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Policy interactions and electricity generation sector CO2 emissions: A quasi-experimental analysis

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ABSTRACT

This paper evaluates the static and dynamic effects of four national climate and energy policies—carbon tax, emission trading system (ETS), renewable energy auctions, and feed-in policy—on reducing CO2 emissions per capita in the electricity generation sector. Using a panel of 109 countries over 30 years, this study applies difference-in-differences (DID) and synthetic DID methods to exploit policy timing, income level, and geographic variations. Results show that while most static policy interactions may not reduce emissions, some reductions are observed when combined carbon pricing and renewable policies. The dynamic interactions of ETS may have contributed to CO2 emission reductions in countries that adopted them, conditional on economic development and governance. Carbon pricing and feed-in policies could mitigate CO2 emissions by promoting renewable energy supply and reducing carbon intensity. Using a quasi-experimental approach, this study contributes to the empirical literature on the effects of four key policy interactions on CO2 emissions in global electricity generation. The findings highlight the need for tailored policy combinations to decarbonize the electricity generation sector, considering each country's specific circumstances, such as development level and governance.

1. Introduction

The electricity generation sector is the main source of CO2 emissions, but it also has the greatest potential to reduce them by accelerating the adoption of clean energy technologies (Luderer et al., 2019), supported by policies (Besley and Persson, 2023; Kemp and Never, 2017; Yergin, 2022). However, there are several challenges to adopting climate and energy policies to promote renewable energy and reduce CO2 emissions, due to different design features such as multiple objectives, scope, integration, budget, implementation and monitoring (Maor and Howlett, 2021). The literature suggests that carbon pricing is the optimal climate policy for CO2 mitigation, but it is not widely applied to the electricity generation sector because it is unpopular (Blanchard and Tirole, 2021). Instead, policymakers tend to favor second-best climate policies (Gugler et al., 2021) that seem to face lesser political constraints (Rhodes et al., 2021). Moreover, the literature emphasizes that solving a complex problem like CO2 emissions mitigation requires a policy mix to address multiple market failures, reduce economic and political barriers, and balance the global imperative of environmental sustainability with national interests (Linsenmeier et al., 2022; Maor and Howlett, 2021; Meckling et al., 2017; Sewerin, 2020; Stechemesser et al., 2024).

This paper evaluates the static and dynamic effects of interactions[1] and their mechanisms of four national climate and energy policies—carbon tax, emission trading system (ETS), auctions for renewable energy, and feed-in policy—on reducing CO2 emissions per capita from the electricity generation sector. This work uses difference-in-differences (DID) and synthetic DID methods to estimate these effects in a panel of 109 countries and 30 years. To do so, this paper takes

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[1] Static policy-interaction effects refer to constant, common effects observed across all four policies that impact all groups uniformly over time (across-static interaction). While dynamic policy-interaction effects refer to heterogeneous effects of the length of exposure to first year implementation within single policies at different points in time (within-dynamic interaction).

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advantage of the heterogeneities of policy implementation in several countries, such as variations in policy timing, income level, and geographic location. Due to sample size constraints by income and region, this paper does not focus on a specific income or geographic group but incorporates these heterogeneities in policy adoption to assess their interaction effects on a global scale.

To identify these effects, this study first exploits a quasi-experimental setting that arises from the variation in the adoption of four policies across countries. Some countries have implemented these policies (the treatment group), while others have never or not-yet adopted them (the control group). The reliance on the random assignment of these policy adoptions is relaxed by conditioning on covariates and/or appropriate time periods for controlling the selection bias (Arkhangelsky et al., 2021). Second, it leverages the different timing of policy adoption by countries to analyze the dynamic effects of policy interactions. Third, it compares the combined effect with the single effect of these policies to analyze the static effects of policy interactions. Fourth, this paper uses an econometric model of carbon emissions for a global sample of countries, based on the same set of determinants, because most of electricity generation sectors worldwide operate under marginal-cost dispatch systems (Gugler et al., 2021). Moreover, electricity generation sectors are typically characterized by low mobility and high fixed assets, which reduce the likelihood of emission reduction through carbon leakage (Bayer and el Aklin, 2020).

This study employs DID and synthetic DID methods—design-based identification approaches well suited for evaluating policy impacts in non-experimental settings across heterogeneous countries over time, accounting for unobserved heterogeneity through unweighted and weighted regressions, respectively (Arkhangelsky et al., 2021; Porreca, 2022; Roth et al., 2023). DID, widely used in the social sciences, relies on the parallel trends assumption, with the Honest DID package offering sensitivity analysis for potential violations of this assumption (Rambachan and Roth, 2023; Roth et al., 2023). Additionally, synthetic DID, developed by Arkhangelsky et al. (2021), further relaxes the parallel trends assumption by reweighting and matching pre-exposure trends, mitigating the influence of outliers. The choice among these methods depends on factors such as the type of interaction effects (static or dynamic), the heterogeneities to exploit, data availability for unbalanced and balanced panels, the validity of control group assumptions, and the flexibility of the functional form (linear or non-linear) to model the relationship between CO2 emissions and their determinants.

This work applies these methods in two stages. In the first stage, it uses the Two-Way Fixed Effects (TWFE) estimator in the DID approach to examine the static effects of interactions across policies on CO2 emissions and leverage income and geographic heterogeneities. However, this estimator may be biased if the policy varies across groups and time (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021). In the second stage, this paper employs the Callaway & Sant'Anna DID, Honest DID and Arkhangelsky et al. synthetic DID estimators to evaluate the dynamic effects of interactions within single policies on CO2 emissions and their potential mechanisms, exploiting the variations in the different timing of these policies, relaxing the parallel trends assumption for an extra degree of robustness, and introducing nonlinear relationships between CO2 emissions and their determinants. Nevertheless, DID and synthetic DID methods cannot be used to analyze dynamic interactions across policies or exploit geographic and income heterogeneities because of the sample size limitation of this study.

The main findings of this study are: First, TWFE estimates indicate that most policies and their static interactions may not have reduced emissions in the electricity generation sector. However, some policy interactions show statistically significant effects when combined carbon pricing and renewable policies. Due to the TWFE estimator's assumption of homogeneous treatment effects—which may not hold if policy effects vary by country or over time (de Chaisemartin and D'Haultfœuille, 2020) —these results should be interpreted with caution, as this could introduce bias by using already-treated groups as controls (Goodman-Bacon, 2021). Second, the dynamic interactions of ETS seems to have reduced CO_2 emissions in adopting countries, conditional on economic development and governance. Using the Callaway & Sant'Anna DID estimator for an unbalanced panel of 109 countries from 1990 to 2019, there is a 10% reduction in CO_2 emissions per capita, primarily driven by European Union countries that adopted ETS in 2005. This finding aligns with the 4%–15% emission reductions reported in systematic literature reviews (Döbbeling-Hildebrandt et al., 2024) and supports evidence that carbon pricing is more effective in developed economies (Stechemesser et al., 2024). To test robustness, a sensitivity analysis of Callaway & Sant'Anna DID estimates was performed using the HonestDiD package (Rambachan and Roth, 2023). The results indicate that the estimated effects are sensitive to potential violations of the parallel trends assumption, a key assumption in DID methods. To address these concerns, the paper applies the synthetic DID method by Arkhangelsky et al. (2021), which relaxes reliance on the parallel trends assumption. Using a balanced panel of 103 countries from 2000 to 2019, this method implies a 43% decrease in CO_2 emissions per capita, exceeding the previous estimated effects—possibly due to the shorter pre-treatment period. Nevertheless, this provides evidence that ETS may have mitigated CO_2 emissions, especially when accounting for potential outliers and when the strict parallel trends assumption may not hold. Finally, while carbon taxes, and feed-in policies may not have directly reduced CO_2 emissions in the sample, they may have promoted renewable energy supply and reduced carbon intensity (the ratio of CO_2 emissions to electricity generation).

The literature on climate and energy policies and their interactions is vast, but few studies have empirically assessed the ex-post effects of policy interactions on mitigating CO2 emissions from the global electricity generation sector using a quasi-experimental approach. Instead, most of the existing studies rely on simulations or qualitative case studies (del Río and Kiefer, 2023; Marcantonini et al., 2017; Martin et al., 2016; Timilsina, 2022). Therefore, this study contributes to the empirical literature by using a quasi-experimental approach to evaluate the static and dynamic effects of interactions across and within four major climate and energy policies on CO2 emissions from the global electricity generation sector and their potential mechanisms.

The study's findings indicate that while most policy interactions may not reduce emissions, some reductions are observed when combined carbon pricing and renewable policies. The literature indicates that effective emissions reduction in the electricity generation sector may require sequenced policy interactions combining subsidies, carbon pricing, and regulatory measures, with the optimal combination varying by sector and level of economic development (Linsenmeier et al., 2022; Stechemesser et al., 2024). Particularly, feed-in policies support the deployment of emerging green technologies, while auctions support the deployment of mature green technologies and enhance the cost-efficiency of feed-in policies (IPCC, 2022). Moreover, carbon pricing may enhance the environmental and cost-effectiveness of second-best policies (Meckling et al., 2017). The green electricity transition requires global participation, aligning with the Paris Agreement's core principle of common but differentiated responsibilities based on national circumstances. This analysis is consistent with this paper's results, which emphasize the importance of combining and tailoring policies for decarbonizing the electricity generation sector according to each country's specific circumstances, such as development level and governance.

This study faces several limitations. First, it focuses on policies implemented at the national level, excluding subnational policies. Second, it considers only four policies and does not account for other measures, such as regulatory interventions, that also contribute to effective policy interactions. Third, it relies on aggregated country-level CO_2 emission data due to the lack of comprehensive global microdata from power plants. Fourth, it excludes some key countries—including Germany, Italy, the United Kingdom, and the United States, to maintain methodological consistency and address data constraints. Fifth, it employs causal inference methods that do not address the spillover effects of policy interactions. Finally, there may be other potential confounders not controlled for in the analysis such as energy technological innovations, energy infrastructure investment, policy marginal abatement cost, political constraints, etc. Consequently, the findings of this study should be interpreted with caution, as constructing an ideal counterfactual for emission mitigation in electricity generation is challenging. Despite these limitations, this work provides exploratory evidence of the static and dynamic interaction effects of four widely adopted national-level policies on CO_2 emissions in the electricity generation sector.

The rest of this paper is structured as follows: Section 2 provides an overview of the four climate and energy policies implemented in the global electricity generation sector; section 3 reviews the related literature; section 4 describes the empirical strategy; section 5 reports estimation results; and section 6 concludes with the main findings and policy implications of this study.

2. Climate and energy policies in the electricity generation sector

This study examines the most popular market-based national instruments to promote clean energy and reduce CO2 emissions from the electricity generation sector: carbon tax, emission trading system (ETS), feed-in policy (includes both fixed tariffs and premiums), and auctions for renewable energy. Fig. 1 displays the number of jurisdictions (not necessarily countries as some states or regions within a country are considered jurisdictions) with climate and energy policies in the electricity generation sector in 2020, classified by regulation (command and control) and market-based instruments.

On the one hand, carbon tax and ETS are regarded as the first-best policies for direct (or explicit) support for climate change mitigation, as they penalize dirty energy. Specifically, the carbon tax imposes a fee on the carbon content of fossil fuels that internalizes the negative externality of CO2 emissions and aligns the gap between the social and private marginal costs of CO2 emissions (Nordhaus, 2021). Similarly, the ETS policy sets a cap on the total allowed emissions and creates a market for emission permits, thus ensuring certainty over the environmental outcome but leaving the price to be determined by the market (Parry et al., 2022; World Bank, 2021). Carbon pricing, such as a carbon tax and ETS, can reduce asymmetric information and government costs because it is a decentralized policy that allows for differences between polluters (Baranzini et al., 2017).

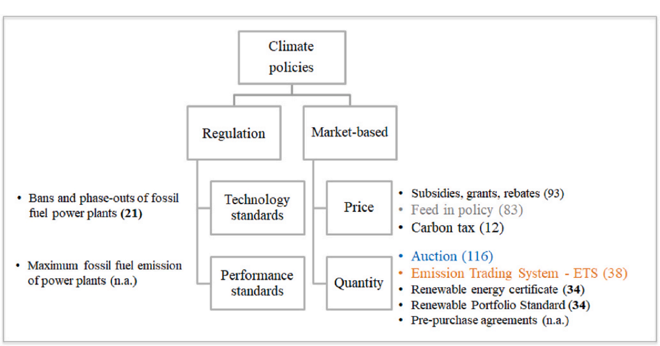

Fig. 1. Number of jurisdictions with climate and energy policies in the electricity generation sector in 2020.
Note: This figure shows the number of jurisdictions with climate and energy policies in the electricity generation sector in 2020 organized by regulation and market-based instruments.
n.a. stands for not available.
Source: Author's own elaboration based on information from Bento et al. (2020), IEA (2021), IRENA (2021), Sterner and Coria (2012), and World Bank (2021).

On the other hand, feed-in policies and auctions are regarded as the second-best policies for indirect (or implicit) support for climate change mitigation, as they incentivize clean energy. A feed-in policy guarantees a government-determined fixed payment per unit of electricity generated from renewable sources over a specified period (e.g., feed-in tariff) or a payment that varies with the wholesale electricity price (e.g., feed-in premium) (del Río and Kiefer, 2023; IRENA, 2021; Reguant, 2019). Feed-in policy is more susceptible to lobby and government failures (Blanchard and Tirole, 2021), and has high initial costs and low guarantee of emission cuts (Meckling et al., 2017). Moreover, auctions for renewable energy are a competitive mechanism that procures renewable energy at the lowest possible price, reduces the asymmetric information on cost heterogeneity among different power technologies, and facilitates the entry of new players (Bento et al., 2020; Fabra, 2021; IRENA, 2021). The level of support for a tender, if needed (often a premium in US$/MWh), is based on the bidding process to get the lowest one (del Río and Kiefer, 2023).

Fig. 2 reports the evolution of these four climate policies in the worldwide electricity generation sector between 1990 and 2020. This figure shows that second-best climate policies (auctions and feed-in policy) were the first instruments to be implemented, followed by first-best climate policies (carbon tax and ETS).

Second-best policies to promote electricity from renewable energy date back to the 1970s when the energy crisis raised concerns about energy security in many of the Organization for Economic Co-operation and Development (OECD) countries (Böhringer and Behrens, 2015). The United States was the first country to apply an early version of the feed-in policy in 1978 through the Public Utility Regulatory Policies Act (PURPA[2]) policy (Couture et al., 2010). Then, The United Kingdom was the first country to employ auctions for renewables in 1990 through the Non-Fossil Fuel Obligation, but it was not very successful, thus it switched to the renewable portfolio standard in 2002, although it reintroduced auctions in 2011 (Woodman et al., 2019). Feed-in policy was the most dynamic instrument for renewable energy development from 1990 to 2005, but competitive auctions have replaced it in many countries to improve cost-effectiveness and increase control over renewable capacity levels (IRENA, 2020). Particularly, the emphasis on auctions can be explained by two approaches (del Río and Kiefer, 2023): the functionalist view, which alleges greater cost-effectiveness (advantages of the instrument itself), and the structuralist view, which stresses the influence of particular interest of policymakers or the pressure from stakeholders behind the growth in adoption (the political economy view).

The adoption of carbon pricing in the electricity generation sector began in Europe in the early 2000s. Estonia was the first country to adopt a carbon tax in 2000 for heat generation, but it was low and could be waived if power plants invest in low-carbon technologies (OECD, 2017). The European Union (EU) implemented the world's first regional Emission Trading System (ETS) that covered the electricity generation sector with initially 25 members in 2005, and later expanded to 31 countries with the inclusion of Romania and Bulgaria in 2007; Norway, Iceland, and Liechtenstein in 2008; and Croatia in 2013 (European Union, 2015).

The interaction of policies is a key design element (Parry et al., 2022). Therefore, this paper builds on the literature on policy mixes, which are a package of different policies with a common goal, motivated by sustainability transition or environmental governance studies (Sewerin, 2020). This literature addresses complex policy challenges, such as climate change, that arise from a combination of market, system, and institutional failures (Sewerin, 2020). Moreover, this literature has

[2] The Public Utility Regulatory Policies Act (PURPA) is sometimes considered the first feed-in policy in the USA. Among other things, PURPA required utilities to buy electricity from qualifying facilities at rates that were based on utilities' "avoided costs (Couture et al., 2010).

