Wei, Y.-M. and Brown, M. A. (2017) ‘Global transition to low-carbon electricity:

A bibliometric analysis', *Applied Energy*, 205, pp. 57–68. doi: 10.1016/J.APENERGY.2017.07.107.

Weber, C. *et al.* (2017) *Asset-level data and climate- related financial analysis: a market survey*. 2°Investing Initiative.

Weber, C. *et al.* (2018) 'Mitigation scenarios must cater to new users', *Nature Climate Change*, 8(10), pp. 845–848. doi: 10.1038/s41558-018-0293-8.

Weigelt, C. and Shittu, E. (2016) 'Competition, regulatory policy, and firms' resource investments: The case of renewable energy technologies', *Academy of Management Journal*, 59(2), pp. 678–704. doi: 10.5465/amj.2013.0661.

Weinhofer, G. and Hoffmann, V. H. (2010) 'Mitigating climate change - How do corporate strategies differ?', *Business Strategy and the Environment*, 19, pp. 77–89. doi: 10.1002/bse.618.

Wernerfelt, B. (1984) 'A resource-based view of the firm', *Strategic Management Journal*, 5(2), pp. 171–180. doi: 10.1002/SMJ.4250050207.

Wieczorek, A. J. (2018) 'Sustainability transitions in developing countries: Major insights and their implications for research and policy', *Environmental Science & Policy*, 84, pp. 204–216. doi: 10.1016/J.ENVSCI.2017.08.008.

World Bank (2021) *World Bank Group Climate Change Action Plan 2021–2025*. Washington, DC: World Bank.

Yandex (2018) 'CatBoost GitHub: GBDT speed benchmarks', *Yandex*. Available at: https://github.com/catboost/benchmarks/blob/master/training_speed/README.md (Accessed: 1 September 2020).

Yi, H. and Feiock, R. C. (2014) 'Renewable Energy Politics: Policy Typologies, Policy Tools, and State Deployment of Renewables', *Policy Studies Journal*, 42(3), pp. 391–415. doi: 10.1111/psj.12066.

Yin, H. and Powers, N. (2010) 'Do state renewable portfolio standards promote in-state renewable generation?', *Energy Policy*, 38(2), pp. 1140–1149. doi: 10.1016/j.enpol.2009.10.067.

Zhang, M., Zhou, D. and Zhou, P. (2014) 'A real option model for renewable energy policy evaluation with application to solar PV power generation in China', *Renewable and Sustainable Energy Reviews*, 40, pp. 944–955. doi: 10.1016/J.RSER.2014.08.021.

Zhang, M., Zhou, P. and Zhou, D. Q. (2016) 'A real options model for renewable energy

investment with application to solar photovoltaic power generation in China', *Energy Economics*, 59, pp. 213–226. doi: 10.1016/J.ENECO.2016.07.028.

Zhang, X. *et al.* (2014) 'A novel modeling based real option approach for CCS investment evaluation under multiple uncertainties', *Applied Energy*, 113, pp. 1059–1067. doi: 10.1016/J.APENERGY.2013.08.047.

Zhao, Y., Tang, K. K. and Wang, L. li (2013) 'Do renewable electricity policies promote renewable electricity generation? Evidence from panel data', *Energy Policy*, 62, pp. 887–897. doi: 10.1016/j.enpol.2013.07.072.

Zhou, W. *et al.* (2010) 'Uncertainty modeling of CCS investment strategy in China's power sector', *Applied Energy*, 87(7), pp. 2392–2400. doi: 10.1016/J.APENERGY.2010.01.013.

Zhou, Y., Wang, L. and McCalley, J. D. (2011) 'Designing effective and efficient incentive policies for renewable energy in generation expansion planning', *Applied Energy*, 88(6), pp. 2201–2209. doi: 10.1016/j.apenergy.2010.12.022.

Zhu, L. and Fan, Y. (2011) 'A real options–based CCS investment evaluation model: Case study of China's power generation sector', *Applied Energy*, 88(12), pp. 4320–4333. doi: 10.1016/J.APENERGY.2011.04.005.

Ziegler, M. S. *et al.* (2019) 'Storage Requirements and Costs of Shaping Renewable Energy Toward Grid Decarbonization', *Joule*, 3(9), pp. 2134–2153. doi: 10.1016/j.joule.2019.06.012.

van der Zwaan, B. C. C., Calvin, K. V. and Clarke, L. E. (2016) 'Climate Mitigation in Latin America: Implications for Energy and Land Use: Preface to the Special Section on the findings of the CLIMACAP-LAMP project', *Energy Economics*, 56, pp. 495–498. doi: 10.1016/j.eneco.2016.05.005.

van der Zwaan, B. *et al.* (2016) 'Energy technology roll-out for climate change mitigation: A multi-model study for Latin America', *Energy Economics*, 56, pp. 526–542. doi: 10.1016/J.ENECO.2015.11.019.

van der Zwaan, B. *et al.* (2018) 'An integrated assessment of pathways for low-carbon development in Africa', *Energy Policy*, 117(April), pp. 387–395. doi: 10.1016/j.enpol.2018.03.017.

Appendices

Appendix A: Supplementary Materials for Chapter 3

nature research

https://doi.org/10.1038/s41560-020-00755-9

Supplementary information

A machine-learning approach to predicting Africa's electricity mix based on planned power plants and their chances of success

In the format provided by the authors and unedited

Supplementary Information

A machine-learning approach to predicting Africa's electricity generation mix in 2030 based on the estimated success chances of power-plant projects

Galina Alova[1 *], Philipp A. Trotter[1, 2], Alex Money[1]

[1] Smith School of Enterprise and the Environment, School of Geography and the Environment, University of Oxford, Oxford, UK
[2] Chair of Operations Management, RWTH Aachen University, Aachen, Germany

* galina.alova@ouce.ox.ac.uk

Supplementary Table 1: Installed capacity forecasts for Africa in 2030 in selected published renewable energy-heavy scenarios

	Actual values, Africa 2018[1]		IEA (2019) – "Africa case" scenario[1]		Trotter et al. (2018) – "Min. political risk" scenario[2]		van der Zwaan et al. (2018) – "2DC" scenario[3]		Taliotis et al. (2016) – "Reference" scenario[4]		IRENA (2015) – "RE-oriented" scenario[5]	
	Capacity	Generation	Capacity	Generation	Capacity	Generation	Capacity	Generation	Capacity	Generation	Capacity	Generation
Total capacity (GW)/ generation (TWh)	**244**	**866**	**550**	**1662**	**605**	**1730**	**-**	**1600**	**-**	**2150**	**620**	**2165**
Fossil fuel share	79.5%	79.4%	49.2%	54.4%	42.5%	53.4%	-	43.8%	-	31.6%	38.5%	42.2%
Nuclear share	0.8%	1.6%	0.7%	1.7%	0.7%	1.6%	-	1.9%	-	5.0%	0.6%	1.3%
Hydro share	14.8%	15.6%	14.1%	18.8%	15.7%	16.8%	-	15.6%	-	20.3%	15.2%	17.0%
Non-hydro renewables share	**4.9%**	**3.4%**	**36.0%**	**25.1%**	**41.2%**	**28.9%**	**-**	**38.8%**	**-**	**43.0%**	**45.6%**	**39.6%**

Note: In some instances, values were read off graphs, i.e. may be subject to small-scale. Imprecisions. Further, energy planning studies on Africa exist which do not present detailed power sector breakdowns but look at different energy-intense sectors. These studies confirm the range of estimated electricity demand in Africa in 2030 to be between 1,600 and 2,150 TWh[6].

Supplementary Table 2: Performance of the gradient boosted trees model

a. Confusion matrix

	Training set		Test set	
	False (prediction)	***True (prediction)***	***False (prediction)***	***True (prediction)***
False (actual)	true negative = 0.734071	false positive = 0.265929	true negative = 0.559541	false positive = 0.440459
True (actual)	false negative = 0.017529	true positive = 0.982471	false negative = 0.030120	true positive = 0.969880

Note: The confusion or error matrix visualises the performance of the machine-learning model on a data set for which true values are known. True positive (TP) and true negative (TN) refer to instances accurately labelled as positive and negative, respectively. False positive (FP) and false negative (FN) refer to instances incorrectly predicted as positive and false, respectively.

b. Prediction's quality metrics

Metric	Training set mean	Test set mean
roc auc	0.974953	0.930022
accuracy	0.936039	0.924426
precision	0.941383	0.942785
Hamming loss	0.063961	0.075574
Brier score loss	0.046416	0.057607

Notes: Roc auc refers to the area under the receiver operating characteristic curve, and is equivalent to the probability that the model will rank a randomly chosen positive instance higher than a randomly chosen negative instance. The higher the roc-auc score the better is the model's performance. The score for the test set has not reached that of the training set, given that out-of-time validation of the model is performed, to estimate the real error and ensure the robustness and reproducibility of the results. Accuracy measures the number of correct classifications as a share of all samples, i.e. $\text{accuracy} = \frac{\text{TP + TN}}{\text{TP + TN+FP + FN}}$ or $\frac{1}{n}\sum_{j=0}^{n-1} \mathbf{1}(y_j = z_j)$ where n is the total number of instances, y_j is the prediction of an instance j, z_j is the actual outcome of the instance j, and **1** is an indicator function. The larger the accuracy, the better is the model's predictive performance. Precision measures the number of true positives as a share of all predicted positives, i.e. $\text{precision} = \frac{\text{TP}}{\text{TP + FP}}$. Hamming loss refers to the fraction of labels (i.e. true or false) that are incorrectly predicted, i.e. $1 - \text{accuracy} = \frac{\text{FP + FN}}{\text{TP + TN+FP + FN}}$ or $\frac{1}{n}\sum_{j=0}^{n-1} \mathbf{1}(y_j \neq z_j)$ where n is the number of prediction instances, y_j is the prediction, z_j is the actual outcome, and **1** is an indicator function. Brier score represents the mean squared error of the prediction, i.e. the difference between the predicted probability and the actual outcome. $\text{Brier score} = \frac{1}{n}\sum_{j=0}^{n-1}(p_j - z_j)^2$, where p_t is a forecast probability z_j is the actual outcome of an instance, j is a forecasting instance. The smaller the value of the Hamming loss and Brier score, the better is the model's predictive performance.

Supplementary Table 3: Performance of the alternative logistic regression model

a. Confusion matrix

	Training set		Test set	
	False (prediction)	***True (prediction)***	***False (prediction)***	***True (prediction)***
False (actual)	true negative = 0.479193	false positive = 0.520807	true negative = 0.348749	false positive = 0.651251
True (actual)	false negative = 0.040773	true positive = 0.959227	false negative = 0.038466	true positive = 0.961534

Notes: see Notes under Table 2a

b. Prediction's quality metrics

Metric	Training set mean	Test set mean
roc auc	0.890746	0.879304
accuracy	0.869643	0.886640
precision	0.889209	0.911477
Hamming loss	0.130357	0.113360
Brier score loss	0.093550	0.077918

Notes: see Notes under Table 2b

Supplementary Table 4: Features included in, and excluded from, the final model

Feature	SHAP value
Included project-level features	
capacity	0.926163
fuel	0.801816
grid connection	0.696953
ownership	0.611543
DFI financing	0.274948
cost (USD, deflated)	0.121888
Included country-level features	
ODA share in GNI	0.195869
corruption	0.177694
share of agriculture in GDP	0.174678
population	0.152130
political stability	0.129699
GINI coefficient	0.127546
democracy score	0.114108
Excluded project-level features	
geographic information (region, province, country)	
temporal features (PPA signing, start of construction/commercial operations)	
Excluded country-level features	
real GDP per capita and GDP PPP	
central government debt (% of GDP)	
gross savings (% of GDP)	
government effectiveness	
regulatory quality	
rule of law	
accountability	
renewable energy share in electricity output	
fossil fuel share in energy consumption	
urban population (% of total population)	
feed-in-tariff (difference in years between a plant's commercial start year and the year of policy's introduction)	
pre- and post-tax energy subsidies in the electricity sector	

Supplementary Table 5: Installed capacity, generation and capacity factors in Africa, 2018 (data source: IEA (2019) [1])

	Capacity [GW]	Capacity share [%]	Generation [TWh]	Generation share [%]	Average capacity factor [%]
Coal	48	19.7	258	29.8	61
Oil[a]	43	17.6	79	9.1	21
Gas	103	42.2	351	40.5	39
Nuclear	2	0.8	14	1.6	77
Solar PV	4	1.6	6	0.8	19
Wind	5	2.0	14	1.6	32
Hydro	36	14.8	135	15.6	43
Biomass	1	0.5	2	0.3	24
CSP[b]	1	0.4	2	0.3	27
Geothermal	1	0.3	5	0.5	64
Total	**244**		**866**		
Non-hydro renewable share		**4.9**		**3.4**	
Total renewable share		**19.7**		**19.0**	

Capacity and generation data from the IEA allows to calculate average capacity factors for all major generation technologies in Africa in 2018. To estimate generation in 2030 from our predicted capacity results, we assume that historic average capacity factors remain constant until 2030, with the exception of natural gas, for which we assume an increase of the average capacity factor to 55% (compared to currently 39%). This is due to new types of natural gas plants being mainly planned to serve baseload demand via combined cycle technology, rather than meet peak demand as in the past. An average capacity factor of 55% is below what new combined cycle natural gas plants are capable of delivering, but on par with the current average capacity factor for operational natural gas plants in the US. The calculation of the resulting generation mix is provided in Supplementary Table 6.

[a] The IEA estimates 43 GW of oil-fired installed capacity in 2018. While the Live Data matches all other values closely, it lists roughly 20 GW less oil-fired capacity to being "operational" than what IEA has as "installed capacity".

[b] CSP = Concentrated Solar Power

Supplementary Table 6: Predicted installed capacity and generation in Africa, 2030

	Total capacity [GW]	Capacity share [%]	Newly added capacity [GW]	Total Generation [TWh][a]	Generation share [%]
Fossil fuels[b]	294	62.2	129	1245	66.3
Nuclear	16	3.4	14	108	5.8
Hydro	80	16.9	56	346	18.4
Non-hydro RE	82	17.4	69	178	9.6
Total	**472**		**269**	**1877**	

[a] Calculated as generation from plants which are still in operation in 2030 (I.e. netted of retired capacity) and from newly added capacity

[b] Includes pure oil-fired plants as well as a share of hybrid, co-fired plants with oil component. Live Data has roughly 20 GW capacity less oil plants classified as "operational" than what the IEA has classified as "installed capacity" in 2018 (see Supplementary Table 5). The capacity factors are assumed to remain at current levels except for natural gas plants where the capacity factor for new generation is assumed to be 55% compared to currently 39% due to these types of plants mainly being planned to serve baseload demand via combined cycle technology rather than meet peak demand as in the past. An average capacity factor of 55% is below what new combined cycle natural gas plants are capable of delivering, but on par with the current average capacity factor for operational natural gas plants in the US.

