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Analyses of topical policy issues

Climate policy choices: An empirical study of the effects on the OECD and BRICS power sector emission intensity

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ABSTRACT

A crucial and challenging part of the worldwide energy transition from fossil fuels to renewable energy is the decarbonization of the power sector. As governments struggle to pass politically feasible, emission-reducing policies that align with other national and international goals, empirical studies can provide insights for policymakers on the question of whether various approaches to combating climate change have effectively contributed to reducing CO_2 emissions. This paper investigates the effect of several key climate policies that governments have implemented in order to reduce CO_2 emission intensity in the power sector; used in this analysis are newly constructed panel data on 34 OECD countries and the 5 BRICS countries that range from 2000 to 2018. The main findings of this paper suggest that, despite a strong theoretical foundation, the market-based policy tested in this analysis does not display a significant negative effect on CO_2 emission intensity. Technological innovation support-policies and deployment-support policies such as feed-in tariffs for wind power production correlate negatively with CO_2 emission intensity. Feed-in tariffs for solar PV and public environmental R&D expenditure do not indicate a significant effect on emission intensity.

1. Introduction

The power sector is a crucial part of modern society and a significant source of global CO_2 emissions worldwide. Electricity and heat generation account for about 25% of global annual emissions. Electricity accounts for about 19% of final energy consumption; this is a share that is expected to rise considerably as more and more countries electrify their economies (IEA, 2018). Understanding how different climate policy choices support a shift towards cleaner technologies becomes an important insight for policymakers as governments plan and implement policies that are aligned with other policy objectives or goals related to energy, including energy demand increases, increases in efficiency and security, and so on, which are pursued concurrently to emission reductions. Given the power sector's position in the transition from fossil fuels to renewable energy (as being arguably the primary potential enabler of a low-carbon economy), interest from scholars in this sector has been rising fast. However, there is no consensus among scholars and experts on what policies might rapidly decarbonize the power sector. Some scholars argue that the most cost-effective way to decarbonize this sector is through market-based approaches such as a carbon tax or an emission cap-and-trade system. By contrast, other researchers propose a less strictly market-based approach where supportive policies, such as feed-in tariffs, R&D funding, and technology- and innovation-support grant enterprises more room to operate in the creation of new markets; furthermore, enterprises are assisted with deploying new capacity for renewable energy generation. This drives down the

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costs for clean technologies through learning curves and economies of scale, which ultimately levels the playing field for renewable technologies.

Despite a strong theoretical foundation that market-based approaches produce the most effective way to reduce carbon emissions, Cullenward and Victor (2020) and Patt (2015) argue against placing the brunt of climate efforts solely on the promises of market-based approaches, as there are clear political, institutional, and enforcement constraints complicating the efforts of setting carbon prices high enough to be significant for environmental outcomes. Given this backdrop, this study presents a comprehensive empirical analysis of the effects of various climate policies on the outcome of CO_2 emission intensity in the OECD and BRICS power sector; I used the latest available data obtained from IEA, being also the first client to receive the data on CO_2 emission intensity that includes the year 2018 (IEA, 2020a). The rest of the data are collected from the World Bank, IRENA, and the OECD databases with new panel data for feed-in tariffs and cross-referenced data on the EU ETS and other emission trading systems around the OECD and BRICS; this is constructed for panel data analysis. Combining both the main market-based instruments and support policies in the power sector in an analysis of the OECD and BRICS countries, this paper covers the majority of the world's power sectors, and it can produce novel insights on the performance of different climate policies that countries in the analysis have implemented. The results of this analysis suggest that despite a strong theoretical foundation, the market-based instrument tested does not hold up to empirical scrutiny. Following those conclusions, the analysis shows that, although not as cost-effective and efficient, other policies (herein labeled deployment- and technological innovation support policies) seem to have contributed to a reduction in CO_2 emission intensity in the studied OECD and BRICS power sectors. This conclusion supports the view that the renewable energy revolution researchers have been witnessing over the last few decades were not enabled by market-based instruments but rather by targeted, generous, and technology-specific policies with substantial subsidies from an active state. Fortunately, now that these renewable energy technologies are competitive and a viable alternative to fossil fuels, the price level at which market-based policies can start to phase out CO_2-intensive power production has been reduced; this thereby sets up more cost-effective approaches for having a potentially greater impact.

The paper is organized in the following sections: Section 2 presents a brief summary of the relevant literature on various climate and energy-related policy choices, Section 3.1 presents the dataset and variables; Section 3.2 follows up with the model specification. Results and a discussion of them are presented in Section 4, which is followed by conclusions and policy implications in Section 5.

2. Literature review

2.1. Market-based approaches

In the OECD and increasingly in the BRICS block, the dominating paradigm in climate policy discussions is centered around market-based solutions. Instruments such as a carbon tax or an emission cap-and-trade system are the preferred solutions by policymakers as they wish to provide a market mechanism that will allocate resources and capital while reaching environmental goals at the lowest possible cost (Baumol and Oates, 1988; Hahn, 1989). By contrast, traditional environmental protection has taken the form of direct governmental regulations, which is often referred to as "command-and-control" regulation; this comes in the form of a technology requirement or emission standards. While standards have been a popular policy tool for policymakers, economists argue that these stringent regulatory approaches leave little flexibility for companies to reach both economic and environmental goals (Portney and Stavins, 2000). On the other hand, market-based instruments "harness market powers, because if they are well designed and implemented, they encourage firms (or individuals) to undertake pollution control efforts that both are in those firms' (or individuals') interests and collectively meet policy goals" (Portney and Stavins, 2000, pp. 31–32). Especially within the OECD, green tax reforms and other forms of carbon pricing are increasingly gaining popularity and support from relevant regulators (OECD, 2018). In the BRICS block, China experimented with eight pilot carbon markets in key jurisdictions and has fully implemented its national carbon-trading scheme as of the 1st of February 2021; the eight pilots have been integrated into the national emission trading system (ETS) (BNEF, 2017; World Bank, 2020a). Moreover, as climate-related issues are moving further up on the political agenda, researchers have witnessed an apparent shift in the handling of climate-related issues from the jurisdiction of the Ministries of Environment towards the Ministries of Finance, and consequently a change in the discussion of climate policy from traditional emission standards regulation towards a push for market-based solutions. Global financial institutions such as the World Bank and the International Monetary Fund (World Bank, 2014; IMF, 2015) are also actively promoting such policy prescriptions.

A contested effect of market-based approaches is that they tend to increase electricity prices, and researchers have studied the so-called CO_2 cost pass-through effect on the prices of wholesale electricity, although the evidence for the described effect is somewhat mixed (e.g., Fezzi and Bunn, 2009; O'Gorman and Jotzo, 2014; Patt, 2015; Wang and Zhou, 2017; Woo et al., 2018). Nevertheless, most scholars agree that this effect occurs in varying degrees in places with carbon pricing policies, and without adjustment, prices tend to be regressive in that they place a greater burden on those with lower incomes relative to those with higher income. However, it can be argued that while an increase in electricity prices stimulates energy savings and efficiency measures, it could also increase the risk of declining social acceptability among consumers, which produces opposition from energy-intensive industries, e.g., through a loss of competitive advantage and lower margins that result from higher electricity prices, as well as their pollution-related externalities (Tobin and Cho, 2010).