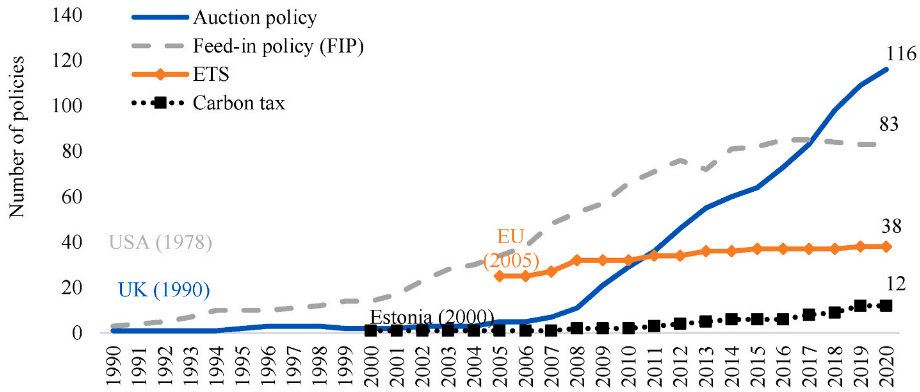

Fig. 2. Evolution of four major climate and energy policies in the electricity generation sector between 1990 and 2020.
Note: This figure shows the evolution of four climate and energy policies implemented in the global electricity generation sector between 1990 and 2020. The country names in the figure refer to the first adopters of these policies, and the years in parentheses indicate the first year of policy implementation.
Source: Author's own elaboration based on data from AURES II, IEA, REN21, and the World Bank's Carbon Pricing Dashboard.

emphasized practical concerns related to effectiveness, temporal development, and potential drivers of policy mixes (Sewerin, 2020). The combination of policies affects their effectiveness because they can interact in complex, unexpected, and nonlinear ways to generate synergistic, counterproductive, and additive effects (Leipprand et al., 2020; Li and Taeihagh, 2020; Maor and Howlett, 2021). Currently, there is a comparative lack of empirical analyses on the temporal changes in policy mixes across countries (Li and Taeihagh, 2020). This paper focuses on the static combination between these policies (across-static interaction) and the dynamic adoptions of several single policies at different points in time (within-dynamic interaction).

The Intergovernmental Panel on Climate Change (IPCC, 2022) observes that the current energy sector policy landscape is composed of a mix of policies, including regulatory, market-based, and other approaches. The choice of policies depends on institutional capacities, technological maturity, and other developmental priorities of governments. First, market-based instruments such as feed-in-tariffs (FIT) have worked best when the technologies are in nascent stages of development and have played a significant role in attracting foreign direct investment in the renewable energy sector, while ETS and auction coupled with a regulatory framework have been a favorable strategy for more mature technologies. Second, equity and distributional impacts of carbon pricing instruments can be addressed by using revenue from carbon tax or ETS to support low-income households, among other approaches. Moreover, auctions enabled the entry of new renewable energy players and reduced the asymmetric information about the evolution and heterogeneity of costs for green power technologies (Fabra, 2021).

Furthermore, policy sequencing, the notion that earlier weak policies can facilitate the adoption of later strong policies, can address the challenges of environmental and cost-effectiveness under political constraints (Linsenmeier et al., 2022; Meckling et al., 2017; Sewerin, 2020). For example, Meckling et al. (2017) argue that low-carbon leaders such as California and the European Union have developed low-carbon policy mixes through a three-stage sequence that has helped overcome some of their political challenges. First, they implemented green innovation and industrial policies, such as renewable-energy support schemes (e.g., subsidies and feed-in tariffs), which created the emergence of clean-energy interest groups by providing more direct and concentrated benefits to low-carbon firms. Second, they added direct carbon pricing to improve the environmental and cost-effectiveness of industrial policies, because such policies as feed-in tariffs tend to require high initial costs and offer little guarantee of emission cuts; they adjusted feed-in policies via auctions to reduce the energy cost. Third, they increased the policy mix over time. This study differs from the literature on policy sequences, which focuses on both the timing and order of policy adoptions. In contrast, this paper focuses on the timing of policy adoptions but not the order in which they are adopted.

3. Related literature

The literature on climate and energy policies and their interactions is vast, but only a few studies have empirically evaluated the ex-post effects of interactions among first-and second-best policies on mitigating CO2 emissions from the electricity generation sector using a quasi-experimental approach (del Río and Kiefer, 2023; Marcantonini et al., 2017; Martin et al., 2016; Timilsina, 2022).

For second-best policies, such as feed-in policies and auctions for renewable energy, qualitative studies (mostly based on case studies) have dominated over quantitative studies because qualitative ones capture more details in the initial stages of the topic analysis, identify key aspects and dimensions, and may propose hypotheses but not necessarily test them (del Río and Kiefer, 2023). Although there are some remarkable quantitative studies, they mostly focus on the effects of these policies on intermediate electricity outcomes such as the increase in installed capacity or generation from renewable energy (Bento et al., 2020; Kilinc-Ata, 2016; Matthäus, 2020; Winkler et al., 2018), but very few assess their impacts on CO2 mitigation. Among these scarce papers, Ari and Sari (2015) find that feed-in tariffs have not reduced the CO2 emission intensity in Turkey's electricity sector since its introduction in 2005 because of insufficient renewable energy installed capacity.

For first-best policies such as carbon tax and ETS, most studies have relied on simulations rather than ex-post analysis due to the challenges of finding valid counterfactuals (unrealized potential outcomes without policies), the lack of suitable worldwide disaggregated data on CO2 emissions at the power plant level, and other constraints (Martin et al., 2016). For example, two ex-post assessment studies show evidence of the effects of the European Union's ETS on CO2 reduction: First, Schäfer (2019) finds that ETS had a lower impact on emissions up to 2010 but not later in the German electricity sector between 2000 and 2015 using a linear regression. Second, Bayer and el Aklin (2020) find a substantial carbon reduction between 2008 and 2016 in highly immobile industries with a large share of fixed assets, such as electricity generation, using a generalized synthetic control method. Additionally, two studies show that the carbon tax introduced in the United Kingdom in April 2013 on top of the ETS has reduced CO2 emissions in the electricity generation sector using a quasi-experimental approach: First, Leroutier (2022) finds a medium-term decline of between 20% and 26% per year on average between 2013 and 2017 using a synthetic control method. Second, Gugler et al. (2023) find a short-term cumulative decline in emissions by 26% (or 36.3 MtCO2) between 2013 and 2015 using a regression-discontinuity-in-time approach.

The literature also emphasizes that few studies have evaluated the ex-post effects of climate and energy policy interactions. Alexopoulos et al. (2017) find that all renewable energy measures had a positive effect on reducing CO2 emissions, with feed-in tariffs exhibiting the greatest impact, using panel data on CO2 emissions from 15 EU countries between 1980 and 2009. Gugler et al. (2021) shows that carbon pricing in Britain was superior to subsidizing wind or solar power in Germany, using a Heckman two-step selection model, and exploiting exogenous variations in high-frequency wind and solar generation determined by the weather in the short term. Linsenmeier et al. (2022) provide descriptive evidence that policy sequences from second-best policies to carbon pricing were a consistent pattern, using data from 37 countries (all G20 economies) across all emission sectors (including the electricity generation sector) and various statistical methods (including matching and linear regression) between 2000 and 2020. Stechemesser et al. (2024) evaluate 1500 climate policies across 41 countries and four sectors from 1998 to 2022 using a difference-in-difference framework enhanced by machine learning. They find that only 11 policies—including carbon pricing, auctions, and feed-in tariffs in seven countries—reduced emissions by 20% in the electricity sector. Successful cases include the United Kingdom, where a combination of a minimum carbon price, renewable energy subsidies, and a coal phase-out plan drove significant emissions reductions, and Portugal, which employed renewable auctions and a carbon tax. The authors highlight that an effective policy mixes in the electricity sector require carbon pricing or price incentives complemented by regulatory measures such as coal phase-outs and emphasize that the optimal policy mix varies by sector and economic development, with carbon pricing being more effective in developed economies and regulatory measures in developing ones.

Literature also highlights that interactions of renewable energy policies and carbon pricing may have some unintended effects, such as limited additional emissions reductions, carbon leakage, and higher abatement costs, arising from the complex interplay among multiple policy instruments, energy markets, and externalities (Lehmann et al., 2019). Possible reasons include: (1) conflicting objectives—while carbon pricing aims for cost-effective emissions reductions, renewable subsidies focus on clean energy deployment, potentially weakening carbon price signals (Lehmann et al., 2019); however, policies like renewable energy auctions may improve cost-efficiency of feed-in policies by shifting from fixed government payments to competitive bidding (Bento et al., 2020; Winkler et al., 2018); (2) overlapping policies might create waterbed and rebound effects (Perino et al., 2019); (3) political and social constraints leading to the adoption of less stringent, second-best policies preceding carbon pricing (Linsenmeier et al., 2022); and (4) institutional, technological, infrastructural limitations (IPCC, 2022).

This study also examines the mechanisms through which these four policies may influence emissions in the electricity generation sector, employing a simplified theory of change (see Fig. 3) informed by the Kaya identity and relevant literature. The Kaya identity, a widely used framework, decomposes CO2 emissions per capita into three key drivers: GDP per capita, energy intensity (energy use per unit of GDP), and carbon intensity (CO2 emissions per unit of energy) (Edenhofer et al., 2014). The analysis focuses on key mechanisms from the literature, including the transition from fossil fuels to cleaner energy sources (Jaumotte et al., 2021), increased renewable energy supply (Bento et al., 2020; Kilinc-Ata, 2016; Matthäus, 2020; Winkler et al., 2018), coal-to-gas substitution in electricity generation (Cullen and Mansur, 2017; Gugler et al., 2023), and reductions in energy and carbon intensities (Chitnis et al., 2014; Goh et al., 2018).

4. Empirical strategy

This paper addresses the following research questions: Are the interactions among four national climate and energy policies effective on reducing CO2 emissions per capita from the electricity generation sector and what are their potential mechanisms? To answer this question, this study employs an empirical strategy that encompasses data collection, identification, and estimation using observational data (Angrist, 2022).

4.1. Data

This work uses unbalanced panel data from 109 countries (though still strongly balanced) between 1990 and 2019 (30 years). This period is important because it accounts for about 42% of the historical cumulative total net CO2 emissions and it is considered a medium-term time scale for the energy transition (IPCC, 2022). The sample of 109 countries represents 81% of CO2 emissions from electricity generation in 2019.

This study employs data from public sources for 12 variables (see Table 1). The dependent variable, CO2 emission per capita from electricity generation, facilitates comparative analysis of heterogeneous CO2 emission outcomes across diverse countries. CO2 emissions from electricity generation encompass electricity and heat CO2 emissions from public utilities, auto-producers, and other energy industries, as collected by the Climate Watch platform. The study contains four policy variables which are dummy variables indicating the year of implementation of auctions for renewables, carbon tax, emissions trading system (ETS) and feed-in policies (including feed-in tariff and/or feed-in

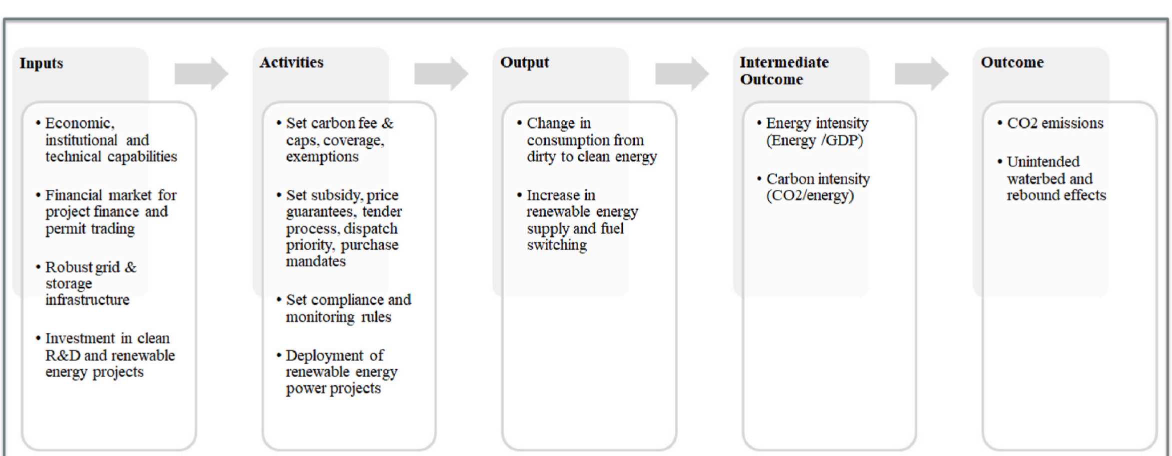

Fig. 3. Theory of change and possible mechanisms by which climate and energy policies may impact CO2 emission from electricity generation.
Note: This figure shows the possible mechanisms by which these policies may impact CO2 emissions in the electricity generation sector.
Source: Author's own elaboration.

Table 1
Variables and data sources.

Type	Variables	Units	Sources*	Mean (sd**)
Outcome	CO2 emission per capita from electricity generation	Metric tons per capita	Climate Watch	2.52 (3.66)
Independent variables				
Policy variables	RE auctions	Dummy	Aures II, Climate Policy Database, IEA, REN21	0.14 ("-")
	Feed-in policy	Dummy		0.26 ("-")
	Carbon tax	Dummy	World Bank's Carbon Pricing Dashboard	0.02 ("-")
	Emissions trading system (ETS)	Dummy		0.13 ("-")
Controls	GDP per capita	Purchasing power parity (PPP), constant 2017 international $)	World Bank	20,598 (20,292)
	Electric power consumption per capita	kWh per capita	EIA/World Bank	3849 (5421)
	Quality of Government	Interval, from low to high (0–1)	Varieties of Democracy (V-Dem)	0.57 (0.21)
	Fossil fuel rents	% of GDP	World Bank	5.13 (10.72)
	Financial Development Index	Interval, from low to high (0–1)	IMF	0.33 (0.22)
	Natural gas real price	Regional benchmarks (US$ constant 2017/MMBTU)	BP	5.80 (3.01)
	Coal real price	Regional benchmarks (US$ constant 2017/ton)	BP	73.61 (27.2)

Note: This table reports the variables, their units of measurement, their data sources, and their basic statistics such as means and standard errors (in parentheses) for the entire dataset. For clarity, the acronyms of the sources are expanded as follows: Auctions for Renewable Energy Support II (Aures II), British Petroleum (BP), Energy Information Administration (EIA), International Energy Agency (IEA), International Monetary Fund (IMF), Renewable energy community of actors from science, governments, NGOs and industry (REN21), and V-Dem Institute at the Department of Political Science of the University of Gothenburg (V-Dem).

premium). Additionally, this paper includes some control variables informed by prior research (Barnea et al., 2022; Bayer and el Aklin, 2020; Leroutier, 2022; Röttgers and Anderson, 2018): 1) GDP per capita; 2) Electric power consumption per capita; 3) the quality of government, reflecting the aggregated average values of indicators of corruption, law and order, and bureaucracy quality from expert assessments (a proxy for governance or institutional dimensions); 4) fossil fuel rents, measuring the contribution of fossil fuel resources (coal, natural gas, and oil) to economic output and serving as a proxy for the lobby in favor of fossil fuels; 5) financial development index and; 6) two fossil fuel real costs (coal and natural gas). Further details of these variables and their sources can be found in **Appendix 1**.

As discussed in **Section 3**, this study examines the mechanisms through which four policies may influence emissions in the electricity generation sector, drawing on the Kaya identity and relevant literature. The analysis relies on publicly available data for five key variables to assess both intermediary outputs (e.g., increased renewable energy supply) and outcomes (e.g., reduced carbon intensity) resulting from policy interventions: 1) renewable capacity share (renewable capacity/total power capacity), 2) renewable generation share (renewable generation/total generation), 3) non-hydro renewable generation share (non-hydro renewable generation/total generation), 4) energy intensity (generation/GDP), and 5) carbon intensity (CO2 emissions/electricity generation). Detailed information on these variables is provided in **Appendix 1**.

Table 2 reports the single policies that were in place in the electricity generation sector for different proportions of countries in the total dataset by the end of 2019: auctions for renewables (61%), feed-in policies (54%), ETS (29%) and carbon tax (9%). Some countries were excluded from the dataset to maintain methodological consistency and address data limitations. The United States and Portugal were removed due to their early adoption of feed-in policies before the dataset's start (1978 and 1988, respectively). Italy and the United Kingdom were excluded because of the non-staggered nature of their auction policies, characterized by intermittent adoptions. Germany was dropped due to missing covariate data from the year preceding its feed-in policy's introduction (1990), which is required for the conditional Callaway & Sant'Anna staggered DID approach. Other countries were removed due to missing data on key variables. (see **Appendix 2** for further explanation and the list of countries considered in the sample). In the dataset, Switzerland was the first to implement a feed-in policy in 1991, Costa Rica was the first to apply auctions for renewables in 1995, Estonia was the first to employ a carbon tax in 2000 for heat generation, and the European Union (EU) implemented the world's first regional ETS in 2005 that covered the electricity generation sector with initially 25 members. Further details of number of countries by policies, income and region are provided in **Appendix 2**.

Table 2
Number of countries treated and untreated and the first year of implementation of the climate policies in the dataset.