Supplementary Table 7: Results of decarbonisation scenarios

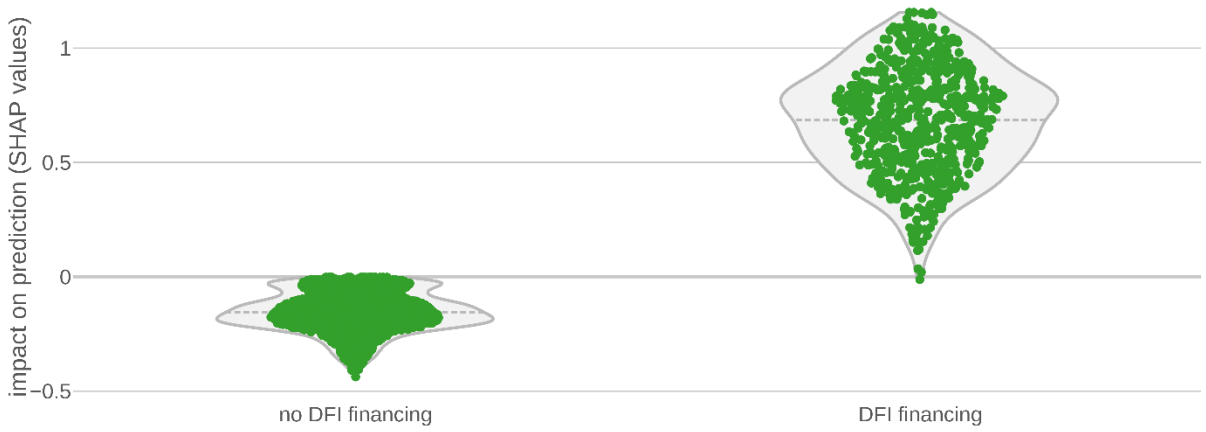
		'Decarbonisation' scenario		'Rapid decarbonisation' scenario		'Rapid decarbonisation and early retirement' scenario	
		Capacity	Generation	Capacity	Generation	Capacity	Generation
Total capacity (GW)/ generation (TWh)		**505**	**228**	**593**	**237**	**675**	**248**
Fuel shares							
	Fossil fuels	53%	63%	39%	52%	31%	44%
	Nuclear	4%	6%	3%	6%	3%	6%
	Hydro	16%	15%	14%	15%	14%	16%
	Non-hydro renewables	26%	14%	42%	25%	52%	32%

The 'decarbonisation' scenario constitutes the cancellation of half of coal and oil planned capacity, and a third of gas capacity from 2025 onwards. The lost generation is replaced by equivalent new non-hydro RE generation. The 'rapid decarbonisation' scenario builds upon the first scenario by assuming immediate cancellation of all coal and oil, and a third of gas capacity. The 'rapid decarbonisation and early retirement' scenario introduces in addition an early retirement of coal and oil plants at 30 years by 2030 (see Supplementary Note 3 for further details).

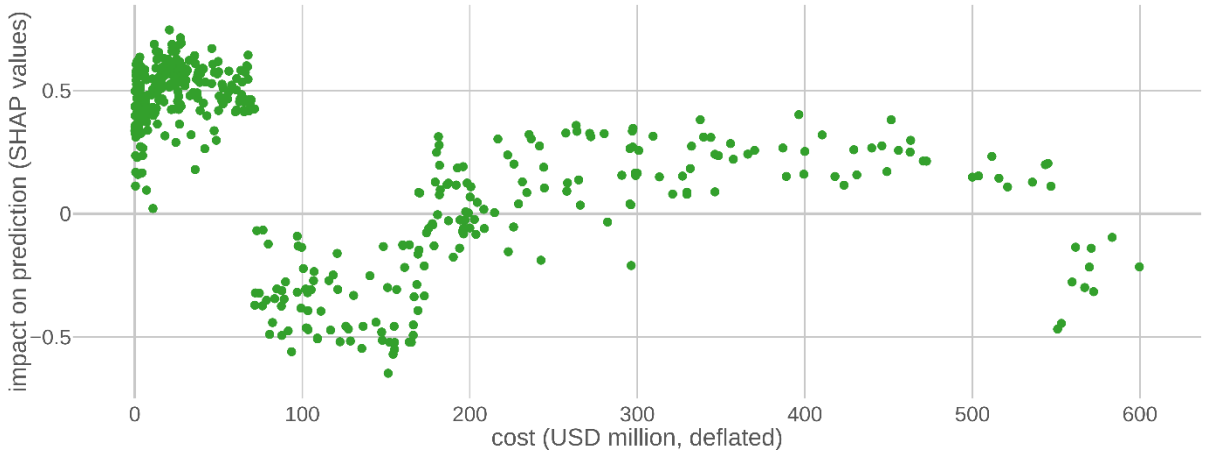
Supplementary Table 8: Hyperparameter tuning

Parameter's name in algorithm	Parameter's full name	Value after tuning
Core parameters		
n_estimators	number of boosted trees to fit	540
learning_rate	boosting learning rate	0.02
num_leaves	maximum number of leaves for base learners	24
Learning control parameters		
subsample	subsample ratio of the training instances	0.5
colsample_bytree	subsample ratio of columns when constructing each tree	0.30000000000000054
min_child_samples	minimum data points in a child (leaf)	14
min_split_gain	minimum loss reduction required to make a further partition on a leaf node	0.4861303569353555
max_depth	maximum tree depth for base learners	6
max_bin	max number of bins that feature values will be bucketed in	561
reg_alpha	L1 regularisation term on weights	0.9080127977246404
max_cat_threshold	maximum threshold points in categorical features	85
cat_l2	L2 regularisation in categorical split	26.60636021141224
cat_smooth	categorical smoothing	8.102236378302079
reg_lambda	L2 regularisation term on weights	0.6201557870041947

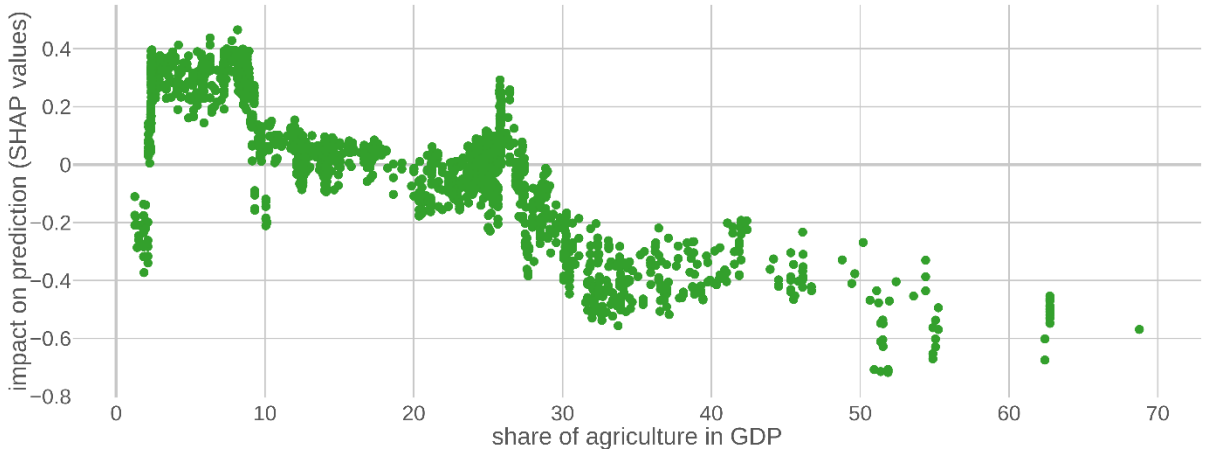
Supplementary Fig. 1: The impact of DFI participation in project's financing on the model's prediction. The feature's impact on the prediction is expressed in SHAP values, i.e. change in log-odds (see Methods for explanation on SHAP values and model interpretation). A positive value implies that a feature increases the chances of a given plant's successful commissioning, while a negative value implies that a feature reduces these chances.



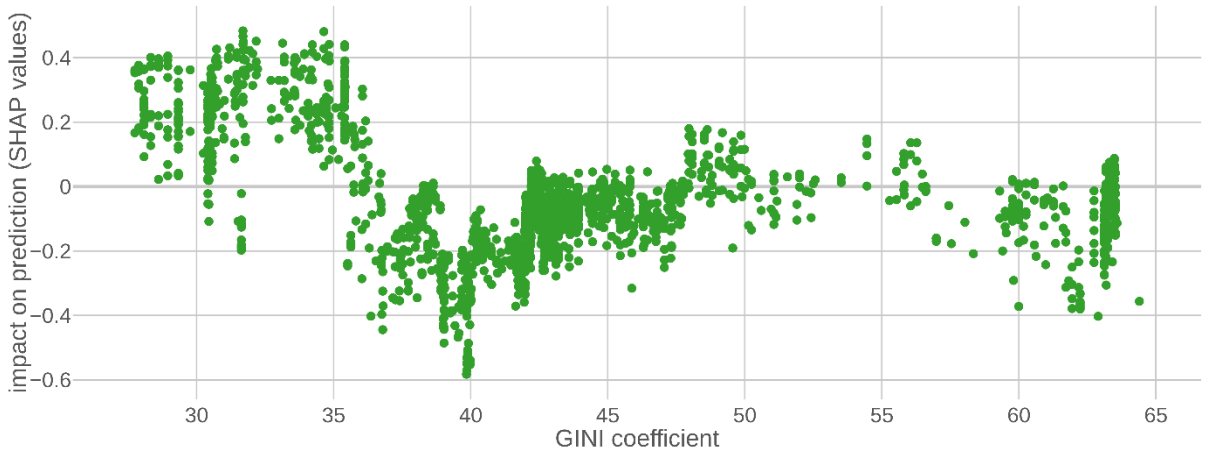
Supplementary Fig. 2: The impact of the project's cost on the model's prediction. The feature's impact on the prediction is expressed in SHAP values, i.e. change in log-odds (see Methods for explanation on SHAP values and model interpretation). A positive value implies that a feature increases the chances of a given plant's successful commissioning, while a negative value implies that a feature reduces these chances. Given the ability of our model to deal well with the gaps in the data (see Methods), we include project cost amongst the variables in the model, despite the high number of the missing values in this data. The obtained results on the cost feature should, however, be viewed with caution. In Live Data, the cost is at times provided in local currencies. We therefore deflate and convert those values into USD to construct the variable. The vertical distribution of data points indicates interaction effect of the feature.



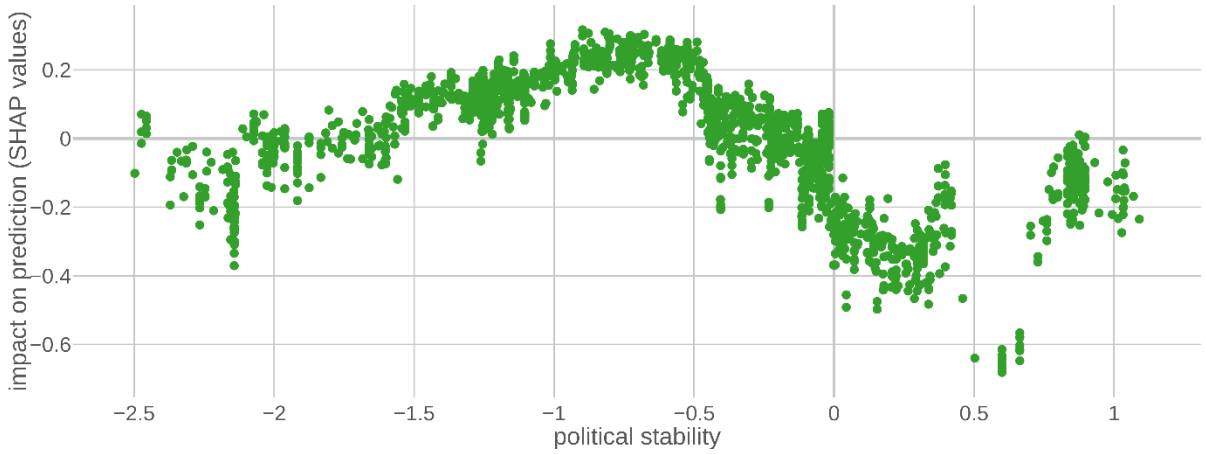
Supplementary Fig. 3: The impact of the share of the country's agricultural sector in its GDP on the model's prediction. The feature's impact on the prediction is expressed in SHAP values, i.e. change in log-odds (see Methods for explanation on SHAP values and model interpretation). A positive value implies that a feature increases the chances of a given plant's successful commissioning, while a negative value implies that a feature reduces these chances. The vertical distribution of data points indicates interaction effect of the feature.



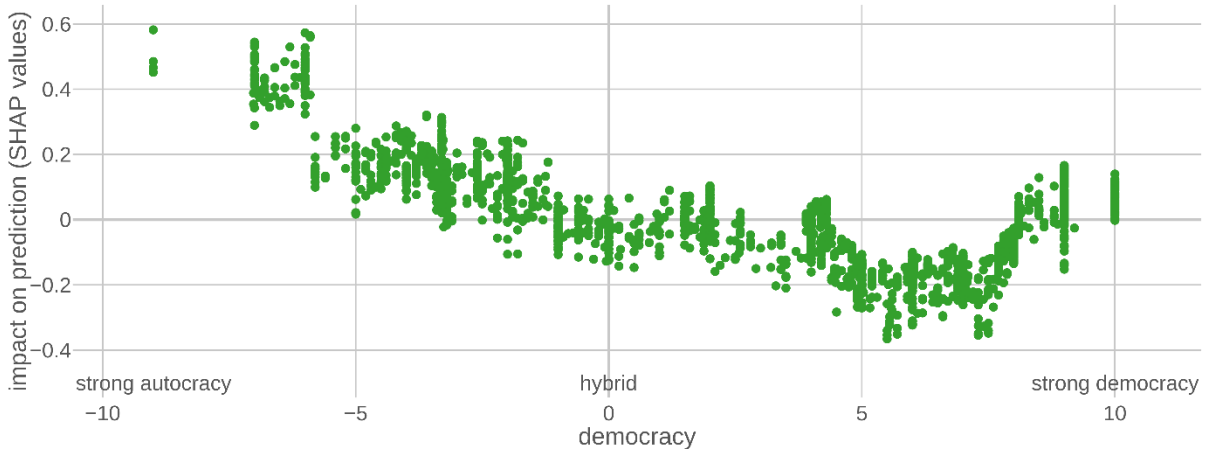
Supplementary Fig. 4: The impact of the country's GINI coefficient on the model's prediction. The feature's impact on the prediction is expressed in SHAP values, i.e. change in log-odds (see Methods for explanation on SHAP values and model interpretation). A positive value implies that a feature increases the chances of a given plant's successful commissioning, while a negative value implies that a feature reduces these chances. The vertical distribution of data points indicates interaction effect of the feature.