However, while market-based instruments have a strong theoretical foundation, the academic literature on their effects on emissions is mixed (to put it very favorably). Most published studies have understandably focused on the EU ETS, while the remaining studies have focused on various sub-national initiatives, including some in the US and the Chinese ETS pilot programs, as well as a few other Asian initiatives. Looking first at the research on the EU ETS, Martin et al. (2016) found in their ex-post analysis of the EU ETS an effect on emissions in regulated sectors in energy and industry in Phase I and the first two years of Phase II. Similar results are found in Anderson and Di Maria (2011) and Bayer and Aklin (2020). Of the studies that do not look at the EU ETS, Gao et al. (2020) uncovered some emission reduction effects when studying the impact of the Chinese pilot ETS programs; their conclusion was that the effect of CO_2 emission reduction is greater in production-based emissions than in consumption-based emissions. A study on the Korean ETS discovered a 2.5% emission reduction from the base case, but an electricity price increase of nearly 4% was associated with it (Choi et al., 2017). By contrast, other studies that form the majority of the literature indicates a far less convincing picture of this effect. Green (2021) provides an ex-post meta-analysis of carbon pricing policies worldwide, with data collected since 1990 and concludes that very few of these policies have actually contributed to significant emissions reductions. The analysis of this study also highlighted that carbon taxes, where applied, have generally been more successful than emission trading schemes (albeit both policies have not delivered the significant reductions promised by economic theorists). Of the studies that focus on the EU ETS, Bel and Joseph (2015) argued that EU emission reductions over the period studied are primarily attributable to the effect of the economic crisis rather than the ETS. Several studies have found a small effect of between around 1% to 2% in emission reduction in the EU ETS over the periods studied (Ellerman and Buchner, 2008; Egenhofer et al., 2011; Ellerman et al., 2016; Dechezleprêtre et al., 2018), while Gloaguen and Alberola (2013) discovered no statistically significant effects of the EU ETS on emissions in their panel data from 2005 to 2011. Outside of the EU ETS, Cullenward (2014) found that the California carbon market had severe carbon leakage, which delivered less of the emission reduction that was promised when accounting for the leakage. Fell and Maniloff (2018) concluded that when looking at the Regional Greenhouse Gas Initiative (RGGI) in the Northeastern US, CO_2 emissions were observed to be down 8.8M tons per year, but the RGGI states leaked about 4.5M tons per year, which puts the actual drop to about 4.3M tons per year. Both Tobin and Cho (2010) and Lin and Li (2011) discovered either no significant effect of environmental taxes and carbon taxes on CO_2 emissions, or that these policies were underperforming in countries that have implemented them; furthermore, Patt (2015) suggested that market-based instruments have been too weak to matter significantly in their outcomes. Lilliestam et al. (2021) went as far as to contend, in a recent paper, that there is no empirical evidence showing the effectiveness of carbon pricing as far as stimulating innovation and zero-carbon investment. Finally, Laing et al. (2013) suggested that enterprises with both top-down and sector-based, bottom-up evaluations could attribute savings in the range of 40 to 80 $MtCO_2$ per year in the EU ETS in all sectors that were covered by the scheme. Furthermore, Laing et al. (2013) concluded that EU ETS has only had a minor impact on investment decisions thus far. As European policymakers continue to affirm their commitment to the European trading system, decision-makers are likely planning for higher prices in the future. Regardless, it is important to underscore that there are large sectorial differences that affect outcomes, and that market-based instruments might work better or worse depending on sector-specific characteristics, e.g., the range of cost-competitive and viable substitutions and regulatory complexity. To pose a testable hypothesis, I relied on the theoretical foundations of market-based instruments, but I am well aware that previous studies suggest that we should not trust those foundations blindly.

2.2. Deployment- and technological innovation-supporting policies

In addition to studying market-based solutions, I evaluated policies focusing on technology support and deployment. The dominant policy promoting rapid deployment and cost reduction of renewable energy technology has been feed-in tariffs (FIT). For solar PV and wind power, in particular, FITs have created several strong domestic markets where both of these technologies have had considerable deployment: Germany is a prime example of this effect. Moreover, while FITs are sometimes defined as a market-based instrument, they operate according to a distinctly different mechanism from a emission cap-and-trade system, usually with a long price-purchasing agreement (PPA), which lasts typically for 15 to 20 years and includes sell-back priority back to the grid with premium pricing; therefore, FITs are better described as a support policy geared for scaling up renewable energy capacity (OECD, 2020). Thus, FITs' objective is to produce renewable energy technologies that support cost-competitive before regular market forces take over (Alizamir et al., 2016). According to a 2008 report by the European Commission, ''well-adapted feed-in tariff regimes are generally the most efficient and effective support schemes for promoting renewable electricity'' (European Commission, 2008). Studies by Alagappan et al. (2011), Dong (2012), Carley et al. (2017) support the notion that feed-in tariffs have been successful in promoting renewable energy and, thus, reducing emissions. Analyses of FIT schemes suggest that their success rate depends on the level at which tariffs are set and how well these tariffs are adjusted over time, particularly in light of new information and technological developments; in turn, this decides the profitability of investments. Aggressive tariffs are shown to increase investors' profitability, generally, but they can lead to less efficient projects that are subsidized at the taxpayers' expense. On the other hand, relatively more conservative tariffs could lead to limited technology deployment by making only the most efficient projects financially viable (Mendonca et al., 2009). A recent systematic review of the evidence of induced innovation in energy technologies by Grubb et al. (2021) discovered that deployment policies, such as feed-in tariffs, have been instrumental in driving down the costs of renewable technologies and that such policies (and their effects) are often overlooked in the policy debate and even more so by the modeling community. The results are what we might call the *vitreous cycle of deployment polices*: technology policies drive deployment which drives down costs; this increases broader uptake, which again drives down costs.

Technology and innovation policy has been another widely used approach in the goal of reducing CO_2 emissions. Newell (2009) argues that "a well-targeted set of climate policies, including those targeted directly at science and innovation, could help lower the overall costs of mitigation", but stresses that poorly designed technology policy could also potentially raise the cost of mitigation rather than lowering it. Newell continues stating that market-based prices on emissions, together with technological support policies, can be particularly effective in technology-areas where the private sector is least eager to invest. He concludes that "effective climate technology policy complements rather than substitutes for emissions pricing" (Newell, 2009, p.38). It is undoubtedly crucial that scientists innovate and develop more efficient climate mitigation technologies, including in renewable energy, storage, and smart grid technologies and systems; however, measuring the innovation or innovative performance of these technologies is notoriously difficult. One such evaluation approach that has been suggested is to look at research and development (R&D) expenditure. Tobin and Cho (2010) discovered a significant negative effect of environmental R&D expenditure on greenhouse gas emission in their study of 26 OECD countries, while Mazzucato (2015) concluded that public R&D expenditure is an important part of measuring the innovative performance of a country, but this is not adequate alone. Thus, another way to meet the goal of evaluation in this sector is to attempt to measure innovation through the study of patents, most commonly as practiced in econometrics (see, for instance Johnstone et al., 2010, 2012). According to Hall (2013), patent statistics are desirable because they are an objective measurement, but assuming that they constitute a stable measurement of innovation, does not follow. Mazzucato (2015) warned that patent statistics alone are an inadequate measurement for innovation or the rate of technological change, but patent statistics can be one part of the picture, together with the aforementioned public R&D expenditure. OECD researchers Haščič and Migotto (2015) suggested that OECD patent statistics such as the variable used in this analysis are analytical tools for assessing countries' innovative performance as these patents are a reliable, albeit far from a perfect, "measure of technological innovation because they focus on the outputs of the inventive process"' (Griliches, 1998 in Haščič and Migotto, 2015, p.15). The use of patent statistics as a measure of innovation has some clear advantages and some notable drawbacks: measures like these are commensurable, widely available, and quantitative in nature; furthermore, they can be disaggregated into sub-categories or domains, lending themselves useful for researchers across fields of study. The most notable drawbacks of patent statistics are that not all innovations are patentable, and not all patentable inventions are patented, and as such data can vary in quality (Haščič and Migotto, 2015).

From a theoretical perspective, it is extremely important to attempt to measure innovation. As I discussed, there are obvious advantages and disadvantages to using patents as an indicator. However, based on the above discussion, patent statistics are a quantitative measurement of innovation outputs, which is arguably the main reason that patents are a good indicator. I can thus propose a testable hypothesis that technological innovation support-policies which are proxied by patent statistics have contributed to a significant reduction in emission intensity, and that despite its shortcomings, it is fairly straight-forward to make a credible argument on why this is the best indicator that researchers currently have to measure innovative performance.