Countries	Feed-in	Auctions	Carbon tax	ETS
Treated	59	67	10	32
Untreated	50	42	99	77
First year of policy adoption	1991	1995	2000	2005

Note: This table reports the number of countries that adopted the policy (treatment group) or did not adopt the policy (control group), along with the corresponding first year of policy implementation in the dataset.

Appendix 3 provides a detailed analysis of the main descriptive statistics of the study**.** CO2 emissions per capita are positively correlated with almost all independent variables except auctions and feed-in policies. Fig. 4 shows the distributions of CO_2 emissions per capita from electricity generation in both levels and logarithms. This figure underlines that CO_2 emissions per capita are right-skewed and not normally distributed: most countries have low emissions, while a few exhibit significantly higher levels. To address this skewness, this paper

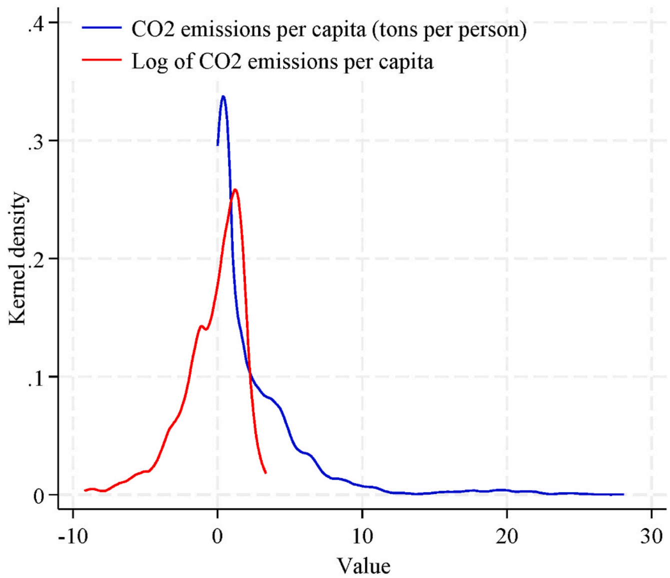

Fig. 4. Distributions of level and logarithm of CO2 emissions per capita from electricity generation.
Note: This figure displays two kernel density curves, a non-parametric method for estimating data distribution. The blue curve represents the distribution of CO_2 emissions per capita from national electricity generation sectors, while the red curve shows the distribution of the logarithm of CO_2 emissions per capita.

applies log transformations, which normalize the data and facilitate better comparisons across estimations. This transformation also mitigates the influence of outliers, particularly for countries with extremely high or low emissions, and allows results to be interpreted as percentage changes in emissions per capita due to changes in policies.

Countries that have adopted the four policies tend to have narrower and lower emissions distributions, while those without these policies exhibit wider, more dispersed distributions skewed towards higher emissions (see Fig. 5). This indicates potential heterogeneous effects and different trends between treated and untreated countries, which this study investigates using log transformation models, and heterogeneity robust methods, such as the Callaway & Sant'Anna DID and Arkhangelsky et al. synthetic DID estimators.

The data shows that countries that adopted second-best policies (auctions and feed-in policies) have lower CO2 emissions per capita compared to their respective control groups. Conversely, countries that implemented first-best policies (carbon tax and ETS) seem to have higher CO2 emissions per capita in relation to their control groups (see Fig. 6). This is one potential source of endogeneity among policy adoptions and CO2 emissions. To address this, the reliance on the random assignment of these policy adoptions is relaxed by conditioning on covariates and/or selecting appropriate time periods (Arkhangelsky et al., 2021).

The descriptive statistics also highlight significant differences in

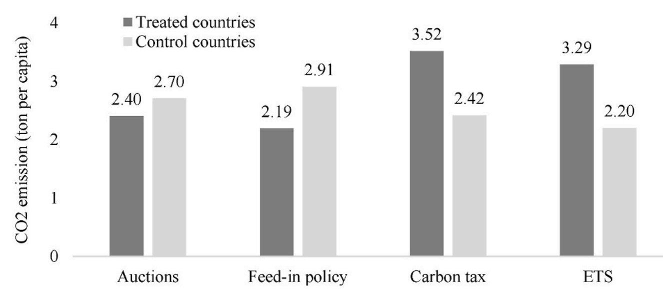

Fig. 6. Means of CO2 emissions per capita from electricity generation by treatment in the sample of 109 countries between 1990 and 2019.
Note: This figure displays the average CO2 emissions per capita from the electricity generation sector among the 109 countries over 30 years (1990–2019) for both treated and untreated countries by policies.
Source: Author's own elaboration.

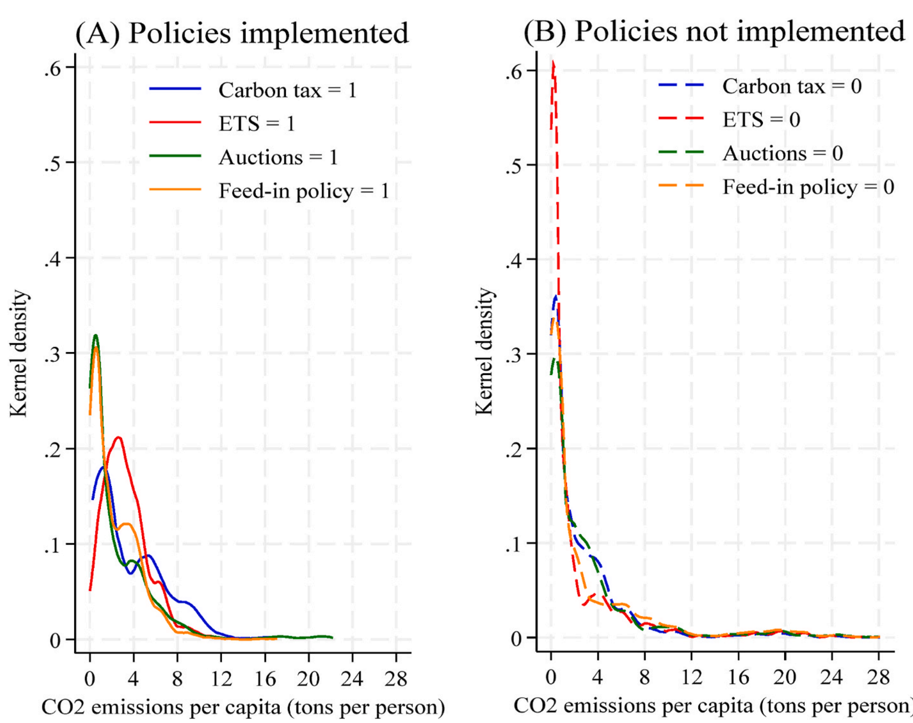

Fig. 5. Kernel distributions of CO2 emissions from electricity generation by four policies.
Note: This figure shows kernel density estimates of per capita CO_2 emissions from national electricity generation sectors, segmented by four policy treatments: carbon taxes, emissions trading systems (ETS), renewable energy auctions, and feed-in policies. Fig. 5A depicts the kernel density distributions of CO_2 emissions when these policies are implemented (dummy variable = 1), while Fig. 5B displays the distributions when the policies are not implemented (dummy variable = 0).

economic development and governance between treated and control countries in 1990, earliest year in the dataset before the large-scale adoption of these four policies, with higher governance quality being more associated with the implementation of carbon pricing compared to second-best policies (see Table 13 in Appendix 3 for further analysis).

4.2. Identification and estimation

4.2.1. Identification strategy

This study first exploits a quasi-experimental setting that arises from the variation in the adoption of four policies across countries. Some countries have implemented these policies (the treatment group), while others have never or not-yet adopted them (the control group). This quasi-experimental approach can be also suitable for evaluating the impacts of these policies because it allows us to control for common events and country-specific constant confounding factors that affect both treated and untreated countries (global economic crisis, country-specific policies, etc.). The reliance on the random assignment of these policy adoptions is relaxed by conditioning on covariates and/or appropriate time periods for controlling the selection bias (Arkhangelsky et al., 2021). Second, it leverages the different timing of policy adoption by countries to analyze the dynamic effects of policies. Third, it compares the combined effect with the single effect of these policies to analyze the static effects of policy interactions. Fourth, this paper uses an econometric model of carbon emissions for a global sample of countries, based on the same set of determinants, because most of electricity generation sectors worldwide operate under marginal-cost dispatch systems (Gugler et al., 2021). Moreover, electricity generation sectors are typically characterized by low mobility and high fixed assets, which reduce the likelihood of emission reduction through carbon leakage (Bayer and el Aklin, 2020).

4.2.2. Estimation procedure

This study employs DID and synthetic DID methods—design-based identification approaches well suited for evaluating policy impacts in non-experimental settings across heterogeneous countries over time, accounting for unobserved heterogeneity through unweighted and weighted regressions, respectively (Arkhangelsky et al., 2021; Porreca, 2022; Roth et al., 2023). DID, widely used in the social sciences, relies on the parallel trends assumption, with the Honest DID package offering sensitivity analysis for potential violations of this assumption (Rambachan and Roth, 2023; Roth et al., 2023). Additionally, synthetic DID, developed by Arkhangelsky et al. (2021), further relaxes the parallel trends assumption by reweighting and matching pre-exposure trends, mitigating the influence of outliers. The choice among these methods depends on factors such as the type of interaction effects (static or dynamic), the heterogeneities to exploit, data availability for unbalanced and balanced panels, the validity of control group assumptions, and the flexibility of the functional form (linear or non-linear) to model the relationship between CO2 emissions and their determinants. **Appendix 4** provides a detailed analysis of the empirical models, assumptions, and limitations of the methods applied in this study**.**

This work applies these methods in two stages. In the first stage, it uses the Two-Way Fixed Effects (TWFE) estimator in the DID approach to examine the static effects of interactions across policies on CO2 emissions and leverage income and geographic heterogeneities. In this study, static policy-interaction effects refer to constant effects across these four policies, that is, common effects to all groups across time. However, as Wooldridge (2021) points out, the TWFE estimator is valid in situations such as staggered interventions if one allows for sufficiently heterogeneous treatment effects to relax the model. Otherwise, the TWFE estimator could produce biased estimates if the policy varies across groups and time (de Chaisemartin and D'Haultfœuille, 2020) because it makes forbidden comparisons by using already-treated groups as control groups (Goodman-Bacon, 2021).

In the second stage, this paper employs the Callaway & Sant'Anna DID, Honest DID sensitivity analysis and Arkhangelsky et al. synthetic DID estimators to evaluate the dynamic effects of interactions within single policies on CO2 emissions and their potential mechanisms, exploiting the variations in the different timing of these policies, relaxing the parallel trends assumption for an extra degree of robustness, and introducing nonlinear relationships between CO2 emissions and their determinants. In this paper, dynamic policy-interaction effects refer to heterogeneous effects of the length of exposure to first year implementation within single policies at different points in time. Nevertheless, these methods cannot be used to analyze dynamic interactions across policies or exploit geographic and income heterogeneities because of the sample size limitation of this study.

5. Results

This section presents the main results of the study in two stages. In the first stage, this study uses the TWFE estimator in a DID approach to examine the static effects of interactions across policies on CO2 emissions and leverage income and geographic heterogeneities. In the second stage, this paper employs the Callaway & Sant'Anna DID and the synthetic DID estimators to evaluate the dynamic effects of interactions within single policies on CO2 emissions and their potential mechanisms, by exploiting the variations in the different timing of policies, relaxing the parallel trends assumption, and introducing nonlinear relationships between CO2 emissions and their determinants.

In this first-stage analysis, this paper compares the combined effects of policy interactions with the effects of individual policies. Table 3 presents the static effects of four single policies and their combinations, estimated using the TWFE approach across the global sample and subsamples by income and region (see **Appendix 5** for further details). The analysis examines four individual policies, 11 possible combinations of two to four policies without repetition, and 11 sampling groups, including one global sample, three income-based subsamples, and seven regional subsamples. This results in 44 possible individual policy effects (4 policies $\times$ 11 sampling groups) and 121 combined effects (11 policy interactions $\times$ 11 sampling groups).

The TWFE estimates indicate that most policies and their interactions may not have reduced emissions from the electricity generation sector. When analyzed individually, the ETS policy appears to contribute to a global reduction in CO2 emissions. Renewable energy auctions may have also played a role in reducing emissions in low-income countries and specific regions, such as Sub-Saharan Africa and East Asia & Pacific. When policies are combined, interactions between second-best policies (e.g., auctions and feed-in policies) show no significant effects. However, some interactions between first-best policies (e.g., carbon pricing) and second-best policies (e.g., auctions and feed-in policies) display significant effects, particularly in the global sample. These results should be interpreted with caution, given the limitations of the TWFE estimator and the small number of observations for some policy interactions. Specifically, TWFE assumes homogeneous treatment effects across units and time periods, an assumption that may not hold if policy effects vary by countries or over time (de Chaisemartin and D'Haultfœuille, 2020), as it may introduce bias by making forbidden comparisons using already-treated groups as control groups (Goodman-Bacon, 2021).

In the second stage, the paper applies the Callaway & Sant'Anna DID and synthetic DID estimators to examine the dynamic effects of interactions within staggered policy implementations and their potential mechanisms. However, these methods cannot be used to analyze the interactions across policies or geographic and income heterogeneities due to the sample size constraint of this study. Column A in Table 4 summarizes the dynamic effects of four individual policies implemented at different times using the Callaway & Sant'Anna DID estimator for an unbalanced panel of 109 countries and 30 years from 1990 to 2019. Countries that adopted ETS policies experienced a 10% reduction in CO2 emissions per capita relative to a never-treated counterfactual, conditional on pretreatment GDP per capita and the quality of government,

Table 3
Summary of static effects of interactions across policies using two TWFE estimations by total sample, income development, and geography: logarithm of CO2 emission per capita from electricity generation.

Variables	Total sample	Income development			Region					
		Low	Middle	High	East Asia and Pacific	Europe and Central Asia	Latin America & the Caribbean	Middle East and North Africa	South Asia	Sub-Saharan Africa
Policies										
Auctions	0.01	−1.16***	0.05	−0.08	−0.40***	0.18**	0.02	0.03	−0.56	−0.78*
	(0.107)	(0.413)	(0.110)	(0.050)	(0.060)	(0.084)	(0.168)	(0.067)	(0.415)	(0.413)
Feed-in	0.17	1.00**	−0.04	−0.00	0.13*	0.01	0.06	0.12	0.64*	0.55
	(0.11)	(0.37)	(0.11)	(0.11)	(0.07)	(0.07)	(0.28)	(0.11)	(0.21)	(0.45)
Carbon tax	−0.05		−0.20**	0.44***	−0.11**	−0.16	−0.05			−0.82*
	(0.12)		(0.09)	(0.12)	(0.05)	(0.11)	(0.22)			(0.41)
ETS	−0.28**		−0.31**	−0.01	0.10	−0.05		−0.16**		
	(0.13)		(0.13)	(0.11)	(0.09)	(0.10)		(0.06)		
Auctions x Carbon tax	−0.13		−0.16	−0.42***		−0.42***				
	(0.16)		(0.12)	(0.08)		(0.12)				
Auctions x ETS	−0.19		−0.13	0.19***	0.03	−0.03		−0.68***		
	(0.12)		(0.14)	(0.07)	(0.06)	(0.07)		(0.10)		
Feed-in x Carbon tax	−0.23		0.05	−0.04		0.14	−0.01			
	(0.17)		(0.09)	(0.13)		(0.15)	(0.20)			
Feed-in x ETS	−0.11		0.15	−0.01	0.05	0.03		−0.57***		
	(0.13)		(0.15)	(0.12)	(0.08)	(0.10)		(0.15)		
Carbon tax x ETS	0.28		0.24*	−0.29*		0.15				
	(0.17)		(0.12)	(0.16)		(0.12)				
Auctions x Feed-in	−0.02		0.05	0.02	0.25***	0.09	−0.11	−0.19	0.21	0.24
	(0.13)		(0.12)	(0.10)	(0.08)	(0.09)	(0.18)	(0.12)	(0.39)	(0.55)
Carbon tax x ETS x Auctions	−0.62***					−0.01				
	(0.16)					(0.16)				
Carbon tax x ETS x Feed-in	0.14									
	(0.29)									
Auctions x Feed-in x Carbon tax	0.15		0.02							
	(0.22)		(0.16)							
Auctions x Feed-in x ETS	−0.09			−0.25*		−0.33**				
	(0.17)			(0.14)		(0.13)				
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.61	0.17	0.39	0.01	0.84	0.00	0.38	0.94	0.49	0.04
Nº Obs	3079	510	1626	932	380	961	580	456	120	552

Notes: This table reports the aggregated average treatment effects on the treated (ATTs) for individual policies and their combinations on the logarithm (log) of carbon emissions per capita from electricity generation, categorized based on the total sample, income level of development, and regions as defined by the World Bank's classification system. The estimation employs a static Two-Way Fixed Effects (TWFE) linear model with seven control variables: log of GDP per capita, log of electric power consumption per capita, quality of government, fossil fuel rents, financial development index, log of regional natural gas real price, and log of regional coal real price.
Empty spaces indicate that the variable was omitted from the regression because of collinearity.
Standard errors are shown in parentheses.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

primarily driven by European Union countries that adopted ETS in 2005. This result aligns with the 4%–15% emission reductions reported in systematic reviews and meta-analyses of ex-post evaluations of carbon pricing effectiveness, accounting for publication bias (Döbbeling-Hildebrandt et al., 2024), and with evidence that carbon pricing is more effective in developed economies (Stechemesser et al., 2024). Although the carbon tax appears statistically significant, its relevance is diminished due to limited observations and the significance of the pre-treatment period in the event-study plot. The remaining two policies (auctions for renewables and feed-in policy) are not statistically significant.

