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Carbon pricing and emissions: Causal effects of Britain's carbon tax

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ABSTRACT

This study estimates that the introduction of a carbon tax in the British power sector in 2013 and its two subsequent elevations in 2014 and 2015 led to a substantial decline in electricity-related CO_2 emissions by 26% (or 38.6 $MtCO_2$) within only three years. Identification of the causal effect relies on discontinuities in electricity generation induced by the policy changes and on a novel and detailed dataset of hourly emissions from all British fossil-fuel power stations. Notably, the carbon tax changed power plants' marginal costs according to their emission intensity, so that "dirty" coal was pushed out of the market, whereas "cleaner" gas filled a large share of the production gap. Our findings suggest that even a moderate carbon tax can induce significant abatement, supporting the notion that a market-based climate policy should be viewed as a viable policy option. We also discuss limitations of this national tax, such as that it likely created emissions abroad via imports and the waterbed effect within the EU Emission Trading System.

1. Introduction

Most economists tend to agree that putting a price on emissions, either in the form of a carbon tax or through tradeable emission permits, reduces carbon emissions most efficiently via market-based incentives (e.g. Borenstein, 2012; Böhringer et al., 2014; Newell and Pizer, 2008), and that the carbon price should be coordinated internationally (Nordhaus, 2018) to avoid carbon leakage. Yet, some scholars argue that there are severe political obstacles against high-enough carbon prices, as to induce significant abatement at an accelerated speed necessary to avoid the potentially disastrous consequences of global warming (e.g. Patt and Lilliestam, 2018; Rosenbloom et al., 2020). So far, the political implementation of effective carbon pricing has been cumbersome, many emission trading schemes suffered from shortcomings in their infantile stages of implementation (Cason and Gangadharan, 2006), a globally coordinated carbon price has turned out illusive (Jo and Carattini, 2021), and taxes are generally unpopular, which threatens the political feasibility of a meaningful carbon price. Emissions trading systems, such as in California, the Regional Greenhouse Gas Incentive (RGGI) in the Northeast of the US, or the EU Emissions Trading System (ETS), yielded low carbon prices (i.e. below central estimates of the social cost of carbon) most of the time (Larsen, 2018).[1]

Consequently, many states try to achieve their emission reduction goals via (uncoordinated) national climate policies, often in the form of subsidies for renewable energies, yet generally fail to meet their climate goals.[2] This may be one reason why many countries are currently discussing national carbon taxes in their climate agendas, whereas only few have already introduced them. Unfortunately, resilient studies about the causal effect of carbon pricing on emissions are scarce, despite the need to rely on accurate measures and to foster public support for carbon pricing (Andersson, 2019).

The goal of this study is thus to assess the causal effect of a carbon tax

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[1] Newberry et al. (2019) argue that the low EU ETS emissions price resulted from too many issued emission permits (likely in fear of carbon leakage and concerns about international competitiveness) and generous crediting of ETS permits from emissions-reducing activities in third party countries, but also from unilateral climate change strategies, such as the fast deployment of subsidized renewable energies.

[2] Gugler et al. (2021), for example, demonstrate that subsidizing renewable energies is less efficient in terms of both emissions abatement and costs relative to carbon pricing.

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on emissions in a key emissions-contributing industry, the power sector, for the case of Britain. Britain introduced a national carbon tax, the "carbon price support" (CPS)[3] for its power sector *on top* of the EU emission allowances (EUA) price in 2013, followed by two significant increments in the subsequent years. The main motivation for the CPS was a largely ineffectively low EUA price. The British case is relevant, because it is the first European country to implement a significantly high carbon tax for its power sector, whereas most EU member states mainly rely on a (so far) low EUA price as well as on national support payments for renewable energies, yet fail their climate targets. Moreover, while many countries discuss strategies to phase out from coal power by the means of prohibitions (such as Germany), Britain's coal share dropped from 39% in 2012 to a negligible share (0.2%) in 2019 (see Fig. 3), and total emissions fell by 64% (see Fig. 2). The suspicion is that the CPS, working in the fashion of a market-based policy, may have contributed significantly to these developments.

Our study analyses the energy sector as the major source of carbon emissions, not only in Britain, before the carbon tax was introduced (i.e. 40% in 2012; BEIS, 2013), but also at the global level (i.e. 29.3% in 2014; EEA, 2016). Hence, assessing the effects of a carbon tax may be most relevant for this sector, as it bears the greatest emissions savings potential. The British case has demonstrated that emissions particularly from the power sector may be replaced in a relatively short period of only a few years, as long as idle gas plants can replace "dirty" coal plants (see Section 2 for details). In other sectors of the economy, such as transportation, carbon taxes may only lead to a moderate reduction in emissions, because of relatively inelastic reactions to changes in the transport fuel price.[4]

The CPS hikes on April 1 of 2013, 2014, and 2015 changed the marginal costs of fossil-fueled power plants immediately and permanently. Our identification of the tax effects thus relies on a regression-discontinuity-in-time (RDiT) approach to estimate causal effects of the discontinuous carbon tax adjustments ("jumps") on carbon emissions. We do this by using hourly data of *all* British fossil-fueled (coal and gas) power plants. The idea of RDiT is that we can estimate the causal effect of the carbon tax, as emissions (or electricity generation) of fossil-fueled power plants would have changed smoothly around the date of the policy change in the absence of treatment (Chen and Whalley, 2012). Hence, we assume that around the arbitrary threshold, treated and untreated units (i.e. thermal power plants before and after the tax jump) are identical in their observable and unobservable characteristics, so that the introduction of the carbon tax represents a local randomized experiment. RDiT thus allows for disentangling the causal effect of the tax jump from other confounding effects, such as variations in electricity demand or infeed from renewable energies, which should have changed smoothly around the dates of the policy changes.[5] We also adjust our estimates for a large set of seasonal fixed effects. Moreover, RDiT circumvents many problems of other regression designs, such as endogeneity concerns or omitted control variables, obviates the need for finding suitable instruments, which are often not available, and places "minimal assumptions" on the identification strategy (Hahn et al., 2001, p. 207). Our reliance on RDiT also enables estimation of causal effects in the absence of a control group. This is relevant, because the CPS affects *all* British thermal power plants, so that there is no cross-sectional variation in the policy implementation. A proper control group of non-treated thermal power plants may thus only be found outside Britain, triggering problems of potentially unobserved confounding shocks (e.g. different business cycles in other countries, different and changing national climate change policies, etc.).

For our RDiT design essential, electricity cannot be stored at large scale, at least not yet at economically sensible costs, which may rule out any *anticipation effects* of the announcement of the carbon tax. Thus, despite knowing in advance that the CPS would be introduced, electricity generators could not *act* in anticipation of the policy change to avoid its effects and produce electricity at the cheaper carbon prices before the CPS hikes and sell it at a later date. Storage facilities of electricity would have been necessary in amounts that simply do not exist. Another possibility is that power plants may reduce their electricity production some days preceding a tax jump (e.g., because production adjustments for ramping and cycling may cause additional costs and take time).[6] If this was indeed the case, our results would (somewhat) understate the "true" effect. To rule out these and related concerns, we run robustness tests using "donut" regressions, in which we eliminate observations of up to one month before the tax jumps. The donut regressions support our main findings. Furthermore, since all CO_2-emitting power plants are treated and were built long before the policy change, *self-selection* into or out of treatment is not an issue, either.[7]

Regarding the choice of the bandwidth, we follow Davis (2008) who argues for a period of investigation of at least one year on either side of the event (using hourly data) to identify a causal effect: "Windows smaller than 2 years [i.e. one year before and one year after treatment] are not considered because it becomes difficult to credibly control for seasonal variation." We thus take one year before and one year after each event[8] to capture a whole business cycle as well as seasonal effects, while we control for possible confounding effects in electricity markets (e.g. by using local polynomials in time and other control variables, such as polynomials of demand, infeed of renewables, day-of-week as well as hour-of-the-day fixed effects[9]). Other applications of RDiT might also suffer from unobservable confounding effects, such as changes in emissions from other sectors (e.g. outside the electricity sector) around the date of the policy change. In contrast, our data on CO_2 emissions are calculated precisely for British power plants, so that changes in

[3] Although the British Government introduced the carbon tax under the term "Carbon Price Floor", it does not work in the fashion of a minimum price (i.e. if the EUA price falls below a threshold, the floor price becomes effective), but it is essentially a top-up tax (CCC, 2014).

[4] For example, Andersson (2019) finds that average annual CO_2 emissions from transport declined by only 6.3% in reaction to a significant carbon tax in Sweden, which rose from US\$ 30/tCO_2 in 1991 to US\$109/tCO_2 in 2004. Lin and Li (2011) estimate the effects of carbon taxes and find merely a 1.7% reduction in CO_2 emissions for Finland along with no statistically significant effects for Denmark, Sweden, Norway, and the Netherlands. However, the authors neither specify for which sectors of the economy the tax applies – we assume that it is foremost transportation – nor describe the precise magnitudes of the taxes.

[5] Although Figure 3 shows descriptively that renewables increased significantly since the introduction of the CPS in 2012, their production depends on weather circumstances, so that only other weather-independent generation technologies, which can adjust their electricity output, such as gas-fired power plants, could immediately fill the production gap from coal.

[6] Gugler et al. (2021) provide a list of inactive (officially shut down or inactive electricity production) British coal power plants. Most plants cease their coal-fueled production around the dates of the tax jumps, which is evidence that the CPS is responsible for their inactivity/exit (in contrast to other potentially confounding policies, such as the Large Combustion Plant Directive; see below for details).

[7] There were no entries of gas-fired power plants during our sample period.

[8] Choosing a sample window of one year before and after treatment is a rather narrow frame for analysis in environmental economics. Hausman and Rapson (2018) mention that many RDiT studies on topics in environmental economics tend to expand the event window to enhance the number of observations (to increase the precision of the estimates) at the trade-off of increasing the likelihood for estimation bias due to potential unobserved confounding effects. The majority of the 14 RDiT studies cited in Hausman and Rapson (2018) indeed apply event windows of multiple years (i.e. "at least two years, and several use eight years or more").

[9] Hausman and Rapson (2018) indeed mention that it is essential in RDiT applications to include day-of-week fixed effects by the means of an example from the electricity production, because a policy change on a particular day (e.g. Monday) may bring about discontinuous impacts on the potential outcome compared to other days (e.g. the weekend).

emissions from other industries cannot bias our estimates.

We estimate that Britain's introduction of the carbon tax and its two subsequent increments reduced emissions from the power sector by 38.6 $MtCO_2$ within three years, which accords to a cumulative abatement of 26.2% relative to pre-treatment emissions. While emissions from coal decreased dramatically by 43.6 $MtCO_2$ (−40.1%), emissions from gas increased moderately by 5.0 $MtCO_2$ (20.6%), because gas plants filled a large part of the electricity production gap from coal. A battery of robustness test confirms these results. Moreover, since we use plant-specific data, we can show that old, and thus relatively inefficient, coal plants react most significantly to the carbon tax, which we explain by changes in the relative marginal costs of individual power plants. Similarly, we find that less efficient gas plants reduce their output, whereas most gas plants are relatively efficient and thus increase their output.

Our findings contribute to the growing literature on the empirical effects of environmental policies in the electricity sector and enriches it by several important aspects. Recent studies looked at the questions of how renewable energies (e.g. Abrell et al., 2019, Cullen, 2013; Kaffine et al., 2013; Novan, 2015; Callaway et al., 2018) or natural gas prices (Lu et al., 2012; Linn et al., 2014; Knittel et al., 2015; Cullen and Mansur, 2017; Holladay and LaRiviere, 2017) affect emissions. There are, however, several topics that have not been analyzed so far. While Cullen (2013) provides counterfactual evidence on the price of CO_2, the effects are simulated but not empirically estimated. Fell and Kaffine (2018) compare the effects of wind generation and natural gas prices on emissions reduction, and Cullen and Mansur (2017) draw conclusions from the effects of natural gas price variations to assess how a carbon price would have performed. We prefer to analyze carbon prices directly. In line with theory, Gugler et al. (2021) estimate that a carbon price is significantly more cost effective than the direct subsidization of renewable energies. While their assessment is on how different carbon prices abate emissions, our study estimates the causal effect of the British carbon tax, which applies on top of the EU ETS price, in order to draw inference about the potential success of such a unilateral policy.

More importantly, issues of identification have not yet been solved satisfactorily by the extant literature, probably in part because suitable instruments for carbon prices are not readily available. Carbon pricing at the EU level underwent many policy interventions, which cannot be viewed as truly exogenous with respect to the general state of the economies and therefore to electricity generation. For example, during and after the great economic crisis of 2008 and thereafter until 2017, too many emission certificates were issued, depressing the carbon price to an ineffectively low level. Our RDiT design of an exceptional policy change circumvents many identification issues.

To our knowledge, two other academic studies, Abrell et al. (2022) and Leroutier (2022), investigate the effects of the British CPS, yet applying different methods. Abrell et al. (2022) construct a counterfactual by a machine learning approach and find that the CPS reduced emissions by 26 $MtCO_2$ (or by 6.2%) during 2013–2016, which is significantly lower than our estimates (38.6 $MtCO_2$ or 26.2%). Their estimations are only on the intensive-margin, estimating the short-term emissions reduction of plants that are *active* during the sample period, thus disregarding power stations which ceased production temporarily or permanently. Another possibility for the divergence in results may be the differences in the data employed and the method applied to construct a counterfactual via machine learning. In contrast, our study accounts for both production adjustments (i.e. the intensive margin impact) and production abolishments (i.e. the extensive margin impact) within our evaluation windows. Leroutier (2022) estimates in a difference-in-differences (DiD) framework an abatement of 143–191 $MtCO_2$ due to the CPS during 2013–2017, relative to a counterfactual constructed via a synthetic control group of other EU countries. This methods has the strength that it addresses both short-run effects (substitution effects between existing power plants according to their emission intensity) and long-run effects (investments in greener electricity generation capacity), whereas a downside is that it may not precisely disentangle the effect of the CPS from confounding effects, such as changes in renewables, demand efficiency measures, other climate policies, or variation in economic activity in Britain relative to the control group after treatment, because DiD attributes any changes in the treatment group relative to the control group to the treatment. This may explain why Leroutier (2022) estimates a higher abatement effect (the author indeed acknowledges that her estimates may also include changes in confounding variables; c.f. Leroutier, 2022, p. 2). Our application of RDiT thus complements the aforementioned studies, because its strength is to precisely estimate a local treatment effect (i.e. a short-term substitution effect between “dirtier” and “cleaner” electricity generation technologies, which should nevertheless last as long as the marginal costs of existing plants are influenced by the new tax rate), whereas it cannot capture any longer-term investment effects. Moreover, the British energy market regulator, Ofgem (2018), uses a simulation model to assess emissions reductions by selected electricity decarbonization policies during 2010–2017, qualitatively supporting our main findings. It concludes that carbon pricing, foremost since the introduction of the CPS, was the most important factor reducing emissions, followed by (large-scale) renewables subsidies, whereas air quality directives (e.g. the Large Combustion Plant Directive) and demand-side policies play only a minor role. Given the mixed findings on the effects of carbon pricing versus other policies, and of the British carbon tax in particular, our study may represent a valuable contribution to the literature, relying on an established and sound methodology to analyze the causal effects of a carbon tax.