Supplementary Fig. 5: The impact of the country's political stability score on the model's prediction. The feature's impact on the prediction is expressed in SHAP values, i.e. change in log-odds (see Methods for explanation on SHAP values and model interpretation). A positive value implies that a feature increases the chances of a given plant's successful commissioning, while a negative value implies that a feature reduces these chances. Data for the political stability score is taken from the "Political Stability and Absence of Terrorism/Violence" World Bank World Governance Indicators (2019), using their scale from –2.5 to 2.5, with higher values indicating less political violence. The political stability variable primarily denotes the occurrence of any sort of political violence such as terrorism or armed insurgencies but does not include institutional stability. For instance, Nigeria has had a comparably strong and stable form of democracy in the last decade which included a peaceful transition of power through the ballot box in 2015, scoring 7 on the Polity IV democracy score (which ranges between -10 and 10). Its political stability score at -2, however, is among the worst in the sample, mainly due to the Boko Haram insurgency in parts of Northern Nigeria. The vertical distribution of data points indicates interaction effect of the feature.

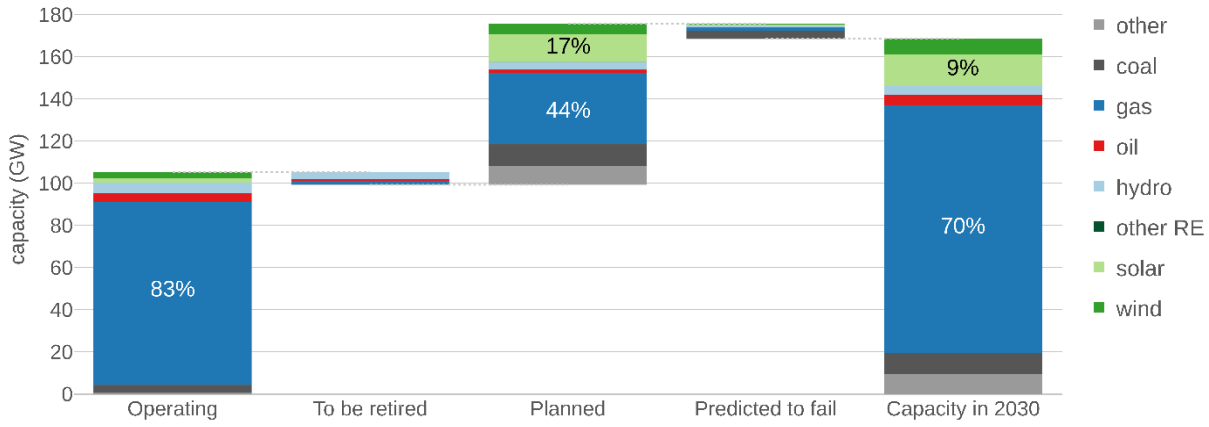


Supplementary Fig. 6: The impact of the country's democracy score on the model's prediction. The feature's impact on the prediction is expressed in SHAP values, i.e. change in log-odds (see Methods for explanation on SHAP values and model interpretation). A positive value implies that a feature increases the chances of a given plant's successful commissioning, while a negative value implies that a feature reduces these chances. Data for the democracy score is taken from the Policy IV dataset, using their scale from –10 to 10, with higher values indicating more democratic regimes. Given that a significant number of African countries began to move towards democracy in the 1990s, albeit at varying degrees of intensity, most regimes in transition are located along low to medium positive values of democracy. The vertical distribution of data points indicates interaction effect of the feature.

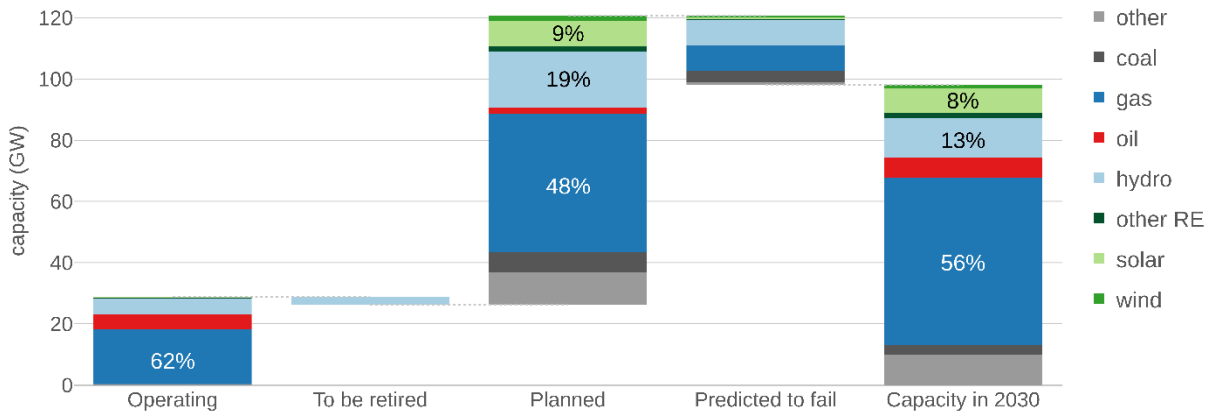


Supplementary Fig. 7: Africa's current and predicted 2030 electricity capacity mix by fuel type and regions, a-e. North Africa (a), West Africa (b), East Africa (c), Central Africa (d), Southern Africa (e). The "Operating" bar refers to the current operating capacity, as of October 2019, when the data was retrieved; "To be retired" – the capacity that in 2030 will be older than 50 years, and under a conservative assumption will be retired by then; "Planned" – the projects currently in the pipeline; and "Predicted to fail" – the plants in the pipeline that are predicted not to be commissioned. Finally, the "Capacity in 2030" refers to the region's power-generation capacity, calculated as the sum of the current installed capacity, net of the capacity assumed to be retired being over 50 years by 2030, and the capacity currently in the pipeline predicted to be commissioned by 2030, based on the estimates of individual project probabilities to be successfully realised.

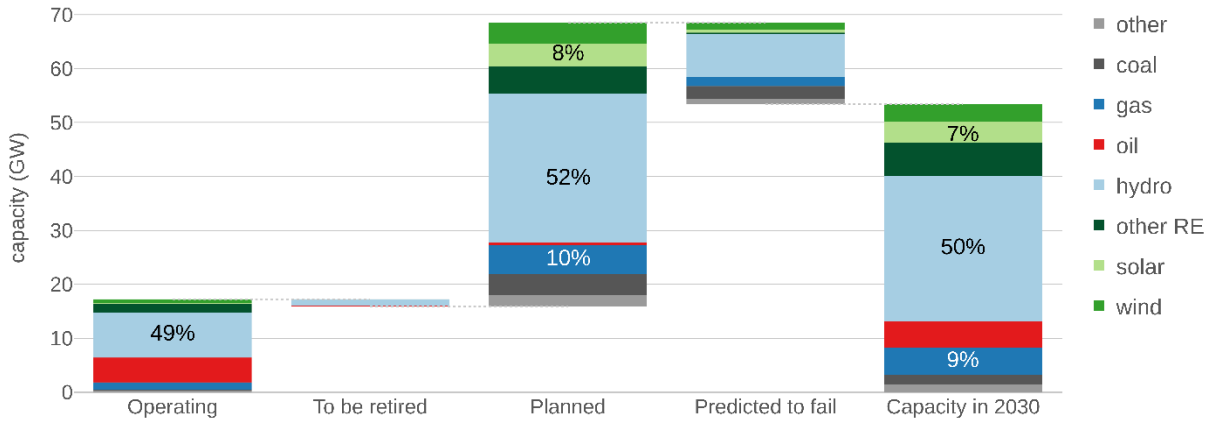
a



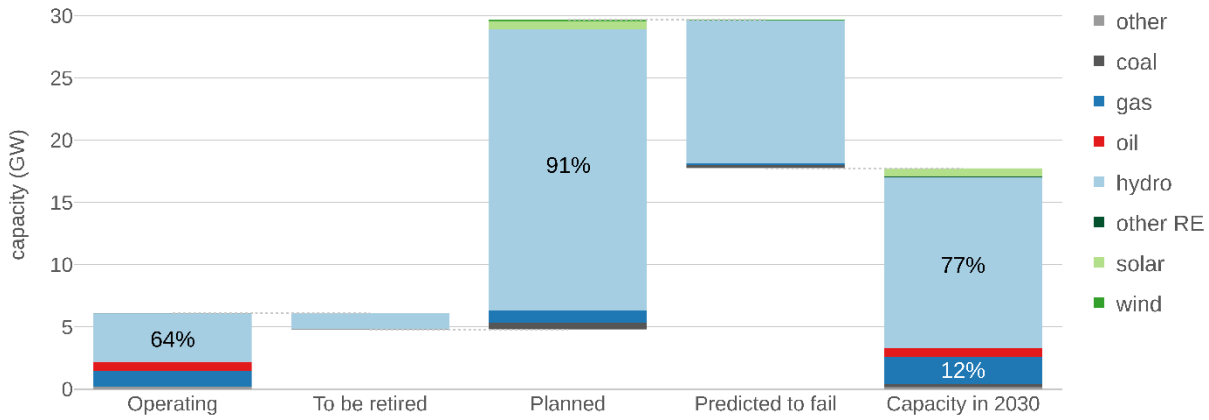
b



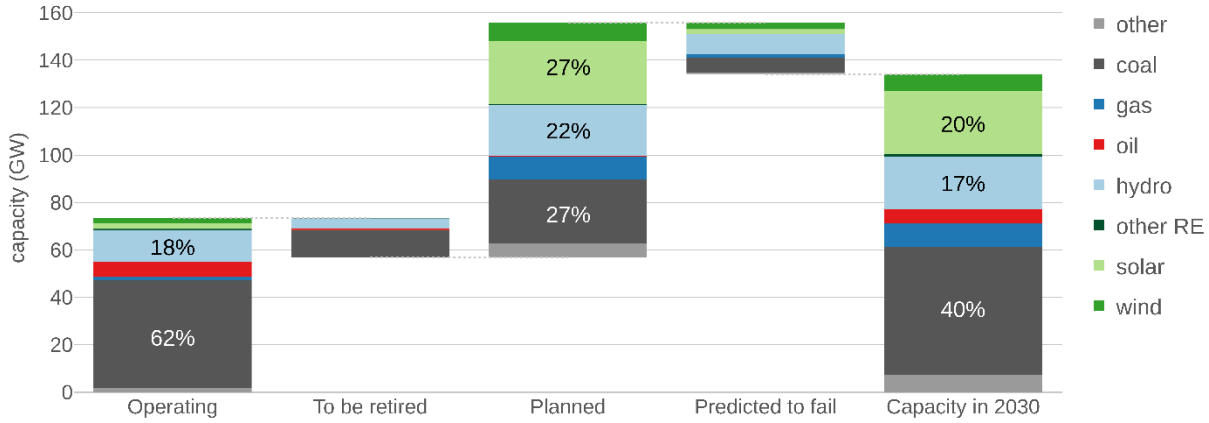
c



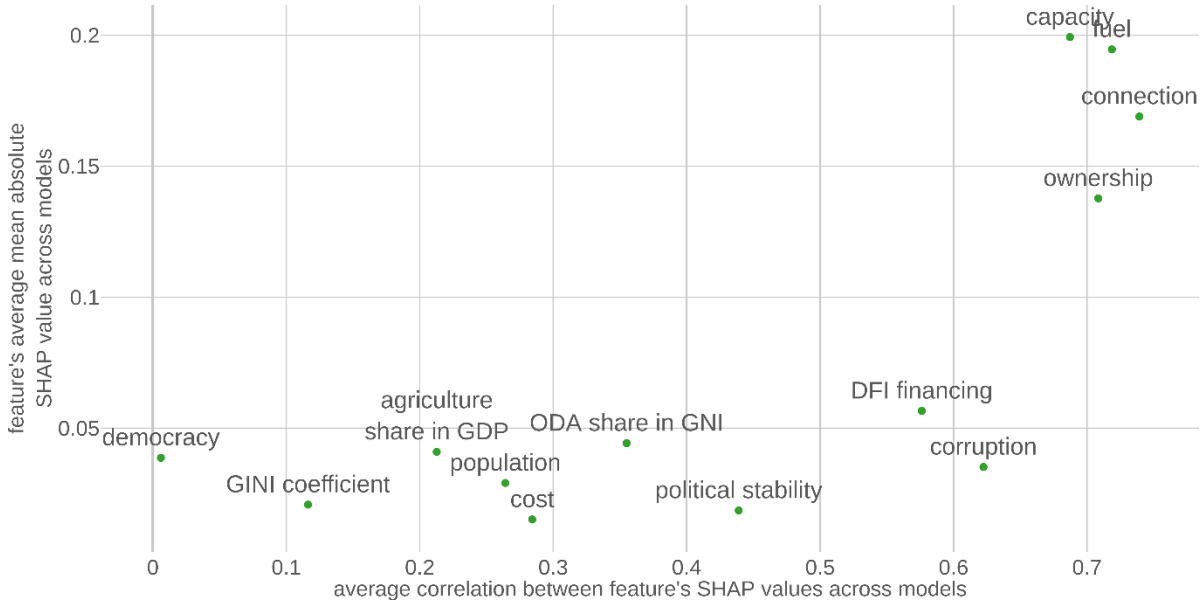
d


30
25
20
15
10
5
0
capacity (GW)
64%
91%
77%
12%
Operating
To be retired
Planned
Predicted to fail
Capacity in 2030
other
coal
gas
oil
hydro
other RE
solar
wind

e

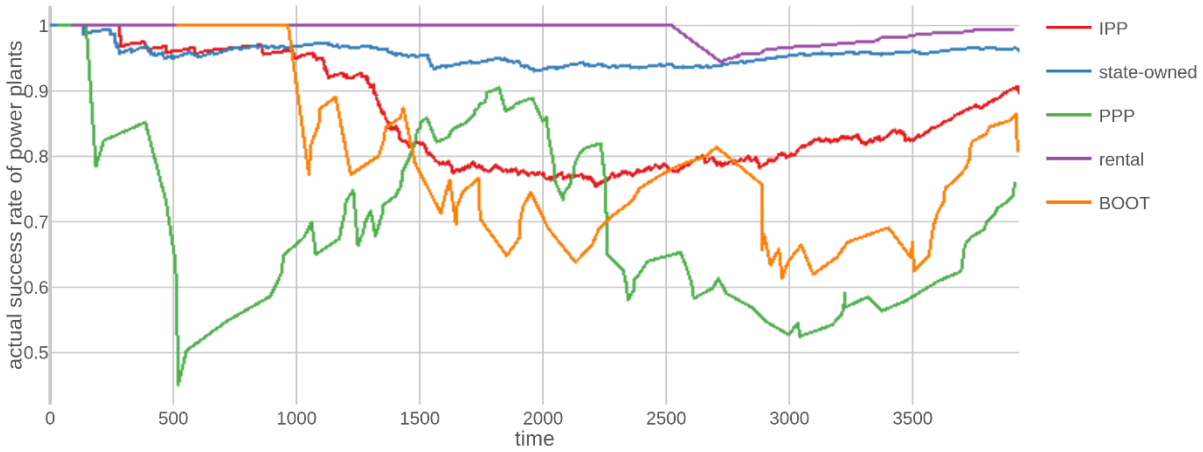

160
140
120
100
80
60
40
20
0
capacity (GW)
18%
62%
27%
22%
27%
20%
17%
40%
Operating
To be retired
Planned
Predicted to fail
Capacity in 2030
other
coal
gas
oil
hydro
other RE
solar
wind

Supplementary Fig. 8: The visualisation of the feature impact and correlation matrix, based on the training of three models with multiple splits. As part of the feature selection process, three models with multiple splits were trained using the training set data, to identify most stable features (see Methods). Here, the figure visualises the features included in the final model. The y-axis presents the average of mean absolute impacts (expressed in SHAP values) of a feature on the predictions of the three models. The x-axis presents the average of the correlations between these impacts, denoting the relationship between what each model learned about the feature's impact. Higher correlations imply higher similarity in this learning, i.e. stronger feature stability and its ability to generalise beyond the training set. Features with a negative mean correlation were excluded from the final model.

