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.

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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

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

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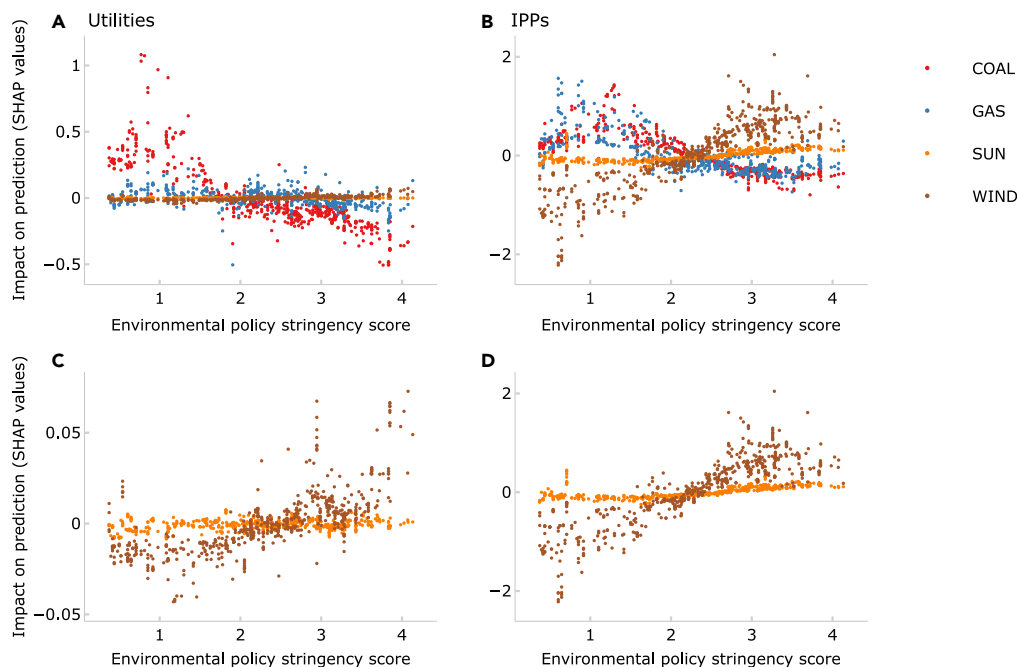
Figure 1. Contributions of environmental policy stringency to capacity growth differentiated by fuel type and ownership

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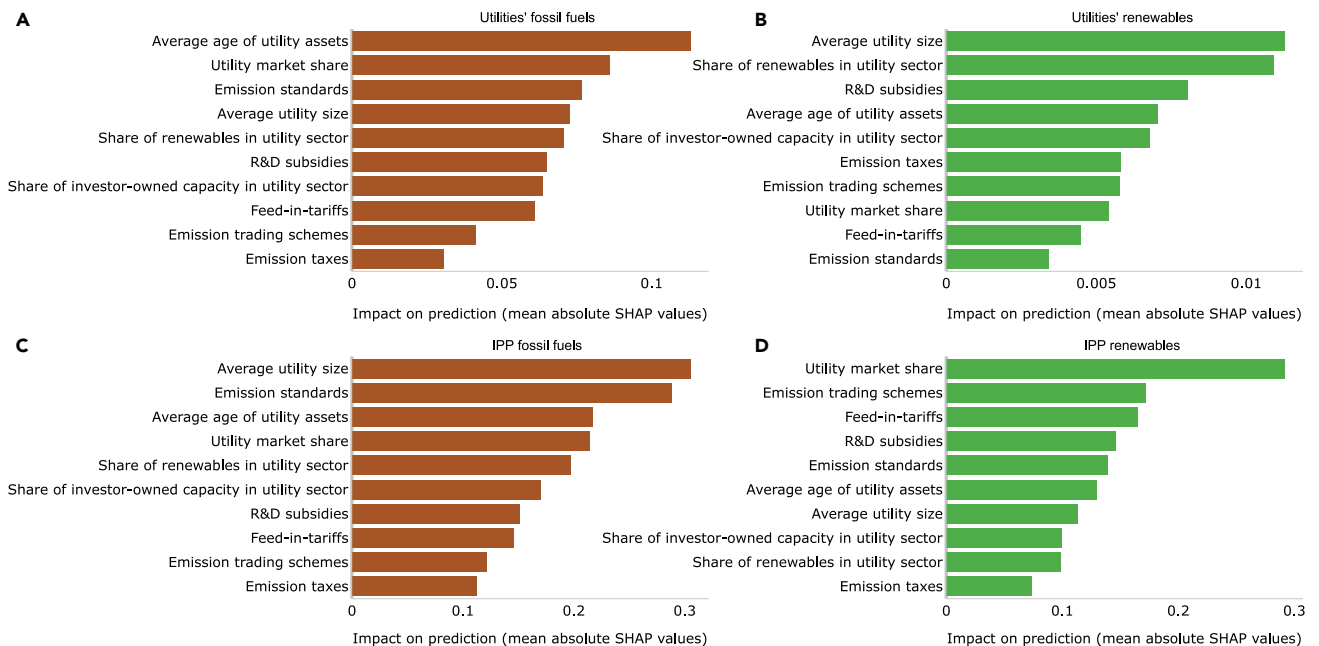
Figure 2. Comparison of feature contributions to generation capacity growth in fossil fuels versus renewables