The paper is organized as follows. Section 2 provides background information about Britain's carbon taxation of the power sector. Section 3 discusses the empirical approach, theoretical predictions, issues of identification, and the data set. Section 4 presents the results of the empirical analysis. Section 5 provides robustness checks. Section 6 concludes.

2. Background

Britain's emissions from the electricity sector have been regulated under the scope of the EU ETS since 2005. However, emission allowances were largely abundant during most of its existence, resulting in a low CO_2 allowances price (see Fig. 1).[10] On April 1, 2013, Britain introduced the CPS, *on top* of the EU ETS price, with the main justification that the EU ETS price was historically low on average, and even falling for over a year before its introduction. The CPS only applies for power plants (whereas the EU ETS also regulates many other industries), most likely because the energy sector was responsible for the majority of Britain's emissions before the policy reform was implemented (i.e. 40% in 2012; BEIS, 2013).

While the EU ETS price hovered around €5/tCO_2 before the introduction of the CPS, the CPS discontinuously topped up this price by £4.94 (€5.84) on 1 April 2013, followed by two further discontinuous elevations in the subsequent two years (i.e. by £9.55 (€11.46) on 1 April 2014 and by £18.08 (€24.63) on 1 April 2015).[11] Given that operators of thermal power plants had to pay a discontinuously higher carbon price from 1 April, 00:00 h on, following the respective CPS jumps, than they had to pay until 31 March, 24:00 h, we can use this for identification via our RDiT approach.

[10] Several adjustments of the EU ETS have been made. For example, during the recent phase 2013–2020, the EU allowances cap has been reduced by 1.74% each year and “a progressive shift towards auctioning of allowances in place of cost-free allocation” was introduced (EC, 2016, p. 2).

[11] The CPS was due to rise further every year until 2020 to a price of £30/tCO_2. However, a rising EU ETS price and in fear of a loss of international competitiveness, the UK Government decided to freeze the CPS at its 2015 level of £18/tCO_2 until 2020 (House of Commons, 2018).

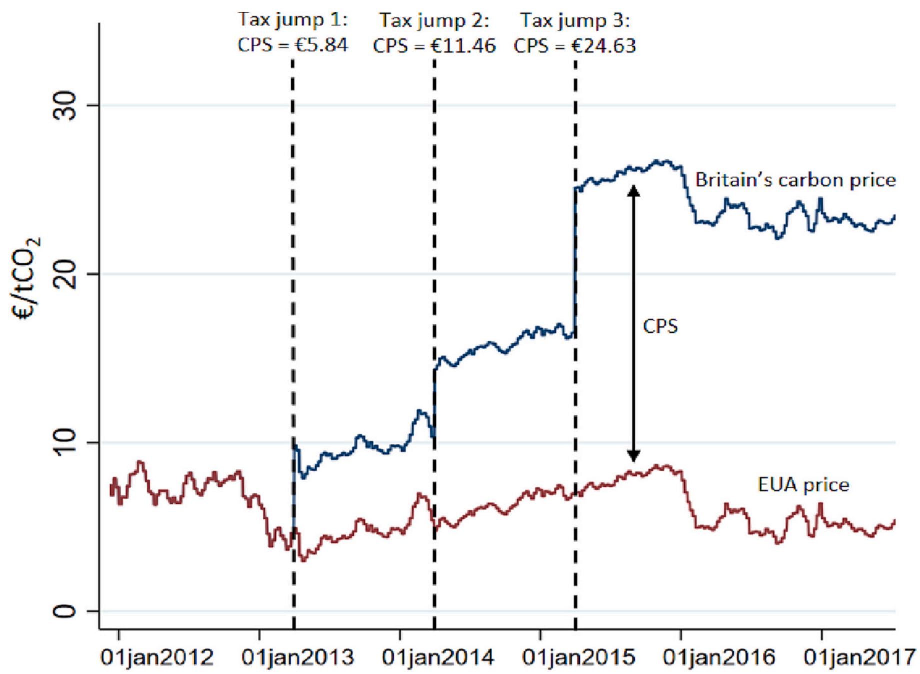


Fig. 1. Britain's effective carbon price.
Notes: 1 April 2013–31 March 2014: CPS = £4.94 (= €5.84); 1 April 2014–31 March 2015: CPS = £9.55 (= €11.46); 1 April 2015–31 March 2021: CPS = £18.08 (= €24.63). Sources: EEX (2018) for EUA prices; House of Commons (2016) for CPS rates (converted into Euros according to daily exchange rates from the ECB, 2019).

Fig. 2 shows that historical emissions from the British power sector increased from 159 $MtCO_2$ in 2000 to a peak of 182 $MtCO_2$ in 2006, followed by a decline, which was most pronounced during the years 2009–2011, and in 2012, the emissions level almost reached that of 2000 again. Many factors can be held responsible for the observed variation in emissions, such as changes in renewable energies, demand efficiency measures, and economic activity. Since the installment of the CPS in 2013, however, we see that total emissions fell at an unprecedented rate to 57 $MtCO_2$ in 2019, with a severe decline in coal-based emissions, and a moderate increase in gas-based emissions. Within only five years following the introduction of the CPS, Britain's emissions were cut by more than half, with the suspicion that the CPS may.

have contributed significantly to this development. Hence, despite a downward trend in emissions since 2007, this is descriptive evidence that emissions may not have fallen as strongly without the CPS in place. Appendix Fig. A1 shows the daily sample emissions and further supports our notion that the CPS may be responsible for significant emissions abatement, because emissions abruptly fell after the respective tax jumps.

From Fig. 3 we can see that Britain's coal share stayed fairly constant until 2012, but then dropped considerably from 39% in 2012 to a negligible share (2.4%) in 2019. This is another hint that the CPS may have changed electricity generation significantly. In parallel, other electricity generation technologies with significantly lower emissions, such as natural gas, and carbon-free technologies, such as renewable energies, significantly increased their production as to fill the production gap. We can also see that electricity demand fell modestly (during our sample from 88 TWh in 2012 to 84 TWh in 2016), imports increased marginally[12] (from 3 TWh in 2012 to 4 TWh in 2016), and the share of nuclear electricity remained fairly constant since the implementation of the CPS in 2013.

To sum up, while many factors may be held responsible for a decline in emissions, such as the growth of renewable energies, the modest fall in electricity demand, and the Large Combustion Plant Directive (LCPD), our suspicion is that the CPS has contributed significantly to the sharp decline in emissions since 2012. Thus, an essential element of our identification strategy is to trace out the discontinuous effects of the CPS from the rather smoothly changing effects of the LCPD, feed-in of renewables, electricity demand, and other potential confounders.

3. Empirical approach

3.1. Identification

In the RDiT approach, identification of the causal effect of the CPS stems from the *discontinuous* change in generation and therefore CO_2 emissions of fossil-fired power plants around the policy change.[13] As outlined above, we view the RDiT approach particularly suited in our case, since the policy changes can be exactly timed and happened always on 1 April, 00:00 h in the years 2013, 2014, and 2015. The policy changes increased *all* CO_2-emitting generators' marginal costs discontinuously, which induced an immediate and permanently lasting rise in thermal power plants' marginal costs. This should thus have changed electricity generation and therefore emissions discontinuously but permanently. Fig. 4 visualizes the discontinuities in emissions in response to changes in the CPS rates, as predicted by our empirical model.

Our approach is in the spirit of an event study, but with a higher-order polynomial time trend, which is estimated separately for the time before and after the treatment. In contrast to a standard cross-sectional regression-discontinuity application (as in the spirit of Lee and Lemieux, 2010), our approach uses time as the running variable and

[12] Guo et al. (2019) find that the CPS increased Britain's electricity imports from France and the Netherlands. Thus, due to the CPS, emissions may have increased in other countries. However, although the effect is statistically significant, compared to fuel switching from coal to gas, the effect of increasing net imports is negligible in economic terms. While net imports increased from 3 TWh in 2012 to 4 TWh in, 2016 (see Figure 3), coal decreased from 34 TWh to 7 TWh during the same period.

[13] Similarly to our study, Chen and Whalley (2012) acknowledge that the identification of the effect of public transportation infrastructure on air quality is challenging, and thus propose RDiT as a suitable solution.

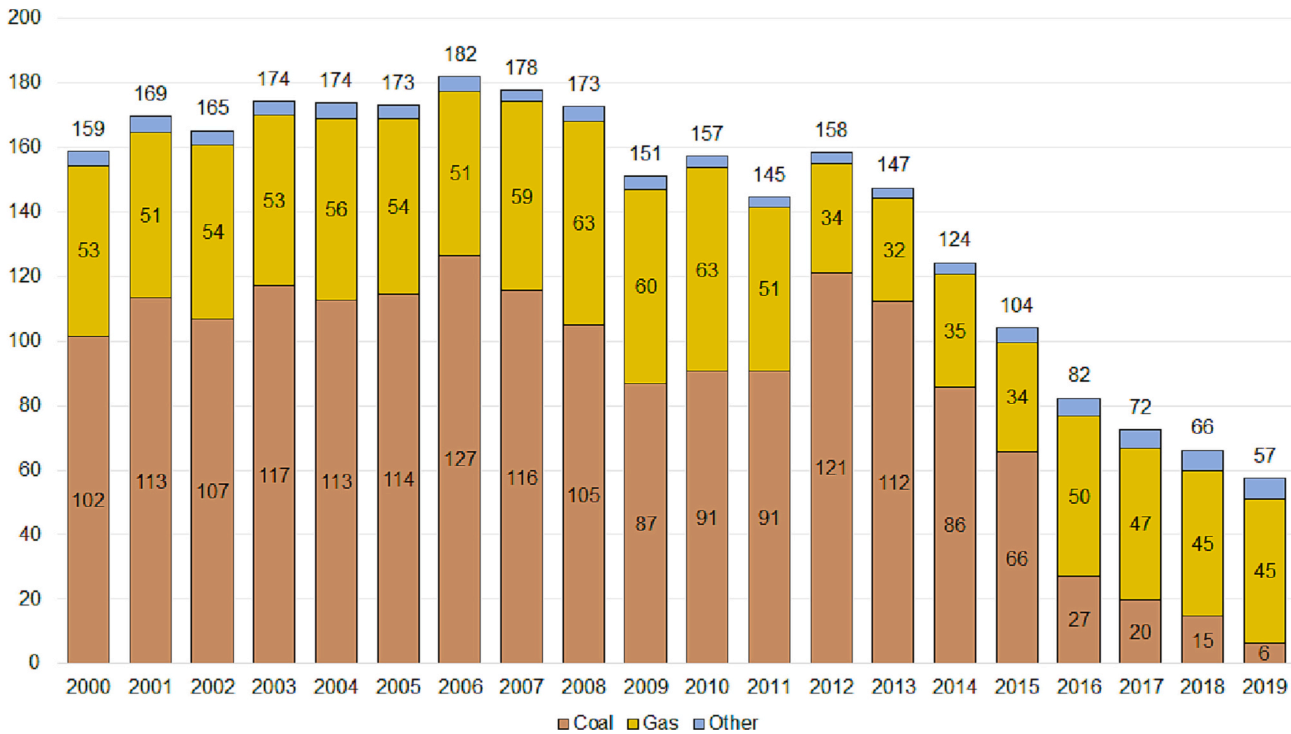


Fig. 2. Britain's power sector emissions by source (MtCO_2).
Notes: Data source: BEIS (2021).

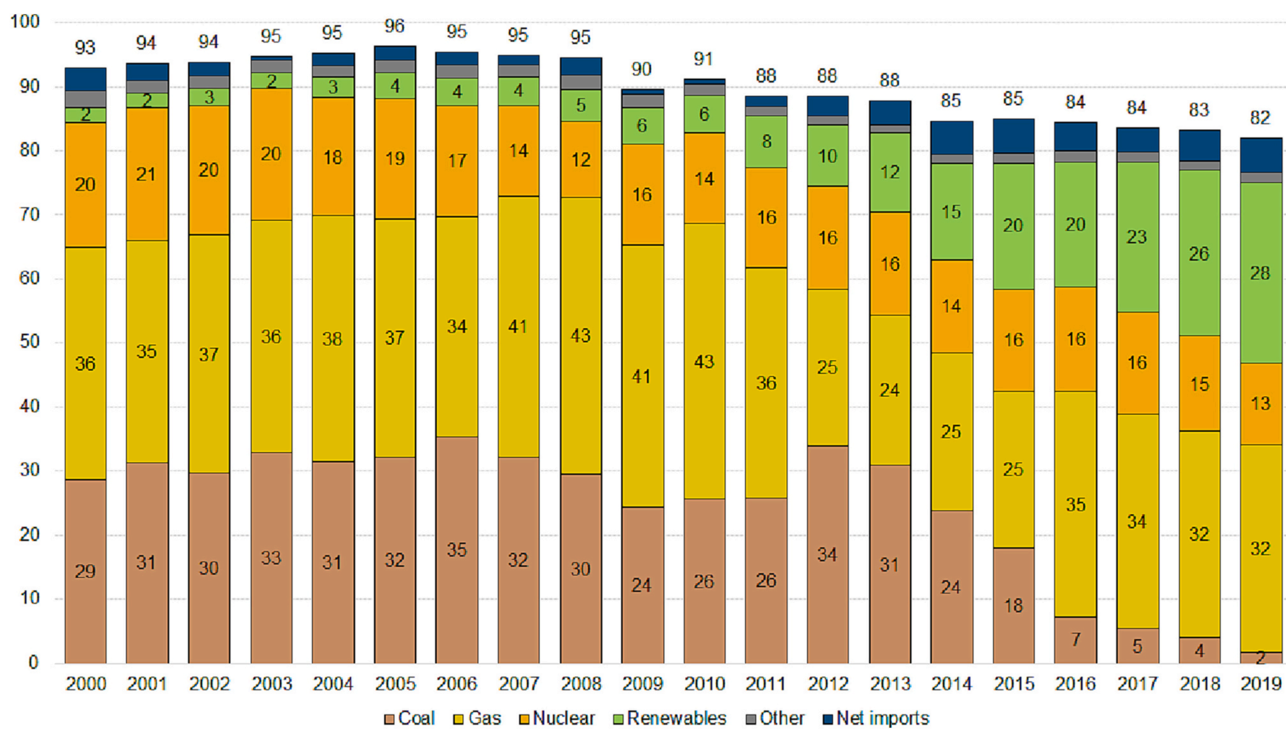
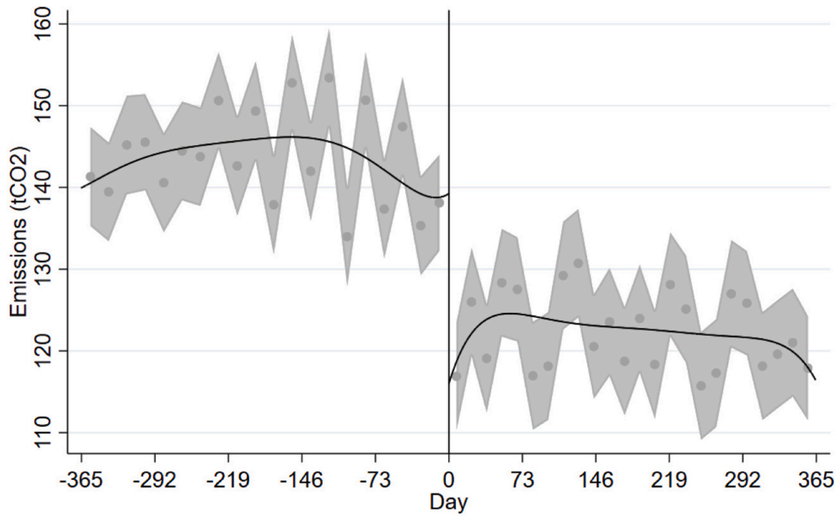
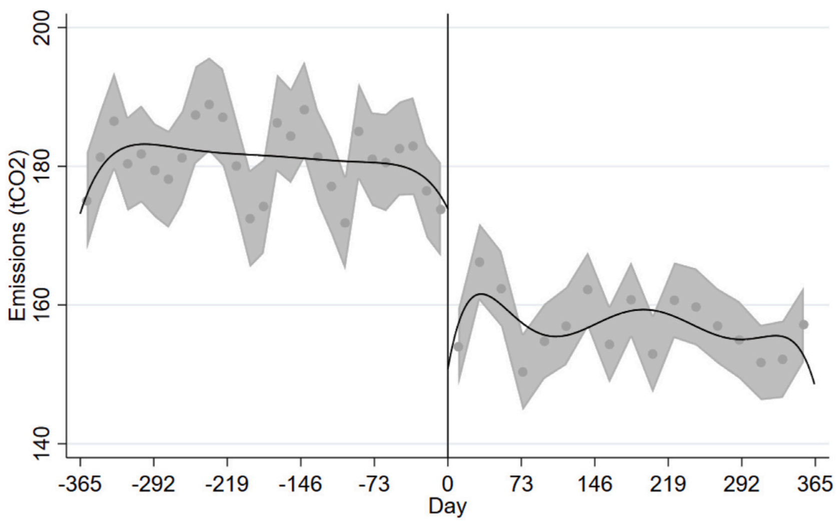