Consistent with common practice, staggered policy adoption in DID methods visually checks event study plots for pre-trends before treatment to test the plausibility of the parallel trends assumption (Roth et al., 2023). Fig. 7 displays the dynamic effects (event study) graphs of staggered adoptions of four individual policies (ETS, carbon tax, auctions, and feed-in policies), bootstrapped at 95% confidence intervals. Of all dynamic interactions within these four policies, only ETS policies appear to be effective in reducing carbon emissions relative to a never-treated counterfactual in the post-treatment period. This dynamic effect seems to increase with longer exposure to this policy. Furthermore, the coefficients of the ETS policies in the pre-treatment period are insignificant, indicating that the null hypothesis of parallel trends cannot be rejected in the pre-treatment period.

As a robustness check of the statistical significance of ETS, this study performs a sensitivity analysis of the Callaway & Sant'Anna DID estimates using the HonestDID package, developed by Rambachan and Roth (2023), to account for potential violations of the parallel trends assumption. The results indicate that the treatment effect may not be robust to moderate violations of this assumption (see **Appendix 6** for details). This suggests that the Callaway & Sant'Anna DID estimates should be interpreted with caution, as they are statistically significant but sensitive to potential differences in pre-treatment trends between treated and untreated groups. Therefore, this paper also applies the Arkhangelsky et al. synthetic DID method which further relaxes the reliance on the parallel trends assumption in DID methods for a balanced panel of 103 countries and 20 years from 2000 to 2019. Column B in Table 4 displays this synthetic DID estimation that calculates a 43% decrease in CO2 emissions per capita relative to a never-treated counterfactual and conditional on time-varying GDP per capita and the quality of government (see **Appendix 7** for more details). This effect exceeds the Callaway & Sant'Anna DID estimate, likely due to the

Table 4
Summary of dynamic effects of interactions within staggered single policies using Callaway & Sant'Anna and Arkhangelsky et al. Synthetic Difference-in-Differences estimators: logarithm of CO2 emission per capita from electricity generation.

Conditional dynamic effects		(A) Callaway & Sant'Anna DID simple average	(B) Synthetic DID
		Unbalanced panel 109	Balanced panel 103
		1990–2019 period	2000–2019 period
Policies			
1st-best policies	**ETS**	−0.10***	−0.43***
		(0.02)	(0.07)
	Observations	447	
	Carbon tax	−0.06***	
		(0.01)	
	Observations	122	
2nd-best policies	**Auctions**	−0.03	
		(0.10)	
	Observations	1575	
	Feed-in policy	0.03	
		(0.10)	
	Observations	1025	
Covariates		Yes	Yes
Country fixed effects		Yes	Yes
Year fixed effects		Yes	Yes

Notes: This table reports the effects of individual policies on the logarithm (log) of carbon emission per capita from electricity generation, conditional on covariates and country-and year-fixed effects. Column A shows a simple weighted average aggregation of all group-time average treatment effects on the treated $[ATT(g,t)]$, conditional on pre-treatment log of GDP per capita and quality of government, derived from Callaway & Sant'Anna DID semiparametric model bootstrapped at 95% confidence intervals for an unbalanced panel data of 109 countries and 30 years from 1990 to 2019. Column B depicts the aggregated average treatment effects on the treated $[ATT]$, conditional on time-varying log of GDP per capita and quality of government, derived from Arkhangelsky et al. synthetic DID estimation bootstrapped 95% confidence intervals for a balanced panel data of 103 countries and 20 years from 2000 to 2019.
Standard errors are shown in parentheses.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

shorter pre-treatment period in this analysis. However, it offers some evidence that ETS may have contributed to CO2 emission reductions, particularly when accounting for potential outliers or high heterogeneity across countries, and when the strict parallel trends assumption may not fully hold. Additionally, **Appendix 8** summarizes Callaway & Sant'Anna DID and synthetic DID unconditional and conditional estimators on different configurations of covariates as an estimation sensitivity of the results. This analysis indicates that most covariates appear relevant in explaining CO2 emissions. Additionally, dynamic, and heterogeneous effects remain similar when conditioned on GDP per capita or electricity consumption per capita, as both serve as proxies for economic development.

While auctions, carbon taxes, and feed-in policies may not have directly reduced CO2 emissions from the electricity generation sector, they may have influenced intermediate outcomes that serve as mechanisms for emission mitigation. Table 5 shows that the primary mechanisms are an increase in renewable energy supply and a decrease in carbon intensity (CO2/electricity generation). Carbon pricing instruments (carbon taxes and ETS) appear to be more effective in promoting renewable energy supply and reducing carbon intensity, whereas feed-in policies appear to be more effective in expanding renewable energy supply.

Fig. 8 presents event-study graphs depicting the dynamic effects of the staggered implementation of three individual policies – ETS, carbon tax, and feed-in policies – on non-hydro renewable generation share and carbon intensity, bootstrapped at 95% confidence intervals and under the unconditional parallel trends (without covariates). The dynamic effects of these policies typically manifest with a delay, particularly in terms of increasing renewable energy supply, due to the extended period required for investment and deployment of renewable energy projects.

6. Conclusions and policy implications

The electricity generation sector is a key contributor to global CO2 emissions, but it can lead to the low-carbon transition with policy support. Several policies can promote renewable energy and reduce CO2 emissions. This paper evaluates the static and dynamic effects of interactions across and within four major climate and energy policies on reducing CO2 emissions per capita from the electricity generation sector among 109 countries over 30 years using DID and synthetic DID methods that exploited the variations in policy adoption across countries, income levels, and geographic locations.

The primary findings of this study are: First, TWFE estimates indicate that most policies and their static interactions may not have reduced emissions from the electricity generation sector. However, some policy interactions display statistically significant effects when combined carbon pricing and renewable policies. Second, the dynamic interactions of ETS may have contributed to CO2 emission reductions in countries that adopted them, conditional on economic development and governance. Carbon pricing instruments (carbon taxes and ETS) and feed-in policies may potentially reduce CO2 emissions by primarily promoting renewable energy supply and reducing carbon intensity. Particularly, carbon pricing may incentivize generation companies to adopt cleaner technologies by making carbon-intensive electricity generation more expensive, thereby shifting investment toward low-carbon alternatives (Cullen and Mansur, 2017; Gugler et al., 2023). Feed-in tariffs may encourage nascent stages of renewable energy deployment by providing financial stability and lowering entry barriers for renewable technologies, leading to an increase in clean energy supply (Bento et al., 2020; IPCC, 2022). Therefore, this study contributes to the empirical literature by using a quasi-experimental approach to evaluate the static and dynamic effects of interactions across and within four major climate and energy policies on CO2 emissions from the electricity generation sector and their mechanisms.

The study's findings indicate that while most policy interactions may not reduce emissions, some reductions are observed when combined carbon pricing and renewable policies. The literature indicates that effective emissions reduction in the electricity generation sector may require sequenced policy interactions combining subsidies, carbon pricing, and regulatory measures, with the optimal combination varying by sector and level of economic development (Linsenmeier et al., 2022; Stechemesser et al., 2024). Particularly, feed-in policies support the deployment of emerging green technologies, while auctions support the deployment of mature green technologies and enhance the cost-efficiency of feed-in policies (IPCC, 2022). Moreover, carbon pricing may enhance the environmental and cost-effectiveness of second-best policies (Meckling et al., 2017). The green electricity transition requires global participation, aligning with the Paris Agreement's core principle of common but differentiated responsibilities based on national circumstances. Since CO_2 mitigation serves as a public good—benefiting all regardless of individual contributions—achieving international cooperation and enforcement may be challenging. Consequently, countries might need to unilaterally adopt diverse policy mixes tailored to their specific development priorities and governance capacities.

These policy mixes have often evolved through the ad hoc layering of new policies onto existing ones rather than through the deliberate design of a comprehensive policy portfolio (Scott et al., 2023). This heuristic policy-maker approach may have led to some unintended

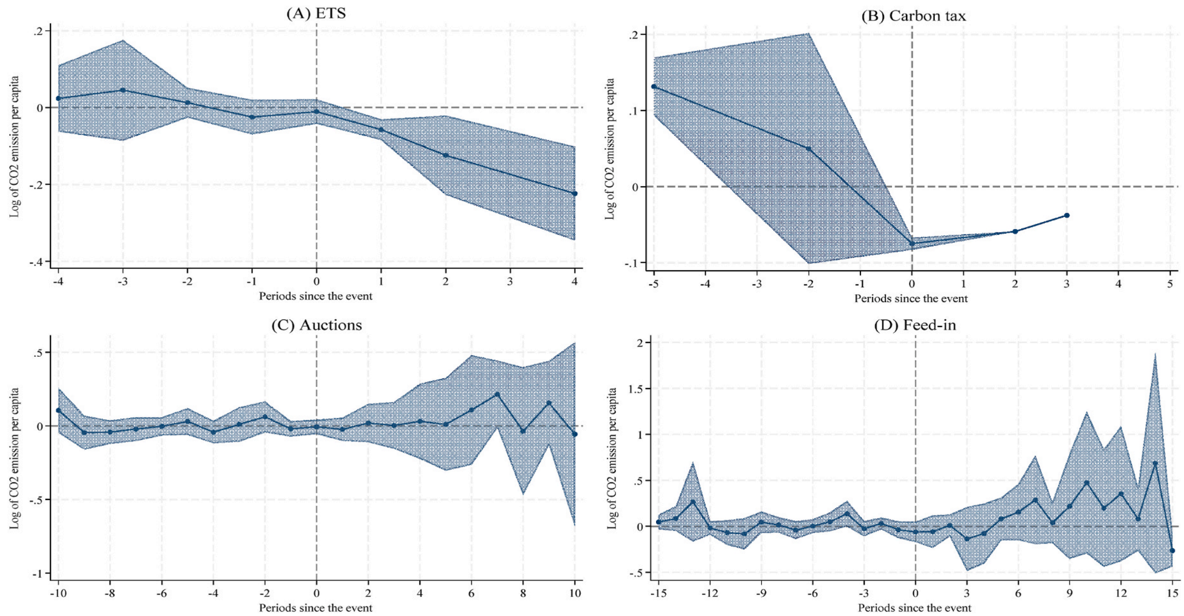

Fig. 7. Event study graphs for dynamic effects of interactions within individual policies on logarithm of CO2 emission per capita from electricity generation using the Callaway & Sant'Anna estimator.

Note: These plots show the balanced event-study effects of individual policies on logarithm (log) of carbon emission per capita from electricity generation, conditional on pre-treatment log of GDP per capita and quality of government, estimated by Callaway & Sant'Anna DID semiparametric model bootstrapped 95% confidence intervals (blue area) for ETS (graph A), carbon tax (graph B), auctions for renewable energy (graph C) and feed-in policy (graph D) for an unbalanced panel data of 109 countries and 30 years from 1990 to 2019.

Table 5
Summary of unconditional dynamic effects of interactions within staggered single policies using Callaway & Sant'Anna on four intermediate outcomes.

Unconditional dynamic effects		Renewable energy supply			Carbon intensity
		Renewable capacity share	Renewable generation share	Non-hydro renewable generation share	
		%	%	%	ton CO2/MWh
Policies					
1st-best policies	**ETS**	0.03***	0.04***	0.03***	−0.05**
		(0.01)	(0.01)	(0.01)	(0.02)
	Observations	653	670	670	670
	Carbon tax	0.05	0.04**	0.03*	−0.14**
		(0.03)	(0.02)	(0.02)	(0.07)
	Observations	235	239	239	239
2nd-best policies	**Feed-in policy**	0.04***	0.05	0.04***	−0.14
		(0.02)	(0.03)	(0.01)	(0.12)
	Observations	1210	1246	1246	1246
Country fixed effects		Yes	Yes	Yes	Yes
Year fixed effects		Yes	Yes	Yes	Yes

Notes: This table reports the effects of individual policies on three renewable energy supply outcomes (renewable capacity share, renewable generation share and non-hydro renewable generation share) and carbon intensity outcome, under the unconditional parallel trends and country-and year-fixed effects. The estimations are a simple weighted average aggregation of all group-time average treatment effects on the treated $[ATT(g,t)]$, estimated by Callaway & Sant'Anna DID semiparametric model bootstrapped at 95% confidence intervals for an unbalanced panel data of 109 countries and 30 years from 1990 to 2019.
Standard errors are shown in parentheses.
*p < 0.1, **p < 0.05, ***p < 0.01.

effects between renewable energy policies and carbon pricing, such as limited additional emissions reductions, carbon leakage, and higher abatement costs, arising from the complex interplay among multiple policy instruments, energy markets, and externalities (Lehmann et al., 2019). Possible reasons include: (1) conflicting objectives—while carbon pricing aims for cost-effective emissions reductions, renewable subsidies focus on clean energy deployment, potentially weakening carbon price signals (Lehmann et al., 2019); however, policies like renewable energy auctions may improve cost-efficiency of feed-in policies by shifting from fixed government payments to competitive bidding (Bento et al., 2020; Winkler et al., 2018); (2) overlapping policies might create waterbed and rebound effects (Perino et al., 2019); (3) political and social constraints leading to the adoption of less stringent, second-best policies preceding carbon pricing (Linsenmeier et al., 2022); and (4) institutional, technological, and infrastructural limitations (IPCC, 2022).

This study faces several limitations. First, it focuses on policies implemented at the national level, excluding subnational policies. Second, it considers only four policies and does not account for other measures, such as regulatory interventions, that also contribute to

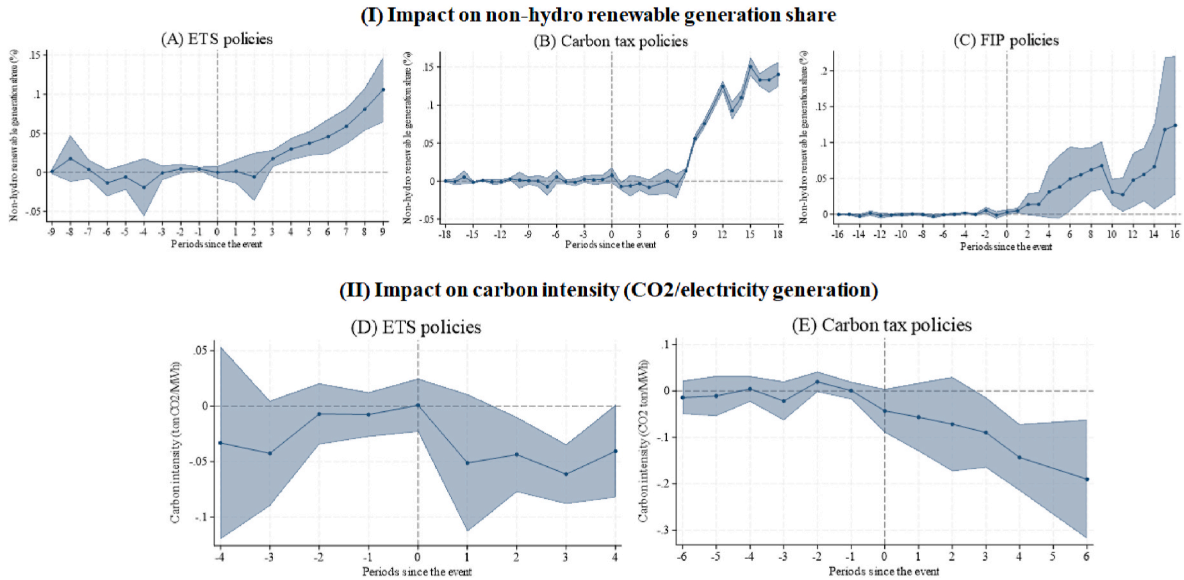

Fig. 8. Event study graphs for dynamic effects of interactions within staggered single policies using Callaway & Sant'Anna on two intermediary outcomes.
Note: These plots show the balanced event-study effects of three individual policies (ETS, carbon tax and feed-in policies) on non-hydro renewable generation share and carbon intensity outcomes, under the unconditional parallel trends and country-and year-fixed effects, estimated by Callaway & Sant'Anna DID semiparametric model bootstrapped 95% confidence intervals.

effective policy interactions. Third, it relies on aggregated country-level CO_2 emission data due to the lack of comprehensive global microdata from power plants. Fourth, it excludes some key countries—including Germany, Italy, the United Kingdom, and the United States, to maintain methodological consistency and address data constraints. Fifth, it employs causal inference methods that do not address the spillover effects of policy interactions. Finally, there may be other potential confounders not controlled for in the analysis such as energy technological innovations, energy infrastructure investment, policy marginal abatement cost, political constraints, etc. Consequently, the findings of this study should be interpreted with caution, as constructing an ideal counterfactual for emission mitigation in electricity generation is challenging. Despite these limitations, this work provides exploratory evidence of the static and dynamic interaction effects of four widely adopted national-level policies on CO_2 emissions in the electricity generation sector.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Witson Pena Tello reports financial support was provided by Predoctoral program AGAUR-FI ajuts (2023 FI-3 00065) Joan Oró of the Secretariat of Universities and Research of the Department of Research and Universities of the Generalitat of Catalonia and the European Social Plus Fund. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendices

Appendix 1: Variables and sources of the study

Outcome variable:

CO2 emission per capita from electricity generation. To facilitate a comparison of CO2 emissions across heterogeneous countries, the outcome variable of CO2 emission per capita from electricity generation is employed. This variable is derived from the ratio of two distinct metrics.

