Carbon Pricing and Power Sector Decarbonisation: Evidence from the UK

Marion Leroutier*

October 20, 2021

Abstract

Decreasing greenhouse gas emissions from electricity generation is crucial to tackle climate change. Empirically, however, little is known about the effectiveness of existing economic instruments in the power sector. This paper examines the impact of the UK Carbon Price Support (CPS), a carbon tax implemented in the UK power sector in 2013. Relative to a synthetic control unit built from other European countries, I find that emissions from the UK power sector declined by 20 to 26 percent per year on average between 2013 and 2017. The tax operated via three mechanisms: a decrease in emissions at the intensive margin; the closure of some high-emission plants at the extensive margin; and a higher probability of closure for plants already at risk due to European air quality regulations.

Keywords: carbon tax, electricity generation, synthetic control method

JEL Codes: D22, H23, Q41, Q48

*Mistra Center for Sustainable Markets (Misum), Stockholm School of Economics. Contact details: Email: marion.leroutier@hhs.se - Postal: Misum, Stockholm School of Economics, Sveavägen 65, 113 83 Stockholm, Sweden. I am grateful to Philippe Quirion, Katheline Schubert, Nicolas Koch, Ulrich Wagner, Mirjam Kosch, Jan Abrell, Francois Libois, and three anonymous referees for their comments and suggestions. I thank seminar participants at PSE, LSE GRI, MCC, PIK and SSE, participants to the 2018 OECD environmental micro-data workshop, conference participants at Mannheim Energy conference, EAERE, FAERE, and participants to the Aix-Marseille GREEN-Econ Spring School and CIRED summer school for useful feedback. I am grateful to Ember (formerly Sandbag) for sharing their ETS data, to Lorenzo Montrone for giving me access to the Global Coal Plant Tracker database, and to Jan Abrell and Mirjam Kosch for sharing data on monthly power production. I have no conflict of interest to declare. Financial support from ANR via the EUR grant ANR-17-EURE-0001 and from Mistra Foundation is greatly appreciated.

1 Introduction

Every country in the world must reduce their greenhouse gas emissions in order to mitigate climate change. In the past two decades, virtually all governments have implemented a variety of abatement policies to address this challenge, including economic instruments in the form of carbon taxes and carbon markets (World Bank and Ecofys, 2018). Although carbon pricing is regarded by economists as the most cost-effective way to reduce emissions, ex-post evaluations of carbon pricing policies implemented in different sectors are still scarce (Rafaty et al., 2020; Green, 2021). This general observation is particularly true in the case of the power sector (Martin et al., 2016), which represented 25% of worldwide emissions in 2010 (IPCC, 2015).

In this paper, I examine the impact of a carbon tax introduced in the UK power sector in 2013, the Carbon Price Support (CPS), on carbon emissions. At that time and during the period of analysis considered in the paper, the UK was part of the European carbon market (European Union Emission Trading System, EU ETS) implemented in 2005. The carbon tax was introduced in response to the low prices prevailing on the EU ETS, while the UK was facing binding emission reduction targets under the 2008 Climate Change Act. The tax rate increased from around £5 (€5.9) per ton of equivalent carbon dioxide (hereafter tCO_2e) in 2013 to £18 (€26) in 2017. During the same period, the UK power sector experienced a remarkable transition: between 2012 and 2017, the share of coal in electricity generation decreased from 40% to 7% and power sector greenhouse gas emissions decreased by 57%. The rapid transformation of the UK power sector received significant coverage in the media and in policy reports (Evans, 2019; Brown, 2017), but how much the UK carbon tax contributed to such transformation is to date unclear.

To estimate this contribution, I apply the synthetic control method (Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015) building a counterfactual UK with a weighted combination of European countries having power sectors with characteristic similar to the UK. I use countries which, like the UK, were part of the European Union (EU) during the period considered (2005-2017) as potential candidates to enter the counterfactual UK, as all these countries were subject to the same European climate and energy policies as the UK had been before the introduction of the CPS, in particular the EU ETS and European air quality regulations. Importantly, I account for CPS-induced spillovers as well as the contributions of three other policies introduced around the same time: a subsidy to encourage the biomass conversion of coal plants, a new scheme for renewable support, and the introduction of a capacity market. Doing so allows me to place bounds around the emissions reductions specifically attributed to the CPS.

My findings indicate that the CPS introduction is associated with emissions reductions - or abatement - of between 143 and 191 million tons of equivalent carbon dioxide (hereafter MtCO2e) over the 2013-2017 period, representing a decrease of 20.5% to 26% per year on average. The upper and lower bounds of this range depend on the assumptions I make regarding spillovers and the other policies. The upper bound assumes that all emissions reductions between the UK and synthetic UK post-2013 can be attributed to the CPS alone, which also entails assuming that biomass conversion is a consequence of the CPS and that emission leakage from the UK to other European countries was negligible.

To construct the more conservative lower bound, I account for reductions associated with the potentially confounding policies and spillovers. I use data on the number of projects and new plants awarded contracts under the renewable energy scheme and through the capacity market to calculate their likely emissions reductions. I find that their impacts are several orders of magnitude smaller than the CPS during the 2013-2017 period, which is primarily due to the time lag associated with securing investment contracts and having new generating units operational. This results in a lower bound that is not too far off from the estimate that does not account for confounding factors.

Back-of-the-envelope calculations suggest that roughly a third of the lower bound impact was driven by UK plants facing a high carbon price responding differently to European air quality regulation. Another third was caused by the closure of a several high-emitting plants and the last third by a decrease in emissions from plants that remained in the market (likely due to fuel switching from coal to gas). A set of placebo tests suggest that this impact is causal, and these results are robust to several sensitivity analyses.

This paper contributes to several strands of the literature: first, it contributes to the growing empirical literature evaluating the impact of regional and national carbon pricing instruments (Martin et al., 2014; Rivers and Schaufele, 2015; Andersson, 2019; Colmer et al., 2020; Kim and Kim, 2016). Cropper et al. (2018) emphasized certain challenges involved with finding a suitable control group for the retrospective analysis of environmental regulation, including carbon pricing. This is especially true for the power sector, as almost all power plants are subject to the policy examined.[1] That both UK and non-UK power plants were subject to European-level energy policies while only UK plants were subject to the CPS offers an opportunity to compare the evolution of UK power sector emissions with that of an appropriately weighted average of European countries.

To my knowledge, two recent papers examine the effectiveness of the CPS, only considering its short-term effects: Abrell et al. (2019) estimate counterfactual electricity generation for each power plant subject to the CPS in the absence of the CPS using machine learning. They find that the CPS induced a total abatement of 26 MtCO_2e over the 2013-2016 period due to the short-term fuel switch from coal-fired to gas-fired plants[2]. Gugler et al. (2020) rely on a Regression-Discontinuity-in-Time (RDiT) approach and exploits the annual change in the CPS tax rate between 2013 and 2015. They estimate a cumulative abatement of 38.6 MtCO_2 over the 2013-2015 period compared to a no-policy scenario.

In contrast to these two papers, my paper adopts a method allowing to take into account more mechanisms: a carbon tax on high-emitting input fuels may induce a decrease in

[1] In the case of the ETS, the only exempted installations are those with a rated capacity of less than 20 Megawatt thermal input (MWth). In the UK, these facilities represented 0.2% of the installed capacity in 2015 (Source: Digest of United Kingdom Energy Statistics)

[2] Fuel switching occurs when carbon pricing increases the relative marginal cost of coal-fired plants compared to gas-fired plants due to the higher carbon intensity of the former. This change in costs modifies the short-term electricity supply curve, defined by the ranking of power plants by ascending marginal cost (the so-called "'merit order"). As a result, the hourly output from high-emitting coal-fired plants' increases while the hourly output from lower-emitting gas-fired plants decreases.

emissions via fuel switching, but also via longer-term mechanisms such as plant closure at the extensive margin and changes in demand or imports - although I find that demand and trade play a limited role compared to changes in the emission intensity of domestic production. Crucially, using a group of other EU countries as a counterfactual enables me to control for the effect of both the EU ETS and a particularly important environmental regulation increasing the risk of closure of some power plants at the period considered, the Large Combustion Plant Directive (LCPD). I also highlight the interactions between the UK carbon tax and the LCPD.

Second, this paper contributes to the scarce literature examining the rapid decarbonisation of the UK power sector. Staffell (2017) links this decrease in emissions to the evolution of electricity demand, capacity, prices, the fuel mix, imports and exports in a descriptive approach. Wilson and Staffell (2018) insist rather on the significance of coal-to-gas fuel switching and underline the likely role of the CPS but do not quantify it. In contrast, the present work builds a comparison group and carefully examines potential confounding factors to estimate a plausibly causal impact of the CPS policy intervention on emission reduction.

Third, this paper is linked to a recent strand in the literature applying the synthetic control method to estimate the impact of environmental policies. The approach adopted here resembles that taken by Andersson (2019) who examines the impact of the Swedish carbon tax on emissions in the transport sector. Kim and Kim (2016) assess the impact of carbon pricing in the power sector in the context of the US Regional Greenhouse Gas Initiative (RGGI), where they focus on fuel switching rather than emission levels. Other recent works include Lee and Melstrom (2018), who estimate the impact of RGGI on electricity imports, and Isaksen (2020), who evaluates the effectiveness of international pollution protocols. A distinctive feature of my paper is to build a country-level outcome variable starting from plant-level emission data. This allows me to account for shocks experienced by individual plants and to document the channels through which the UK carbon tax may operate, an under-investigated area of research in the SCM literature according to Abadie (2021).

Beyond its academic contribution, this paper is relevant from a policy perspective. To be in line with the 2015 Paris Climate Agreement and achieve net-zero emission targets, OECD countries must be coal-power free by 2030 (Rocha et al., 2016). The means necessary to make this transition are still under discussion. Some European countries are considering adopting a carbon price floor to hedge against variations in the ETS price (Newbery et al., 2019). Lessons can potentially be drawn from the UK situation analysed here. My results should be all the more informative for policy-makers since the estimated range of abatement is quite tight. My findings also indicate that the CPS was instrumental in achieving the UK emissions reductions target over the 2013-2017 period: the estimated abatement represents between 60% (lower bound estimate) and 81% (upper bound estimate) of the target.

The paper is organised as follows: Section 2 presents the background, potential effects of a carbon tax in the power sector, and descriptive evidence; Section 3 describes the empirical strategy; Section 4 presents the main results; Section 5 discusses them; Section 6 concludes.

2 The UK carbon tax: context and descriptive evidence

2.1 The UK Carbon Price Support

The Carbon Price Support (CPS) was first introduced in April 2013. This domestic carbon tax was proposed in a double context of low prices on the EU carbon market, and the obligation for the UK to meet national targets for greenhouse gas emissions as defined in the 2008 Climate Change Act. The Climate Change Act set an emission target for 2050 and implemented a system of 5-year carbon budgets. Under the second carbon budget, running from 2013 to 2017, the UK had to reduce its total emissions by 236 $MtCO_2e$ compared to the first carbon budget (covering 2008 to 2012). Low prices on the EU carbon market were perceived as potentially too low to effectively decrease emissions in the ETS sectors.

In this context, the UK Government announced in March 2011 that a Carbon Price Floor (CPF) would be implemented in the power sector for the 2013/2014 budget year[3]. Under this price floor, power installations located in Great Britain (GB)[4] would have to pay a tax called the Carbon Price Support (CPS), for which annual rates would reflect the difference between the desired level of carbon price floor and the expected carbon price on the EU ETS. The announced goal of the CPF was to tackle price uncertainty on the EU ETS and encourage investment in low-carbon technologies in the generation sector; in official communication documents, the CPF was labelled "support and certainty for low-carbon investment" (Hirst, 2018). The price floor was expected to increase over time, with a total carbon price target of £30 (around €35) by 2020.

The CPF was introduced as planned on April 1st, 2013. It was part of a broader reform called the Electricity Market Reform, which includes three other components which I describe in greater detail in the next section: a capacity market aiming at securing production capacity to back up intermittent renewable capacity; support for investments in renewable power capacity in the form of Contracts for Difference (CfDs)[5]; and Emission Performance Standards banning new coal-fired plants not fitted with Carbon Capture and Storage (CCS).

The first rate of the CPS was set at around £5/tCO_2e. However, in 2014 the Government decided to freeze the CPS rate to £18/tCO_2e (€22 in 2016) until 2019/2020, after business representatives expressed concerns over the competitiveness of energy-intensive industries because of generators passing on the tax costs (Ares and Delebarre, 2016). Furthermore, actual ETS carbon prices turned out to be much lower than expected over the observed period. Because of the freeze and the difference between expected and actual carbon prices,

[3]The budget year over which the annual tax rate is set runs from 1 April to 31 March of the next calendar year

[4]power generators located in Northern Ireland are integrated in a separate wholesale electricity market with the Republic of Ireland and are not subject to the policy.

[5]CfDs guarantee a flat payment to low-carbon electricity generators: auctions determine the strike price, which reflects the long-term cost of generating low-carbon electricity for the awarded generators; when the electricity market price falls below the pre-determined strike price, contracted generators are then paid the difference between the strike price and market price; similarly, if the market price surpasses the strike price, contracted generators must pay this difference - See `https://www.emrsettlement.co.uk/about-emr/contracts-for-difference/` for more details.

the nature of the Carbon Price Support changed compared to how it was initially envisioned. It would effectively become a carbon tax with rates set several years in advance. Tax revenue go to the general budget. The CPS applies to almost all power generators located in GB.[6]. The only exemptions are for stand-by generators used to provide emergency electricity supplies if a building's usual power supply is cut, and generators with a rated thermal input smaller than 2 MWth.

Table 1 shows the level of the tax rate confirmed for each period in 2016. Figure 1 overlays annual CPS rates with annual ETS carbon prices converted to British pound since 2009. The sum of the two gives the total carbon price paid by GB generators, which departs significantly from the level of carbon price floor initially envisioned. The CPS component nevertheless implies that GB power generators pay a much higher carbon price than non-GB power generators (only subject to the ETS price). In 2016, the relative difference reached a peak at five-fold. The rate of the tax depends on the carbon content of the input fuel used for power generation. The CPS rate on coal is about 70% higher than the tax on natural gas, in line with the much higher emission factor of coal. The CPS thus substantially increased the relative cost of coal-fired generation compared to gas-fired generation.

Table 1: Level of CPS rate for each period in pound per ton of CO_2e

Period	CPS rate in £/tCO_2e
April 2013/March 2014	4.96
April 2014/March 2015	9.55
April 2015/March 2016	18.08
April 2016/March 2017	18
April 2017/March 2018	18
April 2018/March 2019	18

Source:Ares and Delebarre (2016)

[6]This includes conventional power plants, Combined Heat and Power (CHP) plants producing both electricity and heat (who only pay the CPS on the amount of fuel used to produce electricity for the grid), and auto-generators producing electricity for their own use (HM Revenue & Customs, 2017). Both CHP plants and auto-generators represent a negligible share of power production and emissions.

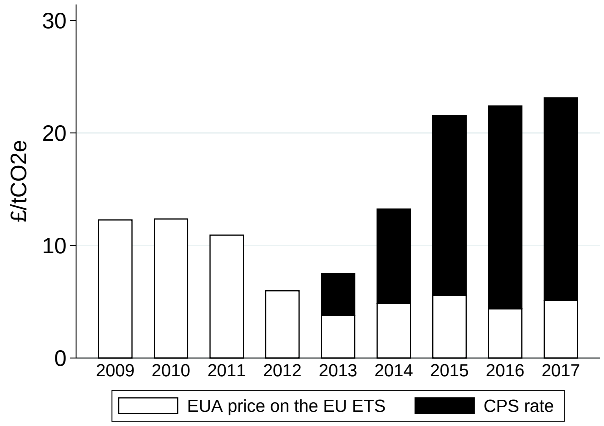


Figure 1: The Carbon Price Support and EUA price on the EU ETS

Notes: EUA stands for European Union Allowance and EUAs are carbon allowances traded on the ETS. Source for EUA price data: Ember website. Source for CPS prices: Hirst (2018). CPS prices adjusted with appropriate weights to reflect the calendar year rather than the April to March period. EUA price data converted to £ using yearly averages of monthly market exchange rates.

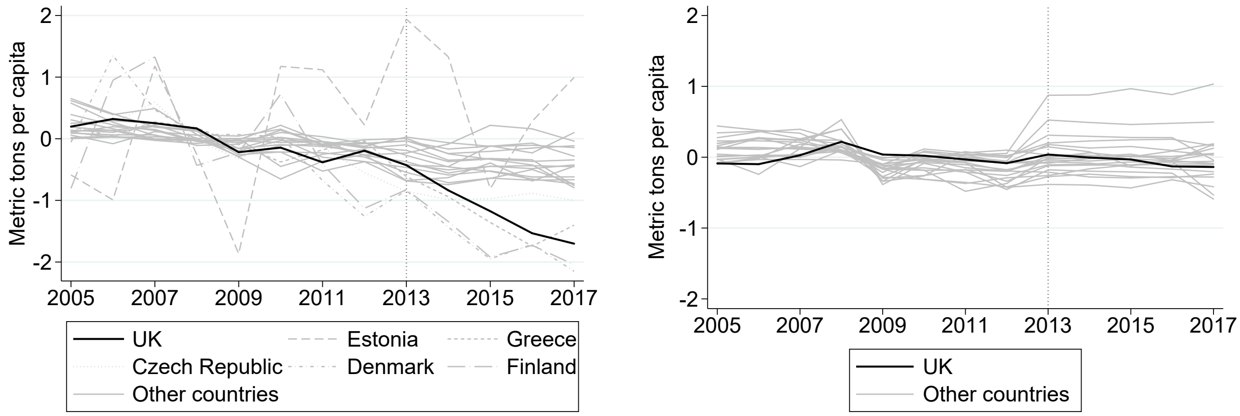
2.2 Descriptive evidence

Power sector emissions are the primary focus of this analysis. I define a variable of country-level per capita power sector emissions as the main outcome variable to facilitate country comparison[7], expressed in tons of carbon dioxide equivalent or tCO_2e. Figure 2a shows de-meaned per capita power sector emissions for each European country between 2005 and 2017, using emission data described in section 3.2. I de-mean emission values by taking the difference between annual per capita power sector emissions and per capita power sector emissions averaged over the 2005-2012 period, which is the pre-treatment period before the introduction of the CPS in 2013.

Most countries have relatively stable per capita emissions, except for a few outliers, whose emissions are shown in dashed or dotted lines[8]. After 2012, UK emissions showed more of

[7]The advantage of calculating emissions per capita rather than per MWh of electricity output is twofold: first, population as a variable is generally more stable over time than gross electricity production, so that the time variation in the outcome is mostly due to variations in emissions; second, decomposing emission per capita allows to analyse what happens to electricity demand and trade, rather than simply focussing on the emission intensity of domestic production.

[8]Estonia's emissions are both high on average and with a high variance; the Czech Republic has the highest average after Estonia; Greece shows decreasing emissions after 2012; Finland and Denmark's emissions have a high variance, likely due to the inter-annual variation in available hydro resources in Finland, and hydro and wind resources in Denmark.



(a) De-meaned per capita power sector emissions

(b) De-meaned per capita non-power sector emissions

Figure 2: Evolution of per capita power and non-power sector emissions in European countries

Notes: For figure a (resp. figure b), per capita emission values were obtained by aggregating plant-level emission data for ETS participants identified as power installations (resp. non-power) at the country level, and dividing by annual country population. De-meaned per capita emissions were obtained by taking the difference between the annual value and the 2005-2012 average. "Other countries" include twenty European countries: Austria, Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, the Netherlands, Poland, Portugal, Slovakia, Spain, Sweden.

a decline relative to most other countries. Three other countries also showed decreasing emissions: Finland, Denmark and Greece. Emissions from Finland and Denmark varied significantly throughout the entire period (see Figure A.1 in Appendix). The decrease in emissions in Greece cannot be traced back to a specific policy, but may be due to the large reforms implemented in all economic sectors around that period following the Greek debt crisis, combined with the deployment of a large amount of solar PV in 2011, 2012 and 2013 under an appealing feed-in-tariff program that was subsequently retroactively cut in 2014[9]. In contrast to the strong decrease in power sector emissions, UK per capita emissions in other ETS sectors follow the same path as other European countries (Figure 2b).

A variety of channels can trigger a pronounced decrease in power sector emissions. The following decomposition helps to understand the channels - for ease of reading, there are no indices, but all the variables should be interpreted as values for a given country c in a

[9] https://www.pv-magazine.com/2014/03/11/greece-brings-new-retroactive-measures-cuts-fit-by-30_100014491/

given year t. Calling P the country population and Q_{CO_2e} the quantity of emissions from the domestic power production[10], $\frac{Q_{CO_2e}}{P}$ are per capita power sector emissions, and are the product of per capita electricity generation $\frac{Q_{elec}}{P}$ and the emission intensity of domestic power generation, $\frac{Q_{CO_2e}}{Q_{elec}}$:

$$\frac{Q_{CO_2e}}{P} = \frac{Q_{elec}}{P}\frac{Q_{CO_2e}}{Q_{elec}} \tag{1}$$

Q_{elec} can be rewritten as the difference between domestic gross electricity consumption C_g and net electricity imports, defined as electricity imports M minus electricity exports X, $(M - X)$. Gross electricity consumption is itself the sum of net consumption C_n (equivalent to demand), the amount of network losses, and the amount of electricity used by power generators. Grouping these two last components in the variable L, this leads to the following equation:

$$\frac{Q_{CO_2e}}{POP} = (\frac{C_n}{POP} + \frac{L}{POP} - \frac{(M-X)}{POP})\frac{Q_{CO_2e}}{Q_{elec}} \tag{2}$$

From the right-hand side of the equation, four different channels may lead to a decrease in per capita emissions: a decrease in consumption per capita $\frac{C_n}{POP}$ (the *demand* channel), a decrease in the amount of network losses and self-consumption of electricity by power generators $\frac{L}{POP}$ (the *network efficiency* channel), an increase in net imports per capita $\frac{(M-X)}{POP}$ (the *trade* channel), and a decrease in the average emission intensity of the domestic power sector (the *emission intensity* channel).