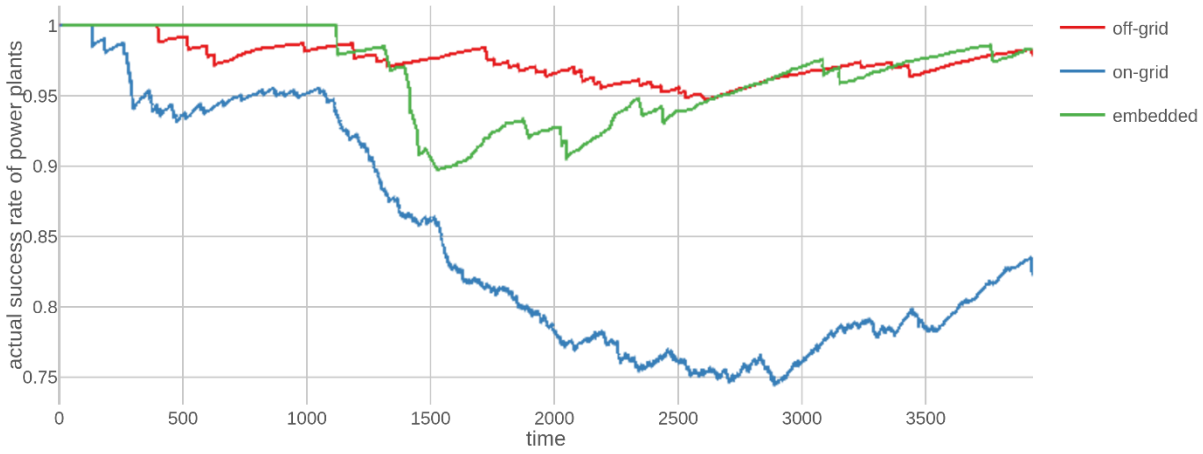


Supplementary Fig. 9: Success rate of historical power plants, a-c. Successful commissioning of power plants based on their ownership (a) (where IPP = independent power producer; BOOT = build, own, operate, transfer; and PPP = public-private partnership), on their connection to grid (b), and on their fuel type (c). The x-axis represents the time period between 1897 to 2020, the time span for which information is available in the dataset on the past commissioned and failed plants. The y-axis denotes the success rate of the power plants in a given time unit.

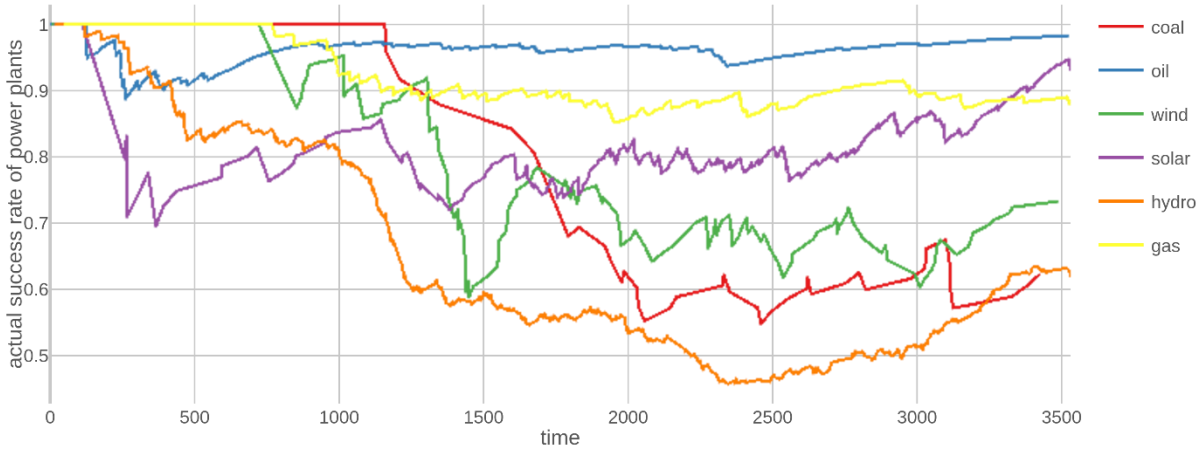
a



b



c



Supplementary Note 1: Data preparation for modelling

Before building our model, we prepare the data involving the following steps. First, we assess the coverage of Live Data. We find that Live Data does not always have full information on all plant characteristics we choose as variables. Data on location, fuel and status are available for virtually all power plants (the small number of the datapoints, for which the information on fuel as recorded in the dataset does not allow determining the exact source of energy, is grouped into the 'other' category), and information on installed capacity, ownership and connection type for over 90% of projects. However, the start date of commercial operations is available for 53% of plants. Where this information is missing for historic plants, we use project background information in Live Data to deduce a year of commissioning, if the text contains relevant dates (e.g. the date of feasibility studies, financial close or construction start), and declare as missing otherwise. For planned plants, where an envisaged date of commissioning is unavailable, we again use the background information to make an estimation. For the rest, we assume a planned year of commissioning informed by average past duration of construction. According to our data, 99% of historic plants were constructed within 12 years, which matches the timespan of our prediction from 2019 to 2030. The average standard deviation of construction time was slightly above five years. We thus fill in the data, using a random year in a conservative range between 2020 and 2030. As a result, the share of missing values of the commissioning year decreases to 13%. The exact year is of secondary importance to our analysis, given that we use one-end timeframe of 2030, and all plant-level variables are fixed over time, while the country-level features are calculated as ten-year rolling averages and are slow-moving (discussed below). Further, the data on cost can be retrieved for only 18% of the projects. As various discrepancies exist in how cost is being reported, this data should be treated with caution.

Second, before merging this country-level data into our asset-level dataset, we calculate ten-year rolling averages for all country-level features, to capture the time between conception and commissioning of power plants. Given that Live Data contains information on planned projects with a commissioning date in the future, we estimate missing future values for country-level data until 2030, employing a linear extrapolation method. While forecasts may introduce uncertainty, this can be expected to be of minor significance here, as most economic and all demographic, institutional and political country-level indicators used in our model are slow-moving in nature, and heavily dependent on historic values. We used the same method to fill in any missing values remaining in the historic data, after the application of the rolling averages. We also ran the model, replacing our extrapolated country-level data with the International Futures forecasts by Hughes et al (2014)[7]. They provide annual forecasts for all country-level variables in our model. The forecasts are derived from an encompassing integrated model which links multiple domains of human and social systems (population, economy, health, education, politics and infrastructure) and models their

respective interactions, covering 183 countries since 1960.The new country-level data had a minimal impact on the results, mostly limited to below 1% in terms of the average project success probability by fuel type.

Finally, after merging plant- and country-level data, we split our combined dataset into a training set (2,969 plants), containing plants that are commissioned (that is still operating (2,355 plants) or already retired (126 plants)), or failed (478 plants), and an application set, comprising the project pipeline of 2,479 plants (that is the plants under planning (2,215 plants) or construction (264 plants)). It is worth noting that we consider a project failed when its status in the Live Data is marked as "abandoned" or "halted", that is officially being cancelled or put on hold, or as "no evidence of progress", that is projects that have no official "abandoned" or "halted" designation, but where tangible on-going developments or progress have stopped. Large hydro plants which have been proposed for a long time without notable progress, such as the 688 MW Wagenia hydro project in the DRC or the 110 MW Bunso hydro dam in Ghana, make up over 50% of these types of plants, with coal and gas being the second and third most significant, respectively. Using desk research, we checked and validated a number of projects we consider failed, based on their status in Live Data. Furthermore, we explored the existence of projects in the dataset that have been planned or under construction for a while. It is not uncommon for some plants, even with on average relatively short lead times, such as solar or wind projects, to take nearly a decade to be realised, as for example Uganda's case has shown (see Supplementary Note 2). That said, we found only six such projects with a construction start date prior to 2010 which have not yet been completed as of 2019, but not listed under one of the "failed" categories either. All of these plants have shown significant signs of progress, despite being subject to different types of delays, with one of them, the Genale Dawa III hydro plant in Ethiopia, being since completed in February 2020. This lends us confidence that the project progress information as recorded by Live Data is accurate and up-to-date.

To train our final model, we only use the data for the past two decades, as we find that the inclusion of older power plants that were commissioned prior to 2000 reduce the model's predictive power. This implies that these datapoints are not relevant for the model's learning process, and on the opposite undermine its prediction, as the factors affecting the successful commissioning of projects might have changed in the meantime. This is also the reason why we are using the model to make a medium-term prediction of 2030. The model might be less accurate in making longer-term predictions, given its underlying assumption of independent and identically distributed variables. This is, however, in line with the data availability on planned projects, which spans a decade in the case of Live Data. Having learned from the training set, the model predicts on the application set the probability of power plants in the pipeline to be commissioned, given their project- and country-level features (see Supplementary Note 2 for a discussion on the rationale for this approach).

Further, while it might be argued that projects for which construction has already started would be more likely to reach their commissioning than planned plants, there is still a degree of uncertainty remaining around their realisation, as they might be suspended mid-construction. For example, the construction of 750 MW Kafue Gorge hydroelectric dam in Zambia was suspended, following financing issues[8]. Similarly, the 10 MW Bardera Dam project in Somalia was at an advanced stage of construction, when the government collapsed[9]. Given this uncertainty, we include the projects under construction into the model to predict their success chances, rather than directly assume 100% probability of their success, when calculating the future capacity mix.

Supplementary Note 2: Rationale for empirical approach to predicting future generation capacity mix

We believe that a key strength of our analysis to predict Africa's medium-term generation capacity mix is its evidence-based and data-driven approach. Our empirical analysis identifies which project- and country-level features are important for predicting the commissioning chances of the plants currently planned, estimating the respective impacts associated with different variables. While based on the analysis of the past data, these effects are expected to stand, given the model's good predictive power, when it is applied to new medium-term data yet unseen by the model (see Methods and Supplementary Table 2 for model's robustness checks and performance). Further, our analysis demonstrates that country-level factors, including policy-related variables, have a limited effect on the realisation of projects already planned. This is the case for policy indicators, such as the existence of feed-in-tariffs or the size of pre- and post-tax energy subsidies in the electricity sector, which all have a small impact on the prediction (each roughly 2% or less of the total features' impact). These variables also exhibit signs of a domain shift, i.e. behave differently on the various subsets of the dataset (see more on feature selection in the Methods). This is likely to be due to policies having a temporary effect on project realisation chances, in that over time their impact wears off, being priced into the pipeline and no longer affecting the commissioning of the projects already planned. As a result, these policy-related variables were excluded from the final model for not being stable predictors and negatively affecting roc-auc on the test set. Similarly, we find that project cost tends to have a limited impact on the prediction. That said, rather than affecting the realisation of projects already planned, the existence or anticipation of certain changes to policies, technology cost or energy demand might well have an impact on the composition of the pipeline, i.e. which projects would be planned. These considerations are implicitly incorporated into our analysis influencing the characteristics of the plants already built or failed, and the projects currently planned. Therefore, besides the knowledge of the past, our analysis also relies on the current view of the future. We expect the data on planned plants to reflect the expectations of governments, project developers and investors regarding how the future might unravel in terms of policy-related or economic factors, which they have priced into the projects they are considering implementing.

As a result, the key issue here to consider is whether an unexpected event could take place in the next decade that has not yet been priced into the current pipeline, and therefore would affect its present size or composition in terms of the type of projects planned, particularly their fuel type. The following characteristics of the electricity sector lend us confidence to believe that dramatic changes to the pipeline, as we currently know it, are unlikely. First, the electricity sector is prone to considerable inertias and thus tends to evolve slowly. While non-hydro RE have penetrated the global power-generation market, becoming increasingly more cost-competitive over the past years, their share in the overall capacity mix remains limited, with fossil-fuelled power generation continuing to expand in tandem. Second, policies that might break this electricity sector's inertia take time to be designed, implemented and reach sufficient stringency to make a difference, as has been the case, for example, with carbon pricing[10]. Furthermore, incumbent policies, such as fossil-fuel subsidies can erode the effectiveness of RE-promoting efforts.

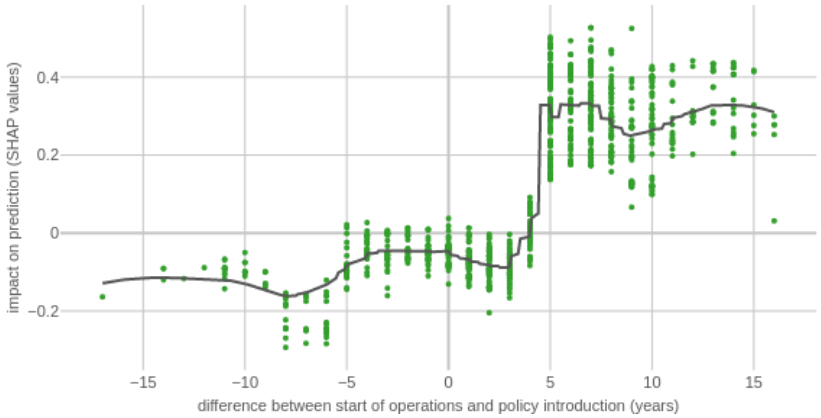
Although to date several African countries have feed-in-tariff and auctions in place (over a fifth and a half of countries, respectively)[11], the realised capacity mix as well as future pipeline attributes a modest role to RE. At the same time, fossil-fuel subsidies across the continent still amount to USD 45 billion, according to 2017 estimates, while post-tax subsidies, which in addition incorporate environmental and other damages associated with the continued use of fossil fuels, total USD 166 billion, with the energy subsidies in the electricity sector accounting for over half and nearly one-fifth, respectively[12]. Nevertheless, only South Africa has currently a carbon tax in place[11] which was introduced in 2019, taking the Parliament nearly a decade to approve. While its baseline price per tonne of CO_2 is ZAR 120, the accompanying tax breaks, aiming to cushion the effect for emitters and give them time to adapt, result in the effective tax rate in the policy's first phase from 2019 to 2022 to vary between ZAR 6 and ZAR 48. The electricity sector enjoys a tax-free allowance up to 90%[13]. This falls significantly short of EUR 30, the lowest conservative estimate of the social cost arising from a tonne of CO_2. In 2015, only 1% of the emissions from the electricity sector across G20 countries, which includes South Africa, were taxed above this level, while a third were not taxed at all[10]. In view of this, it is unlikely that an abrupt large-scale policy action across Africa could occur to considerably alter the composition of its pipeline towards RE in the next decade. Furthermore, as we make a medium-term prediction, even if such a shock does take place, it is unlikely to have an immediate and a full-blown effect on the pipeline before 2030.