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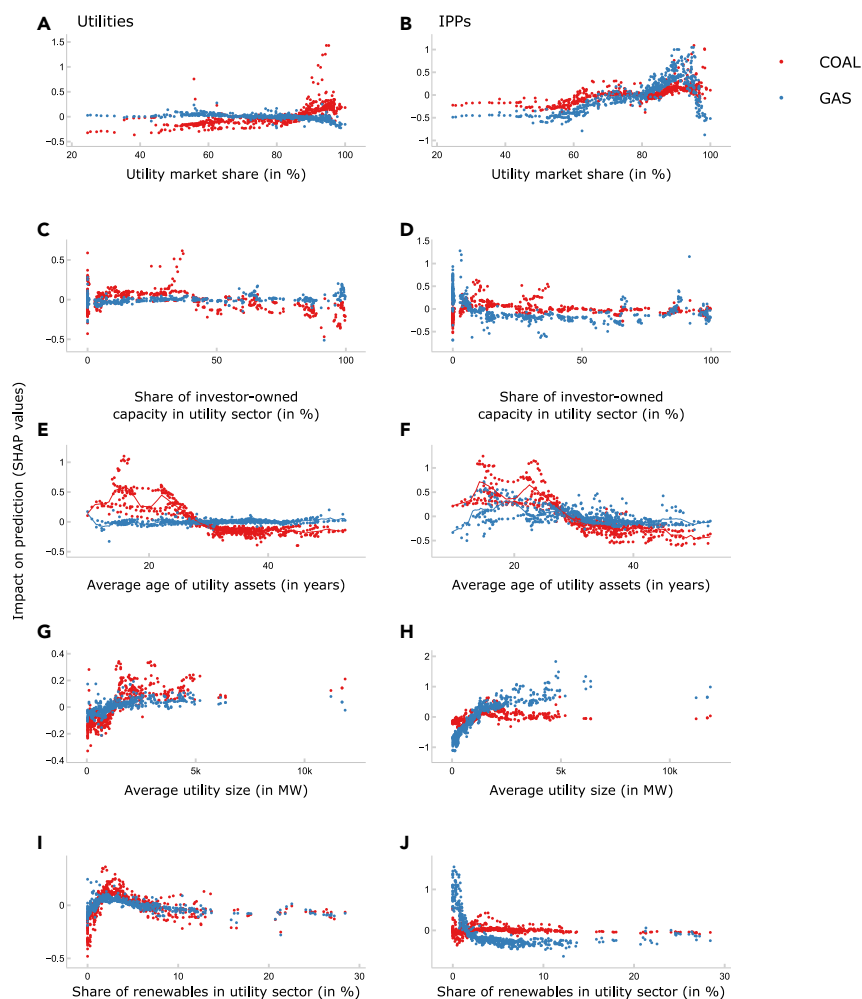
Figure 3. Contribution of market-structure-related features to fossil fuel capacity growth by company sector type