In appendix A.1, I show the evolution of the demand (Figure A.2a), trade (Figure A.2b) and emission intensity (Figure A.2c) channels[11]. I find that UK electricity demand has been declining steadily since 2005 (Figure A.2a), and while UK net electricity imports per capita tended to increase, they remained very low compared to other countries (Figure A.2b). In

[10]Only fossil fuels used for electricity generation generate emissions, so Q_{CO_2e} is the sum of emissions from coal-, gas- and oil- fired power plants.

[11]I leave aside the *network efficiency* channel, which is a technical component stable over time and unlikely to be influenced by carbon pricing. L can be estimated with Eurostat data as gross production Q_{CO_2e} plus net imports $(I - X)$ minus net consumption Y_n. For all European countries, L is constant over time in proportion of total gross production, at about 18%.

contrast, the UK emission intensity of domestic power production can be seen following a similar pattern to total per capita emissions, with a strong decrease after 2013 not observed in other European countries. The decrease is driven by a fall by 30 percentage points of the coal share in domestic production, compensated by an increase in the share of natural gas, of renewable sources including biomass, and of nuclear. This descriptive analysis suggests that the decrease in power sector emissions in the UK after 2013 is mostly due to a marked decline in the emission intensity of domestic production.

2.3 Potential confounders

Isolating the contribution of the CPS to this change in emissions poses certain challenges given that other policies were implemented both in the UK and across Europe during the same period. The fact that the UK and other EU countries were all subject to the same policies enacted at the EU level, in particular the EU carbon market, air quality regulations, and the 2020 strategy setting targets for emission reductions and the deployment or renewable energy, allows me to differentiate out the effect of these policies by using other European countries as a counterfactual. Analysing the effects of UK-specific policies enacted at the same time as the CPS requires a different approach, prompting me to make various assumptions on the effects of these policies to bound their effects during the period considered. Four policies stand out as particularly important and are described in detail in Appendix A.2. Below I offer a brief summary of how each may have impacted UK emissions.

At the European level, the LCP directive (LCPD) is an air quality directive enacted in 2001, and made operational in 2008. It imposes emission limit values for local air pollutants for all combustion plants with a rated capacity above 50MWth. This required regulated plants to take the necessary steps to meet emission standards by 2008, or they could choose to opt out from the directive. Opt-out plants were exempted from the emission standards, but could not operate for more than 20,000 hours between January 1^{st}, 2008 and December 31^{st}, 2015 (European Commission, 2001), and were required to shut down once they had run for 20,000 hours or in 2015 (whichever came first). Plants had to decide by 2004 whether they wanted to opt-out or not[12]. The UK had the highest share of opt-out capacity per capita in 2004, followed closely by Slovakia and Finland[13].

LCPD-induced plant closures could in part explain the decrease in emission levels observed in the UK compared to the averages in other EU countries. To avoid confounding the impact of the CPS and that of these two air quality directives, I control for emission levels from LCP opt-out plants in my estimation strategy. The LCPD was replaced by the Industrial Emissions Directive (IED) in 2016. The IED offered a similar opt-out option, which required that plants decide by 2013. Given that the CPS had already been announced at that time, I consider the decision to opt out from the IED endogenous to the CPS. The UK has two IED opt-out plants, which have limited operating hours between January 1^{st} 2016 and December 31^{st} 2023 and must shut down completely by 2023.

At the UK level, three specific policies that fall under the Electricity Market Reform may have contributed to the decrease in emissions after 2013. First, the UK government subsidised the conversion of coal-fired power plants to biomass starting from 2012, and two plants representing 15% of UK emissions in 2012 benefited from a Contract for Difference for the biomass conversion of part (for Drax plant) or all of their units (for Lynemouth plant). Whether the subsidy for biomass conversion was decided to facilitate the conversion of coal-fired plants facing the CPS, or whether it was independent from the CPS remains somewhat ambiguous. In section 4.2, I develop a strategy to exclude the emission reduction induced by biomass conversion from my estimation.

Second, the Contracts for Difference system introduced in 2014 and its 2012 predecessor, the Financial Investment Decision (FID) Enabling for Renewables, could have impacted the fuel mix by increasing the share of renewable energy in the UK electricity production sector over the 2013-2017 period (outside the specific case of biomass generated by former coal-fired

[12]The decision to opt-out is made for each generating units, and some combustion plants only opted out some but not all of their generating units

[13]Own calculation based on EEA website: 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

plants). However, available data on the projects being awarded a CfD in 2014, 2015 or 2017 and CfD generation reveal that only few of them were operational over the 2013-2017 period. Using the official database on the daily CfD generation by CfD unit[14], I estimate that 1,509 GWh of electricity were generated by CfD units (outside biomass converted units, which I treat separately) over the 2013-2017 period. I estimate an upper bound of the avoided GHG emissions allowed by the CfD policy by assuming that absent CfD generation, these 1,509 GWh would have been produced by coal-fired plants. This is conservative because in reality, the 1,509 GWh would likely have been produced by a mix of coal and gas. I rely on the average capacity-weighted emission rate of UK coal-fired plants reported by Abrell et al. (2019) of 0.89 tCO_2/MWh. I obtain associated avoided GHG emissions of 1.3 $MtCO_2e$[15] over the 2013-2017 period (see Appendix A.2 for more details on the calculations). This amount represents only 0.3% of total UK power sector emissions over the period.

Third, the capacity market introduces payments for electricity generators being awarded a capacity contract, in exchange for providing generation capacity at a pre-determined period of time. Since most of the capacity secured is for after 2018, this policy could only reduce UK emissions over the 2013-2017 period if two conditions are met: first, if the prospective capacity payment incentivised new capacity to be rolled out ahead of the capacity delivery year; second, if this new capacity had a lower emission intensity than existing plants. Using available public data on plants being awarded capacity contracts[16] and new-build conventional plants in the UK between 2014 and 2017[17], I estimate that over the 2013-2017 period, only five new plants, all fired with municipal solid waste, met the following conditions: 1)being awarded a capacity contract between 2014 and 2017 2)starting generation after 2014 and 3)not having been planned before 2014 based on available evidence[18]. These five plants

[14] available at: https://www.lowcarboncontracts.uk/data-portal/dataset/actual-cfd-generation-and-avoided-ghg-emissions

[15] $1,509.10^3 \times 0.89 = 1,343,423$ tCO_2e

[16] available at: https://www.emrdeliverybody.com/CM/Registers.aspx

[17] Data available at: https://www.gov.uk/government/statistics/electricity-chapter-5-digest-of-united-kingdom-energy-statistics-dukes, DUKES 5.11 file

[18] The largest new gas-fired plant which opened in 2016 and won several capacity contracts, Carrington power station, received planning permission before the capacity market was launched, in 2008, see https:

generate zero emissions and represent an installed capacity of 1,141 MW. To estimate the associated avoided emissions, I first calculate the generation associated with this capacity. I assume that generation began on January 1st of the year indicated in the variable "year of commissioning/where generation began", which is conservative. I take as a load factor the average load factor for conventional steam plants in the UK averaged over 2013-2017[19], which is 35%. I obtain an upper bound of the low-carbon power generation imputable to the capacity market of 2,590 MWh over the 2013-2017 period. If this electricity had been produced by coal-fired plants, the associated CO_2e emissions would have been 2.3 MtCO_2e, again using the average capacity-weighted emission rate of UK coal-fired plants reported by Abrell et al. (2019) of 0.89 tCO_2/MWh[20] (see Appendix A.2 for more details on the calculations). This amount represents only 0.5% of UK power sector emissions over the period.

Overall, the Contract for Differences and the capacity market are unlikely to have triggered important changes in power sector emissions over the 2013-2017 period (except for the impact of CfDs on the biomass conversion of coal-fired plants, considered separately).

3 Empirical strategy

3.1 The synthetic control method

To estimate the impact of the Carbon Price Support from other factors, I use the synthetic control method (SCM) developed in Abadie and Gardeazabal (2003) and Abadie et al. (2010, 2015). This method consists in building a counterfactual UK power sector by applying appropriate weights to the set of other European countries' power sectors. Providing that the obtained "synthetic" UK accurately reflects what the UK power sector would have looked like without the CPS, this method allows to estimate the causal impact of the CPS on per

//www.power-technology.com/projects/carrington-gas-fired-power-station-manchester/.

[19] data available at: https://www.gov.uk/government/statistics/electricity-chapter-5-digest-of-united-kingdom-energy-statistics-dukes, DUKES 5.10 file)

[20] $2,590.10^3 \times 0.89 = 2,305,100$ tCO_2e

capita power sector emissions, and more generally on absolute abatement. The SCM method is particularly appropriate in the context of the CPS since the "treatment" applies to one country only, and within the country it affects almost all power installations, without time variation in treatment. Within the UK, there is then no obvious group of installations that could serve as counterfactual for how treated power plants would have evolved absent the policy. Using the notation from the Neyman-Rubin Causal Model (Rubin, 1974), the challenge is to estimate $\beta_{\mathrm{UK}t}$ when t≥2013, defined as:

$$\beta_{\mathrm{UK}t} = Y^1_{\mathrm{UK}t} - Y^0_{\mathrm{UK}t} = Y_{\mathrm{UK}t} - Y^0_{\mathrm{UK}t} \tag{3}$$

$Y^1_{\mathrm{UK}t}$ designates, at each period, UK per capita power sector emissions in the presence of the CPS policy. $Y^0_{\mathrm{UK}t}$ designates, at each period, UK per capita power sector emissions in the absence of the policy. $\beta_{\mathrm{UK}t}$ designates the difference between the two. $Y_{\mathrm{UK}t}$ designates the observed outcome. The challenge to estimate $\beta_{\mathrm{UK}t}$, or "fundamental problem of causal inference" (Rubin, 1974), comes from the fact that $Y^1_{\mathrm{UK}t}$ is observed when t≥2013 but $Y^0_{\mathrm{UK}t}$ is not.

Abadie et al. (2010) show that if the outcome in the absence of intervention, Y^0_{ct}, can be modelled as a linear factor model[21], it is possible to use a function of outcomes observed post-treatment in other countries as an estimator of $\beta_{\mathrm{UK}t}$:

$$\hat{\beta}_{\mathrm{UK}t} = Y_{\mathrm{UK}t} - \sum_{j=1}^{J} w^*_j Y_{jt} \tag{5}$$

Where $\sum_{j=1}^{J} w^*_j Y_{jt}$ is a weighted combination of the outcome for J countries having

[21] Such a model is more flexible than the typical difference-in-difference (DID) model because time effects and individual (country) time-invariant effects are allowed to interact. It can be written:

$$Y^0_{ct} = \delta_t + Z_c\alpha_t + f'_t\lambda_c + \epsilon_{ct} \tag{4}$$

Where δ_t is a time fixed effect, Z_c is a vector of observed exogenous country characteristics, α_t is a vector of unknown parameters, f_t is a vector of unobserved common factors (and f'_t its transpose), λ_c is a vector of unobserved country-specific effects or factor loadings, and ϵ_{ct} is an error term with mean 0 (typically capturing transitory shocks at the country level). .

not implemented the policy, and the vector $W^* = (w_1^*...w_J^*)'$ should satisfy the following conditions:

$$\begin{cases} w_j^* & \geq & 0 \ \forall j = 1..J \\ \sum_{j=1}^{J} w_j^* & = 1 & \\ \overline{Y}_{\text{UK}}^K & = & \sum_{j=1}^{J} w^* \overline{Y}_j^K \\ Z_{\text{UK}} & = & \sum_{j=1}^{J} w^* Z_j \end{cases}$$

With $\overline{Y}_{\text{UK}}^K$ a linear combination of pre-intervention outcomes in the UK and $\overline{Y}_j^K$ a linear combination of pre-intervention outcomes for country j (The linear combination is defined by the vector $K = (k_1, ..., k_{T_0})'$. For example, it can be the simple mean of pre-intervention outcomes $\overline{Y}_j^K = 1/T_0 \sum_{t=1}^{T_0} Y_j$). Abadie et al. (2010) also show that the estimator gets closer to the true parameter $\beta_{\text{UK}t}$ when the number of pre-treatment periods is high compared to the scale of transitory shocks affecting countries.

In practice, to find the appropriate W vector I rely on an algorithm created by Abadie et al. (2010), and implemented in Stata under the **synth** command. The algorithm minimizes the distance between a vector of pre-intervention characteristics (also called predictors) in the treated country, X_{UK} (with dimensions $K \times 1$) and a weighted matrix of pre-intervention characteristics in the non-treated countries, $X_0 W$ (with dimensions $K \times K$). Pre-intervention characteristics are of two types: 1) the linear combinations of pre-intervention outcomes $\overline{Y}_j^K$, and 2) other country characteristics Z_j not affected by the intervention. Taking the values of these characteristics for the pre-treatment period ensures that the values are not affected by the policy, although post-treatment values can also be included if the predictors are not affected by the treatment(Abadie et al., 2010). In practice, when these country characteristics are time-varying, their values are averaged over part of or over the entire pre-treatment period to obtain a unique time-invariant value for each characteristic (see e.g, Abadie et al. (2015); Andersson (2019)). To obtain the W vector, the programme starts with a positive and semi-definite matrix V that defines a dot product. The distance between

X_{UK} and X_0W can then be written as:

$$X_{\text{UK}} - X_0W = \sqrt{(X_{\text{UK}} - X_0W)'V(X_{\text{UK}} - X_0W)} \tag{6}$$

The goal is to find the vector $W^*(V)$ that minimizes this distance. Such minimization comes down to finding the right V matrix, which can be shown to be equivalent to a diagonal matrix assigning weights to linear combination of characteristics in X_{UK} and X_0W. Like Abadie and Gardeazabal (2003), I choose the V minimizing the mean squared prediction error (MSPE)[22] of the outcome variable in the pre-treatment periods. Formally, let Y_{UK} be the (8×1) vector of pre-2013 power sector emissions from 2005 to 2012 for the UK and Y_j be the $(8 \times J)$ matrix of pre-2013 power sector emissions for the J other European countries. Then V^* is chosen among the set V of all non-negative diagonal $(K \times K)$ matrices, such that:

$$V^* = argmin(Y_{\text{UK}} - Y_jW^*(V))'(Y_{UK} - Y_jW^*(V)) \tag{7}$$

The ability to build a good synthetic control can be assessed with at least two criteria: first, pre-intervention characteristics of the treated unit should be close to those of the synthetic unit. This depends on how well these characteristics predict the outcome and can be assessed by comparing pre-intervention characteristics for the treated and synthetic country. Second, the pre-intervention outcomes of the synthetic unit should be close to the pre-intervention outcomes of the treated unit. This can be checked graphically or by computing the MSPE. Compared to the difference-in-difference method, the number of pre-treatment periods should be large to limit the size of the bias, and relatively larger than transitory shocks affecting the countries (Abadie et al., 2010). As explained below, my main outcome variable is only available from 2005, which implies that my pre-treatment period has only eight years for the main specification. This is rather low compared to other

[22] The MSPE gives the average of the squared difference between the treated unit's and the synthetic control's pre-intervention outcomes.

published papers using the synthetic control method. I apply the same method on less precise aggregate data available since 1990 in appendix A.11 to assess whether the results change. The countries entering the synthetic UK are not the same, but the estimate of the impact is very close to the original one.

3.2 The Data

I apply the synthetic control method to a country-level panel, with the UK as the treated unit and other European countries as control units potentially entering the synthetic UK. To build this panel, I first aggregate plant-level data on carbon emissions at the country-level. This variable of per capita power sector emissions is the outcome variable Y^{ct}. I then add different country-level power sector characteristics obtained from different sources.

Power plant-level emission data: this data comes from the European Union Transaction Log (hereafter EUTL), the official register of the EU ETS managed by the EU Commission. The EUTL checks, records and authorises all transactions taking place between participants in the EU ETS. Every year since 2005, the start date of the EU ETS, participants have had to report their CO_2e emissions and surrender enough emission allowances to cover their emissions. Reported emissions are verified by an accredited verifier. The EUTL raw data can be downloaded from the EUTL's website[23] and contains annual emission data on around 11,000 installations from thirty-one European countries. Emission data for one year correspond to the emissions at the end of the calendar year. Given that not all ETS installations are power installations[24], the raw data contains both power plants and other types of plants.

One crucial step, thus, is to identify power installations. The main activity of each installation is publicly available, but there is no specific activity category for power installations. I rely on data provided by the UK-based think-tank Ember (formerly Sandbag) and a one-off

[23]see https://ec.europa.eu/clima/ets/allocationComplianceMgt.do

[24]The ETS covers combustion installations with a rated capacity above 20 MWth, including power installations, and energy-intensive industries

file with more precise activity codes circulated by the EU Commission to identify power installations. Appendix A.3 describes the specific steps followed. Out of the thirty-one countries part of the ETS in 2013, I restrict the analysis to the twenty-one countries that meet the following conditions: first, having been in the ETS since the start of the market in 2005, to obtain a balanced panel[25]; second, being part of the European Union for the 2005-2017 period, because all EU countries are subject to similar policies enacted at the EU level[26]; third, having a power sector of a sufficient size, defined here as having at least 10 power plants subject to the ETS[27]. I identify a total of 4,938 power plants, including 302 in total for the UK, with an average of 190 active power plants per year in the UK over the 2005-2012 period and 189 active power plants per year in the other twenty EU countries.

Almost all the UK power plants subject to the CPS are included in the EUTL data, except those with a rated thermal input between 2 and 20 MWth, not covered by the EU ETS. These small plants logically represent a very small share of total emissions. Two categories of UK power plants present in the EUTL data are not subject to the CPS: power installations located in Northern Ireland, which represent a small share of UK power sector emissions (2.4% in 2012); and standby generators, also representing a small share of emissions[28]. I aggregate plant-level emissions at the country level, separately for power and non-power plants[29], and obtain emission data for a panel of 21 European countries for the 2005-2017 period.

Country-level power sector characteristics: I add to this panel a set of annual country-level variables which I refer to in the descriptive analysis (see section A.1) and which I use in the empirical strategy: country population, installed capacity and power generation by source, electricity consumption, electricity imports and exports, coal and gas prices,

[25]This makes me exclude three countries: Romania, Bulgaria, Croatia

[26]This makes me exclude four countries: Slovenia, Norway, Liechtenstein and Iceland

[27]This makes me exclude three countries: Luxembourg, Cyprus and Malta

[28]Such generators are likely to be found in hospitals. In 2012, the six ETS power installations from the UK belonging to hospitals represent only 0.05% of UK power sector emissions

[29]Non-power plants are only used in figure 2b, to verify that the UK decrease in emissions only occurs in the power sector.

availability of lignite resources (a particularly polluting type of coal only used domestically), and average age of the coal-fired plants. Most of these data come from Eurostat. See appendix A.4 for details on each variable's source. Table 2 shows summary statistics by country for the main variables considered.

3.3 Selecting the predictors

Keeping the notation used in section 3.1, the set of predictors X_0 used to build the synthetic UK should be variables predicting country-level per capita power sector emissions, and which values are not affected by the CPS. As mentioned above, it is common to include two types of pre-intervention characteristics: 1)pre-intervention outcomes $\overline{Y}_j^K$, and 2) other country characteristics Z_j, not affected by the intervention, typically averaged across the pre-treatment period. As pre-intervention outcomes, I use per capita power sector emissions in 2005 and 2012, the first and last year of the pre-treatment period, which is standard in the SCM literature. For the pre-intervention country characteristics, I chose four variables which have been found to influence country-level emissions in the literature (Ellerman and McGuinness, 2008; Van den Bergh and Delarue, 2015; Lee and Melstrom, 2018). I briefly explain each variable below, and Appendix A.4 provides greater detail on data sources.

The first predictor is a country-specific time-varying variable of annual coal-to-gas price ratio. In countries that, like the UK, rely both on coal- and gas-fired power plants for electricity generation, fuel switching has been identified as an important determinant of emissions variation because coal-fired plants have a much higher emission intensity than gas-fired plants. Fuel switching is influenced by the coal-to-gas price ratio (Ellerman and McGuinness, 2008), which is directly impacted by the CPS since the tax rate for coal is higher than for gas.

The second predictor is a time-invariant dummy identifying which European countries have domestic lignite resources. Lignite is a low-quality type of coal with a very high emission intensity, used almost exclusively for power generation and mostly consumed domestically.