Based on the literature review I have presented above, I propose three main hypotheses to be tested empirically:

H1: *Market-based policy instruments such as emission trading systems have resulted in a decrease in CO_2intensity from electricity generation.*
H2: *Deployment supporting policies such as feed-in tariffs for solar PV and wind have resulted in a decrease in CO_2intensity from electricity generation.*
H3: *Technological innovation support policies have contributed to a decrease in CO_2intensity from electricity generation.*

Increases in consumption, along with industrial development, have traditionally implied an increase in fossil-based electricity generation, and while renewables dominate markets today (2020), this was not always the case for the whole time period used in the analysis. According to Asane-Otoo (2016), increases in consumption will mainly depend on the electricity used in a given country; however, as it is a general control variable that covers all 39 countries, I expect an increase in electricity generation to correlate positively with an increase in CO_2 emission intensity. Thus, I expect that increases in GDP per capita, energy consumption from industry, and residential electricity consumption will all correlate positively with CO_2 emission intensity. Furthermore, I expect the last control variable, installed renewable energy capacity, to correlate negatively with intensity of CO_2 emissions.

3. Data and methodological approach

3.1. Data and variables

The analysis investigates collected, processed, and formatted data that ranges from 2000 to 2018, and that covers 34 OECD countries and the 5 BRICS countries (Sæther, 2021). To make a note, the years after the Fukushima Daiichi nuclear disaster in Japan are removed because of the shock it caused to the Japanese power sector (EIA, 2017); this is unfortunate, but it is difficult to control for otherwise. Data on CO_2 emission intensity (CO_2 *emission intensity per* KWh) were purchased

Table 1
CO_2 emission intensity change in percent and changes in grams per KWh.

Country	CO_2 emission intensity change % 2000–2009	Change in grams per KWh 2000–2009	CO_2 emission intensity change % 2010–2018	Change in grams per KWh 2000–2018
OECD:				
Australia	5,1	43,3	−15,0	−125,0
Austria	−4,7	−8,2	−25,2	−50,0
Belgium	−28,2	−84,2	−10,1	−22,5
Canada	−19,9	−43,7	−28,1	−51,3
Chile	10,0	34,3	−3,7	−15,3
Czech Republic	−18,3	−133,9	−15,5	−90,6
Denmark	−10,6	−47,7	−53,5	−193,8
Estonia	1,2	13,1	−17,4	−177,9
Finland	8,6	15,3	−50,0	−117,0
France	3,5	2,7	−31,3	−25,0
Germany	−11,5	−62,3	−15,8	−75,2
Greece	−11,8	−98,5	−25,4	−185,1
Hungary	−33,2	−157,0	−20,9	−66,8
Iceland	−50,0	−0,2	−50,0	−0,1
Ireland	−30,0	−195,0	−29,2	−136,3
Israel	−9,4	−72,9	−29,3	−204,8
Italy	−17,4	−87,7	−25,2	−103,1
Japan	4,9	19,5	16,5	70,9
Korea	−1,6	−9,0	−2,5	−13,5
Luxembourg	−27,2	−128,6	−55,0	−187,6
Mexico	−13,5	−79,7	−9,4	−47,3
Netherlands	−14,5	−72,7	−1,1	−4,5
New Zealand	1,9	3,2	−29,7	−45,7
Norway	841,7	10,1	−62,6	−14,4
Poland	−7,6	−67,0	−11,7	−93,2
Portugal	−22,3	−109,7	14,6	37,6
Slovak Republic	−14,5	−36,4	−21,0	−42,3
Slovenia	−7,3	−25,5	−23,6	−78,1
Spain	−32,1	−141,5	7,7	18,4
Sweden	−17,0	−3,8	−49,6	−13,1
Switzerland	2,6	0,6	4,0	1,0
Turkey	−6,1	−32,6	−0,7	−3,3
United Kingdom	−6,6	−31,6	−49,7	−224,7
United States	−15,9	−99,7	−22,5	−119,4
BRICS:				
Brazil	−27,6	−24,9	13,2	11,6
Russia	1,9	7,7	−15,0	−62,7
India	2,2	17,7	−7,3	−58,8
China	−14,2	−127,8	−18,2	−136,7
South Africa	1,4	12,7	−5,8	−54,5

and obtained from the IEA Emissions Factors database.[1] The decision to focus on CO_2 intensity rather than CO_2 emission is first-and-foremost a question of how to most effectively measure the performance of the power sectors' ability to reduce CO_2 emissions while at the same time attempting to eliminate the underlying growth in electricity demand. According to Ang and Su (2016), a variable measuring CO_2 intensity is a good performance indicator since "a decrease in its value indicates a lower level of CO_2 emissions for each unit of electricity produced than otherwise. This can be taken as a desirable outcome from the environmental and climate change viewpoints" (Ang and Su, 2016, p.57). The measure of intensity is a ratio expressed in grams of CO_2 per KWh. The ratio is based on total emissions from fossil fuels consumed for electricity generation, in both electricity-only and combined heat and power plants (CHP), which is divided by the output of electricity generated from all fossil and non-fossil sources (IEA, 2020b). As a ratio of two physical measurements, CO_2 intensity per KWh is a transparent and unambiguous variable that can be compared across countries and over time (Ang and Su, 2016). Table 1 indicates that power sectors' emission intensity around the world is trending downward. The variable is log transformed in the analysis.

Data on emission trading system quota prices (*Emission Trading System Price*) are cross-referenced from several sources[2] using the mean annual value for the quota price in US$ per ton of CO_2 equivalent. Furthermore, the price was deflated

[1] For full calculation see page 35 in http://wds.iea.org/wds/pdf/CO2KWH_Methodology.pdf (IEA, 2020b).

[2] Weekly data from April 2008 is sourced and calculated to annual data from the EU ETS dashboard that is provided by Sandbag (2020), while prior data is sourced from a range of official EU sources which estimate an annual price for 2005–2007. The rest of the emission trading system data is collected from the World Bank Carbon Pricing Dashboard (World Bank, 2020a).

in order to adjust to inflation in the allowance price by using the CPI index (2010 = 100) that was collected from the World Bank, which is itself based on IMF data (World Bank, 2021). Several previous studies have used a simple dummy variable to measure whether or not a country is connected to an ETS, and this in most instances have been the EU ETS. However, since the effectiveness of the ETS is primarily determined by the price at which emission quotas are traded, it makes more sense to use the actual price of a quota as the annual mean price to measure whether or not it has been effective at reducing emission intensity in the sample countries. In addition to the EU ETS, which covers 23 countries, Australia implemented their own emissions trading scheme called the ERF Safeguard Mechanism — which has been in effect since 1 of July 2016 and at 17 US$. South Korea launched its national ETS in 2015, New Zealand in 2008 (with operations in 2010), and finally Switzerland had their own ETS outside of the EU ETS, with trading beginning in 2011; since January 1. 2020, the Swiss ETS have been linked with the EU ETS. Of the various sub-national ETS around the world, China has introduced 7, and then 8, pilot carbon markets from December 2013 with the eighth coming into operation in late 2016, and California introduced its California Cap and Trade (CaT) system in 2012. The province of Quebec in Canada introduced an ETS in 2013, and while the trading system covers the power sector, it is dominated by hydroelectric power production and is thus excluded outright. In order to include these sub-national emission trading schemes, I coded them by the following formula: the yearly price divided by the number of sub national schemes in a given year, multiplied by the share of the countries power sector emissions in ETS jurisdiction. For China, I have used a mean coverage of 25% (based on a calculation provided in Jotzo and Löschel (2014). The real number is somewhere between 20 and 30% over the time-period since the pilot projects were implemented. For California, I have used a 7% share, as the Californian power sector accounts for about 5%–7% of the total US power sector (DOE, 2015). As a precaution, I ran one stricter model, without the inclusion of modified sub-national ETS (*ETS price (national only)*), and one model without the inflation adjusted ETS price (*ETS price (non-inflation adjusted*); both tests showed no significantly different results and the outcomes can be found in the appendix.