Fig. 3. Britain's electricity generation by source (TWh).
Notes: Renewables comprise hydro (natural flow), wind, solar, bioenergy, and pumped storage. Source: BEIS (2021).

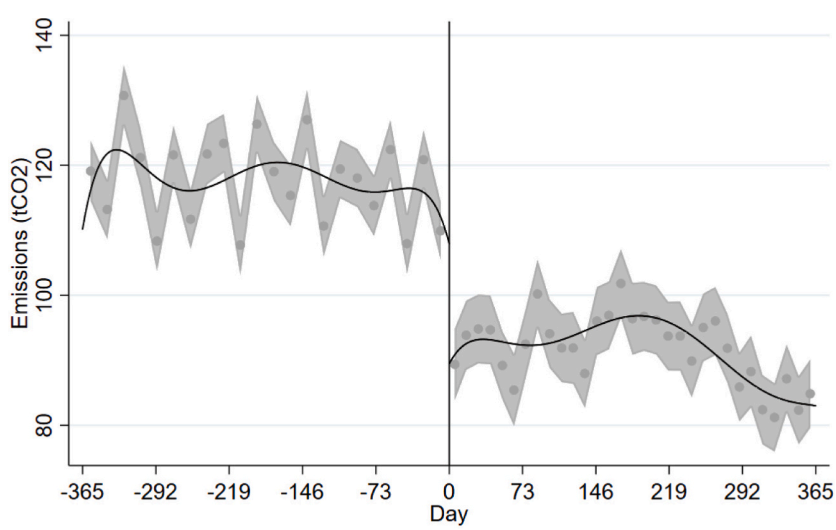
all generators are exposed to the CPS price increase on the same day, i.e. April 1, for three consecutive years, whereas treatment intensity essentially hinges upon the emission intensity of each unit. Lee and Lemieux (2010, p. 289) refer to "standard" regression discontinuity design a "local randomized experiment", if treated and untreated units were sorted right above or below an arbitrary threshold, but otherwise (almost) identical. In our RDiT setting (which gains increasing popularity in environmental economics; Hausman and Rapson, 2018), the quasi-experimental setting depends on the key identifying assumption that treatment discontinuously changed generators' electricity



(a) CPS jump on 1 April 2013



(b) CPS jump on 1 April 2014



(c) CPS jump on 1 April 2015

Fig. 4. Discontinuous changes in CO_2 emissions.
Notes: The graphs plot the predicted average hourly CO_2 emissions by power plant after controlling for renewables, renewables squared, demand, demand squared, hour-of-day and day-of-week fixed effects, and power-plant fixed effects, and a sixth order polynomial trend on either side of the treatment. The dots represent binned sample means, where the bin width is chosen by Stata's command "rdplot" using the option "binselect(qs)", which implements the IMSE-optimal quantile-spaced method using spacing estimators. The shaded area indicates a 95% confidence interval for each bin. (a) average over 131 coal- and gas-fired power plants, (b) average over 109 coal- and gas-fired power plants, (c) average over 107 coal- and gas-fired power plants.

production activity (and thus emissions), while any other confounding variable should not be influenced by treatment. This implies that electricity generation (and thus CO_2 emissions) would have changed smoothly around the dates of the CPS jumps in the absence of treatment. While this assumption is not directly testable, we run placebo tests for hypothetical treatments one year preceding the first CPS jump and one year after the last CPS jump, supporting the notion that emissions changed smoothly around these placebo dates (see Section 5.2). Moreover, we test if observable confounding variables changed smoothly around the treatment dates (see Section 5.4).

A threat to identification would be a confounding event, which had also a step change in emissions or electricity production activity on 1 April of the respective years. To the best of our knowledge, no such event took place. The only potential change that coincides with our treatment date would be the change of the fiscal year in Britain. However, using the donut regressions robustness check (see Section 5.1) as well as placebo regressions for 2012 and 2016 (see Section 5.2), we can rule out that the change of the fiscal year is responsible for a discontinuous drop in emissions. Another policy, which has had an impact on power plant emission and which partly fell in our estimation sample, is the LCPD (EC Directive 2001/80/EC), which was enacted in 2001 and came into force in 2008. It requires EU thermal power plants above 50 MW to limit emissions of sulphur dioxide, nitrogen oxides, and dust. Plants could either comply with the policy or close after 20,000 h of remaining operation ('opt-out' option) until the end of 2015 the latest. In Britain, 9 coal-fired power plants (and 1 oil-fired power plant) opted out, of which 6 are not in our sample because of inactivity during our estimation windows.[14] Hence, three coal plants that opted out appear in our sample. Two coal plants reduced their production activity over time and phased out production during our sample period, whereas production cessation was not discontinuous and can thus not be directly related to a CPS hike. One coal plant remained active until the end of our estimation period. We cannot credibly assess a date when these plants quit production, because we observe a rather smooth reduction in output over time with partly temporal inactivity over days and even weeks. This is, however, evidence that the influence of the LCPD cannot be directly related to the effects of the CPS hikes. In our estimations, we focus on discontinuous changes around the treatment dates, so that we can largely rule out confounding bias from the LCPD.

Furthermore, we are certain that the conditional independence assumption, which requires no self-selection into or out of treatment, is fulfilled, because all fossil-fueled power plants are subject to the CPS hikes.

Another potential threat to identification would be anticipation effects, which we can largely rule out in our case. In power markets, generation decisions are short-run decisions because electricity cannot be stored at a large scale. Generators usually decide one day in advance whether they can compete in wholesale markets and be "in the merit order" or not. These two arguments imply that CO_2 emissions should react immediately to the policy changes. Thus, despite *knowing* in advance about significant jumps in the effective carbon price, power plant owners could not *act* in anticipation of the policy changes to avoid the negative policy effects (e.g. by producing electricity at cheaper carbon prices before the CPS hikes and selling it at a later date). Lemoine (2017) finds anticipation effects of a proposed strengthening of environmental policy (the U.S. Senate's 2010 climate effort). We do not have indications that the British CPS led to similar anticipation effects, e.g. the average annual price of coal remained fairly flat in the years preceding the introduction of the CPS (2011 and 2012). Moreover, coal and gas cannot be stored in large amount and/or over several months either. Even if generators had wanted to preempt the CPS increase, they could not have stored coal or gas in large-enough amounts to use it longer than several days. Thus, in Section 5.1 we run donut regressions, in which we eliminate up to one month of data preceding treatment to rule out any such doubts.

While a standard difference-in-differences approach only allows that unobserved variables affect emissions via a time trend, the RDiT model permits unobserved factors to affect emissions non-linearly ("splines"), so long as they are not discontinuous at the policy changes (Hahn et al., 2001). This leads up the fact that with RDiT, control variables are not needed, but only enhance precision of the estimates. That is, even in the presence of time-varying omitted variables, RDiT delivers a consistent estimate of the effect of interest as long as the omitted variables do not discontinuously change around the event (Davis, 2008, footnote 12). Moreover, an RD approach obviates the need for a proper control group.[15]

Finally, a particularly attractive and convincing feature of our design is that we cannot only estimate average treatment effects, but also *heterogeneous* treatment effects across plants (Hausman and Rapson, 2018, fn. 10). The change in marginal costs induced by a higher carbon price, and therefore the treatment intensity of the policy changes, directly varies with the efficiency factors of the affected plants. Less efficient plants emit more CO_2 per MWh of electricity than more efficient ones. Accordingly, marginal costs of less carbon efficient plants increase more strongly after the policy changes relative to more efficient plants. Thus, we would expect that less efficient coal or gas power plants reduce their output by more than more efficient plants (either through outright exit or marginally). Moreover, we expect that gas-fueled power plants, which emit roughly only half the CO_2 per MWh than coal-fueled plants, should reduce their generation by less than coal-powered plants, or might even increase generation to substitute for the missing electricity from coal.[16] Thus, we get clear predictions on the expected heterogeneous treatment effects of the CPS.

3.2. Theoretical predictions

Electricity supply is structured according to available power plant capacities, ranked by their marginal costs, called the "merit order". Its intersection with electricity demand determines the wholesale price of electricity. All available plants with lower marginal costs are inframarginal and thus make variable profits by producing electricity. Any plant with higher marginal costs is "out of merit" and makes no variable profit. Without a carbon price in place or for a low carbon price (as it was the case before the introduction of the CPS) and for "typical" fuel prices (i.e. coal being cheaper than natural gas), coal plants are ranked before gas plants due to their lower marginal costs. With an increasing carbon price (e.g. due to the CPS hikes), the marginal costs of an inefficient coal plant (i.e. low efficiency factor, high emission factor) increase more strongly than those of an efficient gas plant (i.e. high efficiency factor, low emission factor), so that eventually the plants may change their positions in the merit order. Whenever such substitutions of plants take place at the margin (a "dirty" coal plant becomes extra-marginal, a

[14] In our dataset, we can only observe if a power plant produces or not, but cannot distinguish between temporary inactivity or permanent closure. In any case, power stations with zero production before and after treatment cannot be regarded in the regressions and therefore fall out of the sample. We retrieved our information about opted out plants from the European Environment Agency (EEA), which lists all British power stations, which opted out from the LCPD: https://www.eea.europa.eu/data-and-maps/data/large-combustion-plants-lcp-opted-out-under-article-4-4-of-directive-2001-80-ec-4, access on Dec. 28, 2021.

[15] Since the CPS affects *all* thermal power plants in the UK, there is no cross-sectional variation in the policy implementation. Thus, a proper control group of non-treated thermal power plants could only be found outside the UK, triggering problems of potentially unobserved confounding shocks.

[16] The same reasoning also implies that non-carbon sources of electricity such as hydro or nuclear power plants should either not be affected by the policy changes or might even increase their generation to substitute for the missing coal-based electricity.

"cleaner" gas plant becomes infra-marginal), emissions will be reduced.

We now derive our predictions more formally using a commonly applied definition of marginal costs in the electricity sector (see, e.g., Gugler et al., 2020, especially Appendix A). The marginal costs of producing one unit of electricity, c (in €/MWh), per power-plant turbine can be written as a function of the fuel price, P^{fuel} (the price of gas in €/MWh or the price of coal, offered in €/1000 metric ton of thermal coal, converted into €/MWh using a conversion rate of one ton of hard coal being equal to 8.141 MWh[17]), the carbon price, P^{CO2} (in €/tCO_2), the emission factor, ψ (in tCO_2/MWh), and the efficiency factor, ω ($0 < \omega < 1$):

$$c_{tt,ft,cy,t} = \left[P^{fuel}_{ft,t} + \left(P^{CO2}_{ft,t} \cdot \psi_{ft}\right)\right] \Big/ \omega_{tt,ft,cy}, \tag{1}$$

where the subscripts *tt*, *ft*, *cy*, and *t* denote the turbine type, fuel type, construction year, and the hour of observation, respectively.[18] The efficiency factor, ω, measures the conversion rate of energy input to electricity output. In our data it is a number between 0.3 (least efficient unit) and 0.61 (most efficient unit).[19] Moreover, the emission factor, ψ, measures the emissions (in tCO_2) created per unit of electricity output (MWh) and represents a constant for coal and gas plants (i.e. 0.337 tCO_2/MWh for coal plants and 0.191 tCO_2/MWh for gas plants).[20]

Marginal costs decrease with the efficiency factor and increase with the emission factor (provided that there is a positive carbon price). We can see that a power station's change in marginal costs (and therefore its reaction to the tax) due to a change in the carbon price depends on its emission and efficiency factors:

$$\frac{\partial c_{tt,ft,cy,t}}{\partial P^{CO2}_{ft,t}} = \frac{\psi_{ft}}{\omega_{tt,ft,cy}}. \tag{2}$$

Hence, holding fuel prices constant, an increase in the carbon price by means of a CPS jump leads to a stronger rise in marginal costs the lower the efficiency factor and the higher the emission factor. Against the above, we expect the most outdated coal-fired power plants to react most strongly to an increase in the carbon price, because their marginal costs will increase most substantially. The reactions should be mitigated for more carbon efficient plants.