Table 2: Summary statistics at the country level, average 2005-2012

	(1) UK	(2) Other countries	(3) Donor pool
Nb. ETS power installations	190	190	193
	(13)	(189)	(148)
Nb. ETS non-power installations	626	261	273
	(82)	(269)	(229)
Population	62,047,417	20,142,519	20,229,390
	(1,165,199)	(23,321,330)	(20,035,738)
CO_2e emissions from power installations (tCO_2e)	171,770,195	53,067,594	43,904,503
	(13,562,672)	(78,052,009)	(47,414,350)
Per capita power sector emissions (tCO_2e per capita)	2.78	2.80	2.43
	(0.26)	(2.10)	(1.48)
Final electricity consumption (GWh)	341,442	122,819	122,593
	(13,197)	(147,040)	(119,366)
Gross Power production (GWh)	384,010	139,907	139,013
	(13,570)	(173,760)	(143,684)
Proportion of renewables in production	0.05	0.19	0.19
	(0.0183)	(0.184)	(0.175)
Proportion of nuclear	0.18	0.21	0.24
	(0.0229)	(0.250)	(0.249)
Proportion of fossil fuel	0.776	0.596	0.574
	(0.0316)	(0.271)	(0.271)
Proportion of coal	0.327	0.226	0.235
	(0.0430)	(0.232)	(0.227)
Proportion of gas	0.398	0.230	0.235
	(0.0613)	(0.185)	(0.191)
Coal price (€/kWh)	0.0101	0.0152	0.0170
	(0.00209)	(0.0166)	(0.0188)
Gas price (€/kWh)	0.0201	0.0254	0.0258
	(0.00420)	(0.00572)	(0.00527)
Installed capacity, fossil fuels (MW)	68,414	18,838	18,522
	(2,869)	(22,481)	(18,353)
Installed capacity, wind and solar (MW)	4,732	4,480	3,363
	(3,156)	(9,815)	(5,877)
Lignite resource dummy	0.000	0.250	0.200
	(0.000)	(0.434)	(0.402)
Average age of coal-fired plants	36.04	28.57	28.86
	(1.537)	(6.698)	(7.055)
Observations	8	160	120

Notes: Standard deviations in parentheses;"Other countries" include twenty European countries: Austria, Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, the Netherlands, Poland, Portugal, Slovakia, Spain, Sweden; The "Donor pool" includes fifteen countries: Austria, Belgium, the Czech Republic, Denmark, Finland, France, Hungary, Ireland, Italy, the Netherlands, Poland, Portugal, Slovakia, Spain, Sweden; for the UK, the values are averaged over the 2005-2012 period; for the "Other countries" and the "Donor pool", the values are averaged over the 2005-2012 period, then averaged across countries (without population weights).

Lignite-rich countries have a significantly higher emission intensity of power production than countries without lignite reserved. Since lignite is not traded internationally, it is is not captured in the coal price variable I use to build the coal-to-gas price ratio predictor, which is derived from trade statistics. I identify five European countries with large lignite resources: Germany, Poland, Hungary, Greece, and the Czech Republic[30]. Since the UK value is 0, the lignite variable constraints the programme to find a synthetic UK with as few countries with lignite reserves as possible.

The third predictor is a time-varying variable of residual load per capita. Residual load measures the amount of electricity demand that requires using fossil fuels and biomass once generation from so-called "must-run" power generators (nuclear power plants) and those that generate with almost no marginal cost (solar, wind and hydro) are removed. Power sector emissions are expected to increase with residual load, since the electricity generated with fossil fuels is the one that emits CO_2. I build a country-level time-varying variable of per capita residual load by taking the difference between electricity consumption and the generation from renewables and nuclear power plants, and dividing it by total population.

The fourth predictor measures the amount of per capita CO_2 emissions coming from LCP opt-out plants. This predictor enables me to account for the impact of the European air quality directives mentioned in section 2.3 and in Appendix A.2. These emissions are expected to disappear by 2015, since the LCP opt-out plants have to shut down by 2015 at the latest. Using this predictor ensures that the synthetic UK will have about the same quantity of emissions from plants "at risk of closure" by 2015 as the UK. The opt-out decision had to be made before the CPS was introduced, such that the share of emissions coming from opt-out plants *before* the announcement of the CPS could not have been affected by the CPS. To build the variable of per capita LCP opt-out emissions, I first identify the name and location of those plants that opted-out of the LCP Directive based on the LCP data available on the European Environmental Agency's website. I then manually identify these plants in

[30] The lack of data on lignite reserves covering all Europe prompted me to build a binary rather than a continuous variable (such as the amount of proven reserves by country)

the EUTL installation-level emission data[31] to determine how much CO_2 these plants emit each year. For each country and each year, I calculate the sum of power sector emissions coming from LCP opt-out plants, and divide each sum by the country population to obtain a variable of per capita LCP opt-out emissions. I obtain a country-level time-varying variable of per capita LCP opt-out emissions. As a predictor, I take the value of this variable in 2009, two years before the CPS was announced.

For the optimization, the residual load predictor is averaged for the period 2005-2012 and the coal-to-gas price ratio is averaged for the period 2007-2012 to ensure data consistency over time (see Appendix A.4 for more details). The remaining predictors are taken for one period only (lagged outcome, per capita opt-out emissions) or are time-invariant (lignite dummy) so they do not need to be averaged.

In a sensitivity analysis presented in Appendix A.9, I run the SCM with alternative sets of predictors. The magnitude of the results is unchanged when the installed capacity from plants using combustible fuels, the pre-treatment trend in renewables' installed capacity, the number of heating degree days or the average age of coal-fired plants are included in the set of predictors (although some alternative sets of predictors satisfy less well the requirements of the synthetic control method).

3.4 Selecting countries entering the donor pool

The "donor pool" designates the set of countries not affected by the CPS that will potentially enter the composition of the synthetic UK. The starting pool of countries consists of the twenty European countries included in the European Union (EU), other than the UK, described in the data section. Restricting the donor pool to EU countries rather than including other OECD countries has several advantages and one drawback. The main advantage is that over the period considered, the UK and other EU countries are subject to the same EU-level policies (in particular the EU ETS and the LCP directive, but also other

[31] The LCP data has a different installation identifier from the EUTL identifier

energy policies). European countries would also have been more likely to be affected in a similar way by global shocks on the energy market, such as the 2011 US shale gas revolution. One drawback is that such geographic proximity and sectoral integration makes spillovers between treated and synthetic unit more likely.

Starting with this initial pool of twenty countries, it is important to discard the countries that are likely to be poor counterfactuals (Abadie et al., 2010). This essentially describes three country types: first, countries that suffered idiosyncratic shocks to the outcome of interest, either by directly introducing a policy targeting the power sector or via a more generic exogenous shock likely to affect the electricity sector; second, countries more likely to have been directly affected by the CPS; and third, countries with very different characteristics compared to the UK, which may cause severe interpolation biases.

By 2017, no other European country had adopted a carbon tax or a carbon price floor that would interact with ETS pricing in the power sector (Metcalf and Stock, 2020).[32] The most radical change in other European countries' power sectors is the case of Germany, which unexpectedly decided to phase out nuclear energy following the 2011 Fukushima nuclear accident. I therefore exclude Germany from the donor pool. I also exclude Greece, which economy was significantly affected by the European debt crisis over the period. However, including them in the donor pool does not change the results, as shown in appendix A.10.

Regarding the second country type, tension can occur between excluding countries from the donor pool countries whose outcomes are affected by the treated unit and identifying those sufficiently comparable to the treated unit (Abadie, 2021). While I do not exclude any country based on the risk of spillover, I do discuss this risk and offer an estimation the amount of potential spillovers in section 4.4.

Finally, to avoid including countries that differ too greatly from the UK, I eliminate Estonia, a country where high emissions per capita are due to the unusual use of oil shale for power

[32] France and the Netherlands discussed introducing a carbon price floor as well (Newbery et al., 2019). Only the Netherlands have passed a law in August 2018, and the Dutch top-up tax entered into force on January 1, 2021 (World Bank, 2021).

generation, a high-emitting input fuel. I also exclude the two other Baltic countries, Latvia and Lithuania, which unlike the UK do not use coal for power generation (see Figure A.3). Since coal-to-gas fuel switching is expected to be an important driver of decarbonisation, it is relevant to restrict the analysis to countries with the capacity to do so.

In the end, the donor pool includes 15 EU countries. Appendix A.10 shows that changing the composition of the donor pool does change the composition of the synthetic UK and the estimates, but not their order of magnitude. To ensure that building a convex combination of countries (having positive weights) that closely reproduce the UK's values for predictors and emissions is possible, there needs to be common support between the distribution of the predictors in the donor pool and in the UK. I check that this is the case for all variables (See the histograms in appendix A.5).

4 Results

4.1 Upper Bound

I start by applying the SCM method using the emission outcome variable, donor pool and predictors exposed in the previous section. Figure 3a shows that the obtained synthetic UK (dashed line) reproduces well the trajectory of UK per capita power sector emissions (continuous line) before 2013, with a Mean Squared Prediction Error (MSPE) of 0.01. Compared to the average per capita power sector emissions for the donor pool (dotted line), the synthetic UK has a relatively close trajectory but higher per capita emissions. Table 3 shows the weights received by each country in the synthetic UK, which comprises five countries: Ireland (49.2%), Slovakia (25.6%), the Netherlands (13.7%), Finland (5.8%), and the Czech Republic (5.7%). The remaining potential control countries receive a weight of 0. The large weight observed for Ireland is not surprising: Ireland and the UK have close institutions and energy markets, and like the UK, Ireland has a substantial portfolio of coal- and gas-fired power plants. The Netherlands and Slovakia also show a potential for coal-to-gas fuel switching (see figure A.3a). The Netherlands shows a residual load per capita close to the UK, and Slovakia and Finland show, like the UK, a substantial amount of LCP opt-out emissions.

Table 3: Country weights in synthetic UK

Country	Weight	Country	Weight	Country	Weight
Austria	0	Finland	0.058	Poland	0
Belgium	0	France	0	Portugal	0
Czech Republic	0.057	Hungary	0	Netherlands	0.137
Denmark	0	Ireland	0.492	Slovakia	0.256
Spain	0	Italy	0	Sweden	0

Note: All weights are between 0 and 1 because the Synthetic control method imposes positive weights summing to 1.

The good pre-treatment fit between the UK and synthetic UK suggests that after 2013, the synthetic UK accurately replicates the evolution of per capita emissions in the UK power sector absent the CPS (assuming no other UK-specific confounder). The fit is less good in 2012, where UK emissions peak. This is also the year where the share of coal in the UK fuel input mix is the highest, which can be partly explained by the low coal-to-gas price ratio that year (lowest point since 2007). If power could easily be stored, the 2012 peak could also be interpreted as an anticipation effect of the CPS, which was announced in 2011. Coal-fired plants would then have an incentive to use their coal before being taxed in 2012, store the electricity, and sell it over subsequent years. But electricity cannot be stored, and production has to match demand at every point in time. The generation mix at each point in time depends on the merit order, that is, the ranking of plants' marginal costs. Anticipation can only materialize if some coal-fired plants alter the merit order by accepting to sell at a price lower than their marginal cost in order to get rid of their coal reserves. Power plants scheduled to close because of the LCPD may have had an interest in adopting such measures, especially if they had excess coal stocks that they wanted to get rid of before being taxed[33].

[33] Anecdotally, official data on annual coal consumption and stocks by electricity generators indicate that coal stocks as a share of stocks and consumption are lower in 2012 compared to previous periods (20% vs 27% on average over 2005-2012), although the difference is not large (BEIS (Department for Business, Energy & Industrial Strategy), 2019).

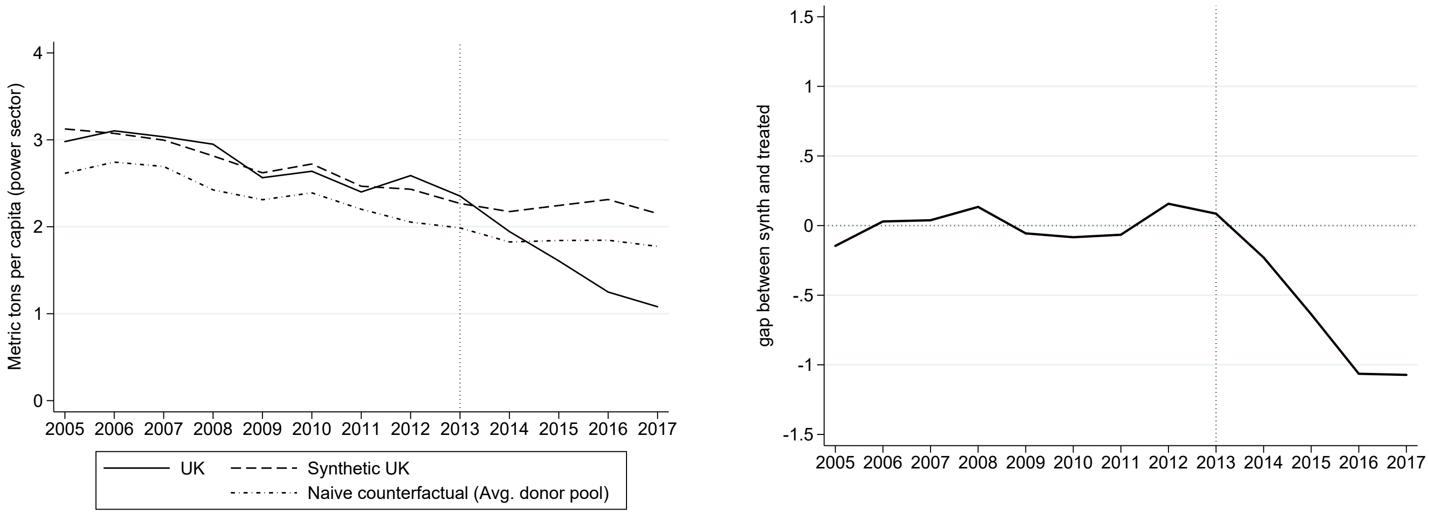
Table 4 shows the average value of each predictor for the UK, synthetic UK, and the average among the donor pool. The values of the predictors for the synthetic UK are close to the values for the actual UK - indicating that the synthetic UK is a relatively good counterfactual to the UK. The balance in predictors' values between the UK and synthetic UK is better than between the UK and the average taken from the donor pool for all predictors, further justifying the use of the SCM method.

Table 4: Predictors' values for the UK, synthetic UK and average of the donor pool

Variable	**UK**	**Synth. UK**	**Avg. Donor pool**
Per capita residual load	4.29	4.30	3.37
Coal-gas price ratio	0.52	0.51	0.71
Per capita LCP opt-out emissions	0.29	0.24	0.22
Lignite dummy	0.00	0.06	0.20
Per capita emissions 2005	2.98	3.13	2.62
Per capita emissions 2012	2.59	2.43	2.05

Notes: The per capita residual load is averaged for the period 2005-12, and the coal-to-gas price ratio for the period 2007-12. LCP opt-out emissions are taken in 2009, the lignite dummy is time-invariant. Outcome lags are taken in 2005 and 2012.

Figure 3b shows the emission gap between the UK and synthetic UK for each period. The gap between the UK and synthetic UK widens significantly between 2014 and 2016, while UK emissions were slightly higher than synthetic UK emissions in 2013. This evolution is consistent with the timing of the introduction of the CPS (April rather than January 2013), with the strong increase in the CPS rate between 2013 and 2015, and the CPS freeze in 2015/2016. The corresponding annual abatement for each year $t \in [2013, 2017]$ can be calculated by multiplying the annual gap in per capita emissions by the UK annual total population. On an average year, emissions decrease by 26 percent, with an associated semi-elasticity of -1.65% of emissions per Euro of the tax on average. Adding up all annual abatements gives a total cumulative abatement of 191 million tCO_2e ($MtCO_2e$) over the 2013-2017 period. Emissions abatement was the most pronounced in 2017, when UK emissions became 50% lower than synthetic UK emissions.



(a) Absolute per capita emissions

(b) Emission gap between treated and synthetic

Figure 3: UK and synthetic UK per capita emissions

Notes: For each period, the variable of per capita emissions corresponds to the sum of CO_2e verified emissions from power installations subject to the EU ETS, divided by the average country population that year. The vertical line is set in 2013, date where the CPS is introduced. The synthetic UK comprises five countries: Ireland (49.2%), Slovakia (25.6%), the Netherlands (13.7%), Finland(5.8%), and the Czech Republic (5.7%).

4.2 Lower bound

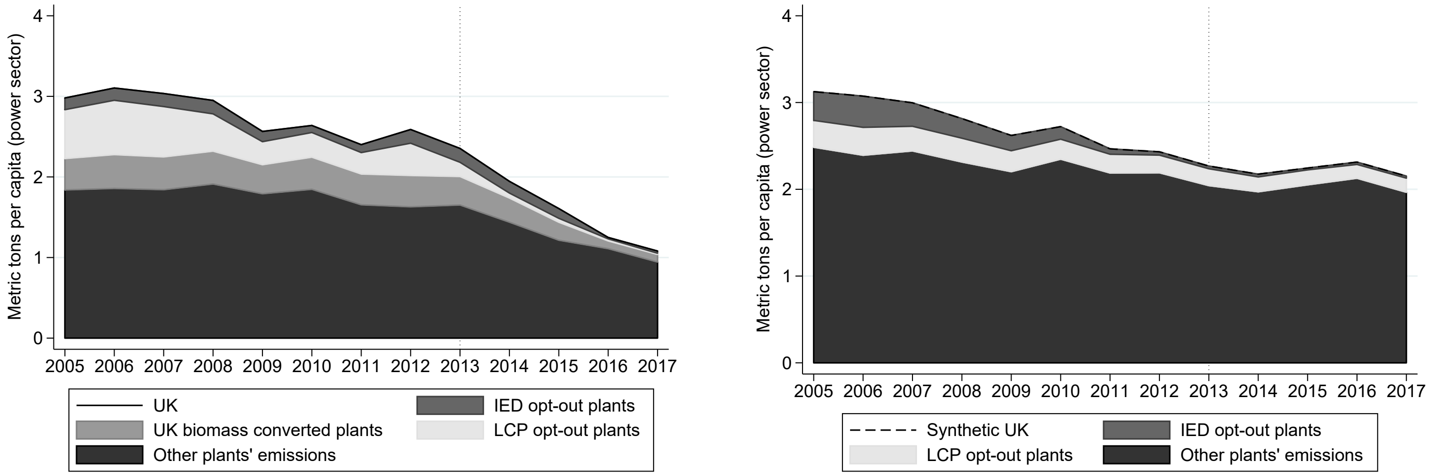
Potential confounders and emission decomposition: In the result presented above, the assumption is that the difference in emissions between the UK and synthetic UK after 2013 resulted solely from the Carbon Price Support. As mentioned in section 2.2, UK-based policies and European policies affecting the UK differently from other countries may have further contributed to the observed decrease in emissions in the UK.

Regarding European policies, the predictor of LCP opt-out emissions should guarantee that the actual and synthetic UK have approximately the same amount of emissions coming from plants facing a high risk of closure. Given the close values of the LCP opt-out predictor, any difference in the evolution of emissions from opt-out plants between the actual and synthetic UK is assumed to be caused by the CPS. For example, the CPS may have affected the way in which the remaining operating hours of each opted-out plant were distributed over the 2005-2015 period; it may also have motivated certain opt-out plants to lobby for government loopholes to allow them to remain operational in spite of set limits on operating hours. The decision to opt out from the IED directive occurred after the announcement of the CPS, so any difference observed in opt-out behaviour between UK and non-UK plants could be a consequence of the CPS.

In contrast, UK-specific policies implemented at the same time as the CPS cannot be controlled for in the SCM framework. In Appendix A.2, I estimate that both the Contracts for Differences and the capacity market likely had a limited impact on the fuel mix over the period considered, with estimated emissions reductions at a maximum of 1.3 $MtCO_e$ for the CfD, and 2.3 $MtCO_e$ at most for the capacity market. The situation is different for the biomass conversion policy: the largest UK coal-fired plant, Drax, converted half of its production units from coal to biomass between 2013 and 2016, and the smaller station Lynemouth stopped using coal in December 2015 to prepare for biomass conversion.

To assess the role of the air quality directives and of the biomass conversion, I rely heavily on plant-level emission data. I decompose emissions into four categories for the UK and synthetic UK: emissions coming from LCP opt-out plants (light grey); emissions from IED opt-out plants (dark grey); emissions from UK plants having benefited from subsidies to convert to biomass (medium grey); and remaining emissions from other plants (black). Figure 4 shows the emission decomposition results in the UK and the synthetic UK.

LCP opt-out emissions are higher in the UK than in the synthetic UK before 2008, but move closer to each other between 2009 and 2012, just before the CPS is introduced. After 2012, LCP opt-out emissions decrease sharply in the UK while they remain relatively constant in the synthetic UK. The evolution of the synthetic UK opt-out emissions may seem surprising: opt-out plants are expected to shut down by 2015 at the latest and we should have zero emissions from opt-out plants in 2016 and 2017, both in the UK and synthetic UK. Singhal (2019) confirmed that as many as 60% of opt-out plants actually continued to operate after 2015. The difference in the trajectory of UK and non-UK LCP opt-out plants suggests that the CPS intensified UK plants' response to the LCP opt-out option



(a) UK

(b) Synthetic UK

Figure 4: Per capita CO_2e emissions by source, UK and synthetic UK

Notes: The synthetic UK comprises five countries: Ireland (49.2%), Slovakia (25.6%), the Netherlands (13.7%), Finland(5.8%), and the Czech Republic (5.7%).

and accelerated their closure[34]. The figure also confirms that the UK emission peak in 2012 mainly comes from LCP opt-out plants, which had an interest in using their polluting inputs before the introduction of the tax. IED opt-out emissions are relatively low in both the UK and synthetic UK just before the opt-out decision.

Finally, the carbon emissions from UK plants that converted to biomass burning represent a substantial share of UK emissions, which decreased after 2013. Drax power plant - responsible for more than 90% of these emissions - had only half of its six units converted to biomass, suggesting that the decrease in emissions after 2013 must be partly explained by the impact of the CPS on the non-converted units. Furthermore, the introduction of the CPS may have influenced the willingness of UK plants to convert to biomass processing. The estimate above implicitly assumes that this was the case.