Another market-based instrument that is often proposed as a cost-effective measure to reduce CO_2 emissions is a pure carbon tax. However, with very few exceptions, like the UK carbon price support (CPS) system, every country that has a carbon tax in the analysis exempted its power sector from it, because these countries, with few exceptions,[3] are also connected to the EU ETS and have decided not to double-tax their power producers; thus, a pure carbon tax variable is omitted from the analysis. Finally, another variable that is sometimes used when studying the effect on emissions in the power sector is a broadly defined energy tax. These measurements are mainly tallied as a percentage of state revenues from energy production. The problem with using such a variable to investigate whether various types of policies affect CO_2 emission intensity, in the power sector, is that renewable and other lower-emission energy production technologies are also taxed and, indeed in some countries, taxed at the same rate as their fossil-based counterparts. Therefore, this analysis only uses the ETS price variable, as it is the only variable measuring this form of intervention, i.e., how a market-based instrument affects CO_2 emission intensity is what I am interested in. Fig. 1 shows the evolution of the ETS quota prices (non-inflation adjusted) in the various countries that have implemented the policy.

The indicator of renewable energy feed-in tariffs (*FIT solar PV*, *FIT wind*) is collected from OECD's Environmental Policy database. The indicator measures mean feed-in tariff for a.) Solar PV, and b.) Wind. The data are comprised of country-level values on the tariff in US$/KWh. There exist data on small hydro, biomass, waste, geothermal, and marine energies, but the focus for this analysis is on solar PV and wind (OECD.stat., 2020a). Figs. 2 and 3 display the feed-in tariffs for solar PV and wind.[4]

Governmental R&D expenditure is an important indicator for technology development and innovation. This analysis uses an indicator measuring the share of public environmental R&D expenditure of total public R&D expenditure (*Public environmental R&D expenditure*). There are several other useful indicators for measuring R&D as it is related to the power sector, such as energy-related R&D, and renewable energy R&D, but these data are incomplete and lack consistent measurement that is suitable for panel data analysis; therefore, the broader environmentally-related R&D indicator is the best available measure, although it lacks data for Brazil, China, India, and South Africa. The variable was collected from the OECD Green Growth dataset (OECD.stat., 2020b).

All patent statistics that are used in this analysis were collected from OECD's Innovation in environmental-related technologies database. The data were compiled by the OECD Environment Directorate, in collaboration with the Directorate for Science, Technology, and Innovation, which used additional data from the Worldwide Patent Statistical Database (PATSTAT). The indicator used in this paper is Technology Diffusion (*Technological innovation support policies*), which is defined as the number of inventions that seek protection through national, regional, or international routes in a given jurisdiction as restricted to the sub-category: *Climate change mitigation technologies related to energy generation, transmission or distribution* (OECD.stat., 2021). This variable is log-transformed.

Finally, the indicators for GDP per capita (*ln(Income)*) have been log-transformed and together with the indicator for residential electric power consumption in MWh (*Residential electricity consumption*), and the variable for related to industry (*Industry share of GDP*), measuring industry (including construction), and value-add as a percentage of GDP, were

[3] The Australian carbon tax experiment from 2012–2014 is an example.

[4] The dataset classifies the various feed-in tariff equivalent schemes in the US as feed-in tariffs; more information can be found here: https://www.eia.gov/todayinenergy/detail.php?id=11471# (EIA, 2013).

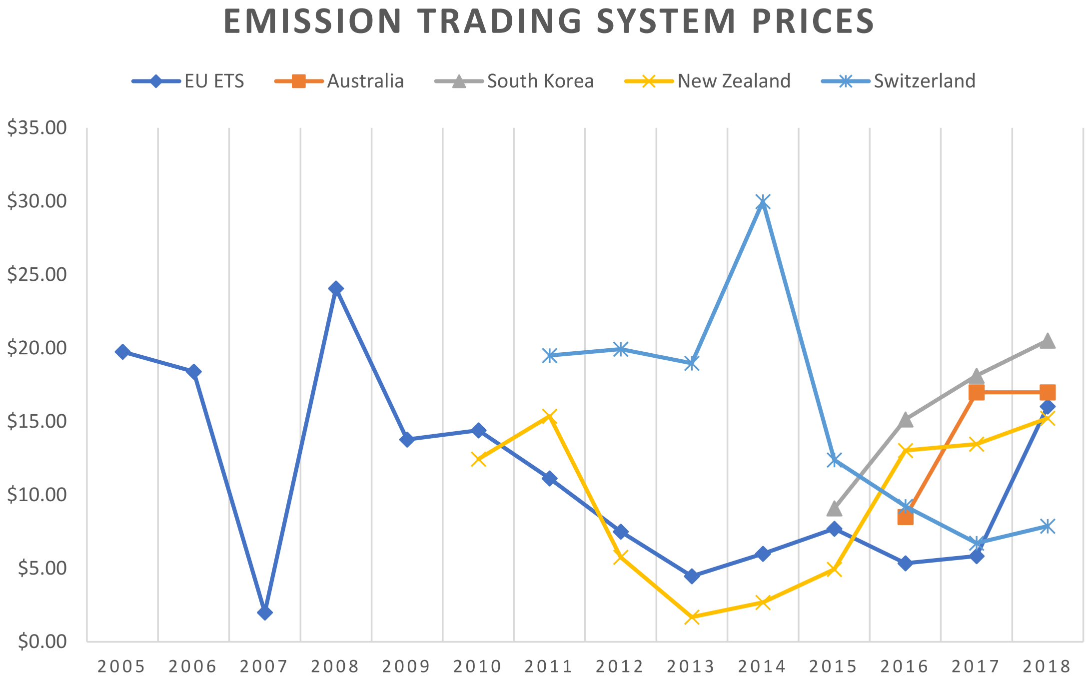

Fig. 1. Annual CO_2 quota price in Emission Trading Systems.
Source: Constructed based on Sandbag EU ETS dashboard and World Bank Carbon Pricing dashboard.

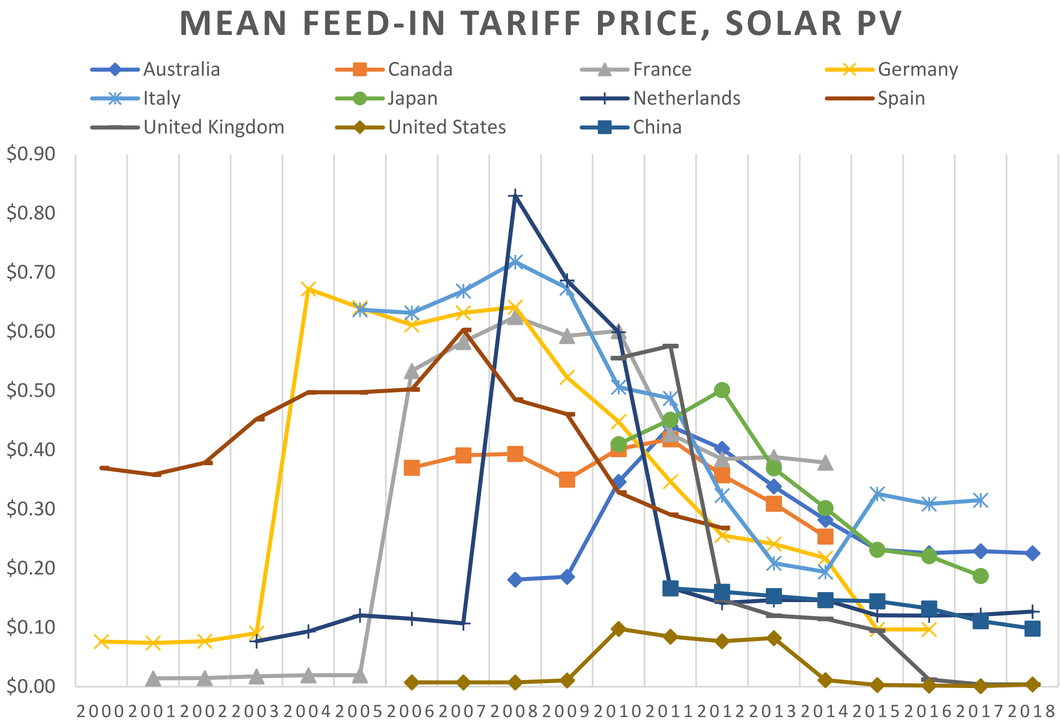

Fig. 2. Feed-in tariffs solar PV in US dollars/KWh.
Source: Constructed based on the OECD Environmental Policy database.