- CO2 emission from electricity generation is measured in millions of metric tons of CO2.
- Population is measured by the number of people.

The resulting CO2 emission per capita from electricity generation is calculated as CO2 ton per person = CO2 emission from power generation x 1000,000/population.

CO2 emission from electricity generation. CO2 emissions from electricity generation encompass electricity and heat CO2 emissions, which primarily originate from electricity and heat production but may also arise from auto producers and other energy industries (WRI, 2015). The Electricity/Heat sub-sector encompasses CO2 emissions from three distinct sources.

- Main activity producers of electricity and heat (formerly known as public utilities): these are undertakings whose primary activity is to supply the public.

- Unallocated auto-producers: these are undertakings that generate electricity and/or heat, wholly or partly for their use as an activity that supports their primary activity.
- Another energy industry's use contains emissions from fuel combusted in oil refineries, for the manufacture of solid fuels, coal mining, oil, and gas extraction, and other energy-producing industries.

Units of measurement.

CO2 emissions from electricity generation are expressed in millions of metric tons ($MtCO_2$).

Sources:

Climate Watch, an online climate data platform managed by World Resources Institute, is designed to empower policymakers, researchers, media, and other stakeholders with the climate data, visualizations, and resources they need to gather insights on national and global progress on climate change. Climate Watch collects data on sub-sector electricity/heat from International Energy Agency (IEA). As of November 2022, Climate Watch Historical Emissions data contains sector-level greenhouse gas (GHG) emissions data for 194 countries and the European Union for the period 1990–2019.

Population. Total population counts all residents regardless of legal status or citizenship.

Units of measurement.

Number of residents in a country whose values are mid-year estimates.

Sources:

Word Bank publishes annual total population data.

Covariates

GDP per capita. GDP per capita is calculated using purchasing power parity (PPP), which converts gross domestic product (GDP) to international dollars, a hypothetical currency that has the same purchasing power as the U.S. dollar in the United States. GDP at purchaser's prices is the sum of gross value added by all resident producers in a country, plus any product taxes, minus any subsidies not included in the value of the products.

Units of measurement.

Data is measured in constant 2017 international dollars. It is calculated without making deductions for depreciating fabricated assets or the depletion and degradation of natural resources.

Sources:

Word Bank annually publishes PPP GDP based on the methodology from the International Comparison Program.

Electric power consumption per capita. Electric power consumption measures the production of power plants and combined heat and power plants less transmission, distribution, and transformation losses and own use by heat and power plants. Data is reported as net consumption (excludes the energy consumed by the generating units). According to the World Bank, an economy's consumption of electricity is a basic indicator of its size and level of development.

Units of measurement.

Electric power consumption (in Billion kWh) is divided by population. As a result, electric power consumption per capita is measured as kWh per person = electric power consumption x 1000,000,000/population.

Sources:

Energy Information Administration (EIA) publishes annually energy net consumption. When missing values of energy net consumption per capita arise, they are supplemented with information from the World Bank's electric power consumption per capita data to ensure comprehensive coverage.

Indicator of Quality of Government. This composite indicator represents the average value of three expert-assessed components: Corruption, Law and Order, and Bureaucracy Quality. These assessments are subject to peer review at the topic and regional levels.

- Corruption (originally 6 points): Corruption within the political system is the focus of this component. While financial corruption is considered, the emphasis lies on actual or potential corruption manifesting as excessive patronage, nepotism, job reservations, favor-for-favors, secret party funding, and suspiciously close ties between politics and business. The overarching concern is the potential for such corruption to escalate to a level that triggers a public backlash, leading to a government collapse, a major overhaul of political institutions, or, at worst, lawlessness, and the inability to govern effectively.
- Law and order (originally 6 points): This component comprises two subcomponents: Law and Order (each comprising zero to three points). The Law subcomponent assesses the strength and impartiality of the legal system, while the Order subcomponent assesses the level of popular observance of the law. A country may exhibit a robust judicial system yet receive a low rating if it suffers from a very high crime rate or if the law is routinely ignored without effective sanction (for example, widespread illegal strikes).
- Bureaucracy quality (originally 4 points): A strong, capable bureaucracy serves as a shock absorber, minimizing policy reversals when governments change. Countries with a competent and efficient bureaucracy are awarded higher points, while those lacking such a cushioning effect are penalized, as changes in government often lead to turmoil in policy formulation and day-to-day administrative functions.

Units of measurement.

This indicator is derived from the average of three International Country Risk Guide (ICRG) variables: Corruption, Law and Order, and Bureaucracy Quality (icrg_qog). It is scaled from 0 to 1, with higher values indicating a higher quality of government. This is one the most comprehensive and continued data on the Quality of Government since 1984 and one of the sources that the World Bank uses to calculate Worldwide Governance Indicators (WGI).

Sources:

Dahlberg, Stefan, Aksel Sundström, Sören Holmberg et al. (2022). The Quality of Government Basic Dataset, version Jan22. University of

Gothenburg: The Quality of Government Institute, https://doi.org/10.18157/qogbasjan22. The original data comes from PRS Group's International Country Risk Guide – Political Risk Services.

Fossil fuel rents. It accounts for the contribution of major fossil fuel resources (coal, natural gas, and oil) to a country's economic output. These rents are calculated as the difference between the value of fossil fuel production at regional prices and the total cost of production. In essence, fossil fuel rents capture the excess earnings, or economic rents, that come from the extraction of these non-renewable resources. Natural resources give rise to economic rents because they are not produced. For produced goods and services competitive forces expand supply until economic profits are driven to zero, but natural resources in fixed supply often command returns over their cost of production.

Units of measurement.

Fossil fuel rents from coal, natural gas, and oil are expressed as a percentage of a country's gross domestic product (GDP).

Sources:

Word Bank publishes annually coal rents, natural gas rents, and oil rents as a percentage of GDP based on the methodology from the World Bank's The Changing Wealth of Nations.

Financial development index (FD). Financial development is defined as a composite of three dimensions: depth (size and liquidity of markets), access (the ability of individuals and companies to access financial services), and efficiency (ability of institutions to provide financial services at low cost and with sustainable revenues, and the level of activity of capital markets).

Units of measurement.

It is an overall weighted index that aggregates high-level sub-indexes for financial institutions and financial markets, each of which is further composed of indicators reflecting financial depth, access, and efficiency. It is scaled from 0 to 1, with higher values indicating a more developed financial system.

Sources:

International Monetary Fund (IMF) publishes annually the Financial Development Index from 1980 onwards.

Fossil fuel prices. They consist of the prices of the primary fossil fuels used globally in electricity generation: coal and natural gas. In the oil industry, coal and natural gas are primarily traded on regional markets, requiring the consideration of diverse price benchmarks based on the regions in which countries are located. In the case of coal prices, reference benchmarks contain: 1) Northwest Europe marker price is regarded as the reference price for Europe and Africa; 2) US Central Appalachian coal spot price index is regarded as the reference price for Latin America and North America; 3) China Qinhuangdao spot price is regarded as the reference price for China; and 4) Japan's steam coal import CIF price is regarded as the reference price for Asia (except for China). In the case of natural gas, reference benchmarks comprise: 1) Japan Korea Marker (JKM) is regarded as the reference price for Asia; 2) The UK NBP index is regarded as the reference price for Europe and Africa; 3) Alberta is regarded as the reference price for Canada; and 4) US Henry Hub is regarded as the reference price for Latin America and North America (except for Canada).

Units of measurement.

To eliminate the distortion caused by inflation, fossil fuel prices are expressed in real terms. This is achieved by applying the GDP Implicit Price Deflator in the United States to the nominal prices of coal (US$/ton) and natural gas (US$/MMBTU). As a result, fossil fuel prices are presented as real prices in US$ constant 2017.

Sources:

BP publishes annually the Statistical Review of World Energy.

Intermediary outputs or/and outcomes: mechanisms

Renewable capacity share. Renewable capacity share represents the ratio of renewable energy capacity relative to total electricity capacity as of December 31. Renewable capacity includes hydroelectricity, wind, solar, biomass, geothermal, fuel cell, tide, and wave. Capacity data consist of both utility and non-utility sources.

Units of measurement.

This variable is expressed as a percentage (%). Both the numerator (renewable capacity) and denominator (total electricity capacity) are measured in million kilowatts (kW).

Sources:

Energy Information Administration (EIA) publishes annually international electricity capacity data.

Renewable generation and non-hydro renewable generation shares. First, renewable generation share represents the ratio of renewable energy generation relative to total electricity generation. Renewable generation includes hydroelectricity, wind, solar, biomass, geothermal, fuel cell, tide, and wave. Second, non-hydro renewable generation share is the ratio of non-hydroelectrical renewable energy generation relative to total electricity generation. Non-hydro renewable generation excludes hydroelectricity.

Generation data consists of both utility and non-utility sources from electricity and combined heat and power plants. Data are reported as net generation, not gross generation, which excludes the energy consumed by the generating units and generation from hydroelectric pumped storage.

Units of measurement.

Both renewable generation and non-hydro renewable generation shares are expressed as percentages (%). Both the numerator (renewable generation or non-hydro renewable generation) and denominator (total electricity generation) are measured in billion kilowatt-hours.

Sources:

Energy Information Administration (EIA) publishes annually international electricity generation data. When there are missing values of net generation, the missing values are supplemented with information on generation from the International Energy Agency (IEA).

Energy intensity. Energy intensity represents the ratio of electricity generation relative to GDP.

Units of measurement.

Electricity generation (in Billion kWh) is divided by GDP (in constant 2017 international dollars). As a result, energy intensity is measured as kWh per constant 2017 international dollars = electricity generation x 1000,000,000/GDP.

Sources:

Energy Information Administration (EIA) provides electricity generation data and the Word Bank provides purchasing power parity (PPP) GDP data.

Carbon intensity. Carbon intensity is the ratio of CO2 emission from electricity generation relative to electricity generation.

Units of measurement.

CO2 emission from electricity generation (millions of metric tons of CO2) is divided by electricity generation (in Billion kWh). As a result, carbon intensity is measured as CO2 tons per megawatt hours.

Sources:

Climate Watch provides CO2 emission from electricity generation data and Energy Information Administration (EIA) provides electricity generation data.

Appendix 2: List of countries in the dataset

To maintain consistency with the staggered DID design methodology, particularly the Callaway & Sant'Anna estimator, and address data availability limitations, several countries were removed from the dataset. First, the United States and Portugal were excluded due to the implementation of their feed-in policies prior to the start of the dataset's time span (1978 and 1988, respectively). Second, Italy and the United Kingdom were eliminated owing to the non-staggered nature of their auction policies, characterized by their turn-on-and-off adoptions. Third, Germany was excluded due to the lack of information on covariates from the previous year before the introduction of its feed-in policy (1990), a requirement for the Callaway & Sant'Anna staggered DID conditional on covariates method. Finally, some countries were dropped due to the absence of data on the key variables of the study. The final list of countries considered in this work is presented in the following table.

Table 6
List of countries in the sample

1	Albania	29	Denmark	57	Kuwait	85	Romania
2	Algeria	30	Dominican Republic	58	Latvia	86	Russian Federation
3	Angola	31	Ecuador	59	Lebanon	87	Saudi Arabia
4	Argentina	32	Egypt, Arab Rep.	60	Libya	88	Senegal
5	Armenia	33	El Salvador	61	Lithuania	89	Serbia
6	Australia	34	Estonia	62	Luxembourg	90	Singapore
7	Austria	35	Ethiopia	63	Malaysia	91	Slovak Republic
8	Azerbaijan	36	Finland	64	Malta	92	Slovenia
9	Bahrain	37	France	65	Mexico	93	South Africa
10	Bangladesh	38	Gabon	66	Moldova	94	Spain
11	Belarus	39	Ghana	67	Mongolia	95	Sri Lanka
12	Belgium	40	Greece	68	Morocco	96	Sudan
13	Bolivia	41	Guatemala	69	Mozambique	97	Sweden
14	Botswana	42	Haiti	70	Myanmar	98	Switzerland
15	Brazil	43	Honduras	71	Namibia	99	Tanzania
16	Bulgaria	44	Hungary	72	Netherlands	100	Thailand
17	Cameroon	45	Iceland	73	New Zealand	101	Togo
18	Canada	46	India	74	Nicaragua	102	Trinidad and Tobago
19	Chile	47	Indonesia	75	Nigeria	103	Tunisia
20	China	48	Iran, Islamic Rep.	76	Norway	104	Turkey
21	Colombia	49	Ireland	77	Oman	105	Ukraine
22	Congo, Dem. Rep.	50	Israel	78	Pakistan	106	United Arab Emirates
23	Congo, Rep.	51	Jamaica	79	Panama	107	Uruguay
24	Costa Rica	52	Japan	80	Paraguay	108	Vietnam
25	Cote d'Ivoire	53	Jordan	81	Peru	109	Zambia
26	Croatia	54	Kazakhstan	82	Philippines		
27	Cyprus	55	Kenya	83	Poland		
28	Czech Republic	56	Korea, Rep.	84	Qatar		

Tables 7, 8 and 9 inform the number of countries by policies, income, and region.

Table 7
Number of countries by policies

Policies	Treated	Untreated	Total
Auctions	67	42	109
Feed-in	59	50	109
Carbon tax	10	99	109
ETS	32	77	109
Auctions x Carbon tax	8	101	109
Auctions x ETS	18	91	109
Feed-in x Carbon tax	5	104	109
Feed-in x ETS	24	85	109
Carbon tax x ETS	3	106	109
Auctions x Feed-in	41	68	109
Carbon tax x ETS x Auctions	1	108	109

(*continued on next page*)

Table 7 (*continued*)

Policies	Treated	Untreated	Total
Carbon tax x ETS x Feed-in	2	107	109
Auctions x Feed-in x Carbon tax	4	105	109
Auctions x Feed-in x ETS	16	93	109
Auctions x Feed-in x Carbon tax x ETS	1	108	109

Note: This table reports the number of countries that adopted the policy (treatment group) or did not adopt the policy (control group) in the dataset.

Table 8
Number of countries by income and policy

Policies	Auction	Feed-in	Carbon tax	ETS	Auctions x Carbon tax	Auctions x ETS	Feed-in x Carbon tax	Feed-in x ETS	Carbon tax x ETS	Auctions x Feed-in	Carbon tax x ETS x Auctions	Carbon tax x ETS x Feed-in	Auctions x Feed-in x Carbon tax	Auctions x Feed-in x ETS	Auctions x Feed-in x Carbon tax x ETS
Low-income															
Untreated	9	9	18	18	18	18	18	18	18	12	18	18	18	18	18
Treated	9	10	0	0	0	0	0	0	0	7	0	0	0	0	0
Subtotal	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18
Lower-middle-income															
Untreated	10	14	30	29	30	30	30	30	31	19	31	31	30	30	31
Treated	22	18	2	3	2	1	1	2	0	12	0	0	1	1	0
Subtotal	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32
Upper-middle-income															
Untreated	9	13	22	20	22	23	24	21	26	17	26	26	24	23	26
Treated	17	13	4	6	4	3	2	5	0	9	0	0	2	3	0
Subtotal	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26
High-income															
Untreated	14	14	28	9	30	19	30	15	29	19	31	30	31	20	31
Treated	18	18	4	23	2	13	2	17	2	13	0	1	1	12	0
Subtotal	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32
Not Available															
Untreated	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
Treated	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Subtotal	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Total															
Untreated	42	50	99	77	101	91	104	85	106	68	108	107	105	93	108
Treated	67	59	10	32	8	18	5	24	3	41	1	2	4	16	1
Total	109	109	109	109	109	109	109	109	109	109	109	109	109	109	109

Note: This table reports the number of countries that adopted the policy (treatment group) or did not adopt the policy (control group) in the dataset by income level.