That said, incremental organic changes to the pipeline might take place, in that some projects not yet planned with technologies of relatively shorter lead times could still be added and reach commissioning until 2030, introducing a data-related limitation to our analysis. We do, however, expect this effect on the overall predicted capacity in 2030 to be small for the following reasons. First, additional substantive capacity increases are unlikely in the ten-year timeframe under consideration, because project pipelines are informed by long-term national and regional capacity addition plans, aiming to match estimated future demand[14]. Second, we find the total planned capacity already in the pipeline to exceed forecasted demand (see Supplementary Table 1), making substantial pipeline additions, such as large-scale natural gas or solar and wind capacity across many countries unlikely. Third, should new projects not currently in the pipeline still be commissioned between 2020 and 2030, they are likely to be smaller plants that are faster to implement, and would not thus substantially affect our capacity prediction. Fourth, countries' lack of prior experience with RE could result in substantial delays in project implementation even if construction times per se are relatively short[15]. For example, based on our data, as of 2019, only 13 African countries had at least three on-grid solar, and only eight had at least three on-grid wind plants in operation. While solar and wind plants might be relatively faster to build compared to gas and coal, and especially hydro and nuclear projects, the time between their conception and financial closure can still span several years, should they require developments in policies, regulations, financial mechanisms and physical infrastructure. The introduction of Uganda's RE feed-in-tariff scheme, first conceived in 2012 and coupled with a plan to add a total of 158 MW from 17 RE projects, is a case in point. Despite its Electricity Regulatory Authority being ranked as the best regulator by the 2019 Electricity Regulatory Index for Africa[16] and the strong support from the German development bank KfW, several projects are not envisaged to come online until 2021, nearly a decade after their conception[17]. For some plants, construction has not yet begun, while others continue to experience delays in transmission infrastructure[17]. Furthermore, we find that the countries that have already commenced their low-carbon transition such as South Africa, Cape Verde, Egypt, Kenya, Morocco and Namibia, do have substantial non-hydro RE capacity in their pipelines. In view of these arguments, while some additional RE capacity might be added beyond the current pipeline before 2030, it is unlikely to fundamentally change the predicted capacity mix, unless a radical policy shift is implemented, the implications of which we explore in our scenario analysis.

Supplementary Note 3: Decarbonisation policy shock

In addition to our main model, we ran a series of decarbonisation scenarios. In order to achieve a low-carbon future, significant policy interventions would be required[18,19]. First, we assume that all African countries adopt RE-promoting policies (e.g. an auction, feed-in-tariff or a renewable-portfolio-standard type of mandate for utilities), which would incentivise RE adoption by the electricity sector. South Africa, that has seen by far the largest RE expansion over the past decade, has all of these mechanisms in place[11]. Second, in line with the assumptions adopted by the existing energy-planning scenarios[20], we assume the reduction of pre-tax fossil-fuel subsidies, particularly by North African countries where these are the highest[21], and the introduction of a carbon pricing mechanism that would compensate for the negative externalities from the continued use of fossil fuels. We do not anticipate for carbon capture and storage (CCS) to play a significant role in Africa in the next decade, given that it has not yet been scaled up to a sufficient level anywhere in the world. RE investments are also known to be a preferred decarbonisation lever compared to CCS, especially in countries abundant in RE resources[22]. In an optimistic case, we assume this combination of decarbonisation policies across the whole continent to be announced at the earliest in time for COP27 in November 2021. Based on the experience of South Africa's carbon tax (see Supplementary Note 2), the design and implementation of this decarbonisation policy package could realistically take a few years after its announcement. Moreover, our results of including a feed-in-tariff variable in the model also point to a several-year lag in the impact of the policy on project realisation. The effect starts to gradually increase prior to the policy being adopted, possibly in anticipation of its launch after the announcement. An actual jump in the impact on the prediction takes place around the five-year mark after the introduction of the policy (see figure below). We expect that the decarbonisation policies would experience a similar lag in their impact on the composition of the pipeline. We therefore assume that the policy shock will start to affect the planned projects towards the second half of the decade and its effect would be limited at first. This is also due to the challenges Covid-19 pandemic in 2020 has posed to public and private finance, and therefore a sudden removal of fossil-fuel subsidies and introduction of new taxation that would further strain power-generating companies could be politically unpopular and thus rather unlikely.

The impact of the feed-in-tariff on the model's prediction. The feature feed-in-tariff constitutes a difference in years between a plant's start of commercial operations and the introduction of a policy. The negative value implies the time before the introduction of a policy. The line is a guide for the eye, and the vertical distribution of data points indicates interaction effects of the feature.



We ran a series of scenarios, assuming that the aforementioned policy interventions result in the following changes to the pipeline, as we currently know it. The first 'decarbonisation' scenario entails the cancellation of half of all planned coal- and oil-fuelled, and a third of gas-fired capacity with an envisaged completion date from 2025 onwards. The relatively lower cancellation rate of gas capacity is to reflect its load-balancing potential and role as a transition fuel[23]. Taking into account the differences in the capacity factors across technologies, the lost fossil-fuelled generation is assumed to be replaced by equivalent non-hydro RE generation, duplicating existing planned projects and ensuring a shift towards favourable project characteristics, to increase their realisation chances. This implies, first, planning smaller projects associated with higher success chances (we therefore quartered capacity of planned RE projects, while increasing their overall number). Second, the development finance lever is also important. This includes offering development finance to the RE projects other than solar that did not have participation from development finance institutions (DFIs) but are associated with relatively lower success rates, and the withdrawal of DFIs from all fossil-fuel-based projects. Furthermore, we assume the government ownership of a fifth of the capacity planned otherwise as owned by independent power producers, given that state-owned projects have had higher success chances in the past, as well as the transfer of all projects designed as public-private partnerships to the government, given that the former are associated with high failure rates. Finally, we assume at least 10% of solar capacity in the pipeline to be off-grid across all countries. As a result, we obtain a new pipeline with considerably less fossil-fuelled and more RE-based capacity planned. Given that our modelling results indicate that country-level variables have a relatively smaller impact on project success chances, and they would arguably also take longer to change dramatically, we have not assumed changes to these features.

The second 'rapid decarbonisation' scenario builds upon the first scenario by assuming an immediate cancellation of all currently planned coal- and oil-fired, and a third of gas-fuelled capacity, and their replacement by equivalent non-hydro RE generation, as explained above. The third 'rapid decarbonisation and early retirement' scenario expands on the second scenario by introducing an early retirement of coal- and oil-fired plants that would reach 30 years by 2030, and the replacement of this lost generation by additional non-hydro RE projects. Based on the probabilities that the projects in the different pipelines will be realised, we arrive at the predicted capacity mixes for 2030 (Supplementary Table 7; Methods).

Supplementary Note 4: Coverage of off-grid plants in Live Data by African Energy

The Live Data have information on 4.7 GW of operating off-grid capacity, of which RE including hydro contribute 721 MW. This accounts for over two-thirds of a recent IRENA's estimate, that covers amongst others industrial and commercial off-grid capacity[24], which is likely to constitute the majority of the plants currently missing from Live Data. That said, Live Data do contain a number of these auto-producer projects, both failed and successful. This is important, since what matters most for our model is the availability of different types of projects in the training set to learn from, rather than the actual number of those plants. Furthermore, industrial and commercial plants are comparatively easy to implement and operate as their developer is usually also the only power off-taker, resulting in a steady and predictable cashflow. They are therefore likely to be associated with lower failure chances. As a result, when they are present in the dataset, they contribute to the overall low failure rate of off-grid plants, at the same time, when they are absent, they do not affect it. By contrast, mini-grids that involve complex off-taking arrangements, operating an autonomous distribution grid in addition to the decentralised power supply, and importantly face higher cost pressures to break even, are expected to see more projects fail. Since mid-2000s, many African countries have implemented off-grid regulations[25], which require the developers of mini-grids, to register these projects and obtain a generation license. This formalisation, together with the local media attention such plants tend to attract, has made it easier to track these projects at their planning stage. The recent rise of widely publicised competitive tenders in off-grid power generation[26] also implies that these plants are made public during their planning period and long before being commissioned. Therefore, we expect a rather good coverage of mini-grid projects in both the past data as well as the pipeline. That said, some mini-grid plants have been associated with operations ceasing prematurely, after they had already been commissioned. Tracking these failures is, however, difficult as operational challenges are not always reported. This situation might improve in the future with organisations such as the Global Off-Grid Lighting Association (GOGLA), Africa Mini-grid Developers Association (AMDA) and the Mini-Grids Partnership (MGP) compiling and publishing more detailed data on mini-grid projects in Africa. Yet, as mini-grids account for less than 20% of off-grid capacity in Africa[24], the effect of this data limitation on our results is likely to be limited. It is also noteworthy that one of the strengths of GBT models, as mentioned below, is their significant robustness to data imbalances, unless there are nearly no data

on a certain type of projects to learn from, which is not the case here. Therefore, the fact that there are fewer failed than commissioned off-grid projects does not affect the prediction. In fact, the bias on the prediction (the difference between predicted and actual average success rate) of off-grid plants is negative and small (-0.8). If data imbalance towards commissioned plants had an impact on the prediction accuracy, one would expect a positive and a significantly higher bias. Finally, given the generally small size of off-grid plants, they are expected to have a minimal impact on the final predicted capacity.

Supplementary References

1. *Africa Energy Outlook 2019* (IEA/OECD, 2019).
2. Trotter, P. A., Maconachie, R. & McManus, M. C. Solar energy's potential to mitigate political risks: The case of an optimised Africa-wide network. *Energy Policy* **117**, (2018).
3. van der Zwaan, B., Kober, T., Longa, F. D., van der Laan, A. & Jan Kramer, G. An integrated assessment of pathways for low-carbon development in Africa. *Energy Policy* **117**, 387–395 (2018).
4. Taliotis, C. *et al.* An indicative analysis of investment opportunities in the African electricity supply sector - Using TEMBA (The Electricity Model Base for Africa). *Energy Sustain. Dev.* **31**, 50–66 (2016).
5. *Africa Power Sector: Planning and Prospects for Renewable Energy* (IRENA, 2015).
6. Lucas, P. L. *et al.* Future energy system challenges for Africa: Insights from Integrated Assessment Models. *Energy Policy* **86**, 705–717 (2015).
7. Hughes, B., Joshi, D. & Moyer, J. *Strengthening Governance Globally: Forecasting the Next 50 Years*. (Paradigm / Oxford University Press, 2014).
8. Africa Confidential reports that Construction of Kafue Gorge Lower hydropower station in limbo as China halts funding. *LusakaTimes* https://www.lusakatimes.com/2020/01/21/africa-confidential-reports-that-construction-of-kafue-gorge-lower-hydropower-station-in-limbo-as-china-halts-funding/ (2020).
9. *Somalia: Energy Sector Needs Assessment and Investment Programme* (AfDB, 2015).
10. *Effective Carbon Rates 2018*. *Effective Carbon Rates 2018* (OECD, 2018).
11. *Renewables 2020 Global Status Report*. *REN21 Secretariat* (REN21, 2020).
12. *Fossil Fuel Subsidies Database* (IMF, accessed 1 April 2020); https://www.imf.org/en/Topics/climate-change/energy-subsidies.
13. *South Africa Carbon Tax: Rethinking Decarbonisation Incentives - Policy Case Studies* (Energy Systems Catapult, 2018).
14. Ouedraogo, N. S. Modeling sustainable long-term electricity supply-demand in Africa. *Appl. Energy* **190**, 1047–1067 (2017).
15. Steffen, B., Matsuo, T., Steinemann, D. & Schmidt, T. S. Opening new markets for clean energy: The role of project developers in the global diffusion of renewable energy technologies. *Bus. Polit.* **20**, 553–587 (2018).
16. *Electricity Regulatory Index for Africa* (AfDB, 2019).
17. *GET FiT Uganda Annual Report 2019* (KfW, 2020).
18. Pfeiffer, A., Hepburn, C., Vogt-Schilb, A. & Caldecott, B. Committed emissions from existing and planned power plants and asset stranding required to meet the Paris Agreement. *Environ. Res. Lett.* **13**, (2018).
19. Calvin, K., Pachauri, S., De Cian, E. & Mouratiadou, I. The effect of African growth on future global energy, emissions, and regional development. *Clim. Change* **136**, 109–125 (2016).
20. *Africa Power Sector: Planning and Prospects for Renewable Energy* (IRENA, 2015).
21. *Global Fossil Fuel Subsidies Remain Large: An Update Based on Country-Level Estimates* (IMF, 2019).
22. Sgouridis, S., Carbajales-Dale, M., Csala, D., Chiesa, M. & Bardi, U. Comparative net energy analysis of renewable electricity and carbon capture and storage. *Nat. Energy* **4**, 456–465 (2019).
23. Mac Kinnon, M. A., Brouwer, J. & Samuelsen, S. The role of natural gas and its infrastructure in mitigating greenhouse gas emissions, improving regional air quality, and renewable resource integration. *Progress in Energy and Combustion Science* **64**, 62–92 (2018).
24. *Off-grid renewable energy solutions: Global and regional status and trends* (IRENA, 2018).
25. *Policies and regulations for renewable mini-grids* (IRENA, 2018).
26. *Prospects for Private Power Investment in Sub-Saharan Africa in the new decade* (University of Cape Town, 2020).

Appendix B: Supplementary Materials for Chapter 4

nature research

https://doi.org/10.1038/s41560-020-00686-5

Supplementary information

A global analysis of the progress and failure of electric utilities to adapt their portfolios of power-generation assets to the energy transition

In the format provided by the authors and unedited

Supplementary Information

A global analysis of the progress and failure of electric utilities to adapt their portfolios of power-generation assets to the energy transition

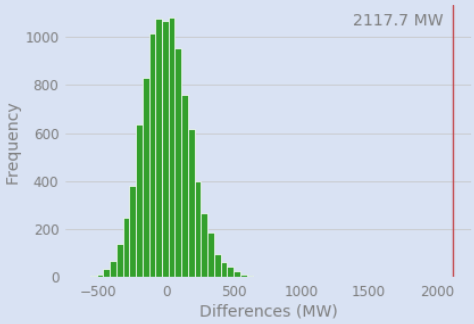
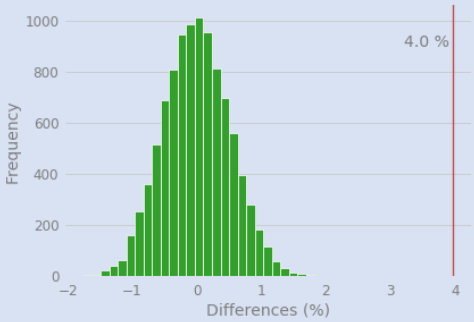
Galina Alova

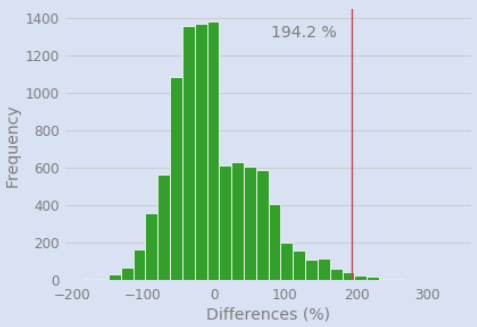
University of Oxford, galina.alova@ouce.ox.ac.uk

Supplementary Table 1: Results of the clustering analysis. RE refer to non-hydro renewables.