To avoid biomass conversion confounding the impact of the CPS on emissions, below I estimate counterfactual CO_2e emissions for the biomass converted plants if they had not

[34]Such an interpretation would also confirm a Guardian journalist's statement that "[UK coal-fired] Plants have closed in recent years as EU pollution standards started to bite, but it was increases in the UK carbon tax that sealed their fate" (Vaughan, 2018).

converted to biomass. In Appendix A.8, I run a second test where I remove from the UK emissions variable all the emissions coming from biomass converted plants and generate a new synthetic UK based on this modified emission variable.

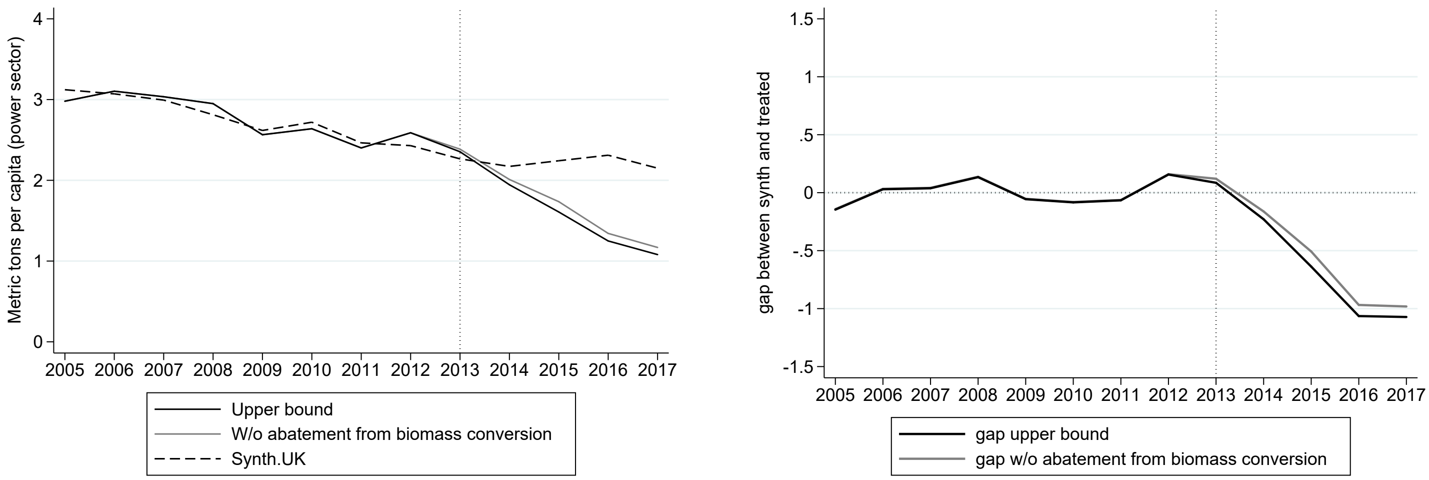
Lower bound: Counterfactual emissions of plants converted to biomass if they had not converted: Appendix A.6 provides details on the imputation of emissions in the absence of biomass conversion. I summarize below the method used for each plant. Estimating what emissions from Drax plant would have looked like in the absence of biomass conversion is relatively straightforward because I observe the evolution of emissions for its coal units which did not convert. I first combine data on the monthly generation of the three Drax coal units over the 2009-2016 period, combined with their average emission intensity (kindly provided by Mirjam Kosch and Jan Abrell) to estimate the amount of CO_2 emissions coming from Drax coal units. I then subtract the emissions coming from the coal units from the total emissions reported for Drax in the EUTL data to estimate the emissions coming from the three units converted to biomass between 2013 and 2016. In 2016, the estimated CO_2 emissions for these units were close to zero, which makes sense given that the three units run entirely on biomass in 2016. I can then assume that their emissions were also zero in 2017, which means that all the emissions reported for Drax in the EUTL in 2017 came from the three coal units. Third, I assume that absent the biomass conversion, biomass converted units would have had a similar emission trend to that observed for the three coal units. Concretely, I start with their estimated CO_2 emissions value for 2012, and I apply the same annual percent change as the annual percent change for the three coal units, which provide me with "counterfactual" emissions for the three units converted to biomass. Finally, I add these "counterfactual" emissions to the actual emissions of the three coal units and obtain counterfactual emissions for Drax in the absence of the biomass conversion policy.

For Lynemouth plant, using the same method is not possible given that the plant as a whole began its conversion in December 2015[35]. I thus formulate a cruder hypothesis that

[35]ee https://www.power-technology.com/projects/lynemouth-biomass-power-station-northumberland/

absent the conversion to biomass, emissions in 2016 and 2017 would have been the same as in 2015. For the two plants, the estimated counterfactual emissions absent the biomass conversion policy only differ from the actual emissions for the 2013-2017 period. For the 2005-2012 period, counterfactual emissions equal actual emissions.

Finally, I generate a modified outcome variable for the UK, which includes both Drax and Lynemouth's counterfactual emissions instead of their actual emissions. UK pre-treatment emissions remain the same as before with this modified variable, such that the synthetic UK obtained in the previous section still represents an appropriate comparison unit for the UK. Figure 5a shows the UK emission trajectory with this modified outcome variable (dark grey), overlaid to the actual UK and synthetic UK emission trajectories (in black). After "removing" the effect of biomass conversion, emissions are logically higher after 2013 for the modified UK emission variable. The gap between UK and synthetic UK is then reduced (Figure 5b). On an average year, emissions decrease by 22.5 percent, with an associated semi-elasticity of -1.41% per Euro of the tax. The total cumulative abatement amounts to 164.3 million of tCO_2e. Withdrawing the upper bound estimate for the effect of the capacity market and the CfD ($\approx$ 3.6 $MtCO_2e$ in total), I obtain a cumulative lower bound abatement of around 161 $MtCO_2e$. The estimated abatement is lower in Appendix A.8, where the emissions from the biomass converted plants are removed from UK emissions; the difference between the two abatement results corresponds roughly to the decrease in Drax and Lynemouth counterfactual emissions (in the absence of biomass conversion) between the pre- and post-treatment period.



(a) Absolute per capita emissions

(b) Gap between treated and synthetic

Figure 5: SCM with counterfactual UK emissions w/o biomass conversion

Notes: The synthetic UK comprises five countries: Ireland (49.2%), Slovakia (25.6%), the Netherlands (13.7%), Finland(5.8%), and the Czech Republic (5.7%).

4.3 Inference

With the SCM method, inference can be derived from a set of placebo tests, which consists in applying the SCM method to untreated units or fake treatment dates (Abadie et al., 2010).[36]. I am able to show that the results are likely driven by the causal impact of the Carbon Price Support by measuring (1) the likelihood of finding an effect of the same magnitude as what I find when I apply the method before 2013 (the in-time placebo test); (2) the likelihood that the result is driven by particular behaviour specific to one country in the donor pool (the leave-one-out test); (3) the likelihood of finding an effect of the same magnitude when I apply the method to other countries (the in-space placebo test or permutation test). The in-time and leave-one-out tests are run for the actual UK emissions used for the upper bound estimation from section 4.1. Results would be the same for the lower bound, given that the composition of the synthetic UK and the trajectory of emissions in the 2005-2012 period are the same. For the permutation test, I show results based both on the upper bound and on the lower bound estimation of abatement.

[36]Having only one treated unit is insufficient for building confidence intervals as found in previous works by Gobillon and Magnac (2016) and Isaksen (2020).

In-Time placebo One way to check that the results observed were indeed caused by the CPS policy is to assume that a similar policy was implemented at another date prior to 2013, apply the same method to generate a synthetic UK, and check that the UK and synthetic UK have similar per capita emissions before and after this artificial intervention date. Figure 6 shows the UK and synthetic UK outcome obtained when treatment is assumed to occur in 2010 rather than 2013. The synthetic UK closely resembles the UK emission trajectory before 2010, and there is no significant gap between treated and synthetic UK in 2011 and 2012.

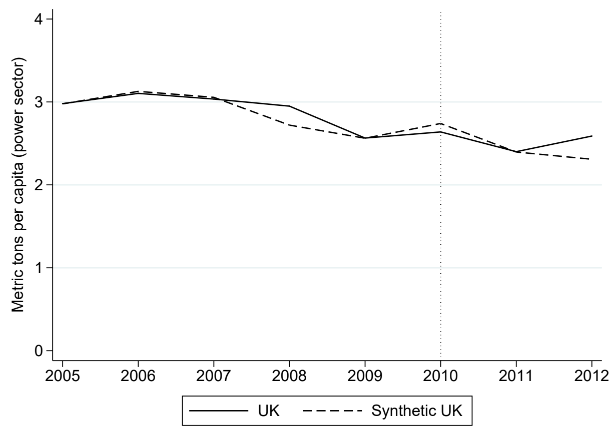
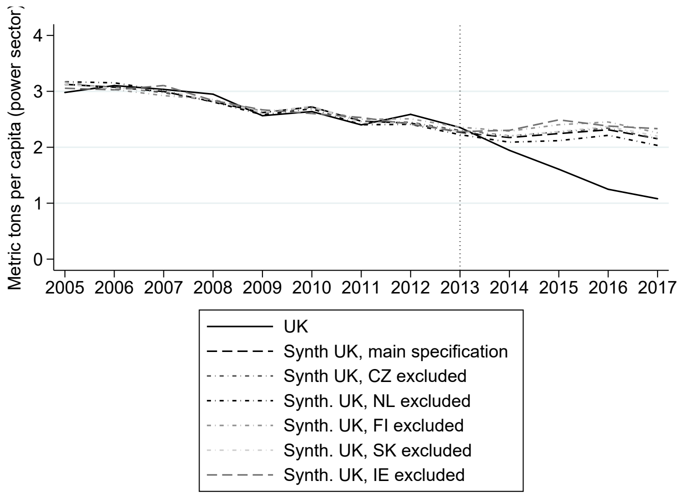


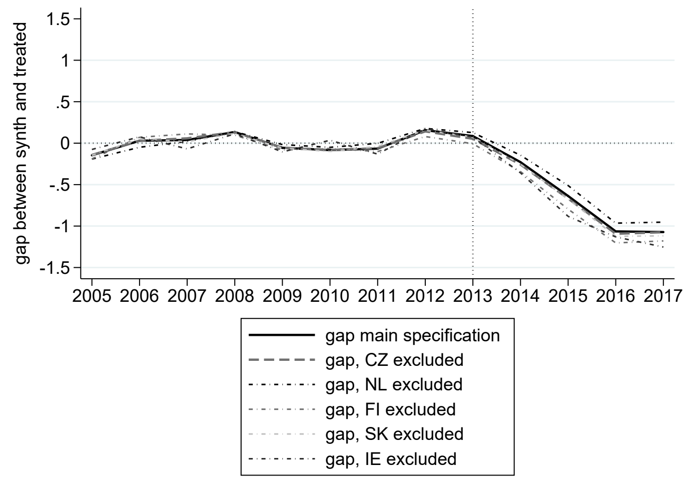
Figure 6: Gap between treated and synthetic UK, CPS assumed to start in 2010

Notes: Predictors are averaged for the period 2005-09, except for the coal-gas price ratio averaged for the period 2007-10. The lagged outcome is taken in 2009 instead of 2012. The synthetic UK comprises seven countries with a weight above 1%: Ireland (45.8%), Slovakia (23.1%), Finland (15.3%), the Czech Republic (3.3%), the Netherlands (3.1%), Sweden (2.3%) and Denmark (1.1%).

Leave-one-out test Another common test recommended by Abadie et al. (2010) is the leave-one-out test, which consists in running the synthetic control method again after iteratively removing each country that receive a positive weight in the synthetic UK baseline estimates. If the results change significantly when a country is removed, it means that the estimated effect may have been caused by the evolution of emissions for that country, rather than by the change in UK emissions. Figure 7 shows that the results change very little across the alternative donor pools. This test suggests that my estimate of abatement is not driven by the presence of a specific country in the donor pool.



(a) Absolute per capita emissions



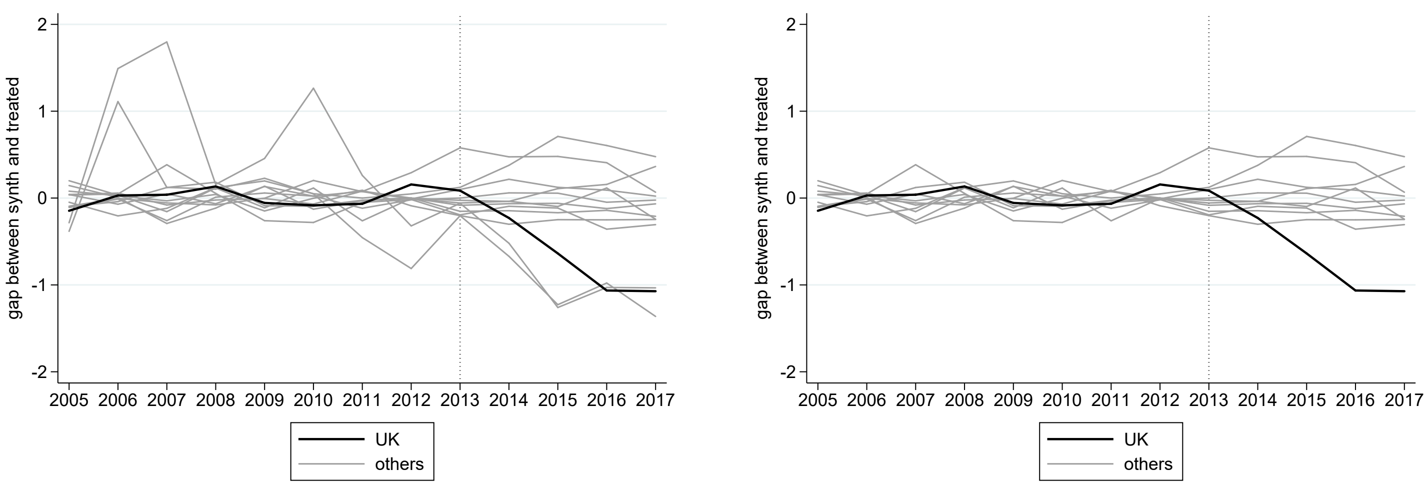
(b) Emission gap between treated and synthetic

Figure 7: Leave-one-out test

Notes: Synthetic UK for the main specification: five countries: Ireland (49.2%), Slovakia (25.6%), the Netherlands (13.7%), Finland(5.8%), Czech Republic (5.7%). Specification without Ireland: four countries: the Netherlands (45.9%), Spain (38%), Denmark (8.6%), and the Czech Republic (7.5%). Specification without Slovakia: five countries: Ireland (52.5%), France (18.4%), the Netherlands (17.5%), the Czech Republic (6.2%) and Finland (5.4%). Specification without the Netherlands: four countries: Ireland (58.0%), Slovakia (26.2%), Finland (10.2%), and Poland (5.7%). Specification without Finland: thirteen countries: Ireland (47.9%), Slovakia (20.5%), the Netherlands (18.8%), Poland (11.1%), all other countries have a weight below 1%. Specification without the Czech Republic: five countries: Ireland (50.9%), Slovakia (22.3%), the Netherlands (14.2%), Poland (6.6%), and Finland (5.9%).

Permutation test The permutation test consists in building a synthetic counterfactual for each country of the donor pool. Then, the gap between each country and its synthetic counterpart is compared with the gap obtained for the UK in the main results section. If for many countries the gap is as large as for the UK, it means that the gap obtained for the UK could have happened just by chance, rather than as a result of the introduction of the CPS. Figure 8a shows the gap between the treated and synthetic country for the UK and all the other countries in the donor pool. For the Czech Republic and France, having respectively the highest and lowest per capita emissions, and for Italy, it is impossible to find a convex combination of countries that will replicate the pre-2013 emissions. These countries are therefore not included. For Denmark and Finland, the pre-2013 fit is poor, with a pre-treatment MSPE more than 10 times greater than the UK.[37] Comparing the UK emission gap with these countries is less meaningful since the conditions for a good synthetic control are not met. Hence Figure 8b drops these two countries, as advised by Abadie et al. (2010). The UK stands out as having the largest decrease in per capita emissions after 2013.

To illustrate the difference in the magnitude of pre- and post-2013 emission gap between the UK and the other permutations, one can also compute the ratio of post to pre-MSPE for all countries (Abadie et al., 2010). We should expect to observe an unusually high ratio for the UK. Figure 9 shows that the UK ratio is indeed the largest, both with the upper bound and lower bound estimates of abatement. We can calculate the estimated probability to observe an effect as large as the one observed for the UK under a random permutation of the intervention on the data, by dividing the number of countries having a higher ratio than the UK by the total number of countries (Abadie et al., 2010). Here the UK has the highest ratio amongst the 13 countries, so the associated probability is $1/13 = 7.7\%$, the lowest possible probability with this sample size.



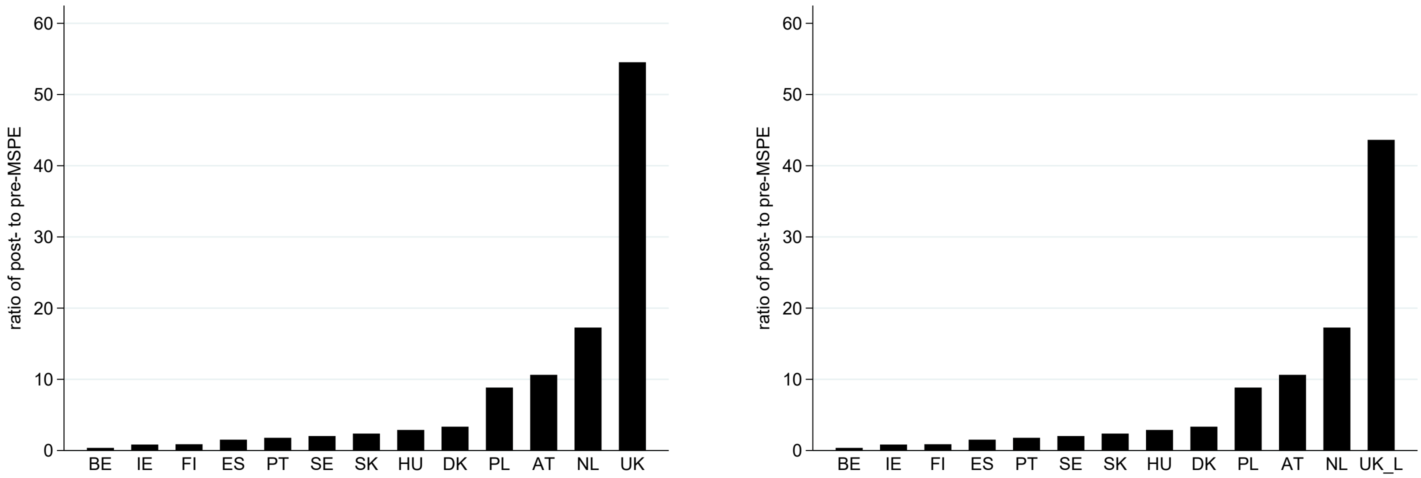
(a) All countries

(b) W/o countries with a large MSPE

Figure 8: Permutation test

Notes: In both figures, the Czech Republic, France and Italy are not included: for these countries it is impossible to find a convex combination of countries replicating pre-2013 emissions. On figure b, the two countries with an MSPE 10 times higher than the UK, Denmark and Finland, are not included.

[37] As mentioned in appendix A.1, Denmark and Finland have a high variability in emissions, likely explained by the large inter-annual variations in renewable sources available for electricity generation.



(a) Upper bound

(b) Lower bound

Figure 9: Ratio of post to pre-MSPE

Notes: the Czech Republic, France and Italy are not included: for these countries it is impossible to find a convex combination of countries replicating pre-2013 emissions.

4.4 Risk of spillovers

For the synthetic control method to identify the causal impact of the intervention, candidate units for the synthetic control group should not be affected by the intervention. As an overlapping policy to an existing carbon market, The CPS could spill over to other European countries' power sectors via two channels highlighted by Perino et al. (2019): internal leakage, that is, an increase in UK net electricity imports from other European countries; or a waterbed effect, that is, an increase in emissions from European power plants not subject to the CPS, due to the negative effect of the CPS on ETS permit prices under a fixed emission cap. Quantifying the magnitude of these two effects for the EU carbon market as a whole goes beyond the scope of this paper, which focuses on the impact of the CPS on UK emissions. What I endeavor to assess is the risk of spillovers to countries entering the synthetic UK, given that they serve as a counterfactual.

I first estimate the amount of emissions from countries in the synthetic UK potentially caused by import spillovers. This amount is naturally bounded by the limited interconnection capacity of the UK with the rest of Europe. I then estimate the amount of emissions in the synthetic UK potentially caused by a waterbed effect. The two effects combined represent

11% of the estimated abatement of the lower bound.

Risk of spillover via increased electricity imports: UK net electricity imports per capita are generally low compared to other European countries (see Figure A.2b), representing 2% of gross electricity consumption in the 2005-2012 period. However, net imports increased to 5% of gross electricity consumption in the 2013-2017 period. If this increase was caused by the CPS, it could threaten the identification strategy because two of the UK trading partners, Ireland and the Netherlands, have a combined weight of 63% in the synthetic UK. The increase in UK net imports would then increase the synthetic UK's emissions *as a result of the CPS* and contaminate the counterfactual. The question is how large in magnitude this contamination is, relative to the estimated abatement. I calculate the maximum amount of synthetic UK emissions that may have been directly caused by the CPS, considering that the increase in UK electricity imports from France, the Netherlands and Ireland after 2012 was entirely caused by the CPS[38]. I estimate the emissions associated with these exports for Ireland and the Netherlands (those countries entering the synthetic UK). In Appendix A.12, I run another test where I exclude all interconnected countries from the donor pool to assess whether the presence of Ireland and the Netherlands in the synthetic UK would drive up the results. The estimated abatement is 14% lower without interconnected countries, but the balance in predictors' characteristics is also less good.