3.3. Model

As shown above, the effect of a jump in the CPS rate on CO_2 emissions crucially depends on the increase in power stations' marginal costs, which in turn changes the output decisions of plant owners. Our main empirical specification is therefore:

$$y_{i,n,t} = \beta_{treat} Treat_t + \boldsymbol{X}'_{i,t}\beta + \boldsymbol{T}'\gamma_T + (\boldsymbol{T} \cdot Treat_t)'\gamma_{T\bullet treat} + \upsilon_i + \varepsilon_{i,n,t}, \tag{3}$$

where the outcome variable y measures CO_2 emissions of power-plant turbine i producing electricity using input n (= coal, gas) at time t (i.e. each hour of the sample). Our parameter of interest, β_{treat}, represents the local average treatment effect (ATE) of the respective CPS change on CO_2 emissions. $Treat_t$ is a treatment indicator that takes a value of one for all hours after the respective policy change and a value of zero otherwise. $\boldsymbol{X}$ is a vector of covariates including linear and quadratic terms of hourly demand and renewables infeed, as well as hour-of-day and day-of-week fixed effects. $\boldsymbol{T}$ represents a vector of a higher-order polynomial time trend[21] to control for time-series variation in emissions that would have occurred in absence of the respective CPS jump. We also allow the time trend to differ after the policy events by including an interaction between the polynomial time trend and the treatment indicator ($\boldsymbol{T} \cdot Treat_t$).[22] υ_i are cross-sectional fixed effects for each power-plant unit. Altogether, these covariates are included to pick up any continuous changes in electricity market characteristics, such as variations in demand and renewables infeed, as well as slowly changing conditions over time, such as other policy changes (e.g. power plant emission standards) or changing trade barriers (e.g. investments in cross-border interconnector capacity). ε is a heteroscedasticity-robust error term.[23]

The key identifying assumption of our empirical approach is that the only reason for emissions to change discontinuously on the event dates is the change in the CPS rate.[24] Other potentially confounding variables that are smoothly changing around the treatment dates, even if they were omitted from the regression, should have no influence on the estimation of the discontinuous treatment effect. Our flexible specification controls for nonlinearities in emissions by using polynomial time trends, and allows us to isolate the changes in emissions attributable to the CPS. Our econometric identification thus also accounts for a negative trend in emissions since 2007, as shown in Fig. 2, because it is unlikely that emissions would have changed discontinuously around the dates of the CPS hikes on April 1 of the years 2013, 2014, and 2015 (besides controlling for any trend effects by our polynomic time-trend specification). Moreover, we expect heterogeneous effects across power stations, since treatment intensity (inversely) varies with efficiency factors, which adds another source of identification.

Another caveat is that there may be a potentially endogenous relationship between emissions and electricity demand, for example if consumers became aware of the negative effects of emissions and thus reduced electricity demand. However, we analyze the wholesale market and not the retail market. Firms in the wholesale market surely do not take into account emissions (other than via the CO2 price) but maximize profits. Consumer awareness of the electricity generation mix in the wholesale market on specific days (or even hours) may be very limited. This, of course, does not rule out secular reactions of consumers over time, such as by choosing green tariffs or saving energy, etc., but we do not expect feedback effects to demand within the granular time span (in the extreme case one hour) we analyze. Hence, in line with other studies on power sector emissions (see, e.g., Cullen and Mansur, 2017; Fell and Kaffine, 2018; Gugler et al., 2021), environmental damages (Fell et al.,

[17] https://www.iea.org/data-and-statistics/data-tools/unit-converter

[18] $tt \in$ {combined cycle, combustion turbine, internal combustion, steam turbine}, $ft \in$ {lignite, hard coal, gas}.

[19] In our sample, coal plants have an average efficiency factor of 0.35, with a minimum of 0.33 and a maximum of 0.48. Gas plants have an average efficiency factor of 0.57, with a minimum of 0.30 and a maximum of 0.61.

[20] These values were provided by the Austrian Transmission System Operator, APG. Similarly, the Department for Business, Energy & Industrial Strategy (BEIS, 2022) reports a U.K. specific emission factor for coal of 0.335 tCO_2/MWh and for natural gas of 0.202. Similar values can be found in German Environment Agency (2016), reporting a CO_2 conversion factor for British bituminous coal ("egg coal, England") of 95.913 tCO_2/TJ, which is equivalent to 0.345 tCO_2/MWh, and for natural gas ("Norway, winter") of 56.12 tCO_2/TJ, which is equivalent to 0.202 tCO_2/MWh.

[21] As we describe later in more detail, we chose a sixth-order polynomial time trend in our main specification.

[22] Similarly, Chen and Whalley (2012) and Lang and Siler (2013) include both a polynomial time trend and its interaction with the post-treatment indicator, whereas Davis (2008) and Auffhammer and Kellogg (2011) apply less flexible specifications using only polynomials in time without interactions.

[23] Applying Newey-West standard errors to control for potential autocorrelation does not alter our main results (i.e. jump 1: ATE = −16.51, p-val. = 0.00; jump 2: ATE = −10.72, p-val. = 0.00; jump 3: ATE = −10.01, p-val. = 0.00).

[24] Even in the presence of time-varying omitted variables, RDiT delivers a consistent estimate of the effect of interest as long as the omitted variables do not discontinuously change around the event (Davis, 2008, footnote 12). In our case, it is hard to think of any confounding effects, which may change discontinuously on 1 April of 2013, 2014, and/or 2015. One such event would be the change of the fiscal year in Britain. However, using the donut regressions robustness check (see Section 5.1) as well as placebo regressions for 2012 and, 2016 (see Section 5.2), we can rule out that the change of the fiscal year is responsible for a discontinuous drop in emissions.

2021), or electricity production from coal-fired power plants (Bushnell and Novan, 2021), we assume electricity demand to be exogenous in the short run.

Our main coefficient of interest, β_{treat}, is a local average treatment effect, which gives the change in emissions in response to the respective policy changes per power station per hour. That is, RDiT may precisely estimate the effect of the CPS, because it investigates a local treatment effect in the form of step changes in emissions, which would not have occurred without the CPS jumps. We thus measure short-run effects in the form of changes in the given supply structure. We can identify substitution effects between power stations using natural gas or coal and for different efficiency factors. However, we cannot identify the long-run effects of the CPS in terms of investments in new generation assets. It would only be possible to empirically observe capacity investments, as triggered by the CPS, with a significant time lag, given that it may take years to plan and build new power plants or add blocks to an existing power plant (Gugler et al., 2020). Such investments would change the supply structure and thus emissions, but cannot be captured by our model. However, the abatement effects of the CPS that we identify will last as long as the marginal costs of existing plants are influenced by the new tax rate. Hence, a higher carbon tax rate will shift the marginal costs and thus the merit order for as long as it is in place. In order to get economically meaningful results, it is worthwhile to calculate longer-term effects by the means of a back-of-the-envelope calculation. That is, we multiply the effect of interest by the number of stations k in the sample ($i = \{1, \ldots, k\}$) times the number of hours per year (i.e. 8760) to arrive at an annual aggregate treatment effect: $\beta_{treat} \cdot k \cdot 8{,}760$. The assumption behind is that the CPS changes the marginal costs of power plants as long as the new CPS rate applies, so that its effect should last for a whole year (and beyond that). It is crucial to mention that this aggregate effect holds only ceteris paribus, meaning for given market circumstances around the treatment dates. Any other significant exogenous events that have an impact on power stations' production or emission activity are not taken into account in this approach.

Moreover, in an alternative regression we interact the treatment indicator with power-plant turbine fixed effects to estimate *plant-specific (heterogeneous) treatment effects*:

$$y_{i,n,t} = \beta_{i,treat} Treat_t \cdot \upsilon_i + X'_{i,t}\beta + T'\gamma_T + (T \times Treat_t)'\gamma_{T \bullet treat} + \upsilon_i + \varepsilon_{i,n,t}. \quad (4)$$

In this case, $\widehat{\beta}_{i,treat}$ is a $1 \times k$ vector of $i = (1, \ldots, k)$ turbine-specific treatment effects.

A few other remarks on our specification are worth mentioning. We apply a polynomial time trend in our main specification, which is differentially estimated before and after the event dates to control for any smoothly changing unobservable factors. We follow related applications of RDiT to environmental issues (e.g. Davis, 2008; Auffhammer and Kellogg, 2011; Chen and Whalley, 2012; Lang and Siler, 2013) using higher-order polynomials, and chose a sixth-order polynomial trend, which minimized the AIC criterion compared to lower-order specifications. Another argument for applying higher-order local polynomials is that these tend to outperform local linear and lower-order local polynomials in terms of their mean squared error, coverage rate of the confidence interval, and confidence interval length, especially when the sample size is large as in our case (Pei et al., 2018).

3.4. Data

We utilize high-frequency data on *hourly* electricity generation of *all* British thermal power plant units (i.e. turbines) to calculate CO_2 emissions at the turbine level over time. The granularity of our data is a key feature of our analysis, because turbine-specific CO_2 emissions at the hourly frequency are, to the best of our knowledge, not available for Britain (or Europe) from publicly available sources. Our data stem from S&P Global Platts, a major independent data and information provider for the energy and commodities markets. Our data sample spans 1 April 2012–31 March 2016, allowing for event windows of one year on either side of the tax jumps.[25] We observe 57 coal units and 74 gas units, which were active[26] during the pre-treatment period (01Apr2012 – 31Mar2013). For these units, we also have information about nameplate capacity, vintage, fuel type, and turbine type.

We are thus able to calculate turbine-specific hourly CO_2 emissions: $y_{i,n,t} = g_{i,n,t} \cdot \psi_n / \omega_{i,n}$, where y are CO_2 emissions, g is electricity production, ψ is the emissions factor, ω is the efficiency factor, and the subscripts denote the turbine i, fuel input n (coal, gas), and sample hour t. The technology-vintage-specific emission and efficiency factors are provided by the Austrian Transmission System Operator, Austrian Power Grid (APG), according to fuel type and plant vintage.[27] These emissions data are also used by Gugler et al. (2021), who mention that the constructed data, aggregated to the annual frequency for the period 2012–2017, are 99% consistent with official statistics reported by the UK Department for Business, Energy & Industrial Strategy (BEIS, 2021).

Regarding the control variables, we obtained the hourly electricity feed-in from intermittent renewable energies in the form of wind and solar power and electricity demand from Gridwatch,[28] an independent data provider, working in collaboration with Sheffield University and Elexon Portal, an information provider under the regulation of the Office of Gas and Electricity Markets (Ofgem). Table A1 provides summary statistics of the variables employed in our regressions.

4. Results

4.1. Average treatment effects

Table 1 summarizes the estimates of the ATEs as the causal effect the CPS averaged over all individual power plants. The estimates are based on the regressions of eq. (3) and their full output is provided in the Appendix Table A2. The reported ATEs are statistically significant at the 1% level (except for the ATE of tax jump 1 for gas plants, which is significant at the 10% level).

We should emphasize that our ATEs measure the average emissions reduction per power plant per hour. We can then extrapolate this estimate over all treated power plants over one year as to provide a reasonable estimate of the overall magnitude of the effect. For the CPS jumps 2 and 3, our estimates give the *additional* abatement associated with an *increase* in the CPS (relative to already abated emissions for the previous CPS changes). This implies that we can eventually aggregate the ATE estimates for each tax jump to arrive at total emissions abatement due to the CPS hikes.

Looking at panel A of Table 1, we estimate that the introduction of the CPS on 1 April 2013 led to an average reduction in emissions across all coal and gas power plants by 16.5 tCO_2 per hour in the post-treatment

[25] We chose one year of data on either side of the respective CPS jump following Chen and Whalley (2012) and Davis (2008), who state that it may become difficult to properly control for seasonal variation with shorter event windows. Although our data would have been available for a longer period, adding information further from the event dates may not significantly enhance the precision of our estimates, but rather imperil validity as the likelihood of unobserved confounding factors increases.

[26] We treat a plant as active as long as it produced electricity (and thus emissions) during the 365 days prior to the respective tax jump.

[27] The reason why we use technology-vintage-specific emission and efficiency factors from an Austrian TSO (APG) is that these data had a higher level of detail and seemed most reliable. That is, APG provided efficiency factors that varied by vintage and electricity production technology. Other publicly available data were not as detailed. Also, the emission factors by electricity-generation technology from APG are of high quality. However, comparing the data from APG with other sources showed generally high consistency. See also Footnote 20 on this issue. Using the same raw data, Gugler et al. (2021) provide a detailed description of how the emissions data are constructed.

[28] www.gridwatch.templar.co.uk.

Table 1
Average treatment effects.

	ATE per plant per hour (tCO_2)		# power plants	Aggregate ATE over all plants for a whole year ($MtCO_2$)	Change relative to period before 1st tax jump
Panel A: coal & gas plants					
Tax jump 1 (01Apr2013)	−16.51	(1.226)	131	−18.9	−11.62%
Tax jump 2 (01Apr2014)	−10.71	(1.294)	109	−10.2	−7.54%
Tax jump 3 (01Apr2015)	−10.03	(1.351)	107	−9.4	−7.06%
Total	*−37.25*			*−38.6*	*−26.21%*
Panel B: coal plants					
Tax jump 1 (01Apr2013)	−36.48	(2.651)	57	−18.2	−13.41%
Tax jump 2 (01Apr2014)	−35.77	(3.051)	41	−12.8	−13.15%
Tax jump 3 (01Apr2015)	−36.73	(3.170)	39	−12.5	−13.50%
Total	*−108.98*			*−43.6*	*−40.06%*
Panel C: gas plants					
Tax jump 1 (01Apr2013)	−1.119	(0.662)	74	−0.7	−2.69%
Tax jump 2 (01Apr2014)	4.394	(0.706)	68	2.6	10.56%
Tax jump 3 (01Apr2015)	5.284	(0.652)	68	3.1	12.69%
Total	*8.559*			*5.0*	*20.56%*

Notes: ATE = average treatment effect. Aggregate ATE = ATE per plant per hour * # plants * 8760 h. Average emissions per plant during period before 1st tax jump (01Apr2012 − 31Mar2013): all coal and gas plants = 142.1 MtCO2, coal plants = 272.1 MtCO2, gas plants = 41.6 MtCO2. Robust standard errors in parentheses.

period 01Apr2013–31Mar2014. Aggregated over all 131 power plants and over 8760 h, this effect translates into emissions abatement of 18.9 $MtCO_2$ per year. Relative to the pre-treatment period 01Apr2012–31Mar2013, our ATE estimate suggests a reduction of CO_2 emissions of 11.6%. We also find significant effects for the two subsequent elevations of the carbon tax. Tax jump 2 brought about an ATE of −10.7 tCO_2 per plant per hour, which gives a total abatement of 10.2 $MtCO_2$/yr over the remaining 109 active power plants, or − 7.54% relative to emissions prior to the introduction of the CPS (01Apr2012–31Mar2013). Finally, tax jump 3 is of a similar magnitude, amounting to an ATE of −10.0 tCO_2 per plant per hour, which accords to −9.4 $MtCO_2$/yr over the remaining 107 active power plants.

Relative to the period before the tax was introduced, this represents a 7.1% reduction of emissions. Our finding that the ATE is highest for the first tax jump can be explained by many inefficient power plants still operating, which display the largest treatment effects (see Section 4.2). After the first tax jump, 16 coal-fired and six gas-fired plants cease their operations. Thus, for the subsequent tax jumps we observe more efficient plants, on average. The *cumulative* effect of the CPS at the end of the third evaluation period (31 March 2016) amounts to a reduction of 38.6 $MtCO_2$ or 26.2% CO_2 emissions from the British power sector compared to a counterfactual situation without the CPS in place.