Table 9
Number of countries by region and policy

Policies	Auction	Feed-in	Carbon tax	ETS	Auctions x Carbon tax	Auctions x ETS	Feed-in x Carbon tax	Feed-in x ETS	Carbon tax x ETS	Auctions x Feed-in	Carbon tax x ETS x Auctions	Carbon tax x ETS x Feed-in	Auctions x Feed-in x Carbon tax	Auctions x Feed-in x ETS	Auctions x Feed-in x Carbon tax x ETS
East Asia and Pacific															
Untreated	7	4	12	10	12	12	13	11	13	8	13	13	13	12	13
Treated	6	9	1	3	1	1	0	2	0	5	0	0	0	1	0
Total	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13
Europe and Central Asia															
Untreated	14	8	33	9	34	20	33	15	34	17	35	34	34	22	35
Treated	22	28	3	27	2	16	3	21	2	19	1	2	2	14	1
Total	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36
Latin America & the Caribbean															
Untreated	5	14	16	20	16	20	19	20	20	16	20	20	19	20	20
Treated	15	6	4	0	4	0	1	0	0	4	0	0	1	0	0
Total	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
Middle East and North Africa															
Untreated	4	10	16	15	16	15	16	15	16	11	16	16	16	15	16
Treated	12	6	0	1	0	1	0	1	0	5	0	0	0	1	0
Total	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
North America															
Untreated	1	1	0	0	1	1	1	1	0	1	1	1	1	1	1
Treated	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0

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Table 9 (*continued*)

Policies	Auction	Feed-in	Carbon tax	ETS	Auctions x Carbon tax	Auctions x ETS	Feed-in x Carbon tax	Feed-in x ETS	Carbon tax x ETS	Auctions x Feed-in	Carbon tax x ETS x Auctions	Carbon tax x ETS x Feed-in	Auctions x Feed-in x Carbon tax	Auctions x Feed-in x ETS	Auctions x Feed-in x Carbon tax x ETS
Total	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
South Asia															
Untreated	0	1	4	4	4	4	4	4	4	1	4	4	4	4	4
Treated	4	3	0	0	0	0	0	0	0	3	0	0	0	0	0
Total	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
Sub-Saharan Africa															
Untreated	11	12	18	19	18	19	18	19	19	14	19	19	18	19	19
Treated	8	7	1	0	1	0	1	0	0	5	0	0	1	0	0
Total	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19
Total															
Untreated	42	50	99	77	101	91	104	85	106	68	108	107	105	93	108
Treated	67	59	10	32	8	18	5	24	3	41	1	2	4	16	1
Total	109	109	109	109	109	109	109	109	109	109	109	109	109	109	109

Note: This table reports the number of countries that adopted the policy (treatment group) or did not adopt the policy (control group) in the dataset by region.

Appendix 3: Descriptive Statistics

This appendix contains a summary of the main descriptive statistics of the study. Table 10 shows the correlations matrix between the main variables of the study.

Table 10
Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Emission per capita	1.0											
(2) RE auctions	−0.1	1.0										
(3) Feed-in policy	0.0	0.2	1.0									
(4) Carbon tax	0.1	0.1	0.1	1.0								
(5) ETS	0.1	0.1	0.4	0.1	1.0							
(6) GDP per capita	0.6	0.0	0.2	0.1	0.4	1.0						
(7) Power consumption per capita	0.5	0.0	0.0	0.0	0.3	0.7	1.0					
(8) Quality of Government	0.3	0.0	0.1	0.0	0.4	0.7	0.6	1.0				
(9) Fossil fuel rents	0.4	−0.1	−0.2	−0.1	−0.2	0.2	0.1	−0.2	1.0			
(10) Financial development index	0.4	0.1	0.3	0.1	0.4	0.7	0.6	0.8	−0.1	1.0		
(11) Natural gas real price	0.1	0.0	0.3	0.0	0.3	0.1	0.1	0.0	0.1	0.2	1.0	
(12) Coal real price	0.1	0.1	0.3	0.0	0.2	0.1	0.1	0.0	0.1	0.2	0.8	1.0

Fig. 9A shows that CO_2 emissions per capita from electricity generation are right-skewed and not normally distributed: most countries have low emissions, while a few exhibit significantly higher levels. Within the panel, three high-income, oil-rich countries—Qatar, Bahrain, and Kuwait—have the highest CO_2 emissions per capita, due to their heavy reliance on fossil fuels for electricity generation (IEA, 2019). Fig. 9B and C presents kernel density estimates showing variations across four income groups and seven regions. The extended right tails in the distributions for upper-middle-income and high-income groups, as well as for North America, the Middle East, and North Africa, indicate that a small number of high-emission countries dominate the upper end of the distribution. Conversely, low-income economies and Sub-Saharan African countries generally have lower emissions. Within the panel, the Democratic Republic of Congo, Ethiopia, and Paraguay have the lowest CO_2 emissions per capita, as their electricity generation relies on renewable energy sources like hydropower (IEA, 2019). These disparities likely reflect differences in economic development, energy consumption patterns, electricity generation mixes, energy infrastructures, climate policies, etc. Such heterogeneity may underscore the necessity for tailored interventions to reduce CO_2 emissions from electricity generation.

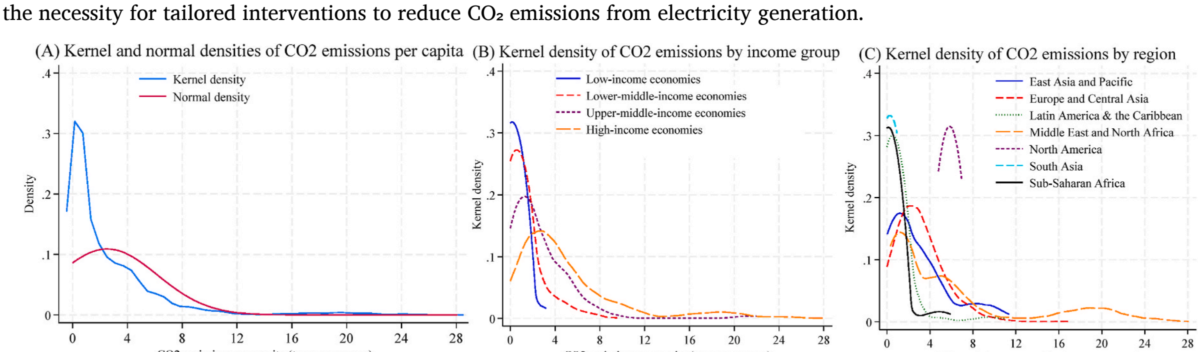

Fig. 9. Distributions of CO2 emissions from electricity generation by seven regions and four income groups.
Note: Fig. 9A presents two density curves for per capita CO_2 emissions from national electricity generation sectors. The blue curve represents the kernel density estimate—a non-parametric method for estimating the data distribution—while the red curve depicts the normal density curve, a parametric estimate assuming a normal (bell-shaped) distribution. Fig. 9B and C displays kernel density estimates of per capita CO_2 emissions for four income groups and seven global regions,

respectively, using a bandwidth parameter of one to smooth the density estimates.

Tables 11 and 12 provide statistical descriptive summaries of CO2 per capita by income and region.

Table 11
Summary statistics of CO2 per capita by income group

Income group	Obs	Mean	SD	Min	Max
Low-income economies	547	0.24	0.57	0.00	3.19
Lower-middle-income economies	945	1.07	1.50	0.00	9.52
Upper-middle-income economies	786	2.66	3.05	0.00	22.19
High-income economies	957	5.06	4.88	0.00	28.08

Table 12
Summary statistics of CO2 per capita by region

Region	Obs	Mean	SD	Min	Max
East Asia and Pacific	390	2.90	2.87	0.04	11.36
Europe and Central Asia	1080	3.01	2.18	0.00	17.13
Latin America & the Caribbean	600	0.88	1.68	0.00	11.00
Middle East and North Africa	480	6.04	6.72	0.31	28.08
North America	30	5.83	0.56	4.79	6.95
South Asia	120	0.28	0.21	0.01	0.93
Sub-Saharan Africa	569	0.38	1.10	0.00	5.91

Table 13 reports the main descriptive statistics of the covariates by treatment status in 1990, which is the earliest year in the dataset before the large-scale implementation of the first-and-second-best policies in the worldwide electricity generation sector and before the declaration of Rio in 1992 that produced a new blueprint for international action on the environment (United Nations, 1992). Significant differences emerge between treated and control countries in 1990, particularly in terms of economic development (measured by GDP or electricity consumption per capita) and government quality. For example, countries that implemented ETS policies tend to show higher levels of economic development compared to control groups, while those that adopted auctions appear to have lower economic development relative to controls. In addition, countries employing carbon pricing mechanisms, such as carbon taxes and ETS, tend to have higher government quality (a proxy for governance) compared to control countries. In contrast, countries implementing second-best policies exhibit no discernible difference in governance between treated and control groups, suggesting that higher governance quality may be more important for the implementation of carbon pricing compared to second-best policies.

Table 13
Summary of means of the covariates by treatment in 1990

Evaluation year (1990)	GDP per capita (PPP constant 2017 international $)	Electric power consumption per capita (kWh/person)	Quality of Government (Interval from 0 to 1)	Fossil fuel rents (% GDP)	Financial Development Index (Interval from 0 to 1)	Natural gas real price (US$ constant 2017/MMBTU)	Coal real price (US$ constant 2017/ton)
Auctions for renewables							
Treated countries	16,112	2193	0.53	5.32	0.23	4.03	70.75
Control countries	14,228	3900	0.54	7.64	0.21	4.14	72.82
Difference	1884	−1707	−0.01	−2.32	0.02	−0.11	−2.08
P-val on difference	0.60	0.05	0.89	0.35	0.61	0.46	0.07
Feed-in policies							
Treated countries	14,953	2328	0.58	2.86	0.23	4.26	73.90
Control countries	15,926	3344	0.49	10.18	0.22	3.85	68.83
Difference	−973	−1016	0.09	−7.32	0.02	0.41	5.07
P-val on difference	0.78	0.24	0.10	0.00	0.58	0.00	0.01
Carbon tax							
Treated countries	22,567	4468	0.70	2.41	0.30	3.49	64.81
Control countries	14,697	2696	0.52	6.60	0.22	4.13	72.24
Difference	7870	1772	0.18	−4.19	0.09	−0.64	−7.44
P-val on difference	0.19	0.26	0.06	0.32	0.15	0.01	0.02
Emission trading system							

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Table 13 (*continued*)

Evaluation year (1990)	GDP per capita (PPP constant 2017 international $)	Electric power consumption per capita (kWh/person)	Quality of Government (Interval from 0 to 1)	Fossil fuel rents (% GDP)	Financial Development Index (Interval from 0 to 1)	Natural gas real price (US$ constant 2017/MMBTU)	Coal real price (US$ constant 2017/ton)
Treated countries	29,880	7273	0.83	1.12	0.34	4.22	74.17
Control countries	10,198	1329	0.43	8.33	0.18	4.01	70.46
Difference	19,683	5944	0.40	−7.21	0.17	0.21	3.71
P-val on difference	0.00	0.00	0.00	0.01	0.00	0.19	0.08

Notes: This table shows the main descriptive statistics of covariates for both treated and untreated countries by policies in 1990. P-values on differences (P-val on the difference) close to zero means that these differences are statistically significant.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Appendix 4: Empirical model and assumptions

Static TWFE

The static TWFE extends the canonical 2x2 DID to a panel data setting. From Roth et al. (2023), this work makes the following identification and estimation assumptions: 1) The stable unit treatment value assumption (SUTVA) implies that the treatment of one country does not affect the potential outcomes of other ones, that is, there are no spillover effects; 2) The no-anticipation assumption implies that there are no unit-specific treatment effects before the treatment occurs; 3) the parallel trends assumption conditional on observed covariates implies that the average outcome for the treated and untreated groups would have followed parallel paths conditional on covariates in the absence of treatment; and 4) the independent sampling assumption implies that the data are randomly drawn from large independent clusters of treated and untreated units. Furthermore, TWFE can handle some types of missing data problems for an unbalanced panel (Wooldridge, 2021). Therefore, the empirical model follows a linear equation:

$$\log\,(emission)_{it} = \beta_0 + \beta_1 policy_{jit}\_combinations(n,k) + \beta_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

$i = 1, 2, \ldots 109;\ j = 1, 2, \ldots 4;\ \textit{and}\ \ t = 0, 1, 2 \ldots 30.$

$$policy_{jit}\_combinations(n,k) = \binom{n}{k} = \frac{n!}{k!(n-k)!} \tag{2}$$

Where the dependent variable is $\log\,(emission)_{it}$ which represents the logarithm (log) of CO2 emission per capita from electricity generation for the country i and period t. The main explanatory variable is $policy_{jit}$ which is a dummy variable that takes a value of 1 when the country i implemented policy j in the electricity generation sector in period t, and 0 otherwise. $policy_{jit}\_combinations(n,k)$ is the number of k policy combinations from one to four policies (n, total number of policies) without repetition. Hence, there are 15 possible combinations from one to four policies without repetition. X_{it} denotes a vector of control variables that are documented in the literature as the main determinants of CO2 emission from electricity generation, such as level of development (measured by logs of GDP or electricity consumption per capita), quality of government, fossil fuel rents, financial development index, log of fossil fuel prices, etc. μ_i and δ_t are country- and year-fixed effects dummies, respectively, to control for time-invariant unit-specific heterogeneity and common shocks. Finally, ε_{it} is an error term.

The main limitation of TWFE is its assumption of homogeneous treatment effects across units and time periods. This assumption may not hold if policy effects vary by countries or over time (de Chaisemartin and D'Haultfœuille, 2020), potentially introducing bias by making forbidden comparisons, such as using already-treated groups as control groups (Goodman-Bacon, 2021).

Callaway & Sant'Anna estimator

Currently, many heterogeneity-robust DID methods exist that typically, although not always, produce similar causal estimators (Roth et al., 2023). Among these methods, this study employs the Callaway & Sant'Anna estimator which relaxes two additional assumptions of the TWFE (Roth et al., 2023): 1) it allows for variations in treatment timing and staggered adoption of the policies in multiple periods (binary absorbing or irreversible treatments, that is, units remain exposed to treatment forever once treated); and 2) it allows for the parallel trends assumption to hold conditional on pre-treatment observed covariates by introducing the additional assumption of strong overlap, which implies that there is a positive probability of being in the untreated group given pre-treatment observed covariates. By conditioning parallel trends assumption on covariates, this estimator gives extra robustness to the random assignment of treatment and could be convenient given the fact that these policies are unlikely to be adopted randomly. Thus, policymakers usually select these policies conditional on some characteristics and trends such as their level of development, quality of government, financial development, etc.