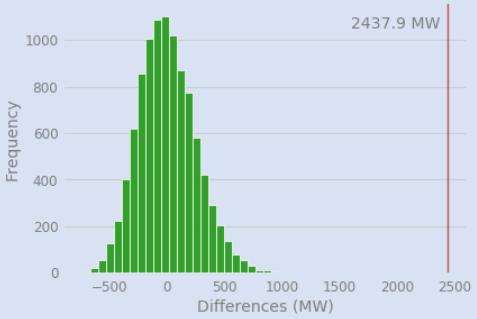
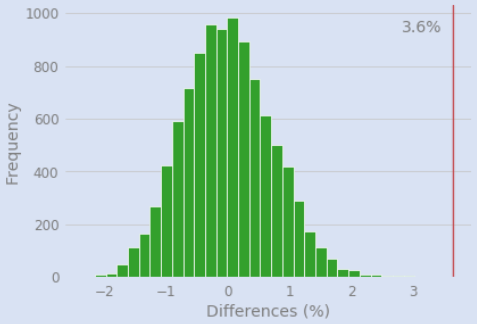
Core and sub-clusters	no. of utilities	average growth in RE capacity	average growth in coal capacity	average growth in gas capacity
passive	2509	-0.1%	-0.1%	-0.2%
gas-prioritising	347	1.0%	0.8%	13.3%
sub-cluster: fast gas-growing	*70*	*-1.3%*	*2.9%*	*26.0%*
fast gas-prioritising	32	0.6%	0.3%	77.9%
RE-prioritising	344	13.8%	0.4%	2.3%
sub-cluster: fast RE-growing with gas	*25*	*48.5%*	*-1.1%*	*18.7%*
coal-prioritising	79	1.0%	27.3%	0.7%
sub-cluster: fast coal-growing	*13*	*0.0%*	*63.2%*	*0.2%*

Supplementary Table 2: Results of the hypotheses testing. The hypotheses were tested using the bootstrap approach (see Methods). H9-H13 include policies either at the national or sub-national level. RE refer to non-hydro renewables. FIT refers to feed-in-tariff, RPS to renewable portfolio standard, ETS to emission trading system, CT to carbon tax.

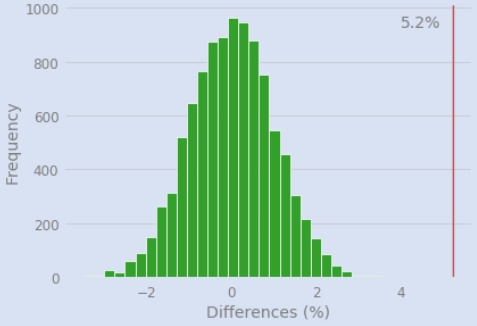
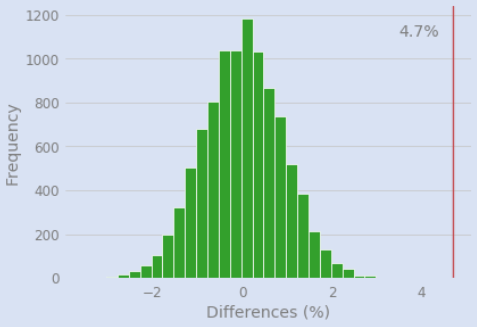
Hypothesis	p-value	observed difference	Histogram of randomly sampled differences, compared to observed difference
Characteristics of the utilities in the passive cluster			
H1: The utilities in the active clusters are larger in terms of their generation capacity than the companies in the passive cluster.	$<10^{-4}$	2,117.7 MW	
H2: The utilities in the active clusters have a larger market share than the companies in the passive cluster.	$<10^{-4}$	4.0%	

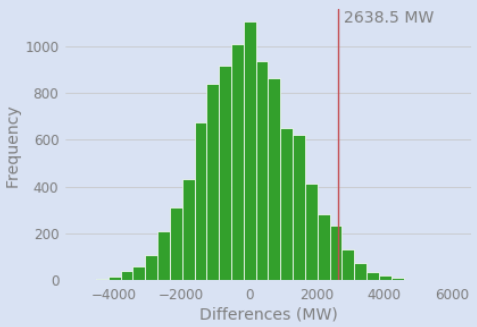
H3: The utilities in the active clusters have larger overall capacity growth than the companies in the passive cluster.	7.8×10^{-3}	194.2%	

Characteristics of the utilities in the renewables-prioritising cluster

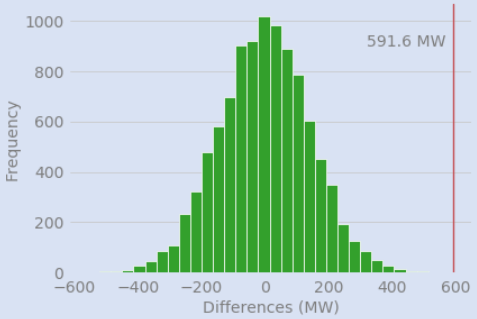
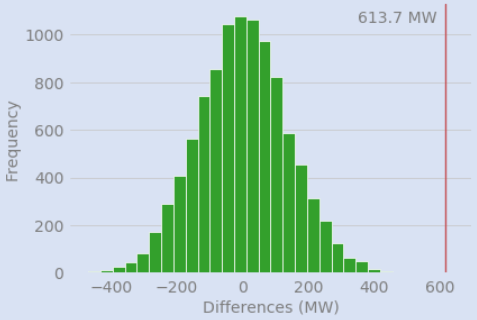
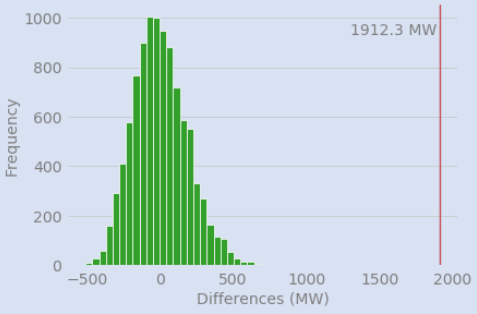
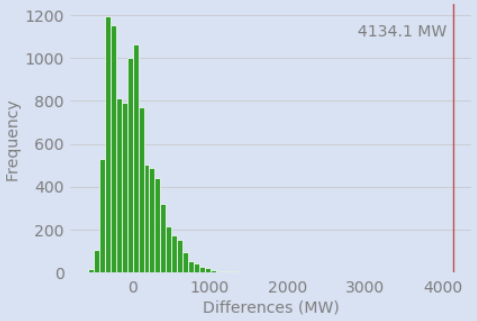
H4: The companies in the RE-prioritising cluster are larger in terms of their generation capacity than the companies in the other clusters.	$<10^{-4}$	2,437.9 MW	
H5: The companies in the RE-prioritising cluster have a larger market share than the companies in the other clusters.	$<10^{-4}$	3.6%	

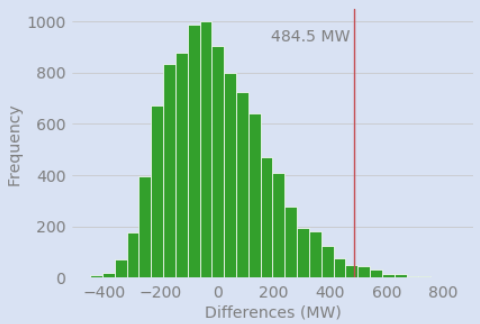
Market structure of the jurisdictions where RE-prioritising utilities operate

H6: The utilities in the RE-prioritising cluster are in the jurisdictions with a higher share of IPP-owned power generation capacity than the utilities in the other clusters.	$<10^{-4}$	5.2%	
H7: The utilities in the RE-prioritising cluster are in the jurisdictions with a higher share of non-utility-owned generation capacity (IPPs and auto-producers) than the utilities in the other clusters.	$<10^{-4}$	4.7%	

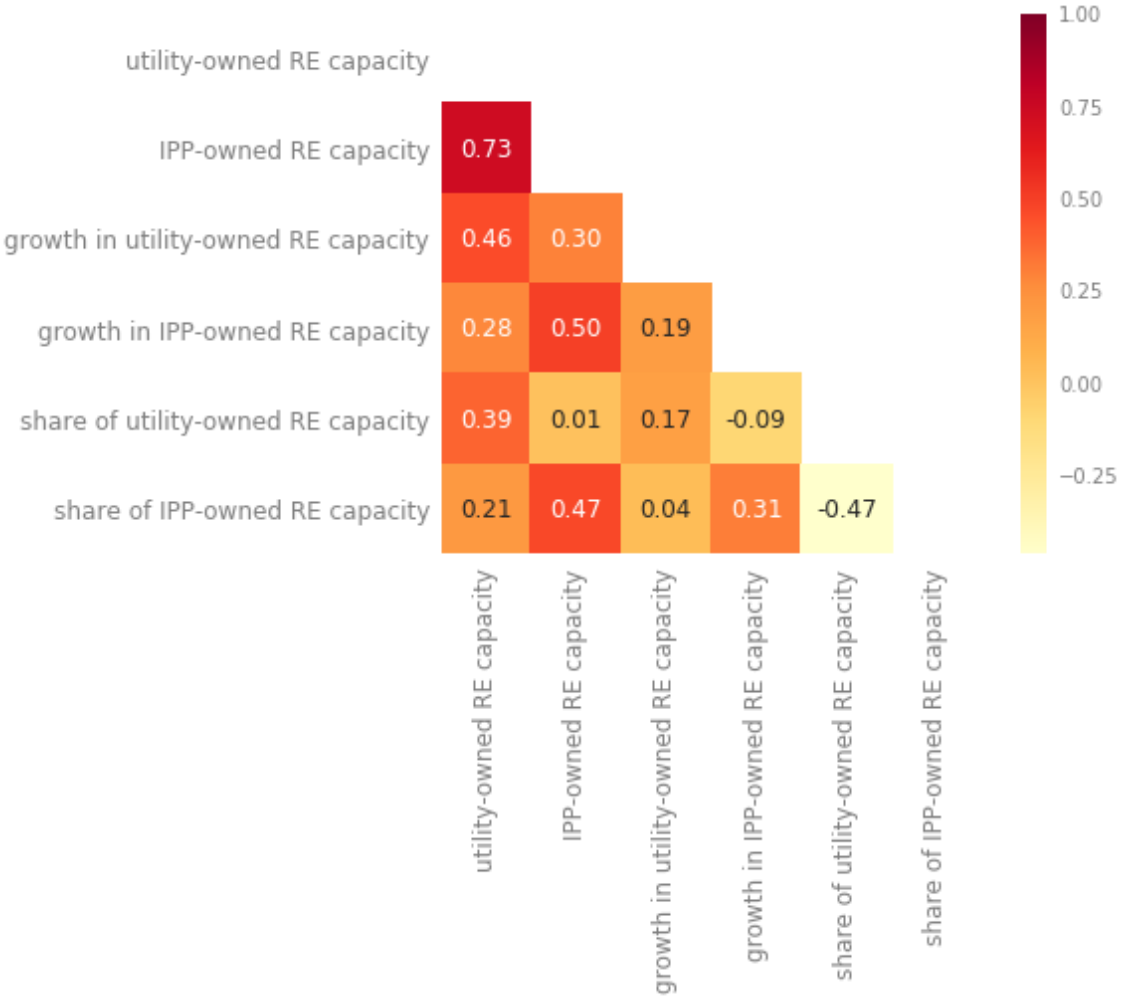
H8: The utilities in the RE-prioritising cluster are in the jurisdictions with higher IPP-owned RE capacity, compared to the utilities in the other clusters.	3.3×10^{-2}	2,638.5 MW	

Relationship between enabling policies and renewables capacity

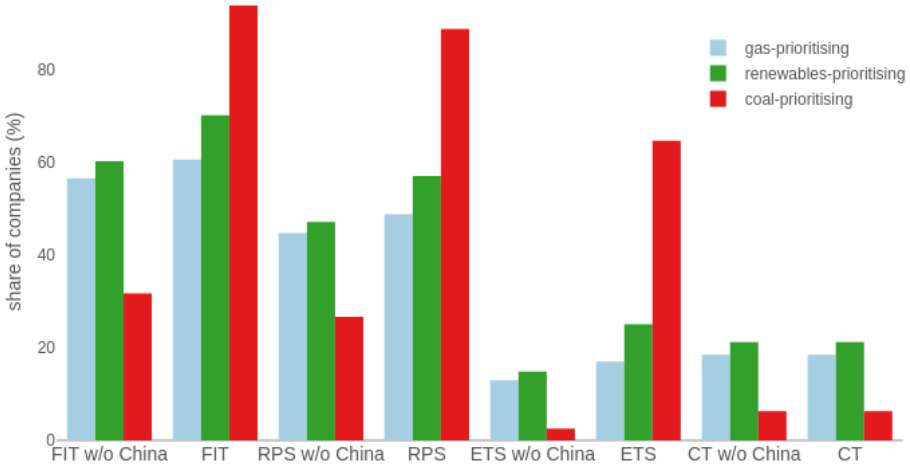
H9: The jurisdictions with at least one or all of the enabling policies (FIT, RPS, CT, ETS) have higher utility-owned RE capacity than the jurisdictions without any of the policy instruments.	$<10^{-4}$	591.6 MW	
H10: The jurisdictions with FIT in place have higher utility-owned RE capacity than the jurisdictions without the policy.	1×10^{-4}	613.7 MW	
H11: The jurisdictions with RPS in place have higher utility-owned RE capacity than the jurisdictions without the policy.	$<10^{-4}$	1,912.3 MW	
H12: The jurisdictions with ETS in place have higher utility-owned RE capacity than the jurisdictions without the policy.	$<10^{-4}$	4,134.1 MW	

H13: The jurisdictions with CT in place have higher utility-owned RE capacity than the jurisdictions without the policy.	$1.3x10^{-2}$	484.5 MW	

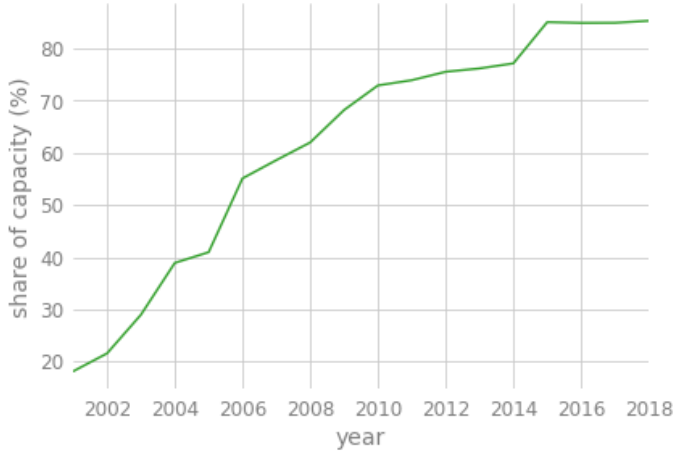
Supplementary Figure 1: Correlations between utility- and IPP owned renewables capacity. The results were obtained, using Spearman method, which is suitable for the data that are not normally distributed.