Let us put these estimates into perspective. According to our data on sample emissions, the average hourly emissions per plant fell by 43.9% from 142.12 tCO_2 during the pre-treatment period 01Apr2012–31Mar2013 to 79.78 tCO_2 during the period 01Apr2015–31Mar2016. Our estimated cumulative ATE (−26.2%) of the CPS, thus, explains about 60% of the total reduction in emissions. The remainder 40% of the drop in emissions can be explained by other confounding effects, as for example the surge in renewable energies, decreasing energy demand, or stricter emissions standards for power plants (e.g. the LCPD).

We now investigate coal and gas plants separately. Panel B of Table 1 estimates that the introduction of the CPS led to a sizable reduction in average hourly coal plant emissions by 36.48 tCO_2. For the 58 active coal plants at that time, we estimate an aggregate ATE of −18.2 $MtCO_2$ in the post-treatment year (01Apr2013–31Mar2014), which is a relative reduction in coal-based emissions by 13.4%. We then estimate an ATE of −35.8 tCO_2 per coal plant per hour from the tax increase on 01 April 2014, which corresponds to an abatement of 13.2% relative to the period before the CPS was introduced. Aggregating over the still active 41 coal plants, this amounts to an emissions abatement of 12.8 $MtCO_2$/yr during 01Apr2014–31Mar2015. Finally, the last tax increase reduced hourly emissions per coal plant by 36.7 tCO_2, which accords to a change of −13.5% relative to the period before the tax was introduced. For the 39 still active plants at that time, the aggregate ATE amounts to −12.5 $MtCO_2$/yr. The cumulative effects for coal plants is thus estimated at −43.6 $MtCO_2$ during 01Apr2013–31Mar2016, which is equivalent to a reduction of 40.1% of coal-based emissions.

Our estimates explain an even larger part of the total reduction in coal-based emissions, which decreased from 272 tCO_2 per coal plant per hour in the year before jump 1 to 123 tCO_2 in the year after jump 3, amounting to a drop by 54.8%. This means that about three quarters of the total drop in coal-based emissions can be solely attributed to the CPS. We conclude that the introduction of the CPS and its two subsequent elevations led to a sizeable reduction in coal-based emissions in Britain.

Panel C of Table 1 shows that the magnitude of the estimated ATEs is much less pronounced for gas plants, because they produce significantly less CO_2 (around 60%) per unit of electricity compared to coal plants. The introduction of the CPS led to a minor reduction in average gas plants' hourly emissions by 1.1 tCO_2 (i.e. -2.7%), amounting to an aggregate ATE of −0.7 $MtCO_2$/yr. It is worth noting that the CPS did not elevate the total carbon price (= ETS price + CPS) enough to induce a fuel switch between coal and gas, as if so, emissions from gas would have increased due to an increase of the electricity production from gas. However, this is exactly what we observe during the two subsequent tax increases in 2014 and 2015. The tax jumps 2 and 3 led to an increase in average gas-based emissions by 10.6% and 12.7%, respectively. Altogether, the cumulative effect of the CPS on gas-based emissions is positive, amounting to 5 $MtCO_2$.

Notably, the first tax jump yielded an aggregate ATE of −18.9 $MtCO_2$, which is significantly more pronounced than the successive ATEs for the second (−10.2 $MtCO_2$) and third tax jump (−9.4 $MtCO_2$), whereas the CPS rate was significantly lower (£4.94 = €5.84) during the first treatment period, 1 April 2013–31 March 2014, relative to the second (£9.55 = €11.46; 1 April 2014–31 March 2015) and third (£18.08 = €24.63; 1 April 2015–31 March 2016). This can be explained by the fact that the first tax jump was already sufficient to introduce a fuel switch between the least efficient coal plants and the most efficient gas plants, which has led to significant abatement. Then, the second and third jumps implied higher tax increases, whereas the switching potential was less pronounced, meaning that only the more efficient coal plants could be replaced. This is something that we investigate further looking at the heterogeneous treatment effects across power stations.

4.2. Heterogeneous treatment effects

We now investigate plant-specific effects of the CPS, allowing for varying treatment intensity by plant. Our prior is that the carbon tax had a stronger impact on relatively inefficient power plants.

Table 2 summarizes the estimates of these heterogeneous treatment effects, as based on regressions of eq. (4).[29] In line with our theoretical predictions (c.f. Section 3.2), the majority of coal plants reduce their emissions significantly, with a total net reduction of -4979 tCO_2/h (i.e. -43.6 $MtCO_2/yr$). While some inefficient gas plants also reduce their emissions due to the CPS (in total by -1305 tCO_2/h), a substantially larger fraction increases emissions (in total by 1880 tCO_2/h), which yields a net increase by 575 tCO_2/h (i.e. 5.0 $MtCO_2/yr$).

We assume that heterogeneous plant efficiencies may explain plant-specific reactions to the tax hikes. We thus run second-stage regressions of the estimated plant-individual effects on each plant's ratio of emission to efficiency factor (in the spirit of eq. (2)) and controlling for capacity (to control for size effects):

$$\widehat{\beta}_{i,treat} = a + b\cdot\left(\frac{\psi}{\omega}\right)_i + c\cdot cap_i + \varepsilon_i.$$

Appendix Table A6 presents the results, which show that less carbon efficient plants reduce generation and therefore emissions by more than more carbon efficient plants, which is in line with our expectations (see Section 3.2). From the pooled regression (column (4)), we estimate that decreasing plant carbon efficiency by one standard deviation ($= 0.32$), the estimated ATE decreases by around 20 tCO_2 per hour, which is sizeable.[30] Interestingly, the estimates of $\widehat{b}$ decrease from -53.3 (2013) over -66.0 (2014) to -71.3 (2015) for consecutively higher CPS rates. This is exactly what we would expect if carbon efficiency becomes increasingly important for higher carbon prices. At high-enough carbon prices, only the most carbon efficient plants stay in the merit order, while the others become extra-marginal.

In conclusion, while our average treatment effects already suggest that the CPS resulted in a significant drop in emissions, it hides significant plant-specific heterogeneity. Thus, our plant-specific estimates reveal that carbon intensive plants reduce their electricity generation by more than less carbon intensive plants.

4.3. Tax implications

Given our estimates of the abatement effects of the CPS, we can discuss the tax implications of this policy by means of a back-of-the-envelope calculation. Our main point is to provide an estimate of tax payments due to the CPS in relation to the amount of emissions abatement. This can be interpreted as a measure of average tax payments per ton of CO_2 abated. From this, electricity consumers may learn how much CO_2 abatement they "buy" for the implemented CPS rate. Thus, with limited state resources or limited possibilities for taxation, it may be interesting which measures are "cheapest". However, we do not further evaluate how the state may redistribute the tax revenues, because we are not able to calculate general equilibrium effects from our model.

During the first period 01Apr2013 – 31Mar2014, the introduction of the CPS at a rate of €5.84/tCO_2 led to tax payments of €810 million from an emissions stock of 139 $MtCO_2$. Evaluated against an abatement of 18.9 $MtCO_2$ due to the CPS, we calculate taxes paid of €43/tCO_2. During the period 01Apr2014 – 31Mar2015, tax payments amounted to €1105 million, given a higher CPS rate of €11.46/tCO_2 and a lower emissions stock of 96 $MtCO_2$. Together with cumulative abatement of 29.1 $MtCO_2$ (in the first two years), the taxes paid per ton of CO_2 abated are even lower at €38/tCO_2. Finally, during the period 01Apr2015 – 31Mar2016, the CPS was raised to a rate of €24.63/tCO_2, with an emissions stock of 75 $MtCO_2$. This created tax payments of €1842 million. Hence, we calculate now somewhat higher taxes paid of €48/tCO_2 for a cumulative abatement of 38.5 $MtCO_2$ (in three years 01Apr2013–31Mar2016). This is evidence that for a moderate carbon tax, it is relatively efficient to abate emissions.

4.4. Other electricity generation sources

The above analysis showed that especially inefficient coal-fired power plants reduce their electricity output in reaction to the CPS jumps. We saw gas reacting to the second and third jumps of the CPS, however, imports or other electricity generation technologies, such as run-of-river hydro or nuclear power plants, as well as demand (see Section 5.4) might also react to the CPS. In economic terms, it becomes relatively cheaper to produce electricity via low-carbon technologies, because their marginal costs decrease relative to fossil-fueled technologies. However, hydro and nuclear plants are baseload technologies, which usually run at already high capacity utilization rates and may thus have limited scope for accommodating their electricity output (in contrast to relatively flexible gas-fired plants). We thus expect hydro and nuclear not to react to the CPS or if, only modestly, given their capacity/flexibility constraints. We use data on hydro and nuclear electricity production from Platts to assess if these technologies change discontinuously in reaction to the CPS. It is worth mentioning that these data are only aggregate time-series and thus have limited predictive statistical power (i.e. 730 daily observations). Fig. 5 visualizes how hydro and nuclear electricity vary around the time of the first tax jump in 2013.

Fig. 5a indicates a moderately positive discontinuous jump in the electricity production from hydropower (+2.99 GWh per day) after the policy change, which turns out statistically significant ($p < 0.01$). Hydropower thus reacted discontinuously but only within its limited scope in reaction to the CPS jump and filled a small part of the production gap from coal. Moreover, Fig. 5b plots the reaction of nuclear power to the CPS. The discontinuous jump is estimated at 16.2 GWh but statistically insignificant (p-value of 0.175).

Finally, the CPS increases the costs of the British electricity supply compared to untreated neighboring countries. Hence, the British imports might increase right after the policy change. Fig. 5c indicates that net imports increase discontinuously by 10.36 GWh per day in order to help reestablish the demand-supply balance. This corroborates the finding by Guo et al. (2019) that part of the electricity gap from coal was filled by imports. As noted by Guo et al. (2019), this created emissions in foreign electricity markets, which we do capture by our analysis.

However, a back-of-the-envelope calculation may help putting the emissions created by the estimated increase in Britain's imports in response to the CPS into perspective. During our sample, about 64% of the British imports came from France, 34% from the Netherlands, and only 2% from Ireland. We ignore the latter for its negligible share. However, the Netherlands had a high share of electricity generation from coal and gas fired power plants (about 80%). We use hourly data on electricity generation by technology (from ENTSO-E, 2022) and average emission and efficiency factors for coal and gas power plants (from our data) to calculate the CO_2 intensity of one MWh of electricity production in the Netherlands, finding an average emission intensity of about 450 $kgCO_2/MWh$. Using the same data sources for France, which mainly employs nuclear and hydro power, resulting in much lower emissions, we find an average emission intensity of only 27 $kgCO_2/MWh$. Thus, one MWh of British imports would create 170 $kgCO_2$ abroad ($= 450$ $kgCO_2/MWh \cdot 0.34 + 27$ $kgCO_2/MWh \cdot 0.64$). For the estimated increase in British imports by 10.36 GWh per day (which amounts to 3781.4 GWh per year) due to the CPS, our calculations yield additional emissions of 0.645 $MtCO_2$ per year, which is relatively small (only 3.4%) compared with the estimated emissions abatement of 18.9 $MtCO_2$ per year (see Table 1) in response to the CPS.

While this shows that carbon leakage within the electricity sector may has had a minor direct effect via imports, there are (at least) two other sources of carbon leakage. (i) It may be the case that the CPS increased the price of electricity as an input for other industrial and commercial goods, thereby leading to leakage in other sectors than

[29] Appendix Tables A3 and A4 provide the full regression outputs for coal and gas plants, respectively.

[30] The range of $(\psi/\omega)_i$ is 0.31–1.02.

Table 2
Heterogeneous treatment effects.

	Negative coefficient				Positive coefficient				Total
	# power plants	Avg. effect (tCO_2/h)	Avg. t-val.	Total effect (tCO_2/h)	# power plants	Avg. effect (tCO_2/h)	Avg. t-val.	Total effect (tCO_2/h)	Net effect (tCO_2/h)
Panel A: coal plants									
Tax jump 1	38	−99.83	−28.65	−3794	19	90.20	23.77	1714	−2080
Tax jump 2	25	−104.45	−26.37	−2611	16	71.55	16.95	1145	−1466
Tax jump 3	24	−102.52	−24.45	−2461	15	68.55	16.50	1028	−1433
Total		*−307*		*−8866*		*230*		*3887*	*−4979*
Panel B: gas plants									
Tax jump 1	34	−17.60	−16.35	−598	40	12.89	12.54	515	−83
Tax jump 2	29	−12.05	−10.07	−349	39	16.62	15.16	648	299
Tax jump 3	23	−15.56	−13.95	−358	45	15.94	15.82	717	359
Total		*−45.21*		*−1305*		*45.45*		*1880*	*575*

Notes: "Avg. effect" gives the effect of the respective CPS jump on emissions (tCO_2) per power plant per hour. "Total effect" is the aggregated effect over all plants (= avg. effect • # plants) per hour. "Net effect" is the sum of positive and negative total effects.

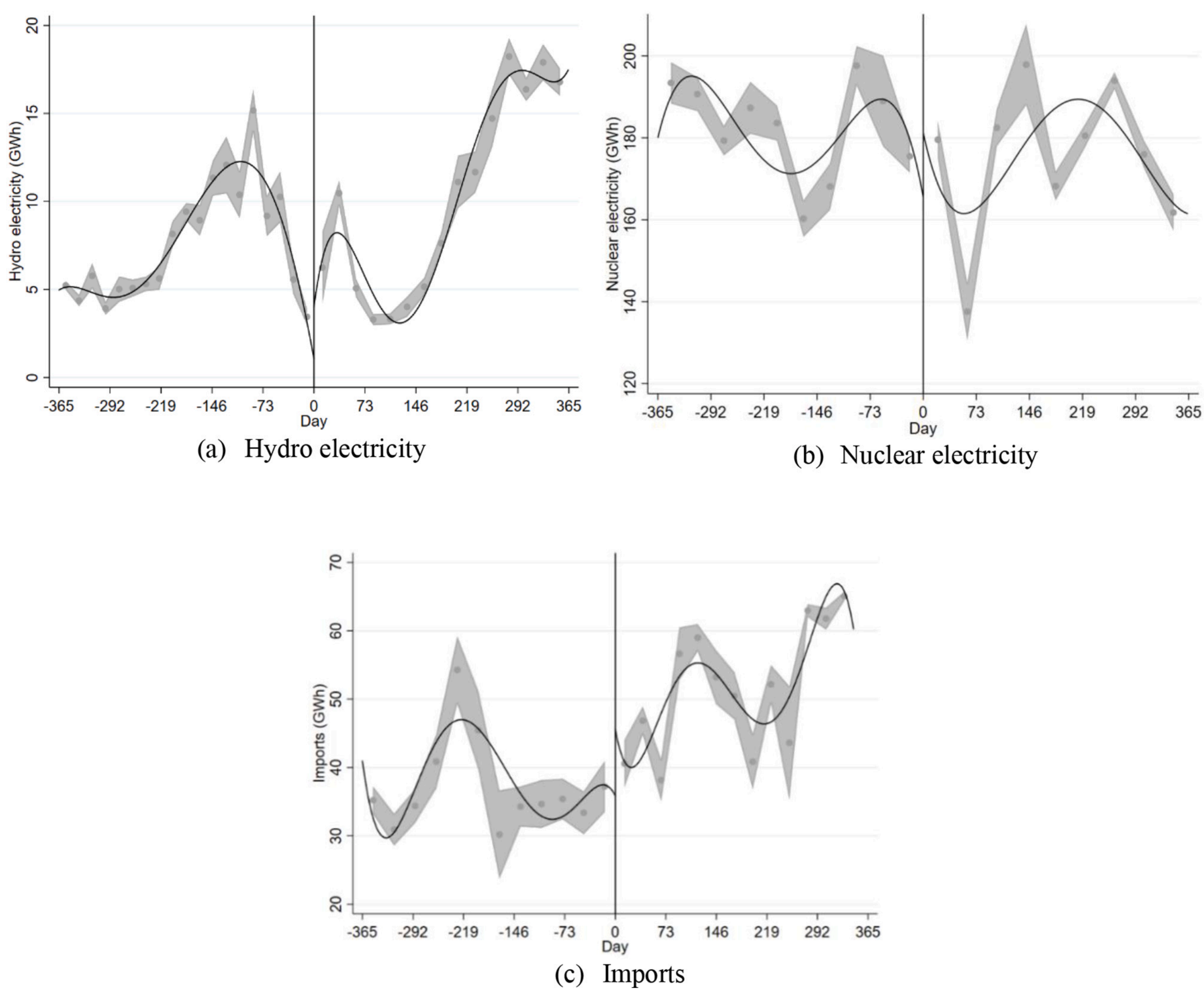


Fig. 5. Developments of hydro electricity, nuclear electricity, and imports.
Notes: coeff. = 10.36, p-value = 0.057.