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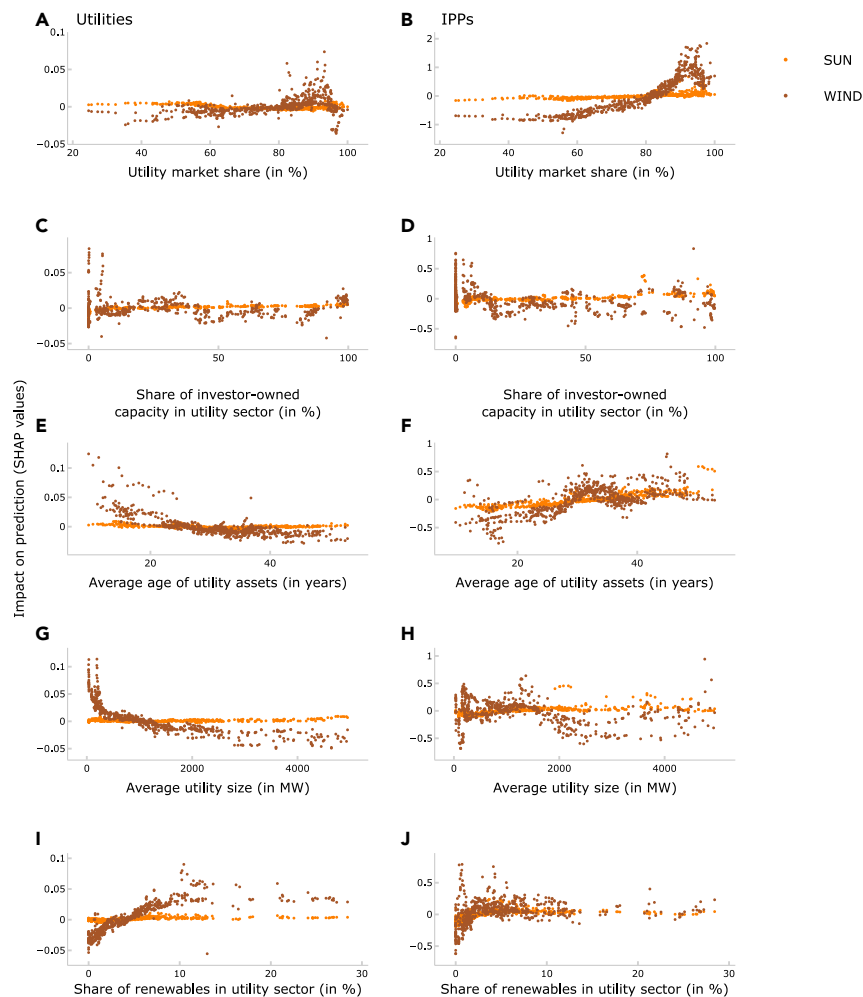
Figure 4. Contribution of market-structure-related features on renewable energy capacity growth by company sector type

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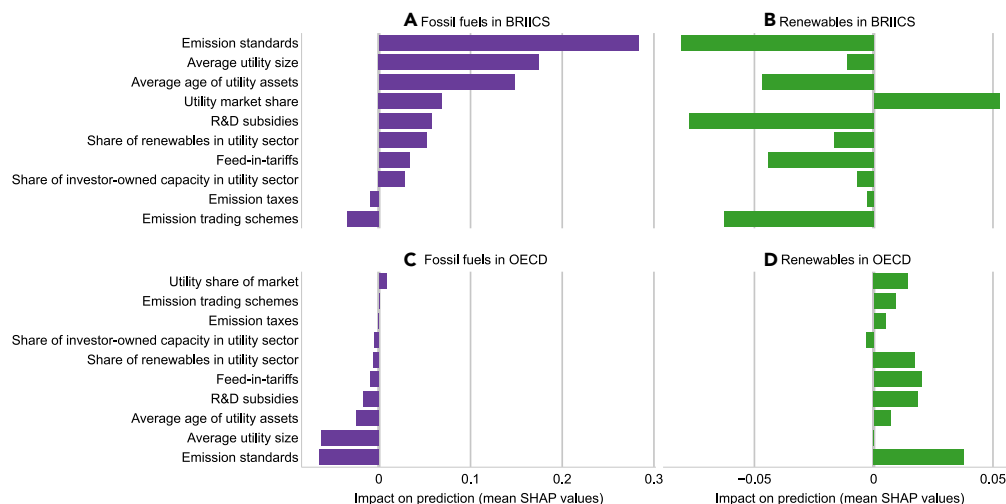
Figure 5. The contributions of policy- and market-structure-related features fossil fuel and renewables growth across BRIICS and OECD countries

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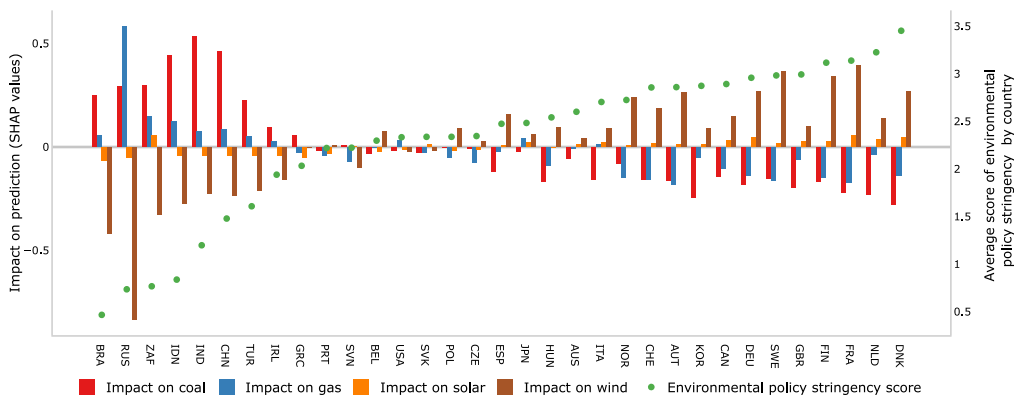
Figure 6. Inter-country differences in environmental policy stringency and implications for technology choices by the electricity sector

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:

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○ 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.

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.

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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).