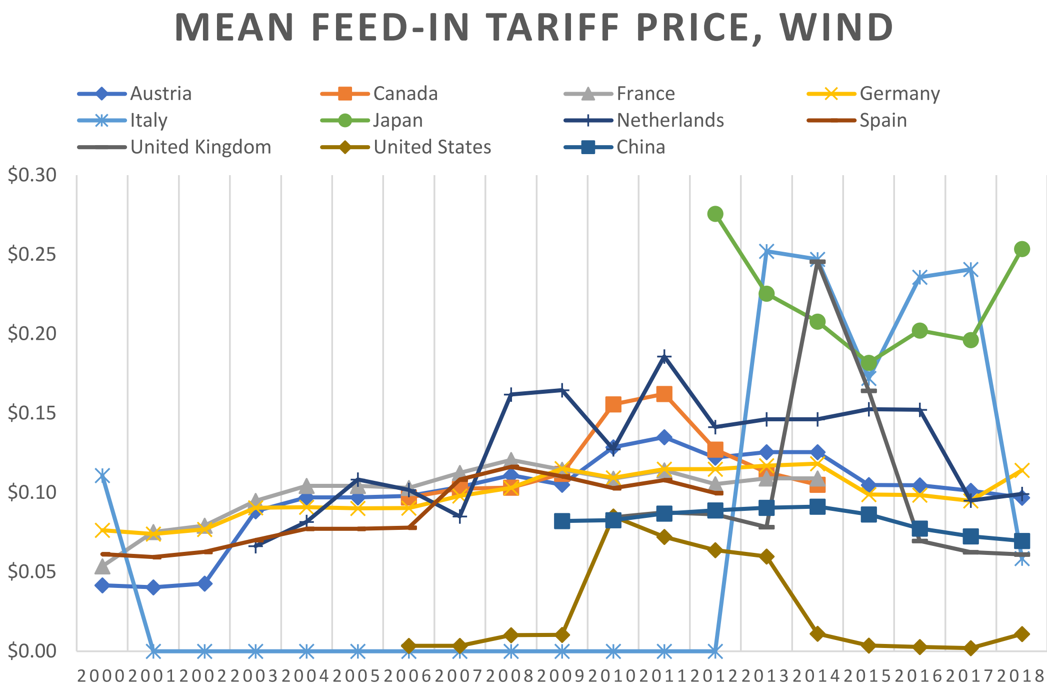

Fig. 3. Feed-in tariffs wind in US dollars/KWh.
Source: Constructed based on the OECD Environmental Policy database.

Table 2
Descriptive statistics.

Variables	N	Mean	St. dev	Min	Max	Unit
CO_2 emission intensity	733	413.75	267.65	0.10	1,096.10	Gram of CO_2 emission per KWh
Emission trading system price (inflation adjusted)	741	5.31	7.44	0	30.21	US$ per tonne of CO_2 equivalent
Feed-in tariff Solar PV	741	0.12	0.20	0	0.83	Mean feed-in tariff in US$/KWh
Feed-in tariff Wind	741	0.05	0.09	0	0.73	Mean feed-in tariff in US$/KWh
Public environmental R&D expenditure	595	2.61	2.09	0	17.66	% of total R&D budget
Technological innovation support policies	741	1,765.26	5,080.44	0	53,501	Number of patents
Income	741	31,405.90	22,621.67	443.31	1,18,823.6	US$ constant
Industry GDP	738	25.91	6.13	10.52	47.56	Value added, % of GDP
Industrial energy consumption	740	27.66	8.31	9.45	56.18	% of total energy consumption
Residential electricity consumption	741	8.38	7.57	0.40	55.10	MWh per capita
Installed renewable energy capacity	741	28.23	59.20	0.01	695.48	Installed GW

all obtained through the World Bank Open Data database (2020b).[5] The alternative indicator used to control for industry energy consumption (*Industrial energy consumption*) measures the share of industrial energy consumption of total energy consumption, and has been collected from the OECD Green Growth dataset (OECD, 2020). Finally, the data on installed renewable energy capacity (*ln(Installed renewable energy capacity)*) have been collected from the IRENA database and measures the cumulative renewable installed capacity from all renewable sources (excl. nuclear power). The variable is log-transformed (IRENA, 2020). Table 2 provides summary statistics for every variable used in the regression analysis.

Table A.1 (with variables included in Table 3) and Table A.2 (with variables included in Table 4) in the Appendix provide pairwise correlation tables for the variables included in the analysis. As policy instruments like ETS can affect energy prices (thus affecting consumption), I have run separate models with and without consumption variables. Furthermore, policies like feed-in tariffs have likely influenced renewables' installed capacity, and can thus lead to some over control in the model and is therefore only included in some model specifications.

[5] GDP per capita and industry share of GDP is collected from World Bank national accounts data, while residential electricity consumption in MWh per capita is based on IEA statistics.

3.2. Model specifications

To investigate the effects of climate policy choices on CO_2 emission intensity in the OECD and BRICS power sector, this study used panel data regression with the fixed-effects estimator with Driscoll–Kraay standard errors. The Driscoll–Kraay method estimates standard errors are robust to spatial correlation and heteroscedasticity when using ordinary least squares (OLS) regression (Driscoll and Kraay, 1998; Hoechle, 2007). By using the fixed-effects estimator, equivalent to the unit centering all observation, researchers can investigate deviations in the mean in each unit over time (Petersen, 2004). Another advantage of using such a model, according to Asane-Otoo (2016), that used a similar regression design to investigate the effect of liberalization of electricity markets on emissions intensity in the OECD, is that the fixed effects model controls for unobserved heterogeneity or time-invariant omitted variables and can provide unbiased estimates even if these variables correlate with explanatory variables. One clear downside to using the fixed-effects model is that it only estimates within-country variation, hence comparisons between countries are not possible. Moreover, a fixed effects model does not allow for time-invariant variables in the analysis (Petersen, 2004; Beck, 2008). In order to investigate whether or not to use a fixed-effects estimator over a random-effects (RE) estimator, the main model has been run with both estimators followed up by a Hausman test. The result of the Hausman test suggests evidently that fixed effects are the proper estimator for the model. Furthermore, the dependent variable in the panel data analysis may suffer from the problem of non-stationarity, or unit-root. After running appropriate tests for this method, the results indicate that there is not a significant problem with the unit-root in the dependent variable in the analysis. The model thus employs a fixed effects estimator, with the general fixed effects equation:

$$Y_{it} = \beta_0 + \beta_{(1,2,\ldots,n)it} X_{(1,2,\ldots,n)it} + (\alpha_i + \varepsilon_{it})$$

4. Results and discussion

The main models in Table 3 contain the dependent variable; logged CO_2 intensity (l$nCOI$) and three independent variables; emission trading system (*ETS*), Feed-in tariffs for solar PV ((FiT_{PV}) and wind (FiT_W) and controls (*Controls*).

Main fixed effects model Table 3:

$$lnCOI_{it} = \beta_0 + \beta_1 ETS + \beta_2 FiT_{PV} + \beta_3 FiT_W + \beta_{(4,5,6,7)} Controls + \beta_8 YearsDummy + \varepsilon_{it}$$

The main models in Table 4 contain the dependent variable; logged CO_2 intensity (l$nCOI$) and five independent variables; emission trading system (*ETS*), feed-in tariffs for solar PV (FiT_{PV}) and wind (FiT_W), public environmental R&D expenditure (*R&D*), and technological innovation support policies (*TISP*), and controls (*Controls*).

Main fixed effects model in Table 4:

$$lnCOI_{it} = \beta_0 + \beta_1 ETS + \beta_2 FiT_{PV} + \beta_3 FiT_W + \beta_4 R\&D + \beta_5 TISP + \beta_{(6,7,8,9)} Controls + \beta_{10} YearsDummy + \varepsilon_{it}$$

Finally, the analysis deploys temporal control by adding year dummies as time fixed-effects in all models.