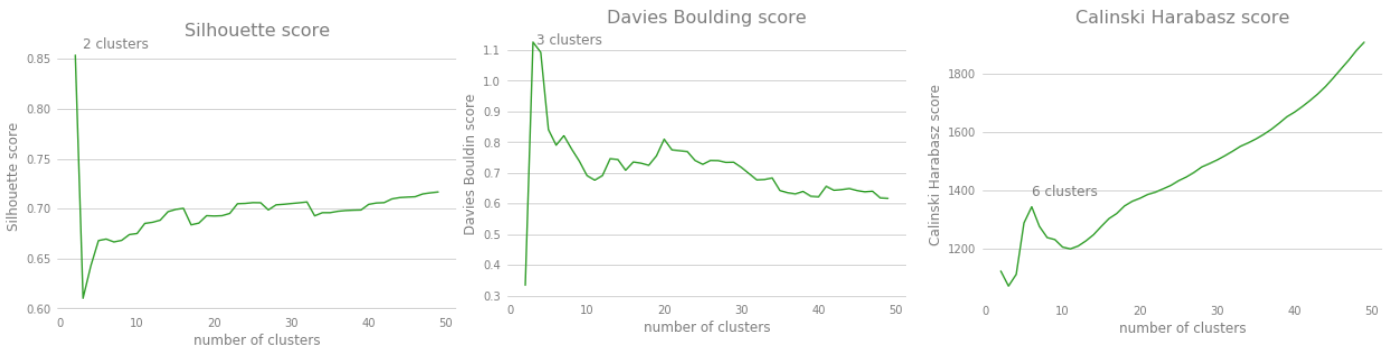
Supplementary Figure 2: Share of the utilities in the renewables-, gas- and coal-prioritising clusters located in the jurisdictions with energy transition-enabling policies. FIT refers to feed-in-tariff, RPS to renewable portfolio standard, ETS to emission trading system, CT to carbon tax. The results are depicted with and without China. In the paper, the results are presented without the Chinese utilities, given that China is a special case and an outlier. It has FIT, RPS and ETS in place, but still dominates the coal-growing companies' landscape. The inclusion of China would skew the analysis on the policy-related characteristics of the clusters, with the results pointing to little evidence of a link between the existence of enabling policies and the companies' allocation to clusters.



Supplementary Figure 3: Share of global power generation capacity covered by at least one renewables-promoting or fossil fuel-inhibiting policy. As in Supplementary Figure 2, the policies included in the calculation comprise FIT, RPS, ETS and CT.



Supplementary Figure 4: Metrics to determine the optimal number of clusters



Supplementary Note 1: Companies' asset ownership

In the analysis, I adopt a bottom-up approach, examining the portfolio developments of the companies immediately owning the power-generation assets, rather than of their parent companies, for the following reasons, data availability and quality aside. First, there seems to be a lack of consensus in the literature on the degree of autonomy exercised by subsidiaries of multi-national companies, including in the energy sector[1], with studies arguing both for parent company controlling subsidiary decision making, and for subsidiary strategies being dictated by local contexts rather than their headquarters[2–4]. Furthermore, subsidiaries might operate in a different energy sub-sector from their parent companies, such as the power subsidiaries of oil majors, e.g. Shell Energy. As a result, I deem it beneficial to explore the transition behaviours of individual subsidiaries, as these might be influenced by location- and business sector-specific circumstances divergent from those of their parent companies and subsidiaries in the other countries.

Second and relatedly, conducting the analysis on parent companies rather than subsidiaries would require careful consideration of the degree of decision-making these companies exercise to determine where to draw a line in this aggregation. For example, in China, where the largest five government-controlled generating companies own over half of current coal capacity, with other state-owned enterprises accounting for a further third[5], individual subsidiaries of these companies could arguably be effectively aggregated to the state itself as their ultimate owner. The landscape of power relationships between these companies and the state, particularly provincial governments, and degree of autonomy they exercise on different decisions is complex and has evolved over time, as a result of a number of reforms[6]. Similarly, aggregating power utilities to their parents, whose core business lies elsewhere, e.g. in oil industry, could also be a debatable decision to take.

Third, aggregating subsidiaries to the parent company could mask the granularity of the individual utilities' behaviour patterns. The key argument here is that the transition of the global power sector implies that utilities at all levels, be it a subsidiary or parent company, are expected, at a minimum, not to grow and reduce their fossil-fuel capacity, and ideally either transition to renewables, other business models or go out of business. These changes would be the clearest at the individual subsidiary level, rather than a parent company. Aggregation could reduce the magnitude and clarity of portfolio growth patterns, which would be diluted by the behaviours of the subsidiaries not growing their fossil-fuel and renewables portfolio, or those with divergent capacity growth strategies. Finally, given that where parent company information was available in the WEPP dataset (see Methods), over 66% of the utilities were not owned by another company (i.e. their name matched the company that was recorded as their parent), I expected that the aggregation of companies to the parent company level would have a limited effect on the results.

To test this in practice, I completed an additional analysis at the parent company level, and examined how this aggregation might affect the results of the clustering at the subsidiary level, should a utility in my sample be owned by another company. I performed the analysis for the period of 2013-2018, for which data on parents are available in the WEPP dataset, to compare the outcome to the results of the original clustering for the same period, conducted as part of the three-period clustering (see Methods). This enabled me to understand how utilities from the original analysis could have been clustered should they have been considered as part of their parent company, provided they had one, rather than on their own. The sample at the parent company level comprises 2,025 companies, compared to 2,403 utilities in the subsidiary sample for the same period.

I find that nearly 90% of the companies did not change their original cluster as a result of the aggregation to their parent company. This might imply that while the two-thirds of the utilities in the original analysis did not have a parent, some that were owned by other companies did share the overall strategy of their parents, and therefore did not change the cluster. Of the utilities that did shift the cluster, over half had come from the passive cluster. This was expected, since parent companies might be relatively more dynamic as a whole than their individual subsidiaries, and can therefore be assigned to an active cluster. For example, over half of the companies that shifted away from their original cluster moved to the renewables-prioritising cohort (these companies came predominantly from the passive cluster). At the same time, the share of renewables capacity in those companies seems to be lower compared to the companies in the subsidiary-level renewables-prioritising cluster. In 2018, over 9% of the renewables-prioritising subsidiaries had over half of renewables in their total capacity, compared to 5% of their parents. This can be explained by the existence of some subsidiaries belonging to the same parent but prioritising fossil fuels or not growing at all.

What is also noteworthy is that company's location does seem to matter, in that over half of the companies that changed the cluster came from a different country than their parent (i.e. had the dominant share of their portfolio in a different country than their parent). This share increases to over 80% when I look at companies' sub-national location, which is particularly important for federal countries such as the US, where the policy environment might differ significantly across the states.

Supplementary References

1. Darmani, A., Arvidsson, N. & Hidalgo, A. Do the strategic decisions of multinational energy companies differ in divergent market contexts? An exploratory study. *Energy Res. Soc. Sci.* **11**, 9–18 (2016).

2. Levy, D. L. & Kolk, A. Strategic Responses to Global Climate Change: Conflicting Pressures on Multinationals in the Oil Industry. *Bus. Polit.* **4**, 275–300 (2002).

3. Dowell, G., Hart, S. & Yeung, B. *Do Corporate Global Environmental Standards Create or Destroy Market Value? Source: Management Science* **46**, (2000).

4. Christmann, P. *Multinational Companies and the Natural Environment: Determinants of Global Environmental Policy Standardization*. *Source: The Academy of Management Journal* **47**, (2004).

5. Cui, R. *et al. A High Ambition Coal Phaseout in China: Feasible Strategies through a Comprehensive Plant-by-Plant Assessment Technical Appendix*. (2020).

6. Zhang, S., Andrews-Speed, P. & Li, S. To what extent will China's ongoing electricity market reforms assist the integration of renewable energy? *Energy Policy* **114**, 165–172 (2018).

Appendix C: Supplementary Materials for Chapter 5

iScience, Volume *24*

Supplemental information

A machine learning model to investigate factors contributing to the energy transition of utility and independent power producer sectors internationally

Galina Alova and Ben Caldecott

Supplemental Tables

Table S1. Features included in the model, Related to STAR Methods

Feature	SHAP value	
	Model I	Model II
Policy features		
Emission standards	0.116965	
Feed-in-tariffs	0.084220	
Emission-related trading schemes	0.082896	
R&D subsidies	0.072981	
Emission-related taxes	0.050898	
Overall environmental policy stringency		0.158092
Market structure features		
Utility market share (utility-owned generation capacity as % of the overall installed capacity)	0.143328	0.182418
Utility-owned renewable energy power plant units (% of overall power plant units owned by the utility sector)	0.108623	0.142591
Average size of a utility company in a given utility sector (in MW)	0.096511	0.120019
Average age of operating power plant units in a given utility sector (in years)	0.096613	0.108769
Investor-owned utility capacity (% of the overall utility-owned capacity)	0.080523	0.100667
Control features		
Solar LCOE difference with coal LCOE (in USD per MWh)	0.138492	0.166918
Country's electricity consumption (kWh per capita)	0.087540	0.116842
Country's onshore wind resource endowment (in GW weighted by class capacity factor)	0.082487	0.101407
Country's solar resource endowment (global horizontal irradiance in kWh per m^2 per day)	0.082394	0.095687

Note: SHAP value is given in absolute mean terms. Model I refers to the model that includes amongst its features policy stringency indices disaggregated by individual policy instruments. Model II includes the aggregate environmental policy stringency.

Table S2. Data sources used in the study, Related to STAR Methods

Data	Source
Power-generation assets	Available from UDI WEPP database under licence agreement with S&P Global Market Intelligence www.spglobal.com/marketintelligence
Environmental Policy Stringency index	Publicly available from OECD Statistics at https://stats.oecd.org/
Electricity consumption per capita	Publicly available from World Bank World Development Indicators at http://wdi.worldbank.org
Country solar resource endowment	Publicly available from Solargis, funded by World Bank's Energy Sector Management Assistance Program, at https://datacatalog.worldbank.org/dataset/global-photovoltaic-power-potential-country
Country wind resource endowment	Publicly available from National Renewable Energy Laboratory at https://data.openei.org
Levelised cost of electricity	Publicly available from Lazard at https://www.lazard.com/perspective/levelized-cost-of-energy-and-levelized-cost-of-storage-2020/

Table S3. Model's evaluation metrics, Related to STAR Methods

	Model I		Model II	
	Training	Test	Training	Test
Mean absolute error	1.197082	1.194258	1.201036	1.193129
Median absolute error	0.284053	0.337052	0.282056	0.336630
Root mean squared error	2.726044	2.678556	2.732350	2.689973

Note: Model I includes five individual environmental policy stringency indices as features, Model II includes an aggregate environmental policy stringency index (see STAR Methods for more information on model specifications).

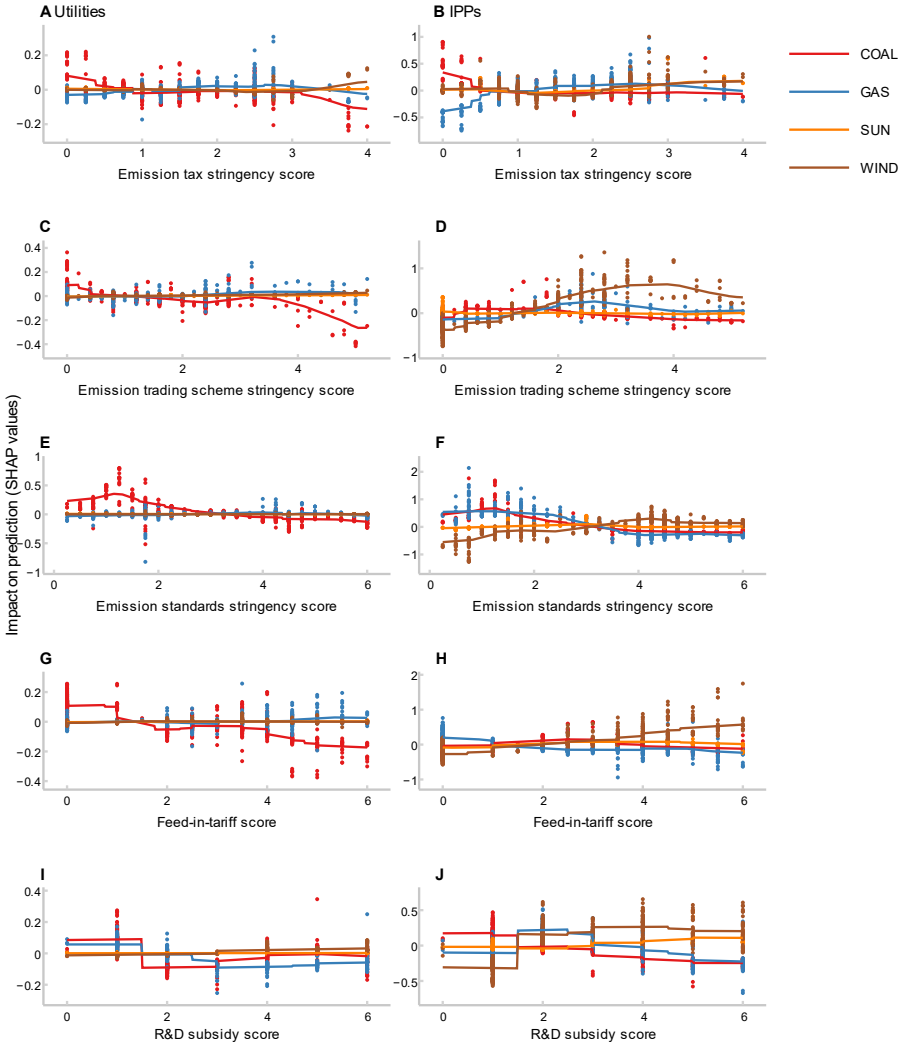
Table S4. Values of tuned hyperparameters for model, Related to STAR Methods

Name of parameter	**Meaning**	**Parameter value**	
		Model I	**Model II**
n_estimators	Number of trees	930	990
learning_rate	Speed at which the model is trained	0.005	0.005
depth	Maximum depth of a tree	6	6
min_data_in_leaf	The minimum number of training samples in a leaf	20	11
rsm	Random subspace method refers to the percentage of features to use at each split selection	0.74961704767429	0.8301163533086889
l2_leaf_reg	Coefficient at the L2 regularization term of the cost function	0.0007530983669306539	0.00022893568099015927
random_strength	The amount of randomness to use for scoring splits when the tree structure is selected	2.4024007814056305	2.1331556427421905
bagging temperature	Defines the settings of the Bayesian bootstrap	1.7172345539315241	0.7909534486735544

Note: Model I includes five individual environmental policy stringency indices as features, Model II includes an aggregate environmental policy stringency index (see STAR Methods for information on features)

Supplemental Figures

Figure S1. Impact of environmental policy instruments on generation capacity growth by technology and company type, Related to Figure 1



Note: Each feature's impact on the prediction is expressed in SHAP values, that is, the change in log odds (see STAR Methods). The trend line is a visual aid to the eye. According to the OECD methodology, the stringency scores of environmental policy range between 0 and 6.