First, I calculate the excess electricity generation in the Netherlands and in Ireland which can be imputed to CPS-induced exports to the UK: to do so, I simply calculate, for every post-treatment year, the difference between electricity exports to the UK that year and average electricity exports to the UK in the pre-treatment period. I use electricity trade statistics from Ofgem to determine quarterly trade flow for each interconnector with the

[38] Guo and Newbery (2020) estimate that 0.9% of the CO_2 emission reduction taking place in the UK between 2015 and 2018 was undone by the increase in electricity imports from France and The Netherlands. I cannot use this estimate because the time period is different, the estimated UK emission reduction is based on a different method - a dispatch model of the 2015 GB power system, see Kong Chyong et al. (2020) -, and the paper only considers France and the Netherlands (two markets coupled with the UK in 2014, which enabled cross-border electricity trading to take place as soon as market prices were different across the two sides of the interconnection) but not Ireland, which represents half of the synthetic UK.

UK.[39] I estimate that on an average year between 2013 and 2017, the Netherlands produced an excess of 2,965 GWh and Ireland produced an excess of 382 GWh.

Second, I calculate the emissions associated with this electricity generation. The emission intensity of this displaced generation depends on which technology is used for marginal generation. According to Guo and Newbery (2020), gas is the marginal fuel most of the time in the Netherlands. Furthermore, the emission intensity of fuel displaced by renewable energy in Ireland in 2012 was estimated at 0.43 tCO_2e/MWh (Sustainable Energy Authority of Ireland, 2014), which is close to the emission intensity of gas in the UK. Assuming a marginal intensity of 0.43 tCO_2e/MWh both in the Netherlands and in Ireland, the excess emissions caused by the CPS are 6.4 $MtCO_2e$ over the 2013-2017 period in the Netherlands, and 0.8 MtCO2e in Ireland (exporting less to the UK than the Netherlands).[40]. Third, I remove these excess emissions from Dutch and Irish emission data over the 2013-2017 period. I then assess how the emission trajectory of the synthetic UK changes when these excess emissions are removed.[41]

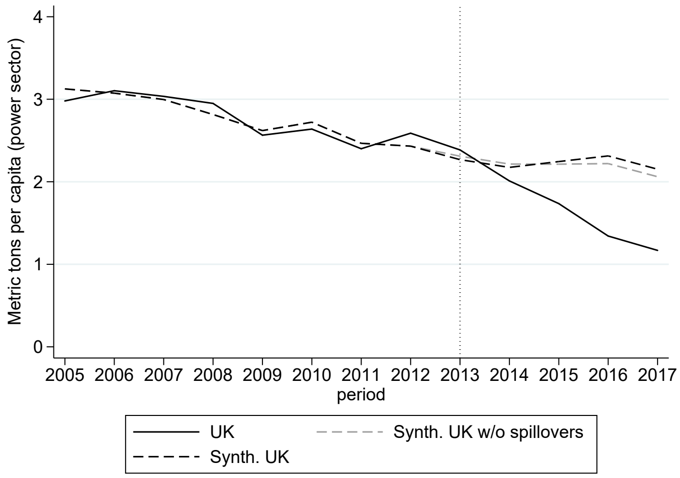
Figure 10a shows how the trajectory of the synthetic UK emission changes after removing these "leaked" emissions from Ireland and the Netherlands. Net imports from both the Netherlands and Ireland are higher than the pre-treatment average in 2015, 2016 and 2017, such that removing the estimated "leaked" emissions reduces emissions from the synthetic UK.[42] Overall, the gap between the UK and synthetic UK is smaller than when these

[39] Since the Netherlands-UK interconnector only became fully operational in April 2011, I average trade flows between the second quarter of 2011 and the fourth quarter of 2012 to get average trade flow pre-treatment (I include the first quarter of 2013 in the post-treatment period to be consistent with the rest of the analysis). For Ireland-UK trade, I consider separately the interconnectors between Ireland and Northern Ireland, open for the entire pre-treatment period and for which I average trade flows for the 2005-2012 period, and the interconnector between Ireland and Wales (East-West interconnector), which only opened in September 2012 and for which I only consider the trade flow of the last quarter of 2012.

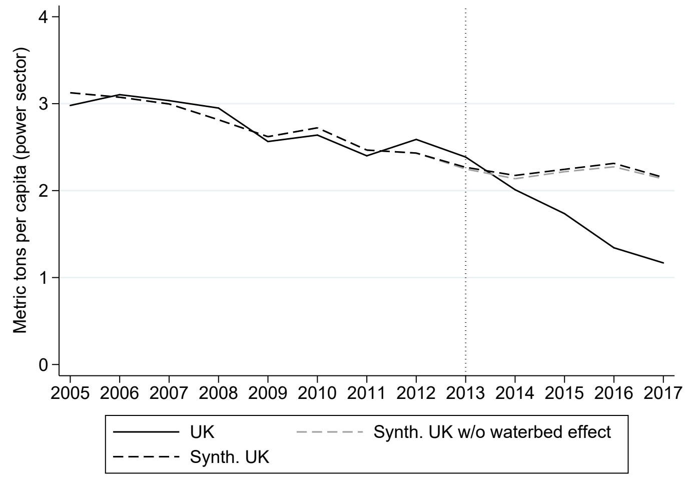
[40] If I instead calculate emissions assuming that gas is the marginal fuel, with an emission intensity of 0.4 tCO_2e/MWh (which is the average for the UK, see (Abrell et al., 2019)), these excess emissions are 5.9 $MtCO_2e$ in the Netherlands and 0.8 $MtCO_2e$ in Ireland . If I assume that coal is the marginal fuel, with an emission intensity of 0.89 tCO_2e/MWh (which is the average for the UK, see (Abrell et al., 2019)), the excess emissions are 13.2 MtCO2e for the Netherlands and 1.7 $MtCO_2e$ for Ireland.

[41] I do not impute these excess emissions back to the UK because the goal is not to estimate the impact of the CPS net of leakage, but rather to accurately estimate the impact of the CPS on UK emissions by making sure that the counterfactual does not include spillover effects.

[42] Emissions slightly increased in the modified synthetic UK in 2013 and 2014, because net imports from



(a) UK and synthetic UK w/o imports spillovers



(b) UK and synthetic UK w/o waterbed effect

Figure 10: Spillover risk

Notes: The synthetic UK comprises five countries: Ireland (49.2%), Slovakia (25.6%), the Netherlands (13.7%), Finland(5.8%), and the Czech Republic (5.7%). UK emission values include estimated counterfactual emissions in the absence of biomass conversion for Lynemouth and Drax plants.

spillovers are not accounted for, which is expected. The resulting cumulative abatement is smaller by 5% compared to that estimated in section 4.2.

Risk of spillover via a waterbed effect Theoretically, the waterbed effect designates the mechanism via which, under a common emission cap (in this case the cap set by the ETS carbon market), any emissions reduction in a given country only leads to an increase in emissions elsewhere (Böhringer et al., 2008; Goulder and Stavins, 2011; IPCC et al., 2014; Perino, 2018). The waterbed effect would arise because the CPS decreases demand for emission permits from UK installations subject to a higher carbon price. On the EU ETS market as a whole, the shift to the left of the demand curve can only be compensated by a price decrease, since the supply is fixed and perfectly inelastic because of the emission cap. With cheaper permits, individual installations subject to the ETS but not to the CPS can buy more allowances and emit more. Aggregate emissions remain unchanged.

The concern for the empirical strategy is a waterbed effect affecting the power installa-

Ireland decreased during this period and were not compensated by the increase in net imports from the Netherlands given the much higher weight of Ireland than the Netherlands in the synthetic UK.

tions included in the synthetic UK. This risk exists but the magnitude of the effect is likely to be small for two reasons. First, UK power installations represent only a small share of the total ETS market (in 2012 they represented 8.8% of total emissions covered by the EU ETS), so the demand-side shock from UK power installations is likely to be small. To illustrate this, Figure 10b simulates a 100% waterbed effect scenario. Under this scenario, the decrease in UK power sector emissions after 2013[43] is assumed to be caused by the CPS and be compensated by an equivalent increase in emissions coming from other ETS installations. Observed power sector emissions outside the UK therefore include a waterbed effect component, compared to what non-UK emissions would have looked like in the absence of the CPS. Assuming that the waterbed effect was spread across the different sectors and countries based on their share in ETS emissions in 2012, I estimate the waterbed effect component for each country's power sector. I then estimate each country's adjusted, *lower* emission value excluding the waterbed effect component[44]. Figure 10b shows the emission trajectory for the modified UK emission variable (corresponding to the lower bound estimate), and for the synthetic UK after removing the hypothesized waterbed component. Given the low weight of UK power installations in the market's total emissions, the waterbed effect component is small once spread over all ETS countries, and the adjusted synthetic UK emissions are only slightly higher than in the main specification. The magnitude of this waterbed component is similar to that of the import spillover component estimated above: the cumulative abatement based on Figure 10b is also smaller by 5% compared to that estimated in section 4.2.

The second reason why a strong waterbed effect is unlikely linked to the specific context of the EU ETS in the 2013-2017 period. At the time, there was a structural oversupply of allowances on the ETS, leading market participants to *bank* more allowances (Ellerman et al., 2016). In this context, if cheaper ETS permits were purchased by non-UK power installa-

[43] using the modified UK emission variable, the one including emissions from biomass converted plants if they had not converted to biomass.

[44] To take a concrete example: in 2014, UK emissions were lower by 25 $MtCO_2e$ than in 2013; Ireland represents 1.2% of ETS power sector emissions in 2012 (excluding the UK); power installations represent 66% of emissions in the whole ETS; the 2014 waterbed component for Ireland is estimated to be $1.2\% \times 66\% \times 25 = 0.2 MtCO_2e$, which represents 1.8% of Ireland's observed power sector emissions in 2014.

tions, these permits are likely to have been banked for future use rather than transformed in contemporaneous emissions, leaving synthetic UK emissions uncontaminated.

Overall, the combined effect of internal leakage and the waterbed effect likely contributed to increasing emissions from other European countries, but this increase is deemed to be small. Emissions in the synthetic UK are thus slightly overestimated compared to what they would be in the absence of the CPS. Taking out the simulated import spillovers and waterbed components from the synthetic UK yields a gap between the UK and synthetic UK that is about 18 $MtCO_2e$ lower than if we assume spillovers to be insignificant.

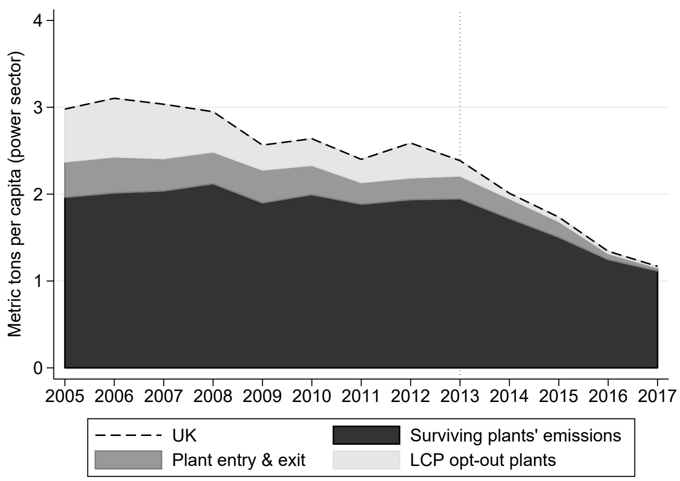
5 Discussion

5.1 Channels contributing to emission reduction

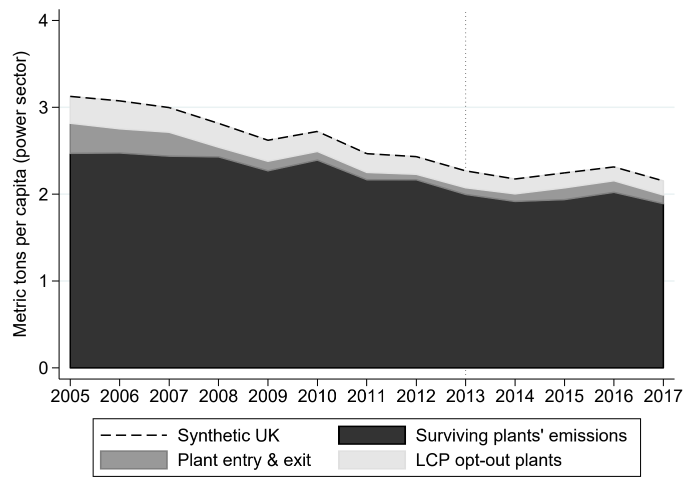
My results suggest that in the absence of the CPS, UK power sector emissions would have been higher by between 143 and 191 $MtCO_2e$. The upper bound is the SCM estimate assuming that biomass conversion was caused by the CPS, that other UK-specific policies had a negligible impact, and that spillovers were negligible. The lower bound estimate extracts from the upper bound 1)the estimated effect of biomass conversion 2) an upper bound for the CfD and capacity market, and 3) an upper bound for import spillovers and the waterbed effect. The corresponding percent decrease in emissions is between 20.5% and 26% per year on average.

Using the plant-level emission data, I estimate the relative contribution of three mechanisms contributing to emission reductions, based on the lower bound estimation from section 4.2: 1) the decrease in the emission intensity of existing plants; 2) the closure of plants having not opted out from the LCP directive; and 3) the differentiated behaviour of UK LCP opt-out plants induced by the CPS. Figure 11 shows the results from this decomposition for the UK and synthetic UK: emissions from installations present in the EUTL data every year over the 2012-2017 period are in black; emissions from installations which appear in the

EUTL data or disappear from it between 2012 and 2017 (which I interpret as a plant entry in the first case and a plant exit in the second case) are in medium grey; and emissions from LCP opt-out installations are in light grey. The difference in black areas reflects the impact of the CPS at the intensive margin (excluding LCP opt-out plants), that is to say how much more or less existing plants emit as a result of the policy. The difference in medium grey areas reflects the impact of the CPS at the extensive margin (excluding LCP opt-out plants), or how much more or less power plants enter and exit the market as a result of the policy; finally, the difference in black areas between the UK and synthetic UK before and after 2013 captures the impact of the CPS on the emission trajectory of LCP opt-out plants.



(a) UK



(b) Synthetic UK

Figure 11: per capita CO_2e emissions by source, UK and synthetic UK, lower bound estimation

Notes: For each period, the variable of per capita emissions corresponds to the sum of CO_2e verified emissions from power installations subject to the EU ETS except those in the UK converted to biomass, divided by the average country population that year. The synthetic UK comprises five countries: Ireland (49.2%), Slovakia (25.6%), the Netherlands (13.7%), Finland(5.8%), and the Czech Republic (5.7%).

Drawing on the difference-in-difference methodology, I calculate for each component the difference between the average pre-treatment and post-treatment emissions, between the UK and synthetic UK. For the pre-treatment period, I take the average over the 2009-2012 period rather than the 2005-2012 period, given that UK and synthetic UK opt-out emissions were different before 2009. These back-of-the-envelope calculations suggest that the different behaviour of LCP opt-out plants contributed roughly 52 $MtCO_2e$ over the 2013-2017 period (difference in the light grey areas). The intensive margin excluding opt-out plants contributed roughly 45 $MtCO_2e$ over the 2013-17 period (difference in the black areas). The extensive margin excluding opt-out plants contributed roughly 50 $MtCO_2e$ over the 2013-17 period (difference in the medium grey areas). This extensive margin effect is the combined effect of having more emission reductions from coal-fired plants shutting down in the UK than in the synthetic UK[45]; and also fewer high-emission plants entering the market in the UK compared to the synthetic UK[46].

5.2 Comparison of the results with existing estimates

Two other working papers, by Abrell et al. (2019) and Gugler et al. (2020), assess the impact of the CPS on emissions reductions, using a different data coverage and different methods. In terms of data coverage, Gugler et al. (2020) consider the 2013-2015 period and Abrell et al. (2019) focus on the 2013-2016 period. Both papers also estimate emissions at the monthly or hourly level by combining hourly generation data with estimated plant-specific emission factors. Doing so, they are able to allocate emissions from January to March 2013 to the pre-treatment period, while I use annual emission data and have to allocate all the 2013 emissions to the pre-treatment period.

The annual results reported by Gugler et al. (2020) using a Regression Discontinuity in Time (RDiT) imply a cumulative abatement of 39 $MtCO_2e$ over the 2013-2015 period. If I restrict my estimates to the 2013-2015 period, I find a cumulative abatement of between 36 $MtCO_2e$ (lower bound from section 4.2) and 51 $MtCO_2e$ (upper bound from section 4.1).

[45]Two large coal-fired UK plants shut down in the period considered while they had neither opted-out from the LCP or IED directives: Rugeley power station closed in March 2012 and Longannet power station closed in March 2016. For Rugeley, the official reason was "a "continued fall in market prices" and increases in carbon costs" (Source: https://www.bbc.com/news/uk-england-stoke-staffordshire-35526894). For Longannet, the official reason was that it was it was ""uneconomic to continue"[..]because of the high transmission charges and carbon taxes."(Source: https://www.theguardian.com/environment/2016/mar/24/longannet-power-station-closes-coal-power-scotland).

[46]three new Dutch coal-fired plants entering the market in 2015 explain the increase in synthetic UK emissions at the extensive margin after 2014

Their results are thus included in my estimate range and are consistent with mine.

Abrell et al. (2019) estimate counterfactual generation for treated plants using a machine learning algorithm based on a short-run equilibrium model of the electricity wholesale market, and find a cumulative abatement of 26 $MtCO_2e$ over the 2013-2016 period. If I restrict my own estimates to the same period, the abatement lies, in contrast, between 100 $MtCO_2e$ (lower bound from section 4.2) and 120 $MtCO_2e$ (upper bound from section 4.1). Abrell et al mention that their estimate "should best be viewed as providing a lower-bound empirical estimate of the environmental effectiveness of the UK carbon tax" (Abrell et al. (2019), p41), and the difference between our results is likely explained by the difference in data coverage and methodology. The main difference is that Abrell et al. only consider large gas- and coal-fired plants running for the whole period of analysis (from 2009 to 2016), while I include all types of power plants, including those closing or opening during the period in question. Doing so allows me to measure the impact of the CPS at the extensive margin and gauge how the CPS interacted with the LCP directive to accelerate closure, while the scope of Abrell et al is more specific to the intensive margin channel identified in section 5.1.

Based on the decomposition analysis from the previous section, I find an abatement of 14.5 $MtCO_2e$ at the intensive margin over the 2013-2016 period. This estimate is closer to the order of magnitude estimated by Abrell et al. It is lower, which may be due to three factors: first, the difference in the method used; second, the difference in the emission scope: the emissions included in my "intensive margin" channels do not overlap perfectly with the emissions included in Abrell et al[47]; third, the difference in the time frame, as my estimate for 2013 includes the Jan-March 2013 period, three winter months with a presumably high electricity consumption where the carbon tax was not yet in force.

[47]Some of the plants they consider are not included in my "intensive margin" emissions, but are instead in the "extensive margin" (for plants that closed in 2016, such as Rugeley) or in the "lcp opt-out" channels; essentially the other way around, some plants included in my "intensive margin" are not included in Abrell et al's analysis, such as the plants from Northern Ireland, not subject to the CPS.

6 Conclusion

My findings suggest that the carbon tax implemented in the UK power sector in 2013 resulted in a large decrease in carbon emissions due to several concurrent mechanisms: a decrease in carbon emissions of plants remaining in the market, a stronger response of opt-out plants to the LCP Directive than in countries with no carbon tax, and the closure of several high-emitting plants. While an advantage of the SCM method applied to aggregated plant-level data is that it takes into account different channels via which carbon pricing impacts emissions, one limitation is that it does not allow for the estimation of heterogeneous treatment effects across the different treated plants.

From the point of view of its effectiveness, the CPS policy can be considered successful. I find that the CPS tax decreased emissions by between 20.5% and 26% per year on average. The estimated cumulative abatement represents between 60% (lower bound estimate) and 81% (upper bound estimate) of the abatement necessary to achieve the target set for the second carbon budget. While this is not the focus of this paper, other work suggests that this abatement has been achieved at a relatively low cost (Gugler et al., 2021).

Regarding the external validity of the results, it is important to keep in mind three factors that arguably enabled the tax to have such a high impact on abatement with limited carbon leakage: the relatively high potential for fuel switching from coal to gas, the relative isolation of the UK from other electricity markets that limited the risk of carbon leakage, and the context playing against new investments in high-emission generation. Several countries meet these criteria and could be good candidates to replicate the UK experience, in particular in Europe, Russia and the US (Wilson and Staffell, 2018). Avoiding carbon leakage may be more difficult for countries with strong interconnections, but a solution could be to implement a carbon price floor at the regional level (Newbery et al., 2019). Finally, my results suggest that the interaction between increasingly stringent regulations of industrial emissions and a carbon price accelerated several plant closures. Such a context is likely to be found in other countries too, given the global trend towards more stringent air quality regulations.

References

Abadie, A. (2021). Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects. *Journal of Economic Literature*.

Abadie, A., A. Diamond, and J. Hainmueller (2010, June). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association 105*(490), 493–505.

Abadie, A., A. Diamond, and J. Hainmueller (2015). Comparative Politics and the Synthetic Control Method. *American Journal of Political Science 59*(2), 495–510.

Abadie, A. and J. Gardeazabal (2003, March). The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review 93*(1), 113–132.

Abrell, J., M. Kosch, and S. Rausch (2019). How Effective was the UK Carbon Tax?—A Machine Learning Approach to Policy Evaluation. *Working Paper*.