Table 3 presents the regression results for the fixed-effect models. The table below displays six models with estimated fixed-effect coefficients with Driscoll–Kraay standard errors. To test the presence of collinearity in the models, I have used variance inflation factors (VIF). All of the VIF values are below threshold levels, which suggests that the explanatory variables are independent of one another. Furthermore, all F-statistics are significant.

Looking at the market-based variable emission trading system price, the estimated coefficients suggest there is a negative correlation with CO_2 emission intensity, but the relationship is not significant in any model. The impact of deployment- and technological innovation support policies is more mixed. The results indicate that feed-in tariffs for wind power have a negative and significant relationship with CO_2 emission intensity across nearly all models in the study at the 0.05 and at the 0.01 significance levels. Feed-in tariffs for solar PV, on the other hand, show no such significant relationship.

Finally, the control variable, income, which measures GDP per capita, displayed a significant positive effect on CO_2 emission intensity, which is robust at the 0.01 significance level across all model specifications, while industrial GPD indicator was not significant in any models. Residential electricity consumption is positively correlated with higher CO_2 power sector emission intensity at the 0.05 significance level in Models 5 and 6. Installed renewable energy capacity displays a negative and significant effect at the 0.01 significance level. Table 4 shows results of the technology innovation support policies. The results from Table 3 stay generally the same with the inclusion of these policy indicators. As for the public environmental R&D expenditure, the results are not significant, while technological innovation support policies show a negative significant effect at the 0.01 significance level across all models. The control variable, Income, stayed positive and significant while residential electricity consumption and installed renewable energy capacity were not significant.

Table 3
Effect of climate policy choices on power sector CO_2 emission intensity.

CO_2 emission intensity per KWh	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE
Emission trading system price	−0.00259		−0.00121	−0.00147	−0.00129	−0.00158
	(0.00340)		(0.00174)	(0.00115)	(0.00114)	(0.00125)
Feed-in tariff Solar PV		0.0417	0.0449	0.0286	0.0268	0.0256
		(0.0324)	(0.0315)	(0.0271)	(0.0279)	(0.0271)
Feed-in tariff Wind		−0.193**	−0.200**	−0.186**	−0.186***	−0.195***
		(0.0790)	(0.0753)	(0.0740)	(0.0673)	(0.0599)
ln(Income)				0.161***	0.164***	0.175***
				(0.0339)	(0.0354)	(0.0395)
Industry GDP				0.00290	0.00346	
				(0.00818)	(0.00825)	
Industrial energy consumption						−0.00213
						(0.00329)
Residential electricity consumption					0.00524**	0.00683**
					(0.00197)	(0.00291)
ln(Installed renewable energy capacity)					−0.0882***	−0.0798***
					(0.0286)	(0.0259)
Constant	5.574***	5.652***	5.652***	4.061***	4.146***	4.176***
	(0.0375)	(0.000996)	(0.000945)	(0.378)	(0.388)	(0.362)
R-squared (within)	0.0067	0.2430	0.2436	0.2573	0.2688	0.2745
Observations	733	733	733	730	730	733
Countries	39	39	39	39	39	39
Time period	2000–2018	2000–2018	2000–2018	2000–2018	2000–2018	2000–2018
Country fixed effects	YES	YES	YES	YES	YES	YES
Time fixed effects	NO	YES	YES	YES	YES	YES

Note: Driscoll–Kraay standard errors in parentheses, all columns include year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.1. Robustness tests

Several robustness tests have been performed. First and foremost, having both OECD countries, which are mostly developed economies together with BRICS, which are primarily developing countries, might suggest we are dealing with different stages of climate policy implementation, and, as such, different policy effects. Since I incorporated the per capita (*ln(income)*) and industrial control variable in the models, I captured some of differences in the development stages and industrial structure. Nevertheless, for robustness purposes, I ran the main models with an OECD-only sample found in Table A.3. Interestingly, the ETS variable is barely significant at the 0.1 significance level in the two models with ETS and feed-in tariffs for solar PV and wind in the OECD-only sample. When including the R&D and technological innovation support policies indicators, the significant results of the ETS disappear. By and large, the rest of the model stays the same as in the OECD and BRICS sample. The results are nevertheless surprising and might suggest that the ETS policies have been more effective in the more developed countries of the OECD, compared to the less-developed countries of BRICS; further research is warranted.

Table A.4 displays the results of the regressions using the more conservative emission trading variables that exclude the adjusted sub-national emission trading systems; Tables A.5 and A.6 shows models with non-inflation adjusted ETS, and the results are nearly identical with the results in Tables 3 and 4. Additionally, I have estimated all models using Cook's distance (Cook, 1977), which looks for influential observations or outliers. I found no significant outliers, further strengthening the robustness of the results.

4.2. Discussion

Considering policies aimed at scaling up renewable energy deployment, the significant negative effect of feed-in tariffs for wind energy generation on the power sector's CO_2 emission intensity is not surprising. Many countries included in this analysis have generous feed-in tariffs for wind power that have likely contributed significantly to cost-reduction, and this explains the accumulated capacity observers see for wind power around the world. The results are robust across all model specifications tested. The finding that feed-in tariffs for solar PV do not seem to display the same significant negative effect as wind power is somewhat surprising, but not entirely unexpected as solar PV electricity production has, until recently, been fairly marginal, even if solar power will have an even greater role for energy production and CO_2 emission reduction in the decades to come. This is partly due to their enormous cost reductions and small areal footprint, not to mention the fact that they can be placed on existing buildings. Areal and visibility disputes surrounding onshore wind power are likely to increase in the coming decades as land becomes scarce, which could inevitably force most new wind power offshore, and even further down the line, into floating offshore wind installations. As onshore wind power is

Table 4
Effect of climate policy choices and technology support policies on power sector CO_2 emission intensity.

CO_2 emission intensity per KWh	(7) FE	(8) FE	(9) FE	(10) FE	(11) FE
Emission trading system price		0.000276 (0.00118)	−0.000606 (0.00107)	−0.000351 (0.00115)	−0.000547 (0.00116)
Feed-in tariff Solar PV		0.0240 (0.0320)	0.00697 (0.0336)	0.00498 (0.0338)	0.00739 (0.0327)
Feed-in tariff Wind		−0.289*** (0.0751)	−0.260** (0.0953)	−0.263*** (0.0882)	−0.284*** (0.0739)
Public environmental R&D expenditure	0.00599 (0.00629)	0.00630 (0.00624)	0.00721 (0.00746)	0.00813 (0.00758)	0.00866 (0.00645)
Technological innovation support policies	−0.0544*** (0.0102)	−0.0546*** (0.0102)	−0.0520*** (0.00955)	−0.0448*** (0.0101)	−0.0460*** (0.0104)
ln(Income)			0.140** (0.0582)	0.129* (0.0686)	0.148*** (0.0482)
Industry GDP			0.00388 (0.0104)	0.00502 (0.0110)	
Industrial energy consumption					−0.00177 (0.00342)
Residential electricity consumption				0.00219 (0.00309)	0.00354 (0.00342)
ln(Installed renewable energy capacity)				−0.0561 (0.0366)	−0.0503 (0.0316)
Constant	5.822*** (0.0567)	5.829*** (0.0575)	4.342*** (0.441)	4.459*** (0.555)	4.444*** (0.476)
R-squared (within)					
Observations	587	587	587	587	587
Countries	35	35	35	35	35
Time period	2000–2018	2000–2018	2000–2018	2000–2018	2000–2018
Country fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES

Note: Driscoll–Kraay standard errors in parentheses, all columns include year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

now one of the cheapest sources of new electricity generation in most places around the world, the results of the empirical analysis suggest that feed-in tariffs for wind power have, while being expensive, significantly contributed to reducing CO_2 emission intensity in the OECD and BRICS countries (with the added benefit of driving down the technological cost for current and future installments: a trend that is likely to, and frankly must, continue, if the world is to have any chance of reaching its climate goals). As policy innovations continue to surround goals to ensure environmental sustainability, new and interesting policies have emerged as the costs of solar PV and wind power have reached more competitive prices. One of these is renewable energy auctions or tenders: this allows governments to tender new capacity in a competitive market of bidders, thus securing competitive prices (IRENA, 2019). This helps alleviate feed-in tariffs' greatest downside, namely its limited price flexibility and long-term "locked-in" prices.