This study employs the following identification, estimation, inference, and aggregation assumptions: 1) the parallel trends assumption holds conditional on covariates and never-treated groups, 2) the estimation uses doubly robust estimands to recover the parameter of interest, 3) the inference procedure employs clustered bootstrapped standard errors at the country level, and 4) the partial aggregation is a balanced event-study sum of dynamic effects to capture the length of exposure to the first year implementation of single policies and the overall aggregation of participating in the treatment is a simple group-size weighted average sum of all available group-time average treatment effects. The parameter of interest is the group-time average treatment effect on the treated $[ATT(g,t)]$ in logarithm, which provides the average treatment effect (in relative terms) among countries that are treated:

$$ATT(g,t) = \mathbb{E}\left[\log Y_{i,t}(g) - \log Y_{i,t}(\infty) | G_i = g\right] \ \ \textit{for}\ t \geq g \tag{3}$$

Where $g \in \{1, \dots g-1, g \dots \mathrm{T}, \infty\}$ and identifies the first treated groups at period g. If $g = \infty$ means it takes never treated group as the counterfactual. $Y_{i,t}(g)$ is the potential outcome path of unit i at time t if it were to first become treated in time period g. If $g = \infty$, then $Y_{i,t}(\infty)$ is the potential outcome path of unit i at time t if it remains never treated through all periods in the sample. $G_i = \min\{t : D_{i,t} = 1\}$ is the earliest period at which unit i has received treatment. $D_{i,t}$ is a binary variable equal to one if unit i is treated in period t and equal to zero otherwise. Thus, if $D_{i,t} = 1$ for all $t \geq G_i$, treatment is an absorbing state (irreversible treatment). $ATT(g,t)$ can be expressed in "event-time" e periods after or before the treatment began to capture the length of exposure to the treatment:

$$ATT(g, g+e) = \mathbb{E}\left[\log Y_{i,g+e}(g) - \log Y_{i,g+e}(\infty) | G_i = g\right] \textit{ for } t \geq g \tag{4}$$

Thus, if $e \geq 0$ means e period after treatment started and $e < 0$ means e period before treatment began. The parallel trends assumption in equation (5) to identify our counterfactual $(Y_{i,t}(\infty)/G_i = g)$ in equation (3) holds conditional on pre-treatment covariates (X_i) and never-treated groups:

$$\mathbb{E}\left[\log \mathrm{Y}_{i,t}(\infty) - \log \mathrm{Y}_{i,t-1}(\infty) | \mathrm{G}_i = g, X_i\right] = \mathbb{E}\left[\log \mathrm{Y}_{i,t}(\infty) - \log \mathrm{Y}_{i,t-1}(\infty) | \mathrm{G}_i = \infty, X_i\right] \tag{5}$$

In the Callaway & Sant'Anna estimator, X_i is a pre-treatment vector of covariates in the baseline period, particularly the first lead or previous year to the first treatment $(g - 1)$. Under the conditional parallel trends assumption in logarithms, it is assumed that only countries with similar characteristics (covariates) would exhibit the same trend in relative CO2 emissions per capita growth in the absence of treatment. To identify the counterfactual, SUTVA, no-anticipation, and strong overlap assumptions are imposed (Callaway and Sant'Anna, 2021). The estimator employs a nonparametric doubly robust approach, which requires either the propensity score weighting or the outcome regression adjustment to be correctly specified, enhancing reliability even if one model is mis specified. This method involves two steps: first estimating a generalized propensity score function $\left[p_g(X_i)\right]$ and a regression adjustment function $\left[m_{g,t}^{nev}(X_i)\right]$, and second, using the fitted values from these previous functions to estimate group-time average treatment effects $[ATT(g,t)]$:

$$ATT_{dr}^{nev}(g,t) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}(G_g)} - \frac{\frac{p_g(X_i)C}{1-p_g(X_i)}}{\mathbb{E}\left(\frac{p_g(X_i)C}{1-p_g(X_i)}\right)}\right)\left(\log Y_t - \log Y_{g-1} - m_{g,t}^{nev}(X_i)\right)\right] \tag{6}$$

Where G_g is a binary variable that is equal to one if a unit is first treated in period $\left(G_{i,g} = 1\{G_i = g\}\right)$. C is a binary variable that is equal to one for units that are never-treated (nev) at any time of the sample. $m_{g,t}^{nev}(X_i)$ is a regression adjustment function equal to $\mathbb{E}\left[\log Y_t - \log Y_{g-1} / C = 1, X_i\right]$. Callaway & Sant'Anna estimator does not require the data to be strongly balanced, as it only uses observations that are balanced within a specific 2x2 design when estimating each treatment effect.

To display dynamic effects graphs of staggered individual policies, the focus is on the event-study (es) or dynamic treatment effects partial aggregation, which is the most common parameter of interest in empirical work (Callaway and Sant'Anna, 2021). This partial aggregation captures the length of exposure to the first-year implementation of single policies. To avoid the compositional change of groups at each time event, this study employs a balanced event-study partial aggregation $[\theta_{es}(e,e')]$, that is, only aggregated $ATT(g,t)$ for a fixed period after and before the treatment was implemented (e'):

$$\theta_{es}(e,e') = \sum_{g=2}^{T} 1\{g + e' \leq T\} ATT_{dr}^{nev}(g, g+e) P(G = g | G + e' \leq T) \tag{7}$$

Where G is the time period when a unit first becomes treated and e' is some fixed even time such that $0 \leq e \leq e' \leq T - 2$. Moreover, this event-study design captures the dynamic treatment effects of policies and investigates whether the parallel trends assumption holds. To do so, it analyzes leads for potential anticipatory effects in the pre-treatment period and lags for possible persistence or decay effects in the post-treatment period (Clarke and Tapia-Schythe, 2022).

To summarize all available group-time average treatment effects of participating in the treatment, this paper uses a simple group-size weighted overall aggregation of all effects across group and time (θ_w^o):

$$\theta_w^o = \frac{1}{k} \sum_{g=2}^{T} \sum_{t=2}^{T} 1\{t \geq T\} ATT_{dr}^{nev}(g,t) P(G = g | G \leq T) \tag{8}$$

Where k is an aggregation of weights $P(G = g | G \leq T)$ that sums up to one to avoid negative weights. One drawback of θ_w^o parameter is that overweighs units that have been treated earlier (Callaway and Sant'Anna, 2021).

Synthetic Difference in Difference

To allow for more heterogeneity of the outcome and relax the reliance on the parallel trends assumption in DID methods, this study uses the synthetic DID method (sdid), developed by Arkhangelsky et al. (2021), which enables the inclusion of both time and unit weights to create a reliable counterfactual (Porreca, 2022). This synthetic DID method also addresses the pretesting parallel trends concerns in event-study estimates and potential outliers (Arkhangelsky et al., 2021).

The synthetic DID method requires a balanced panel of units over time periods, a binary irreversible treatment, and at least two pre-treatment periods from which to determine control units (Arkhangelsky et al., 2021; Clarke et al., 2023). According to Arkhangelsky et al. (2021), the estimation of the ATT of each treatment cohort's individuals in logarithm, conditional on covariates, is calculated through a weighted two-way fixed effects regression ($\widehat{\tau}^{sdid}$):

$$(\widehat{\tau}, \widehat{\mu}, \widehat{\alpha}, \widehat{\beta}) = \underset{\tau, \mu, \alpha, \beta}{argmin} \left\{ \sum_{i=1}^{N} \sum_{i=1}^{T} \left(\log Y_{it}^{res} - \mu - \alpha_i - \beta_t - W_{it}\tau\right)^2 \widehat{\omega_i}^{sdid} \widehat{\lambda_t}^{sdid} \right\} \tag{9}$$

Where $\log Y_{it}^{res} = \log Y_{i,t} - \widehat{\gamma} X_{it}$ is the residual of the logarithm of potential outcome for each unit i in each period t ($Y_{i,t}$) and a regression of $\log Y_{i,t}$ on exogenous time-varying covariates (X_{it}), which some them are in logarithm such as GDP per capita, fossil fuel prices, etc. $W_{i,t}$ is a binary variable equal to one if unit i is treated in period t and equal to zero otherwise. $\widehat{\omega_i}^{sdid}$ are the unit weights that align pre-exposure trends in the outcome of unexposed units with those for the exposed units. $\widehat{\lambda_t}^{sdid}$ are the time weights that balance pre- and postexposure periods for unexposed units by differing by a constant. α_i and β_t are unit and year fixed effects. Finally, μ is a constant.

The aggregate group average treatment effect from the synthetic DID method ($\widehat{ATT}^{sdid}$) is aggregated by (Clarke et al., 2023):

$$\widehat{ATT}^{sdid} = \sum_{for\ a \in A} \frac{T_{post}^{a}}{T_{post}} x\ \widehat{\tau}_{a}^{sdid} \tag{10}$$

Where A indicates the number of distinct adoption dates or first treated date (a). T_{post} refers to the total number of post-treatment periods observed in treated units. This method is conceptually like that of Callaway and Sant'Anna estimator which uses never-treated groups (Porreca, 2022).

Appendix 5: Static TWFE estimations

Table 14

Summary of separate estimations using two TWFE models by total sample, income development, and geography: logarithm of CO2 emission per capita from electricity generation

Variables	Total sample	Income development			Region						
		Low	Middle	High	East Asia and Pacific	Europe and Central Asia	Latin America & the Caribbean	Middle East and North Africa	North America	South Asia	Sub-Saharan Africa
Policies	**1**	2	**3**	4	**5**	6	**7**	8	**9**	10	**11**
Auctions	0.01 (0.107)	−1.16*** (0.413)	0.05 (0.110)	−0.08 (0.050)	−0.40*** (0.060)	0.18** (0.084)	0.02 (0.168)	0.03 (0.067)		−0.56 (0.415)	−0.78* (0.413)
Feed-in	0.17 (0.11)	1.00** (0.37)	−0.04 (0.11)	−0.00 (0.11)	0.13* (0.07)	0.01 (0.07)	0.06 (0.28)	0.12 (0.11)		0.64* (0.21)	0.55 (0.45)
Carbon tax	−0.05 (0.12)		−0.20** (0.09)	0.44*** (0.12)	−0.11** (0.05)	−0.16 (0.11)	−0.05 (0.22)		0.02 (.)		−0.82* (0.41)
ETS	−0.28** (0.13)		−0.31** (0.13)	−0.01 (0.11)	0.10 (0.09)	−0.05 (0.10)		−0.16** (0.06)			
Auctions x Carbon tax	−0.13 (0.16)		−0.16 (0.12)	−0.42*** (0.08)		−0.42*** (0.12)		0.00 (.)			
Auctions x ETS	−0.19 (0.12)		−0.13 (0.14)	0.19*** (0.07)	0.03 (0.06)	−0.03 (0.07)		−0.68*** (0.10)			
Feed-in x Carbon tax	−0.23 (0.17)		0.05 (0.09)	−0.04 (0.13)		0.14 (0.15)	−0.01 (0.20)				
Feed-in x ETS	−0.11 (0.13)		0.15 (0.15)	−0.01 (0.12)	0.05 (0.08)	0.03 (0.10)		−0.57*** (0.15)			
Carbon tax x ETS	0.28 (0.17)		0.24* (0.12)	−0.29* (0.16)		0.15 (0.12)		0.00 (.)			
Auctions x Feed-in	−0.02 (0.13)		0.05 (0.12)	0.02 (0.10)	0.25*** (0.08)	0.09 (0.09)	−0.11 (0.18)	−0.19 (0.12)		0.21 (0.39)	0.24 (0.55)
Carbon tax x ETS x Auctions	−0.62*** (0.16)					−0.01 (0.16)					
Carbon tax x ETS x Feed-in	0.14 (0.29)										
Auctions x Feed-in x Carbon tax	0.15 (0.22)		0.02 (0.16)	0.00 (.)							
Auctions x Feed-in x ETS	−0.09 (0.17)			−0.25* (0.14)		−0.33** (0.13)					
Auctions x Feed-in x Carbon tax x ETS											
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.61	0.17	0.39	0.01	0.84	0.00	0.38	0.94	1.00	0.49	0.04
N° Obs	3079	510	1626	932	380	961	580	456	30	120	552

Notes: This table reports the aggregated average treatment effects on the treated (ATTs) for individual policies and their combinations on the logarithm (log) of carbon emissions per capita from electricity generation, categorized based on the total sample, income level of development, and regions as defined by the World Bank's classification system. The estimation employs a static two-way fixed effects (TWFE) linear model with seven control variables: log of GDP per capita, log of electric power consumption per capita, quality of government, fossil fuel rents, financial development index, log of regional natural gas real price, and log of regional coal real price.
Empty spaces indicate that the variable was omitted from the regression because of collinearity.
Standard errors are shown in parentheses.
*p < 0.1, **p < 0.05, ***p < 0.01.

Appendix 6: Honest DID sensitivity analysis

This appendix presents a sensitivity analysis of the Callaway and Sant'Anna DID estimates, utilizing the HonestDID package developed by Rambachan and Roth (2023). The analysis is designed to explore the robustness of the estimated treatment effects to potential violations of the parallel trends assumption. The original confidence interval, ranging from −0.069 to 0.02, includes zero, implying that the statistical significance of the treatment effect may be sensitive to the assumption of strict parallel trends.

Table 15
Sensitivity analysis - robust confidence intervals that account for potential violations of the parallel trends assumption for Callaway & Sant'Anna DID estimates using Honest DID package: Logarithm of CO2 emission per capita from electricity generation

M*	Lower bound (lb)	Upper bound (ub)
Original	−0.069	0.020
0.50	−0.141	0.096
1.00	−0.237	0.193
1.50	−0.337	0.293
2.00	−0.438	0.394

Note: This table presents the differences between the estimated coefficients and the trend at the 95% confidence level, based on the Callaway & Sant'Anna DID estimator. The model specification assesses the logarithm of carbon emissions per capita from electricity generation, conditioned on the pre-treatment logarithm of GDP per capita and the quality of government.
The sensitivity parameter, M, measures the maximum violation of the parallel trends assumption during the pre-treatment period.
M is the maximum violation of parallel trends in the pre-treatment period. This parameter allows for varying degrees of tolerance toward deviations from the parallel trends assumption, with values ranging from 0.5 to 2.
The table also reports the lower bound (lb) and upper bound (ub) of the 95% robust confidence intervals for the estimated treatment effects at each M value.

Fig. 10 shows that the confidence intervals become wide and include zero at higher values of M which may indicate that Callaway & Sant'Anna DID estimates are sensitive to violations of parallel trends. Therefore, the dynamic treatment effect may not be robust to moderate violations of this assumption.

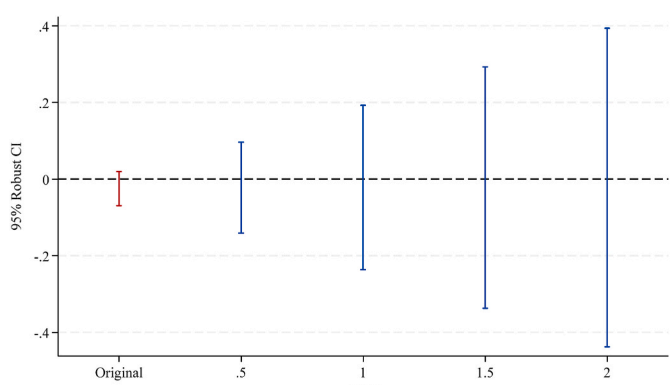

Fig. 10. Sensitivity analysis using relative magnitudes restrictions of Callaway & Sant'Anna DID estimates.
Note: This figure depicts the sensitivity of Callaway and Sant'Anna's DID estimates to varying degrees of deviation from the parallel trends assumption, represented by different values of M along the X-axis (ranging from 0 to 2). The Y-axis captures the 95% confidence intervals of the estimated treatment effects at each level of M. As M increases, the analysis allows for greater violations of parallel trends. The widening of confidence intervals with larger M indicates that higher deviations from the parallel trends assumption introduce greater uncertainty in the estimated treatment effects.

Appendix 7: Arkhangelsky et al. synthetic DID estimation for ETS policies

Table 16
Summary of dynamic effects of interactions within staggered ETS policies using Arkhangelsky et al. synthetic DID: logarithm of CO2 emission per capita from electricity generation

Policy	ATT	Std. Err.	t	P > t	[95% Conf.	Interval]
ETS	−0.43	0.07	−6.49	0	−0.56	−0.30

Note: This table reports the aggregated average treatment effects on the treated [ATT], conditional on time-varying logarithm of GDP per capita and the quality of government, derived from Arkhangelsky et al. synthetic DID estimation bootstrapped 95% confidence intervals.
P-values are based on large-sample approximations.

Appendix 8: Callaway & Sant'Anna DID and Arkhangelsky et al. synthetic DID estimation for ETS policies

Table 17
Summary of dynamic effects of interactions within staggered ETS policies using Callaway & Sant'Anna DID simple average estimator and Arkhangelsky et al. synthetic DID estimator: logarithm of CO2 emission per capita from electricity generation

ETS policies	Unconditional	Conditional							
	1	2	3	4	5	6	7	8	9
Callaway & Sant'anna DID simple average (Unbalanced panel 109 and 1990–2019)	−0.22*** (0.06)	−0.16*** (0.05)	−0.09*** (0.03)	−0.10*** (0.02)	−0.15*** (0.04)	−0.34*** (0.12)	−0.09 (0.08)	−0.25*** (0.06)	−0.19*** (0.06)
Synthetic DID (Balanced panel 103 and 2000–2019)	−0.44*** (0.07)	−0.40*** (0.06)	−0.40*** (0.07)	−0.43*** (0.07)	−0.41*** (0.06)	−0.40*** (0.07)	−0.40*** (0.07)	−0.40*** (0.07)	−0.39*** (0.08)
Covariates	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log of electricity consumption per capita		x	x		x	x	x	x	x
Quality of Government			x	x	x	x	x	x	x
Fossil fuel rents					x	x	x	x	x
Log of GDP per capita				x		x	x	x	x
Financial Development Index							x	x	x
Log of natural gas real price								x	x
Log of coal real price									x

Notes: This table reports the effects of individual policies on the logarithm of carbon emission per capita from electricity generation, unconditional (equation (1)), conditional on different configurations of covariates (equations from 2 to 9), and country-and year-fixed effects. Callaway & Sant'Anna DID semiparametric estimator is a simple weighted average aggregation of all group-time average treatment effects on the treated [$ATT(g,t)$], bootstrapped at 95% confidence intervals for an unbalanced panel data of 109 countries and 30 years from 1990 to 2019. Arkhangelsky et al. synthetic DID estimator is the aggregated average treatment effects on the treated [ATT], bootstrapped 95% confidence intervals for a balanced panel data of 103 countries and 20 years from 2000 to 2019.
Standard errors are shown in parentheses.
*p < 0.1, **p < 0.05, ***p < 0.01.