Andersson, J. J. (2019). Carbon Taxes and CO2 Emissions: Sweden as a Case Study. *American Economic Journal: Economic Policy*.

Ares, E. and J. Delebarre (2016). The Carbon Price Floor. Technical report, House of Commons Library.

BEIS (Department for Business, Energy & Industrial Strategy) (2019). UK Coal statistics.

Böhringer, C., H. Koschel, and U. Moslener (2008). Efficiency losses from overlapping regulation of EU carbon emissions. *Journal of Regulatory Economics 33*(3), 299–317.

Brown, G. (2017). British power generation achieves first ever coal-free day. *The Guardian*.

Colmer, J., R. Martin, M. Muûls, and U. J. Wagner (2020). Does Pricing Carbon Mitigate Climate Change? Firm-Level Evidence From the European Union Emissions Trading Scheme. *CRC TR 224 Discussion Paper Series*.

Cropper, M. L., R. D. Morgenstern, and N. Rivers (2018). Policy Brief—Facilitating Retrospective Analysis of Environmental Regulations. *Review of Environmental Economics and Policy 12*(2), 359–370. Publisher: Association of Environmental and Resource Economists.

Ellerman, A. D., C. Marcantonini, and A. Zaklan (2016). The European Union Emissions

Trading System: Ten Years and Counting. *Review of Environmental Economics and Policy 10*(1), 89–107.

Ellerman, A. D. and M. McGuinness (2008). CO2 Abatement in the UK Power Sector: Evidence from the EU ETS Trial Period. *Working Paper*.

European Commission (2001). Large Combustion Plants Directive (2001/80/EC).

Evans, S. (2015). Old coal and gas plants won largest share of capacity market, final results confirm. *Carbon Brief*. [Online; accessed 12. Jan. 2021].

Evans, S. (2019). Analysis: UK electricity generation in 2018 falls to lowest level since 1994. *Carbon Brief*.

Gobillon, L. and T. Magnac (2016). Regional Policy Evaluation: Interactive Fixed Effects and Synthetic Controls. *The Review of Economics and Statistics 98*(3), 535–551.

Goulder, L. H. and R. N. Stavins (2011). Challenges from State-Federal Interactions in US Climate Change Policy. *American Economic Review 101*(3), 253–257.

Green, J. F. (2021). Does carbon pricing reduce emissions? A review of ex-post analyses. *Environmental Research Letters*.

Gugler, K., A. Haxhimusa, and M. Liebensteiner (2020). Carbon Pricing and Emissions: Causal Effects of Britain's Carbon Tax. *Working Paper*.

Gugler, K., A. Haxhimusa, and M. Liebensteiner (2021). Effectiveness of climate policies: Carbon pricing vs. subsidizing renewables. *Journal of Environmental Economics and Management 106*, 102405.

Guo, B. and D. Newbery (2020). The Cost of Trade Distortion: Britain's Carbon Price Support and Cross-border Electricity Trade. *Cambridge Working Papers in Economics* (2014). Publication Title: Cambridge Working Papers in Economics.

Hirst, D. (2018). Carbon Price Floor (CPF) and the price support mechanism. Technical Report Number 05927, House of Commons Library.

HM Revenue & Customs (2017). Excise Notice CCS 1/6: a guide to carbon price floor. Technical report.

IPCC (2015). *Climate Change 2014: Mitigation of Climate Change: Working Group III Contribution to the IPCC Fifth Assessment Report*. Cambridge: Cambridge University Press.

IPCC, E. Somanathan, T. Sterner, T. Sugiyama, D. Chimanikire, N. K. Dubash, J. Essandoh-Yeddu, S. Fifita, L. Goulder, A. Jaffe, X. Labandeira, S. Managi, C. Mitchell, J. P. Montero, and F. Teng (2014). National and Sub-national Policies and Institutions. In *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.*

Isaksen, E. T. (2020). Have international pollution protocols made a difference? *Journal of Environmental Economics and Management 103*, 102358.

Jaraite, J., T. Jong, A. Kazukauskas, A. Zaklan, and A. Zeitlberger (2016). Ownership links and enhanced EUTL dataset. Accepted: 2019-10-16T15:43:28Z Publisher: European University Institute, RSCAS, FSR Type: dataset.

Kim, M.-K. and T. Kim (2016). Estimating impact of regional greenhouse gas initiative on coal to gas switching using synthetic control methods. *Energy Economics 59*, 328 – 335.

Kong Chyong, C., B. Guo, and D. Newbery (2020). The Impact of a Carbon Tax on the CO2 Emissions Reduction of Wind. *The Energy Journal 41*(1).

Lee, K. and R. T. Melstrom (2018, October). Evidence of increased electricity influx following the regional greenhouse gas initiative. *Energy Economics 76*, 127–135.

Martin, R., L. B. de Preux, and U. J. Wagner (2014, September). The impact of a carbon tax on manufacturing: Evidence from microdata. *Journal of Public Economics 117*, 1–14.

Martin, R., M. Muûls, and U. J. Wagner (2016, January). The Impact of the European Union Emissions Trading Scheme on Regulated Firms: What Is the Evidence after Ten Years? *Review of Environmental Economics and Policy 10*(1), 129–148.

Metcalf, G. E. and J. H. Stock (2020). The Macroeconomic Impact of Europe's Carbon Taxes. *NBER Working Papers* (w27488).

Newbery, D. M., D. M. Reiner, and R. A. Ritz (2019). The Political Economy of a Carbon Price Floor for Power Generation. *The Energy Journal 40*(1).

OFGEM (2013). Electricity interconnectors.

Perino, G. (2018). New EU ETS Phase 4 rules temporarily puncture waterbed. *Nature Climate Change 8*, 262–264.

Perino, G., R. A. Ritz, and A. v. Benthem (2019). Overlapping Climate Policies. *NBER Working Papers* (25643). Publication Title: NBER Working Papers.

Rafaty, R., G. Dolphin, and F. Pretis (2020). Carbon pricing and the elasticity of CO2 emissions. *INET Working Paper* (20116).

Rivers, N. and B. Schaufele (2015). Salience of carbon taxes in the gasoline market. *Journal of Environmental Economics and Management 74*, 23–36.

Rocha, M., B. Hare, P. Yanguas Parra, N. Roming, U. Ural, A. Ancygier, J. Cantzler, F. Sferra, H. Li, and M. Schaeffer (2016, November). Implications of the Paris Agreement for Coal Use in the Power Sector. Technical report, Climate Analytics.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational Psychology 66*(5), 688.

Shearer, C., N. Mathew-Shah, L. Myllyvirta, A. Yu, and T. Nace (2019). Boom and bust 2019. Tracking the Global Coal Plant Pipeline. pp. 14.

Singhal, P. (2019). Are Emission Performance Standards Effective in Pollution Control? Evidence from the EU's Large Combustion Plant Directive. *Working Paper* (ID 3297528).

Staffell, I. (2017, March). Measuring the progress and impacts of decarbonising British electricity. *Energy Policy 102*, 463–475.

Sustainable Energy Authority of Ireland (2014). Quantifying Ireland's Fuel and CO2 Emissions Savings from Renewable Electricity in 2012.pdf. Technical report.

Van den Bergh, K. and E. Delarue (2015). Quantifying CO2 abatement costs in the power sector. *Energy Policy 80*, 88–97.

Vaughan, A. (2018). UK government spells out plan to shut down coal plants. *The Guardian*.

Wilson, I. A. G. and I. Staffell (2018). Rapid fuel switching from coal to natural gas through effective carbon pricing. *Nature Energy 3*(5), 365–372. Number: 5 Publisher: Nature Publishing Group.

World Bank (2021). State and Trends of Carbon Pricing 2021. Technical report, Washington, DC, USA.

World Bank and Ecofys (2018). State and Trends of Carbon Pricing 2018.

A Online Appendix

A.1 Evolution of per capita emissions, demand, trade and emission intensity in the UK and other countries

Per capita power sector emissions : Figure A.1 shows the evolution of per capita power sector emissions for the UK and twenty other European countries[48], using emission data described in section 3.2. While the UK was among the top emitters before 2013, by 2017 its emissions were rather ta the bottom of the distribution.

Demand, trade and emission intensity channels The CPS may impact each of the three channels mentioned in section 2.2: demand, because the CPS increases the marginal cost of producing electricity, and generators are likely to at least partially pass on this cost to consumers, as evidenced in Kong Chyong et al. (2020) and Ares and Delebarre (2016). Trade, because the CPS increases the relative cost of domestically produced electricity compared to imported electricity. Emission intensity, because the CPS can directly impact the fuel mix used for electricity generation, in the short-term and in the long-term. In the short-term, the higher tax on coal relative to gas increases the cost of coal-fired relative to gas-fired power generation. In the long-term, the CPS also makes it less profitable to operate plants running on fossil fuels. The CPS may dampen investments in those plants and encourage investments in low-carbon generation (Van den Bergh and Delarue, 2015). In the next paragraphs, I show how demand, trade and emission intensity evolved over time in the UK compared to other European countries.

Demand, trade and intensity channels Figure A.2 shows the evolution of the three channels of demand, trade and emission intensity. Demand is defined as power consumption per capita, trade is defined as net electricity imports per capita, and emission intensity is

[48]all 28 EU countries except Romania, Bulgaria, Slovenia, Croatia, Malta, Cyprus, and Luxembourg, which are not included in the empirical analysis (see section 3.2)

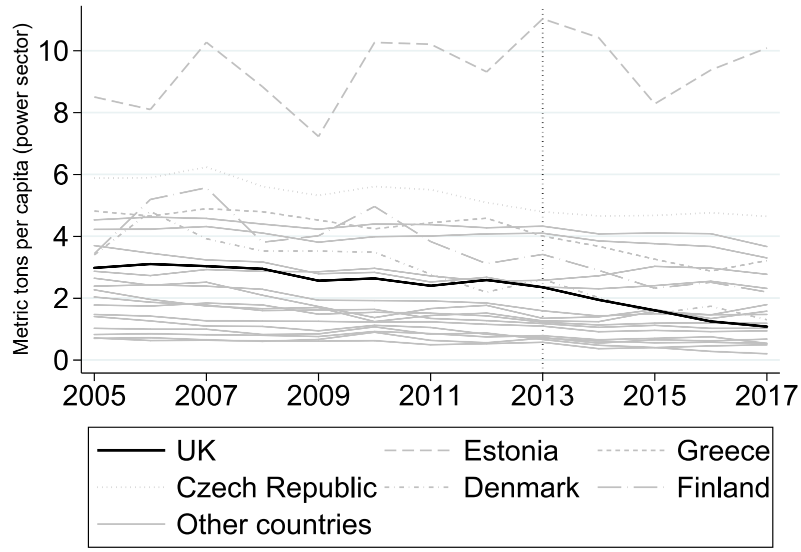


Figure A.1: Per capita power sector emissions in European countries

Notes: Country-level power sector emissions are obtained by summing installation-level emissions for ETS participants identified as power generators at the country level. Country-level power sector emissions are then divided by annual country population to obtain per capita values. "Other countries" include twenty European countries: Austria, Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, the Netherlands, Poland, Portugal, Slovakia, Spain, Sweden.

defined as emissions per gigawatt-hour (GWh) of domestic power production. The three variables are de-meaned in the same way as in Figure 2a. Demand decreases over the whole period in the UK compared to other European countries (figure A.2a). There is no obvious break in trend in 2013. This continuous decrease is consistent with the continuous improvement of energy efficiency in buildings and electric appliances in the UK since 2009 (Staffell, 2017). The lack of a visible link between the CPS and a change in demand can be linked to the finding by Kong Chyong et al. (2020) that only about 60% of the CPS cost has been passed through to the GB day-ahead electricity market. It can also be explained by the financial compensation received by electro-intensive industries to cushion the price effect of the CPS and protect their competitiveness[49] (Hirst, 2018).

Regarding the trade channel, UK net imports per capita are low compared to other coun-

[49] Electro-intensive industries have received a compensation of around £100 million for the period April 2013 to March 2015, and the support has been extended to 2019-2020. This compensation scheme is a specific component of a larger Energy Intensive Industries support introduced to compensate the cost increase induced by climate change policies (Hirst, 2018).

tries (Figure A.2b). Being an island, the UK can only trade electricity via undersea cables and has a limited trading capacity. At the period of interest, the UK can trade electricity with three countries only: via undersea interconnectors with France, the Netherlands and the Republic of Ireland from Great Britain, and via ground connections with the Republic of Ireland from Northern Ireland. Between 2010 and 2012, the UK increased its trading capacity by 50%[50], and UK net imports increased from 2,661 GWh to 11,864 GWh. Net imports increased further between 2012 and 2015, but at a lower rate (from 11,864 GWh to 20,938 GWh), before decreasing in 2016 and 2017. Although imports started to increase before 2013, their increase after 2013 could be associated with the CPS. Using an econometric model of electricity trade, Guo and Newbery (2020) estimate that the CPS increased GB imports by 12,000 GWh per year between 2015 and 2018, after market coupling with France and the Netherlands in 2014. However, taken per capita and compared to other European countries, UK electricity trade remains low: between the 2005-2012 and the 2013-2017 period, UK net imports per capita increase from representing 2% of gross electricity consumption to representing 5% of gross electricity consumption.

In contrast to demand and trade, the UK emission intensity of power generation decreased markedly after 2013 compared to most other European countries (Figure A.2c)[51]. Noting e_i the average emission intensity of technology i used for electricity generation and q_i the share of gross electricity production covered by technology i, the emission intensity $\frac{Q_{CO_2e}}{Q_{elec}}$ can be further decomposed as:

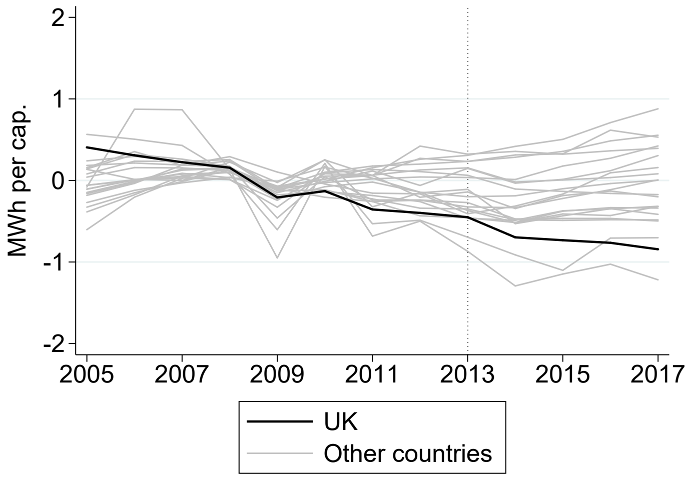
$$\frac{Q_{CO_2e}}{Q_{elec}} = \sum_i e_i q_i \tag{8}$$

Power generation with renewable and nuclear energy sources is emission-free[52]. What

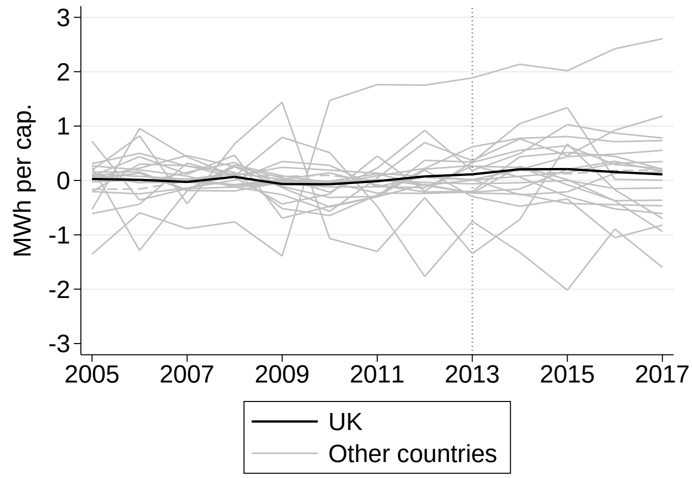
[50]Great Britain became interconnected with the Netherlands in 2011, and in 2012 a new undersea interconnector with the Republic of Ireland was completed (OFGEM, 2013)

[51]The outlier with large variations in the emission intensity is Finland, again due to a large inter-annual variation in generation from renewables.

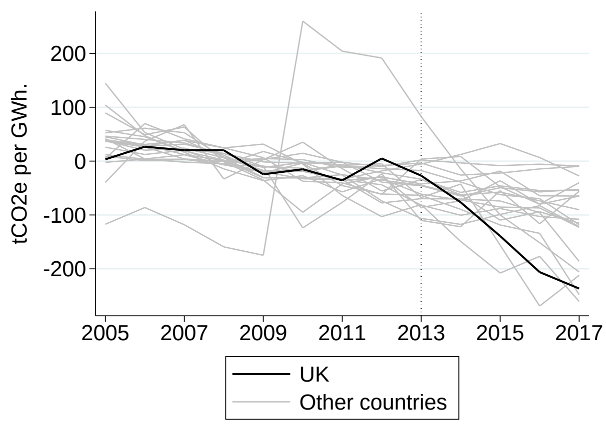
[52]These technologies embody some lie-cycle emissions, but generation itself does not emit CO_2. An exception is for plants using biomass: they do release greenhouse gases, but are not bound to pay the ETS price nor the CPS because the carbon released when solid biomass is burnt is expected to be re-absorbed



(a) De-meaned demand per capita



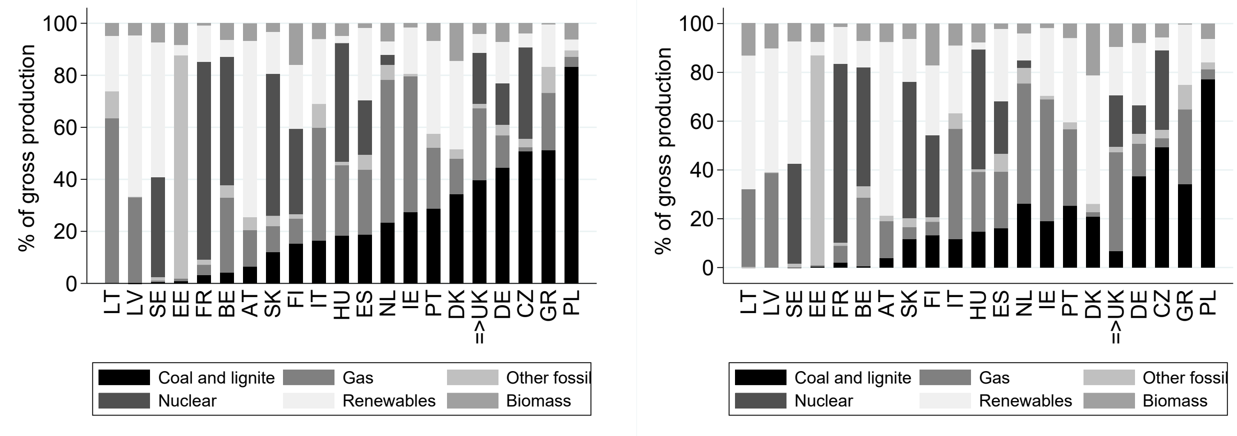
(b) De-meaned net imports per capita



(c) De-meaned emissions per unit of electricity output

Figure A.2: Channels: evolution of electricity demand, trade and emission intensity in the UK and other European countries

Notes: The de-meaned variables were obtained by taking the difference between the initial variable and its average over the 2005-2012 period. "Other countries" include twenty European countries: Austria, Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, the Netherlands, Poland, Portugal, Slovakia, Spain, Sweden.



(a) 2012 (b) 2017

Figure A.3: Power sector's input fuel mix in EU countries, 2012 and 2017

Notes: EU countries are ranked by ascending order of the share of coal in electricity generation in 2012, from left to right. LT: Lithuania; LV: Latvia; SE: Sweden; EE: Estonia; FR: France; BE: Belgium; AT: Austria; SK: Slovakia; FI: Finland; IT: Italy; HU: Hungary; ES: Spain; NL: The Netherlands; IE: Ireland; PT: Portugal; DK: Denmark; UK: United Kingdom; DE: Germany; CZ: the Czech Republic; GR: Greece; PL: Poland. The legend from left to right corresponds to the histogram bar colors from bottom (coal and lignite) to top (biomass). Data come from Eurostat. Renewables include production from hydro, solar, wind, and tide, wave and ocean.

matters in this equation, therefore, is the share of fossil fuel in total electricity generation on the one hand, and the emission intensity of fossil fuel generation on the other hand. Figure A.3 shows the technologies/fuels used for power generation for each European country in 2012 and in 2017. The countries are ranked by their 2012 coal share. The UK coal share fell by 30 percentage points between the two periods, while there was only little variation in most other European countries. The decrease in the coal share was compensated by an increase in the gas share (+ 14 percentage points (pp)), in the share of non-biomass renewables (+ 9 pp) in the biomass share (+ 5 pp) and in the nuclear share (+ 2 pp).

A.2 Potential confounders

This section details the policies implemented at the European or UK level around the same time period as the CPS, which may have contributed to emission reductions.

during tree growth.

European level: LCP Directive and IED Thirteen UK power plants opted out from the LCP Directive. Nine of them, including five coal-fired plants, fully opted out and shut down between 2012 and 2015, and four other plants opted out only partially[53]. These 13 opt-out plants represented 11% of UK power sector emissions in 2011. The LCPD-induced plant closures could explain part of the decrease in the emission intensity of UK domestic production seen on figures A.2c if there were more opt-out plants shutting down in the UK than elsewhere in Europe.