electricity. (ii) The "waterbed effect" (Perino, 2018; Rosendahl, 2019a), which specifically applies for international emission trading schemes, predicts that any national policy measure to abate emissions (e.g. the British CPS) for a fixed emissions cap would free up emission allowances somewhere else (in other economic sectors or other countries within the ETS) and thus lead to zero abatement in aggregate. However, our estimates remain informative about the scope of abatement a carbon price may achieve if the emissions cap in the ETS was reduced according to the emissions abatement by the unilateral policy.[31]

4.5. What filled the gap in electricity supply from coal?

Our combination of data and method (RDiT) at hand are not particularly suitable for answering which other supply technologies or measures filled the discontinuous supply gap from the CPS. We utilize station-level panel data for coal and gas electricity production to infer about the emissions reaction due to the CPS. Data on other variables are quite limited. For example, we have data on electricity production by other main supply technologies, such as hydro and nuclear power, and on electricity imports only at the aggregate level and for the daily frequency. It is thus not the immediate focus of this paper to answer which other technologies filled the supply gap created by the CPS. Let us, nevertheless, try to give a brief answer to this question based on our limited information.

From our estimates on the introduction of the CPS in 2013, we identify a discontinuous decline in coal-fired electricity of 18 GWh per day and 2 GWh gas-fired electricity.[32] Our above estimates suggest that hydro electricity increased by nearly 3 GWh per day (Fig. 5a) and imports filled another 10.4 GWh (Fig. 5c), explaining roughly 67% of the supply gap. For nuclear power, we find a sizeable effect of 16 GWh, which is however statistically insignificant. Given the limited sample size, we cannot rule out though that nuclear electricity may have also filled part of the gap. Unfortunately, we have no precise data on other supply technologies, such as biomass, biogas, waste incineration, or pumped storages, which may have also reacted in response to the CPS.

5. Robustness

5.1. Anticipation effects

Above we have argued that anticipation effects are unlikely because electricity cannot be stored in economically sensible amounts. Thus, despite knowing in advance that the CPS was to be introduced or elevated, it would still be economical for electricity companies to adjust their production in reaction to the change in marginal costs due to the treatment instead of reacting in anticipation. Nevertheless, production adjustments in the form of ramping and cycling may cause additional costs and take time, so that it is possible that power plants may reduce their electricity production some days preceding a tax jump. This would mean that our results slightly understate the "true" effect. To rule out such and related concerns empirically, we apply "donut regressions", in which we eliminate observations (i.e. one week, two weeks, and one month) prior to the treatment dates.

Table 3 summarizes the results. Panel A eliminates a full week of observations (i.e. 168 h) predating the treatment dates. Evidently, the estimated ATEs per plant per hour stay robust to the main results (c.f. Table 1). Moreover, Panel B eliminates two weeks (i.e. 336 h) of data prior to the respective treatments. Again, the results support our main results, indicating that anticipation effects are no threat to our identification strategy. Finally, even dropping the whole month (i.e. March, 744 h) predating the treatment, we arrive at relatively similar ATE estimates. Besides ruling out anticipation effects, our "donut" approach also adds credibility by showing that changes in the bandwidth of up to one months do not significantly alter our results.

5.2. Placebo tests

We are able to conduct placebo tests for the dates April 1, 2012, one year prior to Britain's introduction of the CPS, and April 1, 2016, one year after the last CPS hike. Thus, for these two fictitious treatments, we should not be able to measure any significant discontinuous change in carbon emissions.

The results are depicted in Fig. 6. As expected, we find no statistically significant treatment effect for either of the two placebo treatment dates. This is evidence that our above analysis actually measures treatment effects of the carbon tax jumps. Moreover, this underlines that plant closures in the aftermath of the CPS jumps are actually attributable to the CPS jumps, as we argue above, because there is no evidence of further plant closures in our placebo analysis. This additionally makes clear that plants' electricity production does not vary with the beginning of the new fiscal year in the UK.

5.3. Analysis at the daily frequency

So far, we have employed data at the hourly frequency to estimate the causal effect of the CPS on CO_2 emissions. As a robustness check, we now re-run our main specifications using data at the daily frequency.

Table 4 provides an overview about the estimated ATEs based on

Table 3
Donut regressions: average treatment effects.

	ATE per plant per hour (tCO_2)	# power plants	Aggregate ATE over all plants for a whole year ($MtCO_2$)	Change relative to period before 1st tax jump
Panel A: coal & gas plants: eliminating one week prior to treatment				
Tax jump 1 (01Apr2013)	−17.96	131	−20.6	−12.64%
Tax jump 2 (01Apr2014)	−10.32	109	−9.9	−7.26%
Tax jump 3 (01Apr2015)	−10.06	107	−9.4	−7.08%
Total	*−38.34*		*−39.9*	*−26.98%*
Panel B: coal & gas plants: eliminating two weeks prior to treatment				
Tax jump 1 (01Apr2013)	−19.40	131	−22.3	−13.65%
Tax jump 2 (01Apr2014)	−9.90	109	−9.5	−6.97%
Tax jump 3 (01Apr2015)	−10.55	107	−9.9	−7.42%
Total	*−39.84*		*−41.6*	*−28.04%*
Panel C: coal & gas plants: eliminating one month prior to treatment				
Tax jump 1 (01Apr2013)	−23.09	131	−26.5	−16.24%
Tax jump 2 (01Apr2014)	−10.32	109	−9.9	−7.26%
Tax jump 3 (01Apr2015)	−12.39	107	−11.6	−8.72%
Total	*−45.79*		*−48.0*	*−32.22%*

Notes: ATE = average treatment effect. Aggregate ATE = ATE per plant per hour • # plants • 8760 h. Average emissions per plant during period before 1st tax jump (01Apr2012 − 31Mar2013): all coal and gas plants = 142.1 $MtCO_2$. All ATE estimates are statistically significant at least at the 10% level.

[31] In 2019, the EU ETS was reformed to preclude the waterbed effect. The Market Stability Reserve aims to reduce the supply of emission certificates according to the estimated emissions abatement by additional unilateral policies (Appunn, 2019).

[32] Using average CO_2 emission factors of 0.337 and 0.191 and efficiency factors of 0.348 and 0.566 for coal and gas stations in our sample, we can reconvert the estimated reduction in emissions given in Table 1 to GWh of electricity: $GWh_n = (y_n \cdot \omega_n)/\psi_n$, where y denotes the CO2 emissions, ω the efficiency factor, and ψ the emission factor, by supply technology n (coal or gas).

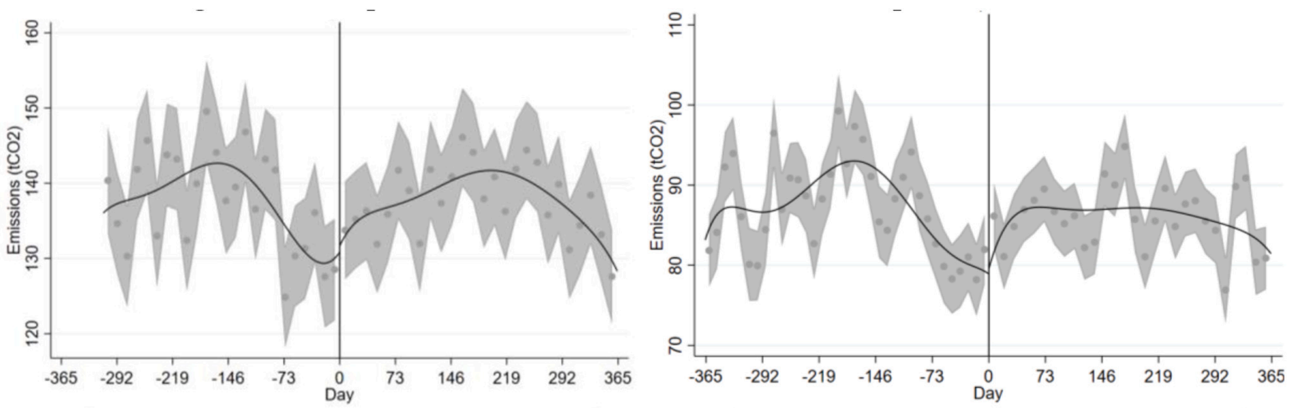


Fig. 6. RDiT placebo tests for fictitious treatment on April 1 of 2012 and 2016.

daily data (the underlying regression output is provided in Appendix Table A6). The analysis of daily data gives a slightly smaller overall effect of −34.1 $MtCO_2$ (= − 22.5%) than using hourly data (where we estimated −38.6 $MtCO_2$). Regarding coal plants, the daily result is −40.7 $MtCO_2$ (= −36.2%), and for gas plants, we estimate a cumulative effect of +6.6 $MtCO_2$ (= 27.1%). One reason for the divergences – which are not pronounced though – may be that our initial analysis also includes hourly fixed effects, and thus may better capture production adjustments during a day. In general, however, the daily analysis adds credibility to our main estimates as the estimates are fairly comparable.

5.4. *Testing for discontinuities in confounding variables*

A fundamental assumption of RDiT is that covariates should be smoothly changing around the policy events, so that we can identify the causal effect of the carbon tax hikes by a discontinuous reaction in emissions. It is possible to test whether renewables or demand indeed show a smooth variation around the tax jumps.

Wind and solar power feed into the electricity system whenever the wind blows or the sun shines. These renewables should thus not be affected by the introduction of the CPS. Indeed, Fig. 7(a) shows that the feed-in from wind and solar power changes smoothly around the treatment date (p-value of 0.845). Moreover, there is a vast amount of empirical studies showing that electricity demand reacts rather inelastically to electricity price changes. Hence, we would expect demand not to react to the CPS, or, in case of a discontinuous reaction, only negatively. Fig. 7(b) shows that demand changes rather smoothly around the treatment date (i.e. p-value of 0.210).

As can be seen from Appendix Table A1, however, electricity demand *gradually declined* (from around 36.8 GWh in 2012/2013 before the introduction of the CPS to around 32.5 GWh in 2015/2016 after the last elevation of the CPS), while electricity production from renewable sources *gradually increased* over time in the UK. Both adjustments helped substituting for the missing coal fired electricity production during that time period (besides more gas-fired electricity and imports).

6. Conclusion

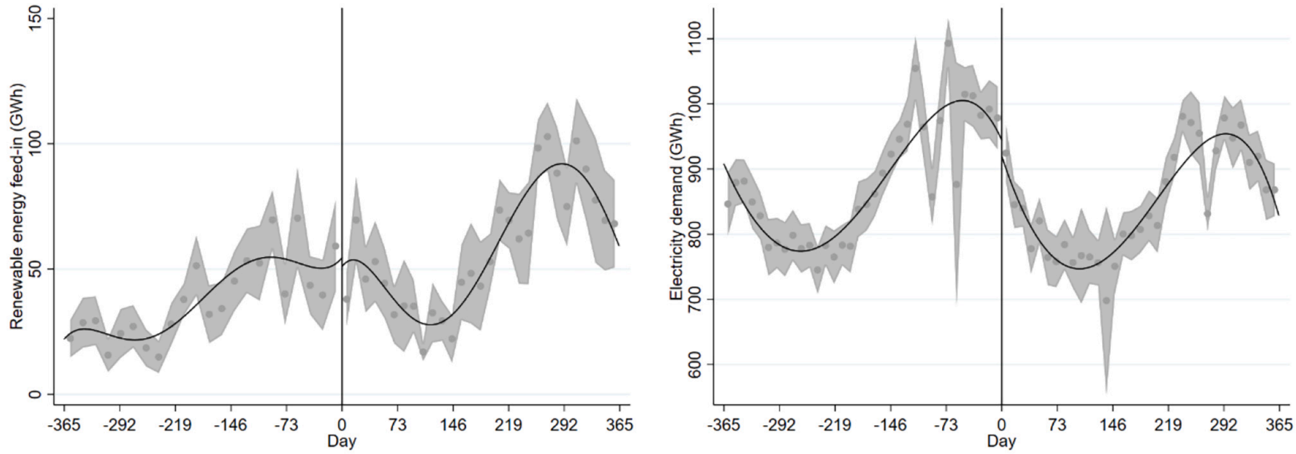
This paper assesses the causal effects of a unilateral tax (the CPS) on carbon emissions from the British power sector. Our identification exploits the discontinuous nature of the CPS introduction in 2013 and its elevations in the two subsequent years. Thus, regression discontinuity in time allows to disentangle the discontinuous effects of the carbon tax jumps on emissions from other confounding factors, such as a rise in renewables, a decline in demand, seasonal patterns, or other policy influences, which should be smoothly changing around the dates of the tax jumps.

Our paper shows that a carbon tax can lead to substantial emission reduction. The British power sector emissions fell by 38.6 $MtCO_2$ within the three years after the respective tax jumps, making up abatement of 26% relative to pre-treatment emissions. The carbon tax is thus responsible for about 60% of the overall decline in emissions by 43.9% during that period. Most notably, we estimate that the carbon tax decreased coal-based emissions significantly by around 40% (43.6

Table 4
Daily frequency: average treatment effects.