Furthermore, as technological innovation support-policies have a significant negative effect on CO_2 emissions, the results indicate that policies that have stimulated overall innovation in climate change-mitigating technologies (i.e. in electricity generation, transmission, and distribution, and for renewable energy technologies specifically) have contributed to CO_2 emission intensity reductions. The finding is in line with the research of, amongst others, Patt (2015), Mazzucato (2015) and Grubb et al. (2021). This suggests that policies aimed at technological innovation support could be an effective way for governments to assist in climate change mitigation efforts. Not all patented innovations will lead to emissions reductions, but the cumulative effort of a country's innovation efforts will surely increase the chance of technological innovations that may have significant emission reduction potential, not only regarding renewable energy technologies but in terms of innovations in transmission and distribution as well.

Finally, the emission trading system variables tested correlated negatively with CO_2 emission intensity, but this is statistically insignificant across all models. This finding is more surprising, and the results are harder to explain, but they are somewhat in line with several other studies that have looked at the effect of market-based instruments on CO_2 emissions, emission intensity, and environmental performance (for instance Green, 2021). These studies, however, have evaluated everything from cross-sectoral taxes to the effect of environmental taxes for emissions in all sectors, and some of them are arguably difficult to compare with the results from this study. This observation also underscores the importance of studies like mine that look at policies that target the power sector in particular, and combine both market-based instruments and deployment- and technological innovation-support policies in the same analysis.

There are two plausible explanations for these results. The first likely explanation for the lack of effect is that the quota prices in the emission trading systems studied are simply too low to have a significant impact. While few observers would argue against an emission trading system with a sufficiently high price on carbon, policymakers have to consider the short-to-medium feasibility of reaching these prices. Because, as Patt (2015) points out, unless prices are high enough to really matter, at least in the short-term, they are only an instrument for more efficient fossil-based electricity production. At the same time, policymakers could also increase electricity prices, which tend to have regressive effects, in addition to its impact on energy-intensive industries (which in turn makes it even harder to pass more strict climate policy measures as these industries ramp up lobbyism; this is combined with a fear of layoffs and loss of national competitiveness). On the other hand, due to coal's high carbon intensity, even a moderate quota price increase should, in theory, result in serious reductions in the use of coal-fired power production. European policymakers have already taken some steps towards strengthening the EU ETS by introducing a Market Stability Reserve (MSR) that attempts to address the current problem of surplus allowances and improve the resilience to shocks by adjusting the supply of allowances that can be auctioned, but this has been introduced too late to have had any effect on my study (European Commission, 2019). Furthermore, while it would make sense to look at the different temporal dimensions of policies as they take time to come into full force, the effect of the price signal should, in theory, be fairly immediate as a higher quota price that should lead to changes in the merit-order by increasing the price of CO_2 intensive sources.

Going forward, as policymakers attempt to find the right mix between political feasibility and cost-effectiveness, some key lessons can be drawn from the discussion of the empirical results of this study. The fact that renewable energy technologies such as solar and wind have already dropped significantly in price and are expected to continue to do so, provides power producers with reliable and cost-competitive substitutes for fossil-based generation. This, in turn, increase the likelihood of the feasibility of passing adequate market-based instruments that will assist in keeping new fossil-based capacities uneconomical and, in the longer term, also to help phase out existing, uneconomical fossil-based generation. Thus, the policy implications presented here suggests that market-based approaches have not been effective enough to decarbonize the power sector and will likely not be able to do so alone going forward. On the contrary, the reason some observers suggest that the power sector is one of the easiest sectors to decarbonize is precisely because generous governmental support policies and long-term commitment to renewable energy development have made them cost-competitive substitutions to coal, gas, and nuclear electricity generation.

4.3. Limitations

Although this study considers many of the prominent climate policy choices policymakers have implemented in an effort to reduce emissions in their power sectors, the analysis does not cover all of them. Green certificates, tax credits, net metering, and the aforementioned competitive bidding auctions/tendering are policies that are not included or investigated in the study. Part of the reason is that some of these policies have only become prominent in recent years due to innovations and due to the falling costs of renewable energy, and therefore they are less relevant for the time period studied (especially as many successful tenders are still in construction). These are nevertheless important policies one should keep in mind when interpreting the results. Thus, the possibility that these policies would have impacted the results if the data were available cannot be discarded.

5. Conclusion and policy implications

This study investigates the effect of several prominent climate policy choices that have been implemented with the aim of reducing CO_2 emissions and emission intensity in the power sector. By analyzing panel data of 34 OECD and 5 BRICS countries taken from 2000 to 2018, the study set out to test the effect of climate policies on CO_2 emission intensity using empirical methods. For the market-based policy tested, the effect of the emission trading systems indicated no significant effect on CO_2 emission intensity. Using an OECD-only sample, the results showed a significant negative effect of emission trading systems at the 0.1 significance level in the OECD sample. This finding is interesting but, considering the weak statistical effect, suggests further research is needed.

Looking at deployment-supporting policies for renewable energy, the results from this analysis suggest that feed-in tariffs for wind have contributed to a reduction in CO_2 emission intensity, while this analysis finds no significant relationship with feed-in tariffs for solar PV. Finally, technological innovation to support policies correlates negatively with CO_2 emission intensity while public environmental R&D expenditure does not.

The results of this study contain some policy implications. While market-based instruments have strong theoretical foundations and are important policies to pursue for policymakers, there is limited evidence to suggest that the renewable energy revolution researchers have witnessed in the last decades has come from the deployment of market-based instruments. Rather, there is more evidence to suggest that deployment and technology-specific policies have been more significant: a result which is much in line with findings of a recent review by Grubb et al. (2021).

Theory suggests that market-based policies can help get governments and people 'over the line' in combating climate change, but research indicates that this will happen only after market-based policies become politically feasible enough to a point where they can really have an effect — these efforts will likely only deliver on their promises if policymakers decide to implement them in conjunction with other policies that support renewable technology deployment (i.e. with an eye to stimulating technological innovation, development, and cost reductions). In conclusion, the results of this study indicate that policymakers are benefited by advocating for a 'mix' of policies where deployment supporting- and technological innovation-supporting policies drive the costs of renewable technologies down, and thereby set up more cost-effective market-based policies for success.

Table A.1
Correlation table (N = 730)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. **COI**	–							
2. **ETS**	−0.1596	–						
3. **FitPV**	0.1210	0.2537	–					
4. **FITW**	0.0748	0.0698	0.3936	–				
5. **inc**	−0.4053	0.3538	0.1858	0.0791	–			
6. **IGDP**	0.1054	−0.1785	−0.1537	−0.1447	−0.4442	–		
7. **IEC**	−0.2759	−0.1667	−0.2037	−0.1768	−0.3317	0.4722	–	
8. **REC**	−0.7460	0.1369	−0.0812	−0.1299	0.5005	−0.1540	0.2859	–
9. **IRC**	−0.1051	−0.1755	0.0080	0.0074	−0.1053	0.1841	0.2266	−0.0550

Table A.2
Correlation table (N = 587)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. **COI**	–									
2. **ETS**	−0.1126	–								
3. **FitPV**	0.1687	0.2107	–							
4. **FITW**	0.1334	0.0477	0.4079	–						
5. **R&D**	0.0938	0.0701	0.0001	−0.0863	–					
6. **TISP**	0.2337	−0.2099	0.1322	−0.0486	−0.0567	–				
7. **inc**	−0.3939	0.2196	0.0918	0.0307	−0.1215	0.0434	–			
8. **IGDP**	−0.0095	−0.1091	−0.1359	−0.1682	−0.0147	0.1206	−0.3898	–		
9. **IEC**	−0.4871	−0.0343	−0.1679	−0.2052	0.0286	−0.1723	−0.0688	0.3590	–	
10. **REC**	−0.7722	0.0375	−0.1506	−0.1726	−0.0403	−0.1843	0.4603	−0.0633	0.5380	–
11. **IRC**	−0.1513	−0.1189	0.0636	0.0074	−0.0946	0.6577	0.1956	0.0381	0.0299	0.0535

Table A.3
Robustness analysis with OECD countries only.