Data availability

Data will be made available on request.
Data 109_Unbalanced.dta (Original data) (GitHub)
Stata codes_reproducibility.do (Original data) (GitHub)

References

Alexopoulos, T., Thomakos, D., Tzavara, D., 2017. A decomposition of the effect of renewable energy sources regulation on CO2 emissions in the EU-15. Environ. Econ. https://www.semanticscholar.org/paper/A-decomposition-of-the-effect-of-renewable-energy-Alexopoulos-Thomakos/30edc10280baec07de5bfec034b4324b6ab50ad7.
Angrist, J.D., 2022. Empirical strategies in economics: illuminating the path from cause to effect. Econometrica 90 (6), 2509–2539. https://doi.org/10.3982/ECTA20640.
Ari, I., Sari, R., 2015. The role of feed-in tariffs in emission mitigation: Turkish case. Renew. Sustain. Energy Rev. 48, 768–775. https://doi.org/10.1016/J.RSER.2015.04.006.
Arkhangelsky, D., Athey, S., Hirshberg, D.A., Imbens, G.W., Wager, S., 2021. Synthetic difference-in-differences. Am. Econ. Rev. 111 (12), 4088–4118. https://doi.org/10.1257/AER.20190159.
Baranzini, A., van den Bergh, J.C.J.M., Carattini, S., Howarth, R.B., Padilla, E., Roca, J., 2017. Carbon pricing in climate policy: seven reasons, complementary instruments, and political economy considerations. Wiley Interdisciplinary Reviews: Clim. Change 8 (4), e462. https://doi.org/10.1002/WCC.462.
Barnea, G., Hagemann, C., Wurster, S., 2022. Policy instruments matter: support schemes for renewable energy capacity in worldwide comparison. Energy Pol. 168, 113093. https://doi.org/10.1016/J.ENPOL.2022.113093.
Bayer, P., el Aklin, M., 2020. The European Union Emissions Trading System reduced CO2 emissions despite low prices. Proc. Natl. Acad. Sci. USA 117 (16), 8804–8812. https://doi.org/10.1073/PNAS.1918128117.
Bento, N., Borello, M., Gianfrate, G., 2020. Market-pull policies to promote renewable energy: a quantitative assessment of tendering implementation. J. Clean. Prod. 248, 119209. https://doi.org/10.1016/j.jclepro.2019.119209.
Besley, T., Persson, T., 2023. The political economics of green transitions. Q. J. Econ. 138 (3), 1863–1906. https://doi.org/10.1093/QJE/QJAD006.
Blanchard, O., Tirole, J., 2021. The major future economic challenges. https://www.strategie.gouv.fr/sites/strategie.gouv.fr/files/atoms/files/fs-2021-rapport-anglais-les_grands_defis_economiques-juin_1.pdf.
Böhringer, C., Behrens, M., 2015. Interactions of emission caps and renewable electricity support schemes. J. Regul. Econ. 48 (1), 74–96. https://doi.org/10.1007/S11149-015-9279-X/TABLES/4.
Callaway, B., Sant'Anna, P.H.C., 2021. Difference-in-Differences with multiple time periods. J. Econom. 225, 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001.
Chitnis, M., Sorrell, S., Druckman, A., Firth, S.K., Jackson, T., 2014. Who rebounds most? Estimating direct and indirect rebound effects for different UK socioeconomic groups. Ecol. Econ. 106, 12–32. https://doi.org/10.1016/j.ecolecon.2014.07.003.
Clarke, D., Pailañir, D., Carleton Athey, S., Imbens, G.W., 2023. Synthetic Difference in Differences Estimation. R&R Stata Journal. https://www.iza.org/publications/dp/15907/synthetic-difference-in-differences-estimation.
Clarke, D., Tapia-Schythe, K., 2022. Https://Doi.Org/10.1177/1536867X211063144. Implementing the Panel Event Study, vol. 21, pp. 853–884. https://doi.org/10.1177/1536867X211063144 (4).
Couture, T.D., Cory, K., Kreycik, C., Williams, E., 2010. A policymaker's Guide to feed-in tariff policy design. https://www.nrel.gov/docs/fy10osti/44849.pdf.
Cullen, J.A., Mansur, E.T., 2017. Inferring carbon abatement costs in electricity markets: a revealed preference approach using the shale revolution. Am. Econ. J. Econ. Pol. 9 (3), 106–133. https://doi.org/10.1257/POL.20150388.

de Chaisemartin, C., D'Haultfœuille, X., 2020. Two-way fixed effects estimators with heterogeneous treatment effects. Am. Econ. Rev. 110 (9), 2964–2996. https://doi.org/10.1257/AER.20181169.
del Río, P., Kiefer, C.P., 2023. Academic research on renewable electricity auctions: taking stock and looking forward. Energy Pol. 173, 113305. https://doi.org/10.1016/J.ENPOL.2022.113305.
Döbbeling-Hildebrandt, N., Miersch, K., Khanna, T.M., Bachelet, M., Bruns, S.B., Callaghan, M., Edenhofer, O., Flachsland, C., Forster, P.M., Kalkuhl, M., Koch, N., Lamb, W.F., Ohlendorf, N., Steckel, J.C., Minx, J.C., 2024. Systematic review and meta-analysis of ex-post evaluations on the effectiveness of carbon pricing. Nat. Commun. 15 (1), 1–12. https://doi.org/10.1038/s41467-024-48512-w, 2024 15:1.
Edenhofer, O., Sokona, Y., Minx, J.C., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Kriemann, B., Savolainen Web Manager Steffen Schlömer, J., von Stechow, C., Zwickel Senior Scientist, T., 2014. Climate change 2014 mitigation of climate change working group III contribution to the fifth assessment report of the intergovernmental panel on climate change. Edited by. www.cambridge.org.
European Union, 2015. EU ETS handbook. https://climate.ec.europa.eu/system/files/2017-03/ets_handbook_en.pdf.
Fabra, N., 2021. The energy transition: an industrial economics perspective. Int. J. Ind. Organ. 79, 102734. https://doi.org/10.1016/J.IJINDORG.2021.102734.
Goh, T., Ang, B.W., Su, B., Wang, H., 2018. Drivers of stagnating global carbon intensity of electricity and the way forward. Energy Pol. 113, 149–156. https://doi.org/10.1016/J.ENPOL.2017.10.058.
Goodman-Bacon, A., 2021. Difference-in-differences with variation in treatment timing. J. Econom. 225, 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014.
Gugler, K., Haxhimusa, A., Liebensteiner, M., 2021. Effectiveness of climate policies: carbon pricing vs. subsidizing renewables. J. Environ. Econ. Manag. 106, 102405. https://doi.org/10.1016/J.JEEM.2020.102405.
Gugler, K., Haxhimusa, A., Liebensteiner, M., 2023. Carbon pricing and emissions: causal effects of Britain's carbon tax. Energy Econ. 121, 106655. https://doi.org/10.1016/J.ENECO.2023.106655.
IEA, 2019. *CO2 Emissions from Fuel Combustion 2019* (CO2 Emissions from Fuel Combustion). OECD. https://doi.org/10.1787/2A701673-EN.
IEA, 2021. Phasing out unabated coal: current status and three case studies. https://iea.blob.core.windows.net/assets/861dc94d-a684-4875-80fb-a1faaf914125/PhasingOutUnabatedCoal-CurrentStatusandThreeCaseStudies.pdf.
IPCC, 2022. Climate change 2022: mitigation of climate change. Contribution of working group III to the sixth assessment report of the intergovernmental panel on climate change. https://doi.org/10.1017/9781009157926.
IRENA, 2020. Renewables 2020 global status report. https://www.ren21.net/wp-content/uploads/2019/05/gsr_2020_full_report_en.pdf.
IRENA, 2021. Renewables 2021 global status report. https://www.ren21.net/gsr-2021/.
Jaumotte, F., Liu, W., McKibbin, W.J., 2021. Mitigating climate change: growth-friendly policies to achieve net zero emissions by 2050. https://www-imf-org.sire.ub.edu/en/Publications/WP/Issues/2021/07/23/Mitigating-Climate-Change-Growth-Friendly-Policies-to-Achieve-Net-Zero-Emissions-by-2050-462136.
Kemp, R., Never, B., 2017. Green transition, industrial policy, and economic development. Oxf. Rev. Econ. Pol. 33 (1), 66–84. https://doi.org/10.1093/OXREP/GRW037.
Kilinc-Ata, N., 2016. The evaluation of renewable energy policies across EU countries and US states: an econometric approach. Energy for Sustainable Development 31, 83–90. https://doi.org/10.1016/J.ESD.2015.12.006.
Lehmann, P., Sijm, J., Gawel, E., Strunz, S., Chewpreecha, U., Mercure, J.F., Pollitt, H., 2019. Addressing multiple externalities from electricity generation: a case for EU renewable energy policy beyond 2020? Environ. Econ. Pol. Stud. 21 (2), 255–283. https://doi.org/10.1007/S10018-018-0229-6/TABLES/6.
Leipprand, A., Flachsland, C., Pahle, M., 2020. Starting low, reaching high? Sequencing in EU climate and energy policies. Environ. Innov. Soc. Transit. 37, 140–155. https://doi.org/10.1016/J.EIST.2020.08.006.
Leroutier, M., 2022. Carbon pricing and power sector decarbonization: evidence from the UK. J. Environ. Econ. Manag. 111, 102580. https://doi.org/10.1016/J.JEEM.2021.102580.
Li, L., Taeihagh, A., 2020. An in-depth analysis of the evolution of the policy mix for the sustainable energy transition in China from 1981 to 2020. Appl. Energy 263, 114611. https://doi.org/10.1016/J.APENERGY.2020.114611.
Linsenmeier, M., Mohommad, A., Schwerhoff, G., 2022. Policy sequencing towards carbon pricing among the world's largest emitters. Nat. Clim. Change 12 (12), 1107–1110. https://doi.org/10.1038/s41558-022-01538-8, 2022 12:12.
Luderer, G., Pehl, M., Arvesen, A., Gibon, T., Bodirsky, B.L., de Boer, H.S., Fricko, O., Hejazi, M., Humpenöder, F., Iyer, G., Mima, S., Mouratiadou, I., Pietzcker, R.C., Popp, A., van den Berg, M., van Vuuren, D., Hertwich, E.G., 2019. Environmental co-benefits and adverse side-effects of alternative power sector decarbonization strategies. Nat. Commun. 10 (1), 1–13. https://doi.org/10.1038/S41467-019-13067-8, 2019 10:1.
Maor, M., Howlett, M.P., 2021. Policy instrument interactions in policy mixes: surveying the conceptual and methodological landscape. SSRN Electron. J. https://doi.org/10.2139/SSRN.3790007.
Marcantonini, C., Teixido-Figueras, J., Verde, S.F., Labandeira, X., 2017. The EU ETS and its interactions with other climate and energy policies. https://doi.org/10.2870/56848.
Martin, R., Muûls, M., Wagner, U.J., 2016. Https://Doi.Org/10.1093/Reep/Rev016. The Impact of the European Union Emissions Trading Scheme on Regulated Firms: what Is the Evidence after Ten Years?, vol. 10, pp. 129–148. https://doi.org/10.1093/REEP/REV016 (1).
Matthäus, D., 2020. Designing effective auctions for renewable energy support. Energy Pol. 142, 111462. https://doi.org/10.1016/J.ENPOL.2020.111462.
Meckling, J., Sterner, T., Wagner, G., 2017. Policy sequencing toward decarbonization. Nat. Energy 2 (12), 918–922. https://doi.org/10.1038/S41560-017-0025-8, 2017 2:12.
Nordhaus, W.D., 2021. The spirit of green: the economics of collisions and contagions in a crowded world. In: Book, first ed. Princeton University Press.
OECD, 2017. *OECD Environmental Performance Reviews: Estonia 2017* (OECD Environmental Performance Reviews). OECD. https://doi.org/10.1787/9789264268241-EN.
Parry, I., Black, S., Zhunussova, K., 2022. Carbon taxes or emissions trading systems?: instrument choice and design. https://www.imf.org/en/Publications/staff-climate-notes/Issues/2022/07/14/Carbon-Taxes-or-Emissions-Trading-Systems-Instrument-Choice-and-Design-519101.
Perino, G., Ritz, R.A., Van Benthem, A., Abrell, J., Borenstein, S., Burtraw, D., Bushnell, J., Fowlie, M., Fullerton, D., Gerlagh, R., Ovaere, M., Rausch, S., Rosendahl, E., Vollebergh, H., Willner, M., Yang, Y., 2019. Overlapping climate policies. https://doi.org/10.3386/W25643.
Porreca, Z., 2022. Synthetic difference-in-differences estimation with staggered treatment timing. Econ. Lett. 220, 110874. https://doi.org/10.1016/J.ECONLET.2022.110874.
Rambachan, A., Roth, J., 2023. A more credible approach to parallel trends. Rev. Econ. Stud. 90 (5), 2555–2591. https://doi.org/10.1093/RESTUD/RDAD018.
Reguant, M., 2019. Https://Doi-Org.Sire.Ub.Edu/10.1086/701190. The Efficiency and Sectoral Distributional Impacts of Large-Scale Renewable Energy Policies, vol. 6, pp. S129–S168. https://doi.org/10.1086/701190 (S1).
Rhodes, E., Scott, W.A., Jaccard, M., 2021. Designing flexible regulations to mitigate climate change: a cross-country comparative policy analysis. Energy Pol. 156, 112419. https://doi.org/10.1016/J.ENPOL.2021.112419.
Roth, J., Sant'Anna, P.H.C., Bilinski, A., Poe, J., 2023. What's trending in difference-in-differences? A synthesis of the recent econometrics literature. J. Econom. https://doi.org/10.1016/J.JECONOM.2023.03.008.
Röttgers, D., Anderson, B., 2018. Power struggle: decarbonising the electricity sector. https://www-oecd-ilibrary-org.sire.ub.edu/environment/power-struggle_900f4c72-en.
Schäfer, S., 2019. Decoupling the EU ETS from subsidized renewables and other demand side effects: lessons from the impact of the EU ETS on CO2 emissions in the German electricity sector. Energy Pol. 133, 110858. https://doi.org/10.1016/J.ENPOL.2019.06.066.
Scott, W.A., Rhodes, E., Hoicka, C., 2023. Multi-level climate governance: examining impacts and interactions between national and sub-national emissions mitigation policy mixes in Canada. Climate Policy 23 (8), 1004–1018. https://doi.org/10.1080/14693062.2023.2185586.
Sewerin, S., 2020. Understanding complex policy mixes: conceptual and empirical challenges. A Modern Guide to Public Policy 191–202. https://doi.org/10.4337/9781789904987.00021.
Stechemesser, A., Koch, N., Mark, E., Dilger, E., Klösel, P., Menicacci, L., Nachtigall, D., Pretis, F., Ritter, N., Schwarz, M., Vossen, H., Wenzel, A., 2024. Climate policies that achieved major emission reductions: global evidence from two decades. Science (New York, N.Y.) 385 (6711), 884–892. https://doi.org/10.1126/SCIENCE.ADL6547/SUPPL_FILE/SCIENCE.ADL6547_SM.PDF.
Sterner, T., Coria, J., 2012. Policy Instruments for Environmental and Natural Resource Management.
Timilsina, G.R., 2022. Carbon taxes. J. Econ. Lit. 60 (4), 1456–1502. https://doi.org/10.1257/JEL.20211560.
Winkler, J., Magosch, M., Ragwitz, M., 2018. Effectiveness and efficiency of auctions for supporting renewable electricity – what can we learn from recent experiences? Renew. Energy 119, 473–489. https://doi.org/10.1016/J.RENENE.2017.09.071.
Woodman, B., Fitch-Roy, O., Mária, B.-L., Dézsi, B., Szabó, L., von Bluecher, F., Klessmann, C., Wigand, F., 2019. *Auctions for the support of renewable energy in the UK* (Issue 1). http://aures2project.eu/wp-content/uploads/2019/10/AURES_II_UK_case_study.pdf.
Wooldridge, J.M., 2021. Two-way fixed effects, the two-way mundlak regression, and difference-in-differences estimators. SSRN Electron. J. https://doi.org/10.2139/SSRN.3906345.
World Bank, 2021. Carbon pricing dashboard. https://carbonpricingdashboard.worldbank.org/map_data.
WRI, 2015. CAIT country greenhouse gas emissions: sources & methods. http://cait.wri.org/historic.
Yergin, D., 2022. Bumps in the Energy Transition. IMF. https://www.imf.org/en/Publications/fandd/issues/2022/12/bumps-in-the-energy-transition-yergin.