	ATE per plant per day (tCO_2)	# power plants	Aggregate ATE over all plants for a whole year ($MtCO_2$)	Change relative to period before 1st jump
Panel A: coal & gas plants				
Tax jump 1 (01Apr2013)	−466.6	131	−22.3	−13.68%
Tax jump 2 (01Apr2014)	−142.0	109	−5.6	−4.16%
Tax jump 3 (01Apr2015)	−157.8	107	−6.2	−4.63%
Total	*−766.4*		*−34.1*	*−22.47%*
Panel B: coal plants				
Tax jump 1 (01Apr2013)	−1003.0	57	−20.9	−15.36%
Tax jump 2 (01Apr2014)	−677.1	41	−10.1	−10.37%
Tax jump 3 (01Apr2015)	−682.7	39	−9.7	−10.46%
Total	*−2362.8*		*−40.7*	*−36.18%*
Panel C: gas plants				
Tax jump 1 (01Apr2013)	−53.6	74	−1.4	−5.36%
Tax jump 2 (01Apr2014)	180.6	68	4.5	18.08%
Tax jump 3 (01Apr2015)	143.2	68	3.6	14.33%
Total	*270.3*		*6.6*	*27.05%*

Notes: ATE = average treatment effect. Aggregate ATE = ATE per plant per hour • # plants • 365 days. Average emissions per plant per day during period before 1st tax jump (01Apr2012 − 31Mar2013): all coal and gas plants = 3411 $MtCO_2$, coal plants = 6530 $MtCO_2$, gas plants = 999 $MtCO_2$.



(a) Renewable energy feed-in

(b) Electricity demand

Fig. 7. Developments of renewable energies and electricity demand.
Notes: RES stands for electricity in-feed from wind and solar power. The discontinuous jumps in (a) and (b) are statistically insignificant.

$MtCO_2$). Gas, which is associated with less than half the carbon emissions of coal, became more economical than coal after the tax increase in 2014. While imports mainly filled the electricity production gap from coal after the first carbon tax jump, gas in addition helped to fill the gap after the second and third jumps. This has led to an increase in gas-based emissions by 5.0 $MtCO_2$. Moreover, electricity demand *gradually* declined and renewables feed-in gradually increased over time, helping to establish system stability. Looking at the plant-specific estimates, we find that inefficient (highly pollutive, outdated) coal plants react most significantly to the carbon tax. We also find that less efficient gas plants reduce their output, while the majority of gas plants is relatively carbon efficient and thus increases output. Robustness tests concerning main threats to our identification (e.g. anticipation effects, or discontinuously changing control variables) support our main results.

In terms of external validity, our estimates show that it is possible to achieve a significant decline in emissions from the power sector by means of a carbon tax, but only if the tax is high enough to shift power stations' marginal costs so that less emissive gas turbines become marginal and push coal turbines out of the market. Emissions abatement also depends on the scope of the fuel-switching potential, i.e. how much coal-fired generation capacity can be replaced by gas-fired generation capacity. A study by Delarue et al. (2008) suggests that there is a significant abatement potential from a coal-to-gas switch across European countries. Moreover, as it its essentially the relative marginal costs of coal- and gas-fired power stations, which determine their position in the merit order, fuel prices play a major role as well. In the U.S., a decline in the price of natural gas due to the shale-gas revolution has induced a fuel switch between coal and gas and led to a significant decline in CO_2 emissions (Cullen and Mansur, 2017; Fell and Kaffine, 2018). Although a fuel switch may help reduce emissions in Europe, the U.S., and elsewhere, a full decarbonization of the power sector may only be possible by eventually pushing out any form of fossil-based electricity generation. This may only happen if other carbon-free supply technologies can be deployed, which depends on their resource availability, flexibility measures (e.g. energy storage, network expansion, demand flexibility), and energy efficiency measures.

Unfortunately, within the EU ETS, a unilateral environmental policy, such as the CPS, may induce the waterbed effect (Appun, 2019; Perino, 2018; Rosendahl, 2019). It is argued that emissions saved in one country that is covered by the ETS results in a release of emissions in an equal amount in another country as long as the emissions cap stays unchanged. Another, more direct for of carbon leakage created by the CPS may be via electricity imports that may have caused emissions elsewhere (depending on the available interconnector capacity and supply structures in exporting markets; see also Guo et al., 2019). Nevertheless, our paper is reassuring that even a moderate carbon tax can indeed lead to pronounced emissions abatement at the national scale and may also serve as a viable policy to reduce emissions at a larger scale if properly coordinated with other countries (to avoid the waterbed effect and deal properly with trade-induced emissions abroad).

CRediT author statement

K.G., M.L. and A.H. designed and conceived the study, designed the econometric model, and wrote the paper. M.L. and A.H. compiled and processed data and ran the regressions.

Declaration of Competing Interest

None. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Appendix A. Appendix

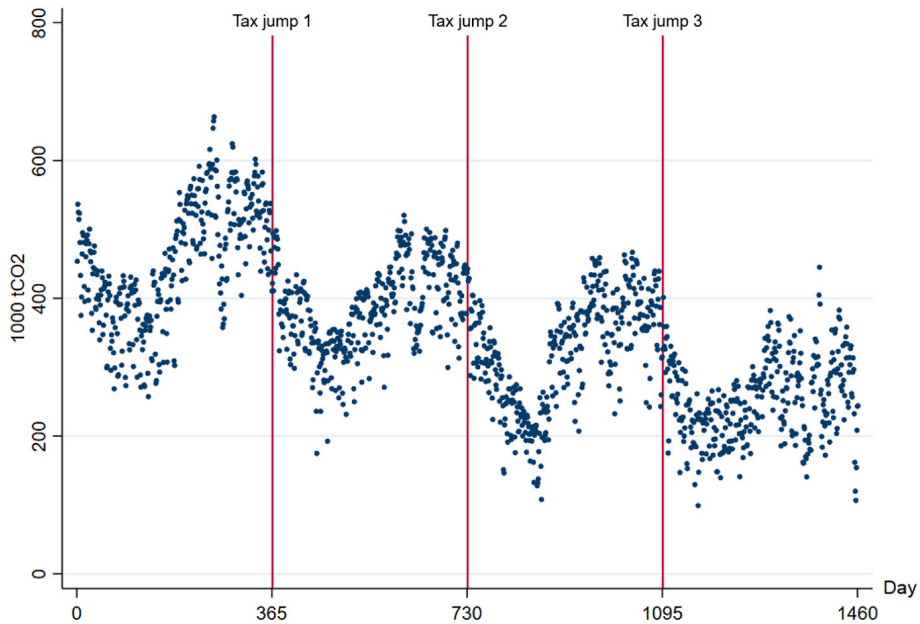


Fig. A1. British power sector emissions per day (1000 tCO_2).

Table A1
Sample statistics.

Variable	Obs.	Mean	StD	Min	Max
01Apr2012 – 31Mar2013					
Emissions: all thermal plants (tCO_2)[a]	1,161,356	142.12	202.90	−1.27	639.31
Emissions: gas plants (tCO_2)[a]	654,900	41.62	67.59	−1.27	382.00
Emissions: coal plants (tCO_2)[a]	506,456	272.07	241.98	0.00	639.31
Renewable energy feed-in (MWh)[b]	1,161,356	1596.11	1200.63	8.00	5284.00
Demand (MWh)[b]	1,161,356	36,798.64	7214.50	21,385.00	56,678.00
01Apr2013 – 31Mar2014					
Emissions: all thermal plants (tCO_2)[a]	1,160,159	120.89	193.84	−0.68	639.31
Emissions: gas plants (tCO_2)[a]	654,225	36.73	66.05	−0.68	382.00
Emissions: coal plants (tCO_2)[a]	505,934	229.72	243.96	0.00	639.31
Renewable energy feed-in (MWh)[b]	1,160,159	2427.28	1546.15	22.00	6203.00
Demand (MWh)[b]	1,160,159	35,474.77	6758.38	20,892.00	52,793.00
01Apr2014 – 31Mar2015					
Emissions: all thermal plants (tCO_2)[a]	1,164,016	100.95	176.77	0.00	639.31
Emissions: gas plants (tCO_2)[a]	656,400	43.12	67.59	0.00	283.37
Emissions: coal plants (tCO_2)[a]	507,616	175.72	236.29	0.00	639.31
Renewable energy feed-in (MWh)[b]	1,164,016	2402.83	1697.89	0.00	6742.00
Demand (MWh)[b]	1,163,617	34,341.45	6773.71	19,777.00	54,923.00
01Apr2015 – 31Mar2016					
Emissions: all thermal plants (tCO_2)[a]	1,164,681	79.78	153.44	−0.17	639.31
Emissions: gas plants (tCO_2)[a]	656,775	46.05	68.65	−0.17	382.00
Emissions: coal plants (tCO_2)[a]	507,906	123.40	211.00	0.00	639.31
Renewable energy feed-in (MWh)[b]	1,164,681	2545.06	1572.01	0.00	6254.00
Demand (MWh)[b]	1,164,681	32,554.37	6445.54	17,867.00	53,780.00

[a] Variation per plant per hour. [b] Time-series variation (identical per plant).

Table A2
Average treatment effects (tCO_2 per plant per hour).

	Coal & gas plants			Coal plants			Gas plants		
	Jump 2013	Jump 2014	Jump 2015	Jump 2013	Jump 2014	Jump 2015	Jump 2013	Jump 2014	Jump 2015
Treat	−16.51	−10.71	−10.03	−36.48	−35.77	−36.73	−1.119	4.394	5.284
	(1.226)	(1.294)	(1.351)	(2.651)	(3.051)	(3.170)	(0.662)	(0.706)	(0.652)
RES	−0.00385	−0.00457	−0.00541	−0.00523	−0.00765	−0.0113	−0.00279	−0.00272	−0.00202
	(0.000219)	(0.000241)	(0.000237)	(0.000471)	(0.000576)	(0.000578)	(0.000119)	(0.000124)	(0.000124)
RES^2	−1.81e-07	−2.18e-07	−1.05e-07	−1.57e-07	−1.80e-07	3.67e-07	−1.99e-07	−2.42e-07	−3.77e-07
	(3.97e-08)	(3.94e-08)	(3.97e-08)	(8.52e-08)	(9.45e-08)	(9.67e-08)	(2.19e-08)	(2.03e-08)	(2.06e-08)

(continued on next page)

Table A2 (*continued*)

	Coal & gas plants			Coal plants			Gas plants		
	Jump 2013	Jump 2014	Jump 2015	Jump 2013	Jump 2014	Jump 2015	Jump 2013	Jump 2014	Jump 2015
Demand	0.00525	0.00509	0.00320	0.0139	0.0159	0.00883	−0.00145	−0.00145	−2.56e-05
	(0.000136)	(0.000171)	(0.000166)	(0.000288)	(0.000400)	(0.000401)	(7.48e-05)	(8.70e-05)	(8.67e-05)
Demand^2	−2.55e-08	−1.94e-08	1.29e-08	−1.23e-07	−1.44e-07	−2.85e-08	4.96e-08	5.56e-08	3.66e-08
	(1.67e-09)	(2.14e-09)	(2.18e-09)	(3.49e-09)	(4.97e-09)	(5.23e-09)	(9.59e-10)	(1.14e-09)	(1.16e-09)
Plant FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Hourly FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Dow FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Polyn. trend	yes	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	2,286,605	1,904,448	1,873,142	994,935	716,352	682,734	1,291,670	1,188,096	1,190,408
Nr. plants	131	109	107	57	41	39	74	68	68
R^2	0.591	0.552	0.473	0.453	0.363	0.384	0.390	0.404	0.417

Notes: Plant FE indicate power plant-specific fixed effects. Hourly FE indicate fixed effects for each daily hour. Dow FE indicate day-of-week fixed effects. The regression includes a polynomial time trend of order six, which is also interacted with the treatment indicator to allow the trends to differ after the tax jumps. Robust standard errors in parentheses.

Table A3
Coal plant-specific effects.

	Tax jump 1			Tax jump 2			Tax jump 3		
	Coef.	Std. Err.	p-val.	Coef.	Std. Err.	p-val.	Coef.	Std. Err.	p-val.
Treat*υ1	−562.43	3.317	0.000	−482.08	3.709	0.000	−263.85	4.001	0.000
Treat*υ2	−227.20	3.419	0.000	−228.66	4.115	0.000	−204.87	4.185	0.000
Treat*υ3	−214.67	3.369	0.000	−228.26	4.285	0.000	−201.41	4.029	0.000
Treat*υ4	−214.39	3.369	0.000	−211.08	3.805	0.000	−149.70	4.249	0.000
Treat*υ5	−209.98	3.800	0.000	−171.02	3.969	0.000	−149.69	3.939	0.000
Treat*υ6	−171.99	3.943	0.000	−147.86	3.933	0.000	−146.77	4.385	0.000
Treat*υ7	−130.01	3.347	0.000	−146.21	4.151	0.000	−136.11	4.368	0.000
Treat*υ8	−125.40	3.332	0.000	−140.51	4.088	0.000	−124.71	4.282	0.000
Treat*υ9	−123.76	3.279	0.000	−119.81	4.333	0.000	−123.56	4.453	0.000
Treat*υ10	−121.05	3.288	0.000	−108.27	4.007	0.000	−117.78	4.266	0.000
Treat*υ11	−121.03	4.076	0.000	−96.17	3.746	0.000	−117.10	4.211	0.000
Treat*υ12	−120.77	3.769	0.000	−95.49	3.721	0.000	−98.86	4.146	0.000
Treat*υ13	−118.69	3.297	0.000	−79.81	4.352	0.000	−73.25	4.295	0.000
Treat*υ14	−118.49	3.913	0.000	−79.38	4.040	0.000	−69.61	4.388	0.000
Treat*υ15	−116.73	3.762	0.000	−78.06	4.007	0.000	−68.87	4.090	0.000
Treat*υ16	−99.43	3.625	0.000	−48.66	3.983	0.000	−65.10	4.405	0.000
Treat*υ17	−93.21	3.707	0.000	−47.67	3.861	0.000	−61.63	3.674	0.000
Treat*υ18	−93.08	4.444	0.000	−47.50	3.722	0.000	−61.40	4.362	0.000
Treat*υ19	−84.41	4.282	0.000	−17.08	4.390	0.000	−58.15	4.251	0.000
Treat*υ20	−82.57	3.570	0.000	−13.11	4.007	0.001	−44.70	4.112	0.000
Treat*υ21	−73.02	3.942	0.000	−8.78	4.464	0.049	−44.44	4.101	0.000
Treat*υ22	−70.37	2.867	0.000	−8.44	3.199	0.008	−43.10	4.752	0.000
Treat*υ23	−65.30	3.914	0.000	−3.45	3.204	0.282	−22.65	4.732	0.000
Treat*υ24	−61.47	3.713	0.000	−3.34	4.199	0.427	−13.25	4.176	0.002
Treat*υ25	−59.38	3.720	0.000	−0.66	4.176	0.874	6.55	3.778	0.083
Treat*υ26	−50.72	2.721	0.000	7.38	4.005	0.065	22.79	4.114	0.000
Treat*υ27	−45.76	2.712	0.000	15.14	4.030	0.000	26.56	4.208	0.000
Treat*υ28	−35.00	2.714	0.000	17.01	3.604	0.000	33.60	3.403	0.000
Treat*υ29	−33.08	3.612	0.000	19.55	4.349	0.000	40.97	4.649	0.000
Treat*υ30	−32.97	2.672	0.000	25.05	4.101	0.000	45.37	3.362	0.000
Treat*υ31	−30.41	2.605	0.000	29.91	4.176	0.000	49.17	4.375	0.000
Treat*υ32	−21.61	3.665	0.000	40.61	3.193	0.000	51.34	4.694	0.000
Treat*υ33	−19.33	4.143	0.000	44.61	4.212	0.000	57.85	3.351	0.000
Treat*υ34	−14.98	2.729	0.000	48.48	4.706	0.000	65.61	3.390	0.000
Treat*υ35	−14.71	2.722	0.000	57.51	4.084	0.000	77.40	4.270	0.000
Treat*υ36	−9.81	3.500	0.005	74.54	4.318	0.000	112.18	4.144	0.000
Treat*υ37	−4.81	3.335	0.150	120.86	3.993	0.000	119.55	4.677	0.000
Treat*υ38	−1.36	3.465	0.694	122.67	4.654	0.000	124.61	4.398	0.000
Treat*υ39	14.38	2.611	0.000	162.47	4.459	0.000	194.71	4.447	0.000
Treat*υ40	16.62	2.628	0.000	165.19	4.335	0.000			
Treat*υ41	18.98	4.015	0.000	193.81	4.123	0.000			
Treat*υ42	30.31	3.260	0.000						
Treat*υ43	36.00	3.785	0.000						
Treat*υ44	37.62	3.812	0.000						
Treat*υ45	43.81	3.892	0.000						
Treat*υ46	52.03	3.625	0.000						
Treat*υ47	52.54	4.359	0.000						
Treat*υ48	56.89	3.493	0.000						
Treat*υ49	68.16	3.638	0.000						
Treat*υ50	75.19	3.949	0.000						