The LCPD was replaced by the IED in 2016. The IED was enacted in 2010 and has a similar opt-out option as the LCPD. Plants had to decide by 2013 whether they wanted to opt-out or not under a limited lifetime derogation (LLD). Under the LLD opt-out option, plants are exempted from the emission standards but cannot not operate for more than 17,500 hours between 1 January 2016 and 31 December 2023, and have to shut down once they have run for 17,500 hours or in 2023 (whichever comes first). Two UK power plants opted out from the IED[54]. Given that plants had until 2013 to decide whether to opt-out or not and the CPS was announced in 2011, the IED opt-out decision was endogenous to the CPS.

UK level: support to biomass conversion The UK government supported the conversion of coal-fired power plants to biomass burning starting from 2012. This support first took the form of dedicated Renewables Obligation Certificates (ROCs). The ROCs were part of the broader Renewables Obligation scheme designed to support the deployment of large-scale renewable electricity generation; they created an obligation for electricity suppliers to source a proportion of their electricity from plants with ROCs. The ROCs were replaced by the FID Enabling for Renewables scheme in 2012, and then by the Contract for Difference scheme (CfD) introduced in 2014 as part of the 2013 Electricity Market Reform. Two coal-fired plants received government support for conversion to biomass burning: the

[53]see https://www.eea.europa.eu/data-and-maps/data/large-combustion-plants-lcp-opted-out-under-article

[54]The list of IED opt-out plants is available here: https://www.eea.europa.eu/data-and-maps/data/industrial-reporting-under-the-industrial-3

Drax plant and the Lynemouth plant. The Drax plant, representing 14% of UK power sector emissions in 2012, had already started to co-fire biomass in 2004. The company owning the plant, Drax group, announced its intention to fully convert three of its six units to biomass in September 2012. The plant benefited from Renewable Obligations Certificates for the conversion of its two first units, which were completed in 2013 and 2014 respectively, and from the FID Enabling for Renewables scheme for the conversion of its third unit, which was completed in 2016. By 2017, the last period considered in this analysis, three of the six units were converted to biomass, and the three remaining units continued to run with coal[55]. The Lynemouth plant, much smaller than Drax in terms of production capacity,, also received support under the FID Enabling for Renewables scheme. The plant stopped burning coal and started the biomass conversion process in December 2015[56].

The biomass conversion of these two plants led to a decrease in their carbon emissions over the 2013-2017 period, since biomass is considered a zero-emission fuel. These emission reductions should not be imputed to the CPS. However, the government may have decided to support the biomass conversion of coal-fired plants partly as an attempt to reduce the economic costs associated with the CPS for coal plant owners. In this case, the biomass conversion could be viewed as a direct consequence of the CPS.

UK level: Support to renewable energy other than biomass. Beyond their impact on the biomass conversion of coal plants, the FID Enabling for Renewables and CfD schemes could have impacted the fuel mix by increasing the share of renewable energy in UK electricity production over the 2013-2017 period. However, only few CfD projects became operational over that period, representing a low production capacity. I estimate an upper bound of the policy effects by using the official database on the daily CfD generation by CfD unit[57], which includes an estimation of the electricity generation and associated GHG avoided thanks to

[55] https://www.drax.com/about-us/our-history/

[56] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/805441/LCP_Review_Lynemouth_DD-FP3137CG-V009-draftdecision.pdf

[57] available here: https://www.lowcarboncontracts.uk/data-portal/dataset/actual-cfd-generation-and-avoided-ghg-emissions

CfD generation, by day and by CfD unit. Summing up avoided CfD generation across all the CfD units - except for the biomass conversion projects which effect is estimated seperately - gives a total CfD generation of 1,509 GWh over the 2013-2017 period. This represents just 0.4% of the total electricity generated with renewable energy sources in the UK over that period. The associated avoided GHG emissions are estimated to be 0.5 $MtCO_2e$ over that period. This result relies on the implicit assumption of an average emissions intensity of 0.33 MtCO2e per Megawatt-hour of electricity generated (0.5/(1,509/1000)=0.33). To estimate an upper bound of the policy impact on emissions, I take a more conservative approach and assume that absent CfD generation, these Megawatt-hours would have been produced by coal-fired plants. I take the average capacity-weighted emission rate of UK coal-fired plants reported by Abrell et al. (2019) of 0.89 tCO_2/MWh, and obtain associated avoided GHG emissions of 1.3 $MtCO_2e$[58] over the 2013-2017 period. This amount represents only 0.3% of total UK power sector emissions over the period.

Other support policies to renewable energy exist in the UK, but the bundle of feed-in-tariffs, support to R&D for renewable energy, and regulatory instruments does not look fundamentally different from that implemented in other European countries, according to the IEA's Policies and Measures Database listing the support policies implemented in each country since the 1970s[59]. All in all, the decrease in emissions observed after 2013 in the UK and not elsewhere may be partly driven by a UK-specific support to biomass conversion, but not by another UK-specific support to renewable energy.

UK level: capacity market The capacity market introduced in 2013 may impact emissions in two ways: first, before the capacity payment starts, securing a capacity contract can incentivize investing in new capacity, as auction payments can be seen as a subsidy for new power generation. Indeed, the capacity market was initially supposed to facilitate in-

[58] $1,509.10^3 \times 0.89 = 1,343,423$ tCO_2e

[59] The database can be accessed here: https://www.iea.org/policies. For the electricity sector only, there were more than 200 support measures in force in the 28 EU countries over the period considered. Examining each piece of legislation goes beyond the scope of this article.

vestments in new gas capacity (Evans, 2015). Second, once the capacity payment starts, the payment can keep a plant being economically profitable even with at low generation levels. The first auction took place in 2014 for capacity secured for 2018, and most of the following auctions have this 4-year lag between the auction and the start of the contract. Since my 2013-2017 period of analysis is before the auction payments start, the capacity market can only impact UK emissions via the first channel.

I combine data on new-build plants being awarded a contract between 2014 and 2017 [60] and data listing all UK power plants with a capacity greater than 20MW with the year of commission or year generation began [61], to gauge if the capacity market incentivized the construction of plants having a lower-than-average emission intensity over the 2013-2017 period. Only six plants were awarded a capacity contract in 2014, 2015, 2016 or 2017 and had a date of commissioning/where generation began between 2014 and 2017. One is a large gas-fired plant (CCGT), Carrington power station. The five others are smaller waste plants. The opening of Carrington power station cannot be imputed to the capacity market because the plant received planning permission before the capacity market was launched, in 2008[62].

On the other hand, the five waste plants may have opened as a direct consequence of being awarded a capacity contract, and have a lower-than-average emission intensity. These five plants generate zero emissions and represent an installed capacity of 1,141 MW. To estimate the associated avoided GHG emissions, I first calculate the generation associated with this capacity. I assume that generation began on January 1st of the year indicated in the variable "year of commissioning/where generation began", which is conservative. I take as a load factor the average load factor for conventional steam plants in the UK averaged over 2013-2017[63], which is 35%. I obtain an upper bound of the low-carbon power generation imputable to the capacity market of 2,590 MWh over the 2013-2017 period. This represents

[60] available at: https://www.emrdeliverybody.com/CM/Registers.aspx

[61] available at: https://www.gov.uk/government/statistics/electricity-chapter-5-digest-of-united-kingdom- DUKES 5.11 file

[62] https://www.power-technology.com/projects/carrington-gas-fired-power-station-manchester/

[63] data available at: https://www.gov.uk/government/statistics/electricity-chapter-5-digest-of-united-kingdom-energy-statistics-dukes, DUKES 5.10 file)

0.6% of the UK electricity generated with renewable sources and 0.2% of total electricity generation. If this electricity had been generated with coal-fired plants instead, it would have caused CO_2e emissions of 2.3 MtCO_2e[64] over the 2013-2017 period, assuming an average emission intensity of 0.89tCO_2e/MWh for the coal-fired generation. These 2.3 MtCO_2e can be seen as an upper bound of the capacity market impact over the 2013-2017 period. It represents just 0.5% of UK power sector emissions over the period.

A.3 Identification of power installations

The EUTL plant-level emission data do not provide information on which plant is a power generator. The UK-based think-tank Ember (formerly Sandbag) gave me access to EUTL emission data for the 2008-2016 period, supplemented with an indicator variable identifying all power plants. This identification was performed internally by Ember in two steps: in the first step, Ember carried out an exact matching based on a file circulated by the European Commission in 2014, containing a list of individual participants with their sectoral classification. This classification is based on the European statistical classification of economic activities, NACE rev2. It contains two-digit *divisions*, divided into three-digit *groups*, themselves divided into four-digit *classes*. Power installations are generally found in division 35 "Electricity, gas, steam and air conditioning supply", group 35.1 "Electric power generation, transmission and distribution", class 35.11 "Production of electricity". Ember classified as a power installation all the ETS participants with class 35.11. In the second step, Ember identified other power installations which either were not classified in class 35.11 (for example because they were part of an industrial site), or started operations after the file was circulated by the European Commission, based on desk-based research and manual matching. For the verified emissions variable, the data provided by Ember are the same as the raw data retrieved from the EUTL.

The Ember dataset only covers the 2008-2016 period and does not give the power plant

[64] $2,590.10^3 \times 0.89 = 2,305,100$ tCO_2e

status for ETS participants leaving the market before 2008 or joining in 2017 (my last period of analysis). There are no ETS installations entering the market in 2017. To retrieve the power plants status of the few plants that shut down before 2008, I used the "Accounts to Firms Matching" dataset hosted by the Florence School of Regulation (FSR) (Jaraite et al., 2016), listing participating installations until 2013 with their Nace rev 2 sectoral classification. I first matched the FSR and Ember data to check the quality of Ember's power sector classification. Among the installations found in both the FSR and Ember data, 100% of the division 35 installations having sectoral class 35.11 according to the FSR data are classified as power installations by Ember. 96% of the division 35 installations with a sectoral class different from 35.11 are also classified as power installations by Ember.[65]

To be consistent with Ember's classification, I classify the few plants only present in the FSR but not in the Ember dataset as power installation when their group is 35. This way, I identify 314 additional power plants which shut down before 2008. Finally, I identify 4 additional installations having a missing sectoral division as power installations based on their name (containing "power station" or its equivalent in one of the European languages). Finally, there are only 0.8% of ETS installations for which the power plant status is missing and which report positive emissions over the period considered.

A.4 Data sources

Coal-to-gas price ratio (predictor used in the main specification): To my knowledge, there is no harmonized series of country-level coal-to-gas price ratio for the period considered. I thus build a price ratio variable combining coal trade data from Eurostat and gas wholesale price data for large industrial consumers, also from Eurostat. The coal trade

[65]Installations from sectoral class 35.11 represent only 30% of the installations classified by Ember as power installations, but 80% of the carbon emissions. Installations from division 35 but with a different class from 35.11 represent 61% of Ember's power installations, but only 7% of emissions. Installations from division 35 but with a missing division or a missing class represent another 6% of Ember's power installations, and 11% of emissions. The remaining 3% of Ember's power installations, representing just 1% of emissions, have a division that is either different from 35, or missing.

data reported in Eurostat comes from Comext, the official source for EU trade statistics[66]. I aggregate the price and volume data for all the CN6 codes designating categories of coal that may be used for coal generation[67] and obtain average nominal unit prices for imported coal. I fill the few data gaps by applying the growth rates from the closest non-missing data source, the IEA nominal coal price index for industry[68]. For the countries for which both data are available, the obtained coal price series compare well with the IEA price series in the electricity generation sector.

For gas, I use Eurostat data on wholesale gas prices for non-household consumers[69]. I take wholesale prices excluding VAT and other recoverable taxes and levies for the second largest consumption band. This band corresponds to the average consumption of large gas-fired power plants as reported in the European Environmental Agency's Large combustion plant database. I fill the few data gaps by imputing values from the third largest consumption band, or, if it is also missing, from the IEA gas price data [70]. One drawback of this data source is that the consumption band categories and the methodology changed in 2007, which makes it difficult to build a consistent series of coal/gas price ratio before 2007. I therefore only calculate coal-to-gas price ratios for the 2007-2016 period. I convert the obtained coal and gas price series to the same unit. I then divide the coal price by the gas price to obtain annual coal-to-gas price ratios for all European countries over the 2007-2016 period. The obtained price ratios compare well with the price ratios available from national statistical institutes for some countries[71].

[66] The data can be downloaded from the 'EU trade since 1988 by HS2,4,6 and CN8" table available here: https://ec.europa.eu/eurostat/web/international-trade-in-goods/data/database

[67] The coal subcategories included are: "anthracite whether or not pulverised, non agglomerated", "coal whether or not pulverised, non agglomerated" and "bituminous coal whether or not pulverised, non agglomerated"; the coal subcategories not included are: "coking coal whether or not pulverised, non agglomerated" and "briquettes, ovoids and similar fuels manufactured from coal", two subcategories not used for electricity generation.

[68] The data can be downloaded from here: https://www.iea.org/data-and-statistics/data-product/energy-prices#wholesale-and-retail-price-indices-for-energy-products

[69] The data can be downloaded from here:https://ec.europa.eu/eurostat/web/energy/data/database

[70] The IEA data can be downloaded from here: https://www.iea.org/data-and-statistics/data-product/energy-prices#end-use-energy-prices-and-taxes-for-oecd-countries

[71] For example, in the UK the Department for Business, Energy and Industrial Strategy publishes such data

Lignite resources (predictor used in the main specification): Data on lignite resources in Europe come from the European Association for Coal and Lignite, an industry body[72]. I create an indicator variable equal to 1 for countries with lignite resources greater than 0.5 Gt in 2012, and 0 otherwise. The variable is equal to one for Germany, Poland, Hungary, Greece, the Czech Republic, and Bulgaria.

Residual load per capita (predictor used in the main specification): Residual load is defined as the difference between electrical energy available for final consumption taken from Eurostat, and generation from renewables and nuclear power plants, also taken from from Eurostat[73]. Generation from renewables is the sum of total net electricity production from the five renewable sources hydro, tide wave and ocean, solar PV, solar thermal and wind[74]. Generation from nuclear power plants is the sum of total net electricity production from nuclear power plants, including conventional plants, auto producers, and co-generation plants. This variable is then divided by the average country population given by Eurostat.

Emissions from LCP opt-out plants in 2009 (predictor used in the main specification): The list of LCP opt-out plants is available on the European Environmental Agency's website[75]. Since there is no common identifier between the EUTL and LCP data, I manually matched the 172 LCP opt-out installations located in the UK or in a country from the donor pool to the EUTL emission data. I did the manual matching using information on the plant name and location. I successfully matched the two for all plants except two LCP opt-out plants, one from Finland and one from Poland. I then added up CO_2e emissions from the LCP opt-out power plants at the country-level to obtain a country-level variable of emissions from LCP opt-out plants. Finally, I divided the variable by country population to

each quarter, available here: https://www.gov.uk/government/collections/quarterly-energy-prices

[72] The data can be downloaded from here: https://euracoal.eu/info/euracoal-eu-statistics/

[73] The data can be downloaded from here: https://ec.europa.eu/eurostat/web/energy/data/database, "Production of electricity and derived heat by type of fuel" table

[74] geothermal, biomass and waste are not included since they are available on demand

[75] It can be downloaded from here: 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

obtain a per capita value.

Number of heating degree days (predictor used in the sensitivity analysis): The data is available on Eurostat[76].

Per capita capacity for combustible fuels, gas and coal (predictor used in the sensitivity analysis): The variable is derived from Eurostat data on electricity production capacities for combustible fuels by technology and operator[77]. I added up capacities across technologies and operators to obtain total installed capacity. I then divided by country population to obtain a per capita variable.

Growth in per capita renewables capacity (predictor used in the sensitivity analysis): The variable is derived from Eurostat data on net electrical maximum capacity by renewable technology[78]. I added up capacities for wind, solar, tide wave and ocean, hydro and geothermal, divided the capacities by country population to obtain per capita variables, and calculated the average annual growth rate between 2010 and 2012. 2010 is the year where the Europe 2020 strategy was adopted (including the target of increasing the share of renewable energy in final energy consumption to 20% by 2020), and 2012 is the last year before the introduction of the CPS.

Average age of operating coal-fired plants above 30 MWth (predictor used in the sensitivity analysis): The variable is derived from the Global Energy Monitor's "Global Coal Plant Tracker" (Shearer et al., 2019), a publicly available database categorizing every known coal-fired generating unit with a rated capacity above 30 MWth. I used information on the status of the unit (operating/retired/mothballed) and its commissioning date to build

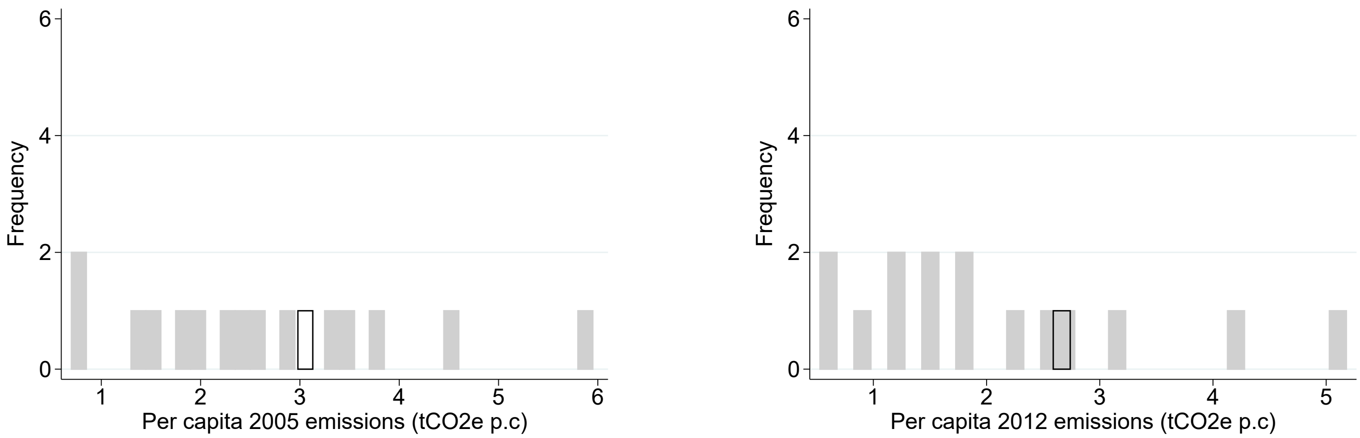
[76]It can be downloaded from here: https://ec.europa.eu/eurostat/web/energy/data/database, "cooling and heating degree days by country - annual data" table.

[77]The data is available here: https://ec.europa.eu/eurostat/web/energy/data/database, "Electricity production capacities by main fuel groups and operator" table

[78]The data is available here: https://ec.europa.eu/eurostat/web/energy/data/database, "Electricity production capacities for renewables and wastes" table

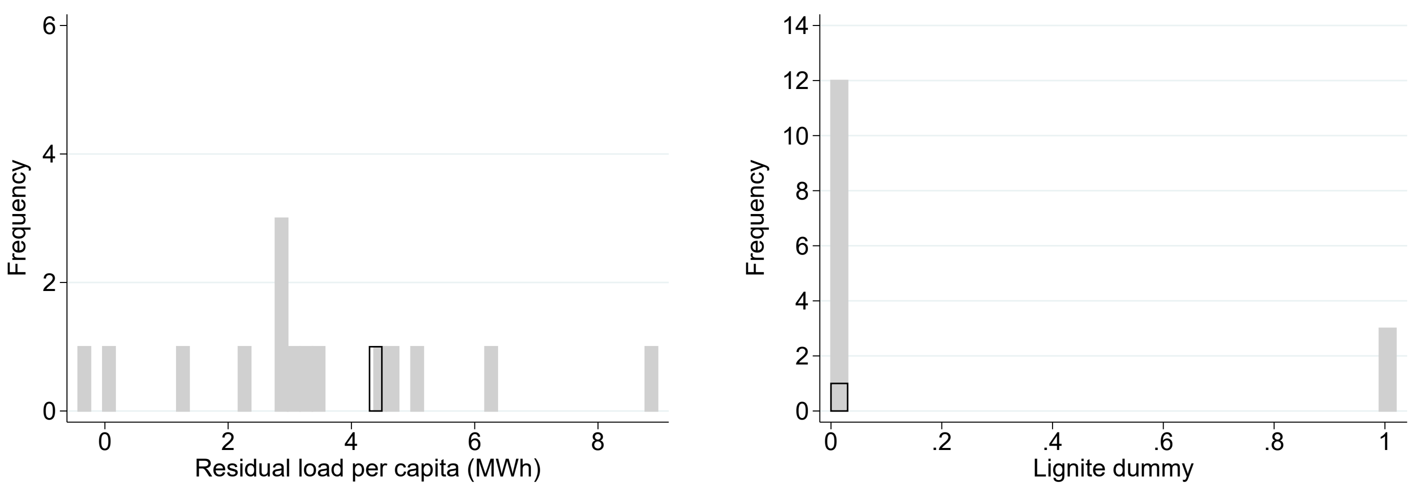
a country-level variable of the coal fleet's age, defined as the average capacity-weighted age of the coal-fired power plants operating every year.