CO_2 emission intensity per KWh	(12) FE	(13) FE	(14) FE	(15) FE
Emission trading system price	-0.00208^{*} (0.000948)	-0.00222^{*} (0.00115)	−0.000359 (0.00121)	−0.000615 (0.00122)
Feed-in tariff Solar PV	−0.00427 (0.0317)	−0.00761 (0.0316)	0.00447 (0.0340)	0.00588 (0.0332)
Feed-in tariff Wind	-0.138^{**} (0.0538)	-0.132^{***} (0.0467)	-0.263^{***} (0.0892)	-0.284^{***} (0.0741)
Public environmental R&D expenditure			0.00810 (0.00755)	0.00859 (0.00650)
Technological innovation support policies			-0.0447^{***} (0.0100)	-0.0458^{***} (0.0103)
ln(Income)	0.233^{**} (0.0872)	0.249^{***} (0.0697)	0.131 (0.0813)	0.154^{**} (0.0539)
Industry GDP	0.00325 (0.0106)		0.00496 (0.0113)	
Industrial energy consumption		0.00397 (0.00390)		−0.00172 (0.00341)
Residential electricity consumption	0.00642^{**} (0.00264)	0.00476 (0.00340)	0.00220 (0.00313)	0.00356 (0.00342)
ln(Installed renewable energy capacity)	−0.0654 (0.0425)	−0.0541 (0.0335)	−0.0561 (0.0369)	−0.0504 (0.0316)
Constant	3.293^{***} (0.786)	3.102^{***} (0.690)	4.435^{***} (0.665)	4.378^{***} (0.527)
R-squared (within)	0.3130	0.3200	0.3491	0.3484
Observations	635	638	582	582
Countries	34	34	34	34
Time period	2000–2018	2000–2018	2000–2018	2000–2018
Country fixed effects	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES

Note: Driscoll–Kraay standard errors in parentheses, all columns include year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4
Robustness analysis with ETS price national only.

CO_2 emission intensity per KWh	(16) FE	(17) FE	(18) FE	(19) FE	(20) FE
ETS (national only)	−0.00393	−0.00161	−0.00170	−0.00160	−0.00193
	(0.00361)	(0.00185)	(0.00123)	(0.00119)	(0.00129)
Feed-in tariff Solar PV		0.0456	0.0289	0.0274	0.0263
		(0.0314)	(0.0270)	(0.0279)	(0.0270)
Feed-in tariff Wind		−0.202**	−0.187**	−0.188**	−0.196***
		(0.0748)	(0.0735)	(0.0671)	(0.0596)
ln(Income)			0.160***	0.164***	0.174***
			(0.0336)	(0.0351)	(0.0390)
Industry GDP			0.00288	0.00340	
			(0.00817)	(0.00823)	
Industrial energy consumption					−0.00226
					(0.00328)
Residential electricity consumption				0.00535**	0.00704**
				(0.00199)	(0.00292)
ln(Installed renewable energy capacity)				−0.0881***	−0.0796***
				(0.0284)	(0.0257)
Constant	5.581***	5.652***	4.071***	4.153***	4.184***
	(0.0357)	(0.000940)	(0.373)	(0.383)	(0.357)
R-squared (within)	0.014	0.244	0.257	0.269	0.275
Observations	733	733	730	730	733
Countries	39	39	39	39	39
Time period	2000–2018	2000–2018	2000–2018	2000–2018	2000–2018
Country fixed effects	YES	YES	YES	YES	YES
Time fixed effects	NO	YES	YES	YES	YES

Note: Driscoll–Kraay standard errors in parentheses, all columns include year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.5
Robustness test of models in Table 3, with ETS price non-inflation adjusted.

CO_2 emission intensity per KWh	(21) FE	(22) FE	(23) FE	(24) FE	(25) FE	(26) FE
Emission trading system price (n-inf. adj.)	−0.00400		−0.00164	−0.00177	−0.00166	−0.00199
	(0.00362)		(0.00185)	(0.00123)	(0.00119)	(0.00129)
Feed-in tariff Solar PV		0.0417	0.0458	0.0291	0.0276	0.0265
		(0.0324)	(0.0314)	(0.0270)	(0.0279)	(0.0271)
Feed-in tariff Wind		−0.193**	−0.202**	−0.187**	−0.188**	−0.196***
		(0.0790)	(0.0749)	(0.0736)	(0.0672)	(0.0596)
ln(Income)				0.161***	0.164***	0.175***
				(0.0336)	(0.0352)	(0.0390)
Industry GDP				0.00284	0.00337	
				(0.00816)	(0.00823)	
Industrial energy consumption						−0.00228
						(0.00328)
Residential electricity consumption					0.00536**	0.00705**
					(0.00199)	(0.00292)
ln(Installed renewable energy capacity)					−0.0879***	−0.0793***
					(0.0285)	(0.0258)
Constant	5.581***	5.652***	5.652***	4.068***	4.151***	4.180***
	(0.0356)	(0.0001)	(0.0009)	(0.3730)	(0.3830)	(0.3570)
R-squared (within)	0.0145	0.2430	0.2441	0.2576	0.2692	0.2749
Observations	733	733	733	730	730	733
Countries	39	39	39	39	39	39
Time period	2000–2018	2000–2018	2000–2018	2000–2018	2000–2018	2000–2018
Country fixed effects	YES	YES	YES	YES	YES	YES
Time fixed effects	NO	YES	YES	YES	YES	YES

Note: Driscoll–Kraay standard errors in parentheses, all columns include year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.6
Robustness test of models in Table 4, with ETS price non-inflation adjusted.

CO_2 emission intensity per KWh	(27) FE	(28) FE	(29) FE	(30) FE	(31) FE
Emission trading system price (n-inf. adj.)		−0.000479	−0.000401	−0.000135	−0.000386
		(0.00136)	(0.00121)	(0.00128)	(0.00131)
Feed-in tariff Solar PV		0.0237	0.00689	0.00485	0.00734
		(0.0320)	(0.0336)	(0.0339)	(0.0328)
Feed-in tariff Wind		−0.288***	−0.259**	−0.261***	−0.283***
		(0.0744)	(0.0945)	(0.0877)	(0.0734)
Public environmental R&D expenditure	0.00599	0.00636	0.00718	0.00812	0.00864
	(0.00629)	(0.00627)	(0.00745)	(0.00755)	(0.00646)
Technological innovation support policies	−0.0544***	−0.0546***	−0.0521***	−0.0448***	−0.0460***
	(0.0102)	(0.0102)	(0.00951)	(0.0101)	(0.0104)
ln(Income)			0.138**	0.127*	0.147***
			(0.0578)	(0.0686)	(0.0488)
Industry GDP			0.00393	0.00509	
			(0.0104)	(0.0110)	
Industrial energy consumption					−0.00178
					(0.00343)
Residential electricity consumption				0.00219	0.00358
				(0.00310)	(0.00342)
ln(Installed renewable energy capacity)				−0.0565	−0.0505
				(0.0367)	(0.0316)
Constant	5.822***	5.829***	4.360***	4.478***	4.458***
	(0.0567)	(0.0575)	(0.442)	(0.558)	(0.481)
R-squared (within)	0.331	0.338	0.346	0.349	0.348
Observations	587	587	587	587	587
Countries	35	35	35	35	35
Time period	2000–2018	2000–2018	2000–2018	2000–2018	2000–2018
Country fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES

Note: Driscoll–Kraay standard errors in parentheses, all columns include year fixed effects.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Disclaimer

This work is partially based on the data from the Emissions Factors database developed by the International Energy Agency, © OECD/IEA 2021, but the resulting work has been prepared by the author, *Simen Rostad Sæther* and does not necessarily reflect the views of the International Energy Agency.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The dataset in the article can be found at: http://dx.doi.org/10.17632/vs899t86tv.1, *an open-source online data repository hosted at Mendeley Data (*Sæther, 2021*)*

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Appendix. Supplementary material

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