Figure S2. Interaction effect graphs, Related to Figure 1

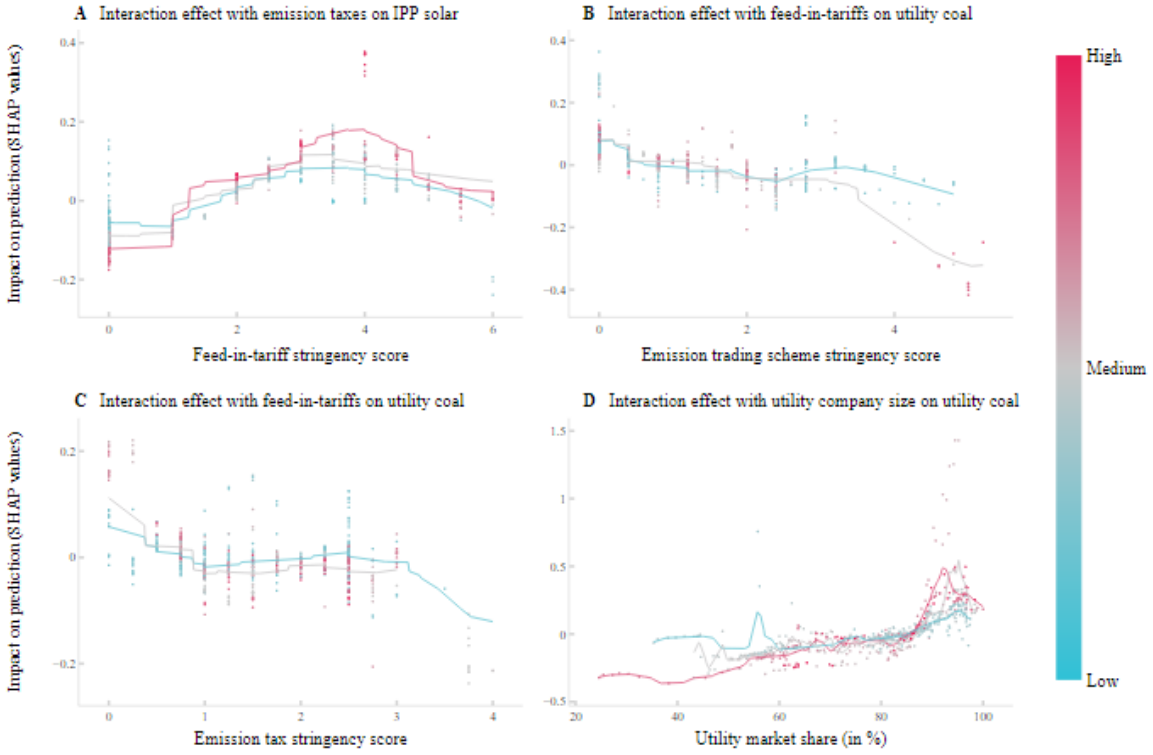
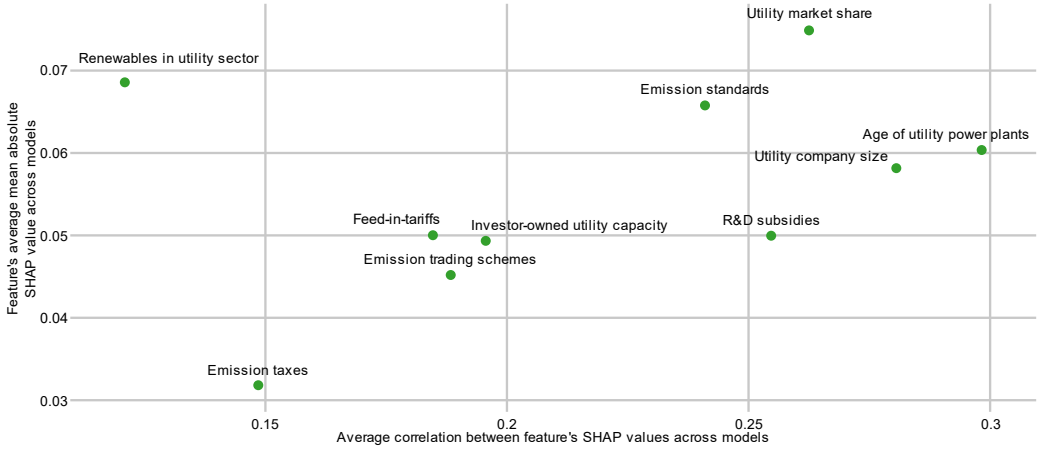


Figure S3. Correlation matrix: Visualisation of the feature impact and correlation matrix, Related to STAR Methods



Note: As part of the feature selection process, three models with multiple splits were trained using the training set data, to identify most stable features (see STAR Methods). Here, the figure visualises the features included in the final model. The y-axis presents the average of mean absolute impacts (expressed in SHAP values) of a feature on the predictions of the three models. The x-axis presents the average of the correlations between these impacts, denoting the relationship between what each model learned about the feature's impact. Higher correlations imply higher similarity in this learning, i.e. stronger feature stability and its ability to generalise beyond the training set. Features with a negative mean correlation were excluded from the final model.

Appendix D: Overview of gradient boosted decision trees

This section offers further technical detail on the gradient boosted decision trees (GBDT) models that I built in the analysis in Chapter 3 and Chapter 5, beyond the information already provided in the Methods sections of these chapters.

GBDT models are a supervised machine-learning-based technique, in that a target variable is predicted using the information from several input variables, i.e. features. These models can be used both for classification problems, as in Chapter 3, or a regression analysis, as in Chapter 5[1]. Being an ensemble method, the aim of the GBDT models is to derive a prediction from an ensemble of shallow trees, where every next tree reduces the loss of the previous tree[2]. In that respect, GBDTs are trained in a sequential additive manner, and in simple terms, can be written as follows:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i)$$

Where, $\hat{y}_i$ are predictions, f is a function, x_i are input variables, and K is the number of trees built. When looking at individual trees as we learn them, building a new tree at each step t, it follows that at the first step:

$$\hat{y}_i^{t=1} = f_1(x_i)$$

We then fit the next tree $f_2(x_i)$ to the residual $\delta_1 = y_i^{t=1} - f_1(x_i)$ of the previous tree $f_1(x_i)$ and add this new tree to the existing model to reduce this residual, i.e. to improve the overall model's accuracy:

$$\hat{y}_i^{t=2} = f_1(x_i) + f_2(x_i) = \hat{y}_i^{t=1} + f_2(x_i)$$

[1] Hastie, T., Tibshirani, R. and Friedman, J.H. (2009), The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second edi., Springer, New York.
[2] XGBoost (2021), Introduction to Boosted Trees, https://xgboost.readthedocs.io/en/latest/tutorials/model.html

By building more trees we examine how well each new tree does in terms of minimising the loss function L. The goal is that the loss incurred in the model consisting of these two trees is lower than in the model with only the first tree, that is: $L_2 < L_1$. As a result, the second tree $f_2(x_i)$ could also be expressed as the derivative of the loss function with respect to the previous decision tree:

$$f_2(x_i) = -\frac{\partial L}{\partial\, f_1(x_i)}$$

This is essentially the gradient of the loss function with respect to the output of the previous tree model. This is where GBDT models get 'gradient' in their name. So $\hat{y}_i^{t=2}$ could also be expressed as:

$$\hat{y}_i^{t=2} = \; f_1(x_i) \; - \frac{\partial L}{\partial\, f_1(x_i)}$$

Adding new trees to the model results in gradient descent, i.e. in moving along the gradient, minimising the loss between the actual target value and our prediction of the target. The resulting ensemble of models allows reducing variance, making better predictions.

We continue building our model in this manner, by adding new trees $f_3(x_i), \ldots, f_T(x_i)$

$$\hat{y}_i^{t=3} = f_1(x_i) + \; f_2(x_i) + \; f_3(x_i) = \hat{y}_i^{t=2} + f_3(x_i)$$

…

We do so until we reach the T number of trees or early stopping, which is used to avoid model overfitting on the training set, that is performing well in-sample but poorly out-of-sample. This means that the model stops building more trees, when additional trees no longer reduce loss on the validation set, i.e. a sub-set of the data held out form the training set, while might still be reducing loss on the training set, leading to overfitting.

$$\hat{y}_i^{t=T} = \sum_{k=1}^{K=T} f_k(x_i) = \hat{y}_i^{t=T-1} + f_T(x_i)$$

We can also re-write this formula to include μ as a learning rate which controls the extent to which each tree can modify the previous tree, essentially it is the size of the steps allowed along the gradient descent of the loss function:

$$\hat{y}_i^{t=T} = \sum_{k=1}^{K=T} \mu f_k(x_i) = \hat{y}_i^{t=T-1} + \mu f_T(x_i)$$

Taking smaller steps to the goal, i.e. minimum loss, helps to reduce overfitting, by creating more trees, thereby reducing variance through the ensemble of models, and by preventing us from moving too far and too fast along the gradient missing the point of minimum loss. Setting the learning rate too low, however, comes at a computational cost, as it might take the model a long time to reduce loss.

Appendix E: Dissemination of DPhil research at conferences

Major international conferences and workshops that I have presented at during my DPhil include:

Applied Machine Learning Days (AMLD) Africa, September 2021

The Sixth Annual Meeting of the Sustainable Energy Transitions Initiative (SETI), June 2021;

39th International Energy Workshop (IEW), June 2021

International Conference on Sustainable Finance and Investment, April 20201

NeurIPS workshop on Tackling Climate Change with Machine Learning, December 2020

GRASFI 2020, September 2020 – *Best paper prize on Emerging Market Actors*

The Fifth Annual Meeting of the Sustainable Energy Transitions Initiative (SETI), June 2020

GRASFI 2019, September 2019

Achieving NetZero, September 2019 (Oxford ECI)

ETH PhD Academy on Sustainability and Technology, June 2019

Appendix F: Author contributions to Chapters 3-5

Chapter 3

As the first author of the study in Chapter 3, I was responsible for:

- co-designing the research approach
- cleaning the asset-level data and designing features for the model
- building the machine-learning-based model
- validating and interpreting the model
- producing the visuals for the results presentation in the paper and Supplementary Information, exc. Fig. 3.
- leading on drafting the manuscript
- leading on addressing comments of the three peer-review rounds
- working on disseminating the findings, through journalist interviews, conference presentations and op-eds

As the second author, Philipp Trotter:

- worked with me on co-designing the research approach
- prepared the country-level data
- produced Fig. 3
- co-drafted with me the manuscript
- supported me in addressing peer-review comments
- participated with me in results dissemination

As the third author, Alex Money:

- conceived the original research idea
- sourced the asset-level data
- provided an early draft of the paper

Chapter 4

As the single author of the study in Chapter 4, I was responsible for everything from its conception, to the analysis, to post-production results dissemination.

Chapter 5

As the first author of the study in Chapter 5, I was responsible for:

- gathering and cleaning data
- building the machine-learning-based model
- validating and interpreting the model
- producing graphics for results presentation
- drafting and revising the article in response to peer-review comments

As the second author, Ben Caldecott:

- contributed to conceptualising and writing the paper
- reviewed the drafts

SCHOOL OF GEOGRAPHY AND THE ENVIRONMENT

CO-AUTHORSHIP DECLARATION

SECTION 1 – to be completed by the Student.

Name	GALINA ALOVA-BEITNER
Thesis Title	Quantifying patterns of the power generation sector's low-carbon transition using machine learning and asset-level datasets
Title of co-authored chapter(s)	Chapter 3. A machine-learning approach to predicting Africa's electricity mix based on planned power plants and their chances of success

SECTION 2 – to be completed by the co-author for each chapter.

Name	PHILIPP TROTTER
Institution	University of Oxford, RWTH Aachen University
Email address in case of queries	philipp.trotter@smithschool.ox.ac.uk
Please describe the candidate's contribution to the chapter(s).	Galina is the first author of this study. She co-designed the research approach and merged asset- and country-level data. She then built, validated and interpreted the machine-learning-based model and produced the visuals of its results, except for the map (Figure 3). Galina also led with her co-authors' support on writing the manuscript, responding to peer-reviewers' comments and on the post-publication dissemination. The author contribution statement is also available as part of the published article on https://www.nature.com/articles/s41560-020-00755-9.

Signature		Date	29/10/2021

SCHOOL OF GEOGRAPHY AND THE ENVIRONMENT

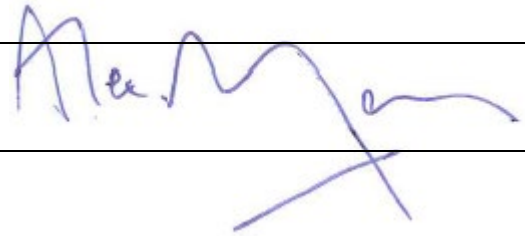
CO-AUTHORSHIP DECLARATION

SECTION 1 – to be completed by the Student.

Name	GALINA ALOVA-BEITNER
Thesis Title	Quantifying patterns of the power generation sector's low-carbon transition using machine learning and asset-level datasets
Title of co-authored chapter(s)	Chapter 3. A machine-learning approach to predicting Africa's electricity mix based on planned power plants and their chances of success

SECTION 2 – to be completed by the co-author for each chapter.

Name	ALEX MONEY
Institution	University of Oxford
Email address in case of queries	alex.money@smithschool.ox.ac.uk
Please describe the candidate's contribution to the chapter(s).	Galina is the first author of this study. She co-designed the research approach and merged asset- and country-level data. She then built, validated and interpreted the machine-learning-based model and produced the visuals of its results, except for the map (Figure 3). Galina also led with her co-authors' support on writing the manuscript, responding to peer-reviewers' comments and on the post-publication dissemination. The author contribution statement is also available as part of the published article on https://www.nature.com/articles/s41560-020-00755-9.

Signature		Date	25/10/2021

SCHOOL OF GEOGRAPHY AND THE ENVIRONMENT

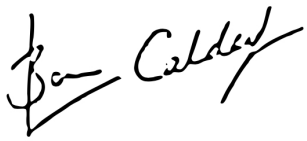
CO-AUTHORSHIP DECLARATION

SECTION 1 – to be completed by the Student.

Name	GALINA ALOVA-BEITNER
Thesis Title	Quantifying patterns of the power generation sector's low-carbon transition using machine learning and asset-level datasets
Title of co-authored chapter(s)	Chapter 5. A machine learning model to investigate factors contributing to the energy transition of utility and independent power producer sectors internationally

SECTION 2 – to be completed by the co-author for each chapter.

Name	BEN CALDECOTT
Institution	University of Oxford
Email address in case of queries	ben.caldecott@smithschool.ox.ac.uk
Please describe the candidate's contribution to the chapter(s).	Galina is the first author of this study. She conceived the research idea, sourced the data, built, validated and interpreted the machine learning model, produced the visuals of the results, and wrote the paper. I contributed to conceptualising and writing the paper and reviewed the drafts. The author contribution statement is also available as part of the published article on https://www.cell.com/iscience/fulltext/S2589-0042(21)00897-X.

Signature		Date	25th October 2021