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Table A3 (*continued*)

	Tax jump 1			Tax jump 2			Tax jump 3		
	Coef.	Std. Err.	p-val.	Coef.	Std. Err.	p-val.	Coef.	Std. Err.	p-val.
Treat*υ51	94.74	3.417	0.000						
Treat*υ52	115.92	4.215	0.000						
Treat*υ53	145.26	3.774	0.000						
Treat*υ54	152.16	4.060	0.000						
Treat*υ55	217.22	3.670	0.000						
Treat*υ56	225.13	3.929	0.000						
Treat*υ57	260.91	3.897	0.000						

Table A3 continued. Coal plant-specific effects			
Controls	yes	yes	yes
Plant FE	yes	yes	yes
Hourly FE	yes	yes	yes
Dow FE	yes	yes	yes
Polyn. trend	yes	yes	yes
Obs.	994,935	716,352	682,734

Notes: Each regression includes RES, RES^2, demand, and $demand^2$ as control variables. Plant FE indicate power plant-specific fixed effects. Hourly FE indicate fixed effects for each daily hour. Dow FE indicate day-of-week fixed effects. The regression includes a polynomial time trend of order six, which is also interacted with the treatment indicator to allow the trends to differ after the tax jumps.

Table A4
Gas plant-specific effects.

	Tax jump 1			Tax jump 2			Tax jump 3		
	Coef.	Std. Err.	p-val.	Coef.	Std. Err.	p-val.	Coef.	Std. Err.	p-val.
Treat*υ1	−145.63	1.094	0.000	−162.02	1.740	0.000	−49.48	1.457	0.000
Treat*υ2	−78.44	1.348	0.000	−27.62	1.152	0.000	−49.00	1.221	0.000
Treat*υ3	−66.39	1.495	0.000	−26.73	1.004	0.000	−41.46	0.946	0.000
Treat*υ4	−29.33	0.997	0.000	−17.33	0.962	0.000	−38.74	0.993	0.000
Treat*υ5	−24.50	0.994	0.000	−17.33	0.931	0.000	−24.71	1.576	0.000
Treat*υ6	−22.28	1.239	0.000	−13.11	0.963	0.000	−22.84	1.729	0.000
Treat*υ7	−17.55	0.875	0.000	−9.05	0.861	0.000	−17.35	1.020	0.000
Treat*υ8	−14.95	0.999	0.000	−8.54	0.840	0.000	−16.94	1.096	0.000
Treat*υ9	−14.81	1.090	0.000	−8.50	1.666	0.000	−14.88	1.049	0.000
Treat*υ10	−13.77	0.721	0.000	−5.95	0.772	0.000	−13.22	1.170	0.000
Treat*υ11	−11.59	1.694	0.000	−5.43	1.040	0.000	−12.15	0.849	0.000
Treat*υ12	−10.76	1.499	0.000	−5.20	0.953	0.000	−10.02	0.821	0.000
Treat*υ13	−10.49	0.935	0.000	−4.29	0.880	0.000	−8.53	1.281	0.000
Treat*υ14	−10.41	1.061	0.000	−2.82	0.752	0.000	−7.35	0.994	0.000
Treat*υ15	−10.26	0.706	0.000	−2.82	0.752	0.000	−6.47	0.899	0.000
Treat*υ16	−10.26	0.706	0.000	−2.81	0.754	0.000	−4.54	0.805	0.000
Treat*υ17	−10.06	1.013	0.000	−2.78	0.753	0.000	−4.52	0.886	0.000
Treat*υ18	−8.92	1.088	0.000	−2.72	0.752	0.000	−3.92	0.754	0.000
Treat*υ19	−8.40	1.002	0.000	−2.72	0.752	0.000	−3.80	0.769	0.000
Treat*υ20	−8.34	0.719	0.000	−2.69	0.856	0.002	−2.77	0.977	0.005
Treat*υ21	−7.59	0.826	0.000	−2.66	0.752	0.000	−2.25	0.879	0.010
Treat*υ22	−7.41	0.917	0.000	−2.66	0.752	0.000	−1.68	0.923	0.069
Treat*υ23	−6.95	0.942	0.000	−2.66	0.752	0.000	−1.18	1.003	0.241
Treat*υ24	−6.67	1.001	0.000	−2.66	0.752	0.000	0.33	0.733	0.657
Treat*υ25	−6.23	0.932	0.000	−2.55	0.753	0.001	0.52	1.218	0.671
Treat*υ26	−6.16	1.009	0.000	−2.28	0.867	0.008	1.92	0.725	0.008
Treat*υ27	−5.38	0.929	0.000	−1.58	1.263	0.211	1.93	0.789	0.015
Treat*υ28	−4.97	0.854	0.000	−1.21	0.762	0.111	2.01	0.724	0.006
Treat*υ29	−4.68	0.797	0.000	−0.66	0.798	0.406	2.03	0.854	0.017
Treat*υ30	−4.50	0.881	0.000	0.22	0.952	0.819	2.05	0.725	0.005
Treat*υ31	−3.83	0.874	0.000	2.47	0.826	0.003	2.05	0.725	0.005
Treat*υ32	−3.14	0.924	0.001	2.68	0.783	0.001	2.05	0.725	0.005
Treat*υ33	−2.51	1.019	0.014	3.22	0.940	0.001	2.08	0.725	0.004
Treat*υ34	−1.19	0.982	0.225	3.33	0.927	0.000	2.09	0.724	0.004
Treat*υ35	0.13	0.739	0.865	3.84	0.813	0.000	2.25	0.723	0.002
Treat*υ36	0.77	0.719	0.284	3.99	0.974	0.000	2.25	0.723	0.002
Treat*υ37	0.86	1.670	0.607	4.64	0.860	0.000	2.57	0.726	0.000
Treat*υ38	0.87	1.054	0.412	4.73	0.833	0.000	2.79	0.764	0.000
Treat*υ39	1.85	0.828	0.026	4.80	1.049	0.000	6.99	0.833	0.000
Treat*υ40	3.02	0.721	0.000	5.72	0.990	0.000	7.05	1.064	0.000
Treat*υ41	3.24	0.717	0.000	6.43	1.484	0.000	7.19	0.745	0.000

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Table A4 (*continued*)

	Tax jump 1			Tax jump 2			Tax jump 3		
	Coef.	Std. Err.	p-val.	Coef.	Std. Err.	p-val.	Coef.	Std. Err.	p-val.
Treat*υ42	3.32	0.719	0.000	6.57	1.047	0.000	7.43	1.016	0.000
Treat*υ43	3.54	0.712	0.000	7.11	0.904	0.000	7.94	0.886	0.000
Treat*υ44	3.66	0.712	0.000	7.74	1.023	0.000	8.17	0.965	0.000
Treat*υ45	3.69	1.047	0.000	8.29	0.990	0.000	8.41	0.970	0.000
Treat*υ46	3.78	0.712	0.000	11.10	1.082	0.000	8.84	0.979	0.000
Treat*υ47	3.82	0.712	0.000	11.35	0.975	0.000	8.84	0.991	0.000
Treat*υ48	3.83	0.712	0.000	12.24	1.081	0.000	8.93	1.709	0.000
Treat*υ49	3.84	0.712	0.000	12.99	0.927	0.000	14.40	0.872	0.000
Treat*υ50	3.84	0.712	0.000	14.11	1.670	0.000	15.62	0.724	0.000
Treat*υ51	3.84	0.712	0.000	14.59	0.992	0.000	15.62	0.724	0.000
Treat*υ52	3.88	0.712	0.000	15.70	1.033	0.000	16.66	1.053	0.000
Treat*υ53	3.88	0.712	0.000	17.38	0.915	0.000	18.00	1.450	0.000
Treat*υ54	3.98	0.711	0.000	17.84	1.054	0.000	19.01	0.761	0.000
Treat*υ55	4.02	0.712	0.000	17.99	1.146	0.000	21.10	1.011	0.000
Treat*υ56	5.16	0.856	0.000	19.72	0.743	0.000	23.17	1.698	0.000
Treat*υ57	5.35	0.793	0.000	19.72	0.743	0.000	23.67	1.019	0.000
Treat*υ58	5.42	0.909	0.000	25.30	0.764	0.000	26.49	1.196	0.000
Treat*υ59	5.79	0.816	0.000	27.60	1.012	0.000	30.72	0.972	0.000
Treat*υ60	7.16	0.820	0.000	29.31	1.045	0.000	31.80	0.871	0.000
Treat*υ61	8.99	0.744	0.000	29.88	1.336	0.000	32.31	0.882	0.000
Treat*υ62	9.66	0.721	0.000	30.69	1.525	0.000	38.47	0.994	0.000
Treat*υ63	11.70	1.033	0.000	34.90	1.086	0.000	40.18	1.597	0.000
Treat*υ64	14.63	1.748	0.000	35.67	1.590	0.000	42.72	1.208	0.000
Treat*υ65	15.22	1.400	0.000	38.24	1.679	0.000	43.54	1.357	0.000
Treat*υ66	19.26	0.966	0.000	39.84	1.001	0.000	45.81	0.956	0.000
Treat*υ67	25.73	1.051	0.000	43.43	1.059	0.000	53.46	0.915	0.000
Treat*υ68	28.03	1.003	0.000	52.83	1.572	0.000	55.62	0.979	0.000
Treat*υ69	29.35	0.951	0.000						
Treat*υ70	30.98	0.839	0.000						
Treat*υ71	41.74	1.471	0.000						
Treat*υ72	46.03	2.194	0.000						
Treat*υ73	54.60	0.908	0.000						
Treat*υ74	87.05	1.157	0.000						
Controls	yes			yes			yes		
Plant FE	yes			yes			yes		
Hourly FE	yes			yes			yes		
Dow FE	yes			yes			yes		
Polyn. trend	yes			yes			yes		
Obs.	994,935			716,352			682,734		

Notes: Each regression includes RES, RES^2, demand, and $demand^2$ as control variables. Plant FE indicate power plant-specific fixed effects. Hourly FE indicate fixed effects for each daily hour. Dow FE indicate day-of-week fixed effects. The regression includes a polynomial time trend of order six, which is also interacted with the treatment indicator to allow the trends to differ after the tax jumps.

Table A5
Heterogeneous effects with respect to ratio of emission to efficiency factor.

	Tax jump 1	Tax jump 2	Tax jump 3	Pooled
Ratio emission to efficiency factor	−53.31	−66.03	−71.29	−63.07
	(23.75)	(24.19)	(19.44)	(13.09)
Capacity	−0.02	−0.02	−0.02	0.02
	(0.04)	(0.04)	(0.03)	(0.02)
Constant	27.08	37.03	39.24	34.04
	(23.36)	(23.55)	(18.54)	(2.67)
Obs.	131	109	107	347

Notes: The dependent variable is the estimated plant level ATE. "Ratio emission to efficiency factor" is the ratio of the emission to the efficiency factor at the plant level. The average ratio is 0.59. Capacity is nameplate capacity of the plant. Robust standard errors in parentheses.

Table A6
Daily frequency: Average treatment effects (tCO_2 per plant per day).

	Coal & gas plants			Coal plants			Gas plants		
	Jump 2013	Jump 2014	Jump 2015	Jump 2013	Jump 2014	Jump 2015	Jump 2013	Jump 2014	Jump 2015
Treat	−466.6	−142.0	−157.8	−1003	−677.1	−682.7	−53.55	180.6	143.2
	(136.4)	(141.0)	(147.4)	(297.7)	(335.0)	(340.9)	(64.35)	(68.81)	(64.65)
RES	−0.00401	−0.00426	−0.00492	−0.00506	−0.00616	−0.0103	−0.00320	−0.00311	−0.00184
	(0.00110)	(0.00122)	(0.00118)	(0.00238)	(0.00294)	(0.00288)	(0.000504)	(0.000537)	(0.000564)
RES^2	−5.28e-09	−1.05e-08	−7.90e-09	−4.87e-09	−1.85e-08	9.46e-09	−5.59e-09	−5.60e-09	−1.78e-08
	(8.35e-09)	(8.43e-09)	(8.43e-09)	(1.82e-08)	(2.04e-08)	(2.06e-08)	(3.92e-09)	(3.68e-09)	(3.92e-09)

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Table A6 (*continued*)

	Coal & gas plants			Coal plants			Gas plants		
	Jump 2013	Jump 2014	Jump 2015	Jump 2013	Jump 2014	Jump 2015	Jump 2013	Jump 2014	Jump 2015
Demand	0.00363	0.00414	0.00412	0.00875	0.0120	0.0112	−0.000314	−0.000600	9.31e-05
	(0.000539)	(0.000786)	(0.00153)	(0.000920)	(0.00128)	(0.00367)	(0.000205)	(0.000283)	(0.000686)
Demand^2	3.54e−10	3.48e-10	4.82e-10	-1.43e-09	−2.95e-09	−1.63e-09	1.73e-09	2.34e-09	1.69e-09
	(3.40e-10)	(4.95e-10)	(9.41e-10)	(6.22e-10)	(9.06e-10)	(2.24e-09)	(1.44e-10)	(1.90e-10)	(4.20e-10)
Plant FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Dow FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Polyn. trend	yes	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	95,630	79,570	78,217	41,610	29,930	28,509	54,020	49,640	49,708
Nr. plants	131	109	107	57	41	39	74	68	68
R^2	0.632	0.598	0.526	0.489	0.399	0.430	0.478	0.491	0.495

Notes: Plant FE indicate power plant-specific fixed effects. Dow FE indicate day-of-week fixed effects. The regression includes a polynomial time trend of order six, which is also interacted with the treatment indicator to allow the trends to differ after the tax jumps. Robust standard errors in parentheses.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106655.

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