A.5 Common Support for predictors



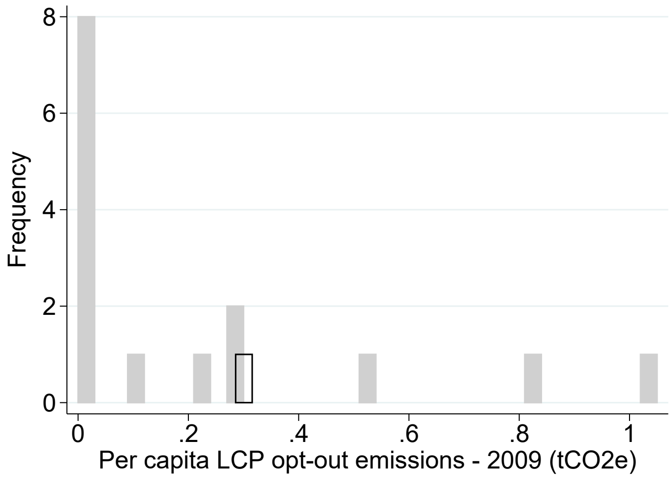
(a) Per capita CO_2e emissions (2005)

(b) Per capita CO_2e emissions (2012)

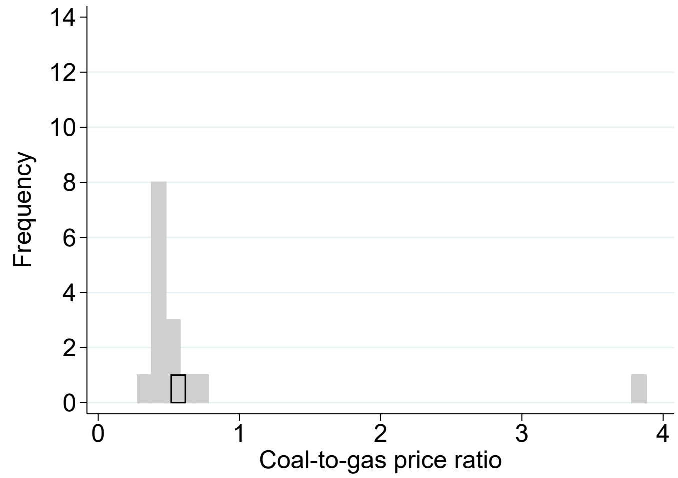


(c) Residual load per capita

(d) Lignite dummy



(e) LCP opt-out emissions per capita (2009)



(f) Coal-to-gas price ratio (2007-2012)

Figure A.4: Histograms of main predictors. UK: black with transparent fill; donor pool: grey fill.

Notes: Unless otherwise specified, all variables are averaged for the 2005-12 period

A.6 Counterfactual emissions in the absence of biomass conversion for Drax and Lynemouth plants

Table A.1: Counterfactual CO_2 emissions in the absence of biomass conversion, Drax

	(1) Total CO_2e	(2) Generation coal units (MWh)	(3) Estimated CO_2e coal units	(4) Estimated CO_2e biomass units w/o conversion	(5) Estimated CO_2e total w/o conversion (3)+(4)
2005	20,771,624	-	-	-	20,771,624
2006	22,764,847	-	-	-	22,764,847
2007	22,160,413	-	-	-	22,160,413
2008	22,299,778	-	-	-	22,299,778
2009	19,851,702	11,584,366	10,425,929	9,425,773	19,851,702
2010	22,392,487	13,537,600	12,183,840	10,208,647	22,392,487
2011	21,465,607	15,093,899	13,584,509	7,881,098	21,465,607
2012	22,694,684	14,592,305	13,133,075	9 561 609	22,694,684
2013	20,319,513	14,398,937	12,959,044	9 434 905	22,393,948
2014	16,595,193	13,364,881	12,028,393	8 757 339	20,785,732
2015	13,192,780	13,808,137	12,427,324	9 047 783	21,475,107
2016	6,261,692	7,120,958	6,408,862	4,666,008	11,074,871
2017	6,215,220	-	6,215,220*	4,525,026	10,740,246

Notes: column (1): emission data come from the EUTL. Column (2): generation data for the coal part over the 2009-2016 period come from Abrell et al. (2019). Column (3): emissions for the coal units over the 2009-2016 period were estimated by applying an average emission factor of 0.9 tCO_2/MWh, the average emission rate reported by Abrell et al. (2019) for Drax plant. *2017 Emissions are estimated to be the same as emissions for the entire plant as reported in column (1), since all biomass units are fully converted by then and emit zero CO_2. Column (4): emissions for the biomass units if they had not converted to biomass are estimated differently for the 2009-2012 and for the 2013-2017 period: for the 2009-2012 period, the units had not yet converted to biomass, so their emissions are simply the difference between EUTL emissions and emissions estimated for the coal units (column (1) - column (3)). For the 2013-2017 period, the units had started to convert to biomass, as reflected in the total EUTL data. Emissions if those units had not converted to biomass are estimated assuming that they would have followed the same evolution as emissions from the coal units: I multiply the estimated emissions for the coal units each year (column (3)) by the ratio of emissions from the biomass units over emissions from the coal units in 2012 (column (4)/column (3): 9,561,609/13,133,075=0.73). Column (5): total emissions in the absence of biomass conversion are simply the sum of estimated emissions for the coal units and estimated emissions for the biomass units if they had not converted to biomass (column (3) + column (4)).

Table A.2: Counterfactual CO_2 emissions in the absence of biomass conversion, Lynemouth

	(1) Total CO_2e	(2) Estimated CO_2e total w/o conversion
2005	2,685,512	2,685,512
2006	2,693,932	2,693,932
2007	2,695,748	2,695,748
2008	2,802,040	2,802,040
2009	2,543,017	2,543,017
2010	2,551,364	2,551,364
2011	2,612,450	2,612,450
2012	2,050,363	2,050,363
2013	2,284,177	2,284,177
2014	2,717,964	2,717,964
2015	1,287,305	1,287,305
2016	1,059	1,287,305 *
2017	2,421	1,287,305 *

Notes: Column (1): emission data come from the EUTL. Column (2): same as column (1), except in 2016 and 2017. *I assume that in absence of biomass conversion, emissions would have been the same in 2016 and 2017 as in 2015.

A.7 Estimated avoided emissions from CfD units

Table A.3: Estimated avoided emissions by CfD unit

	(1) Allocation round	(2) Technology	(3) Date of first generation	(4) Generation 2013-2017 (MWh)	(5) Avoided GHG 2013-2017 (tCO2e)	(6) Avoided GHG 2013-2017 coal (tCO2e)
Burbo Bank Extension Offshore Wind Farm	FID EfR	Off. Wind	11/04/2017	631,687	190,325	562,202
Dudgeon Phase 1	FID EfR	Off. Wind	27/04/2017	255,701	77,042	227,574
Dudgeon Phase 2	FID EfR	Off. Wind	02/08/2017	401,176	120,873	357,047
Dudgeon Phase 3	FID EfR	Off. Wind	01/10/2017	146,835	44,241	130,683
Walney Extension Offshore Wind Farm Phase 1	FID EfR	Off. Wind	19/12/2017	49,562	14,933	44,110
Charity Farm	AR1	Solar PV	30/06/2016	19,985	6,209	17,787
Triangle Farm Solar Park	AR1	Solar PV	18/07/2017	4,517	1 361	4,020
Total				1,509,464	454,982	1,343,423

Notes: Columns (1)-(5): data comes from the LCCC file on "Actual CfD Generation and avoided GHG emissions" (available here: https://www.lowcarboncontracts.uk/data-portal/dataset/actual-cfd-generation-and-avoided-ghg-emissions). In Column (2), "FID EfR" stands for "FID Enabling for Renewables" and "AR1" stands for "Allocation Round 1". In Column (3), "Off. Wind" stands for offshore wind; Column (6) is obtained by multiplying values from column (4) with the average emission factor of coal plants from Abrell et al. (2019), of 0.89 $MtCO_2e/MWh$.

A.8 Lower bound removing emissions from plants converted to biomass

I estimate a more conservative lower bound of the CPS impact accounting for biomass conversion, where I consider that the emission reductions from the two plants converted to biomass are entirely caused to the biomass conversion and not to the CPS. I apply the synthetic control method on a modified outcome variable, where emissions from UK plants having partly or fully converted to biomass are removed from the UK emissions for the entire period of analysis. The new per capita emission variable is 15% lower for the UK after removing emissions from these plants, while emissions from countries in the donor pool stay the same. I run the synthetic control method again based on the modified UK emission variable. It is harder to accurately build a synthetic UK using the initial set of predictors with this modified outcome. I therefore add a third predictor of lagged outcome for the year 2010. Figure A.5 shows the original UK and synthetic UK emission trajectories (in black) and the UK and synthetic UK emission trajectories for the modified outcome variable (dark grey).

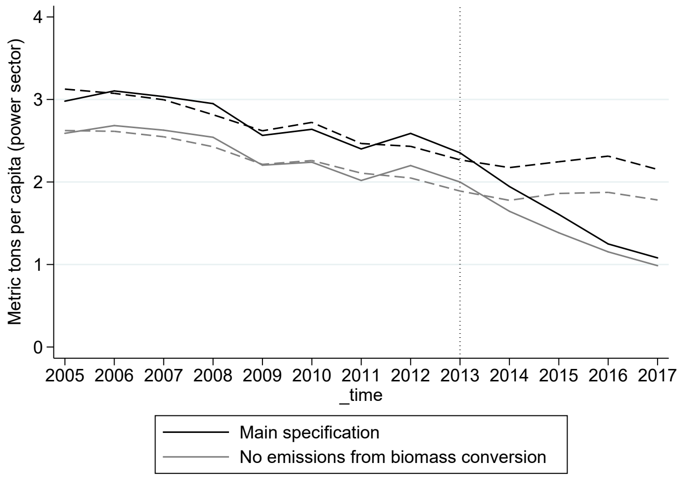
The new synthetic UK comprises seven countries: Italy (35.9%), Ireland (23.5%), Slovakia (21.3%), the Netherlands (15%), Finland (3%), Poland (0.4%), and Denmark (0.9%). Country weights are shown in table A.4. Table A.5 shows that predictors' values are still closely aligned across the actual and synthetic UK, except for the residual load per capita which is lower for the synthetic UK than for the UK. It makes sense because UK emissions from fossil plants, which typically cover this residual demand, have been made artificially lower than they truly are by removing the two plants converted to biomass.

The gap between the UK and synthetic UK per capita emissions is smaller than with the original outcome variable, which is expected. On an average year, emissions decrease by 18.1%. The total cumulative abatement is 132 million of tCO_2e. The difference between the total abatement from this lower bound and the one from section **??** is 164-132=32 $MtCO_2e$, which is close to the hypothesised emission decrease for Drax and Lynemouth if all their units had continued to run with coal, estimated to 26.5 $MtCO_2e$.

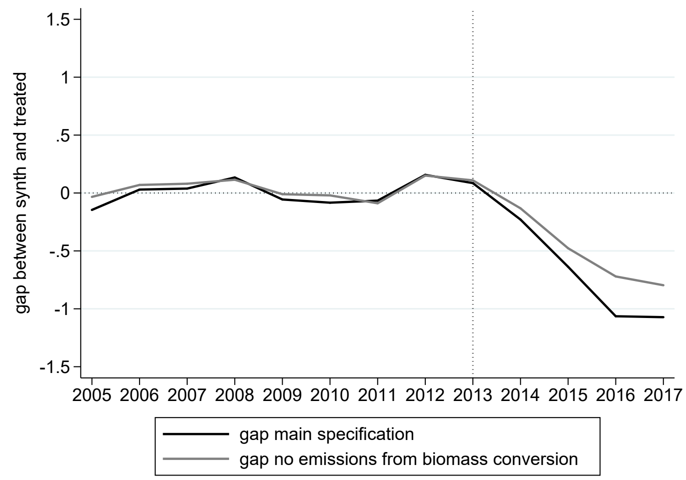
Table A.4: Country weights in Lower Bound synthetic UK

Country	**Weight**	**Country**	**Weight**
Austria	0	Ireland	0.235
Belgium	0	Italy	0.359
Czech Republic	0	Netherlands	0.15
Denmark	0.009	Poland	0.004
Spain	0	Portugal	0
Finland	0.03	Sweden	0
France	0	Slovakia	0.213
Hungary	0		

Note: All weights are between 0 and 1 because the Synthetic control method imposes positive weights summing to 1.



(a) Absolute per capita emissions



(b) Emission gap between treated and synthetic

Figure A.5: Synthetic control method excluding emissions from plants having converted to biomass

Notes: The synthetic UK comprises the following countries for each specification: Main specification: five countries: Ireland (49.2%), Slovakia (25.6%), the Netherlands (13.7%), Finland(5.8%), the Czech Republic (5.7%). Lower Bound synthetic UK without emissions from plants converted to biomass: seven countries: Italy (35.9%), Ireland (23.5%), Slovakia (21.3%), the Netherlands (15%), Finland (3%), Denmark (0.9%) and Poland (0.4%).

Table A.5: Predictors' values for the UK, synthetic UK and average of the donor pool, lower bound

Variable	**UK**	**Synth. UK**	**Avg. Donor pool**
Per capita residual load	4.29	4.27	3.37
Coal-gas price ratio	0.52	0.49	0.71
Per capita LCP opt-out emissions	0.29	0.29	0.22
Lignite dummy	0.00	0.004	0.20
Per capita emissions 2005	2.59	2.62	2.62
Per capita emissions 2010	2.24	2.26	2.39
Per capita emissions 2012	2.20	2.05	2.05

Notes: The per capita residual load is averaged for the period 2005-12, and the coal-to-gas price ratio for the period 2007-12. LCP opt-out emissions are taken in 2009, the lignite dummy is time-invariant. Outcome lags are taken in 2005, 2010 and 2012.

A.9 Sensitivity of the results to the choice of predictors

I test the sensitivity of the upper bound results to four alternative sets of predictors used to generate a synthetic UK. Note that the results would be the same if applied on the lower bound from part 4.2, since the composition of the synthetic UK is the same in the upper and lower bound. In the first alternative set of predictors, I replace the per capita residual load with the annual number of heating degree days, a variable approximating the demand for energy needed for heating, likely to capture variations in peak power demand mostly covered by fossil fuels[79]. In the second alternative set of predictors, I add as predictor a measure of installed capacity for combustible fuels. This variable may influence the potential for fuel switching. Ideally, one would like to add specific variables for coal installed capacity and gas installed capacity, but these variables are not publicly available for all countries in the donor pool.

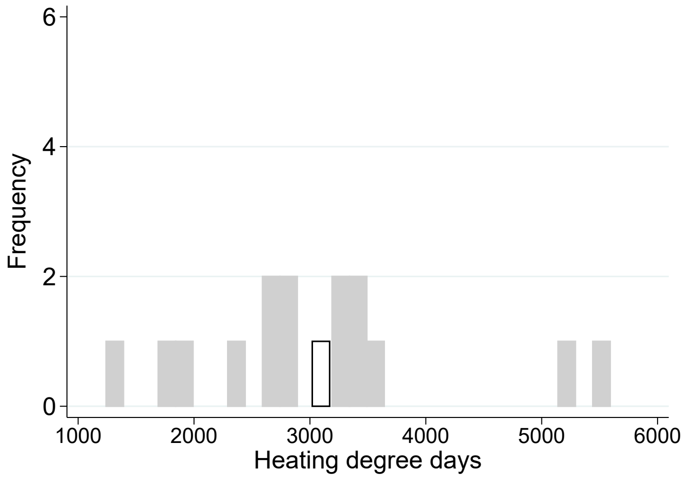
In the third alternative set of predictors, I add a predictor reflecting the growth in renewable capacity just before the introduction of the CPS. This variable can be considered as a proxy for the business-as-usual growth in renewables' capacity, which would occur absent the CPS policy. I average this variable between 2010 and 2012. 2010 is the year of implementation of the Europe 2020 strategy, which sets a target for the share of renewables in final energy consumption to be reached by 2020 for EU countries. This announcement may be followed by a growth in renewable capacity in all European countries. 2012 is the last year of pre-treatment, which makes sure that the growth in renewable capacity is not affected by the CPS.

In the last alternative set of predictors, I add a predictor reflecting the age of the fleet of coal plants for each country. More recent coal-fired plants tend to be more efficient and have a lower emission intensity. We may expect the average age of coal power plants to

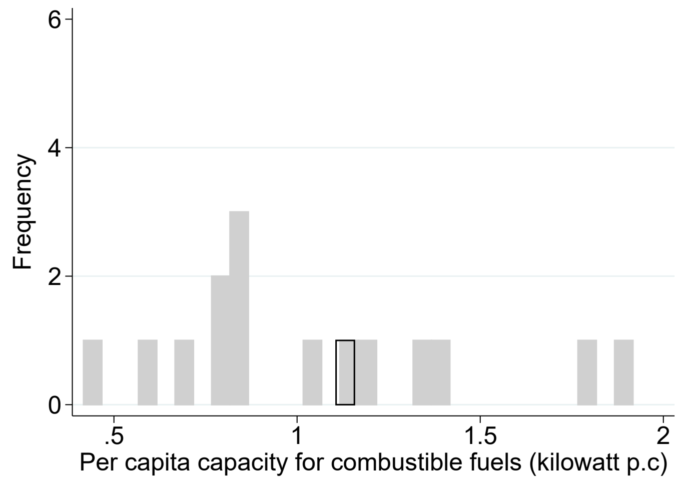
[79]In the EU, the number of heating degree days is measured as the number of days of the year where the average temperature is below a reference temperature of 15.5°C - under which energy for heating is needed - times the difference between this reference temperature and the temperature of the day. Compared with the average annual temperature used in other papers for predicting power demand, this variable better captures demand for power generation at low-temperature periods.

influence a country's emissions. Only plants with a capacity above 30 MWth are included in the calculation of the average age of coal plants at the country level because the data source only includes such plants (see appendix A.4) - but we expect these plants to be responsible for most of coal-based power generation.

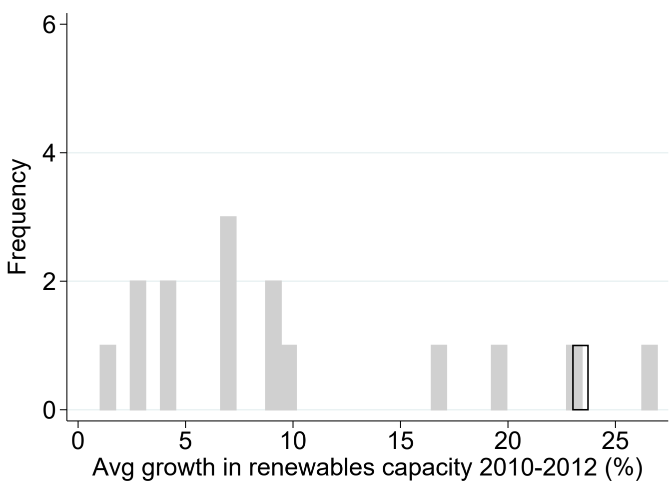
Figure A.6 shows the common support for these four predictors. For each predictor, the UK value falls within the distribution of other countries' values. Figure A.7 shows the emission paths for the different synthetic UKs obtained with these alternative sets of predictors. The country weights are indicated below the figure for each synthetic UK. The emission path of each new synthetic UK is relatively close to the original one. The fit is less good for the specification with the number of degree days and the one with the average age of coal-fired plants. Table A.6 shows the predictors' values for the UK, for the original synthetic UK, and for the four alternative synthetic UKs. The alternative predictors' values are close between the UK and the different synthetic UKs. For the synthetic UK using the growth in renewable capacity as predictor (Alt. 3) and the synthetic UK using the average age of coal-fired plants (Alt. 4), having close values for the new predictor comes at the expense of a poorer predictor balance for some of the other predictors (lignite dummy and per capita opt-out emissions for Alt.3; lignite dummy and residual load per capita for Alt.4).



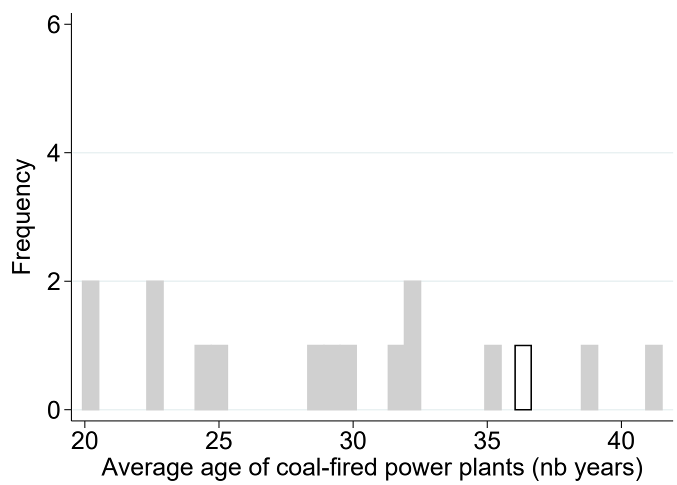
(a) Number of heating degree days



(b) Per capita capacity for combustible fuels



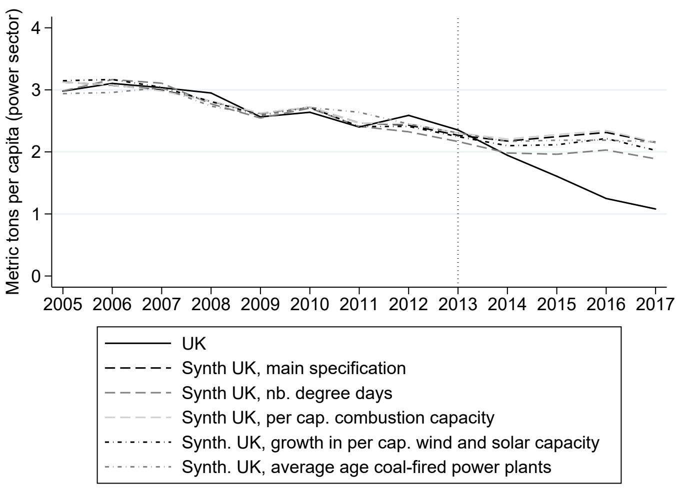
(c) Average annual growth in per capita renewables capacity (2010-2012)



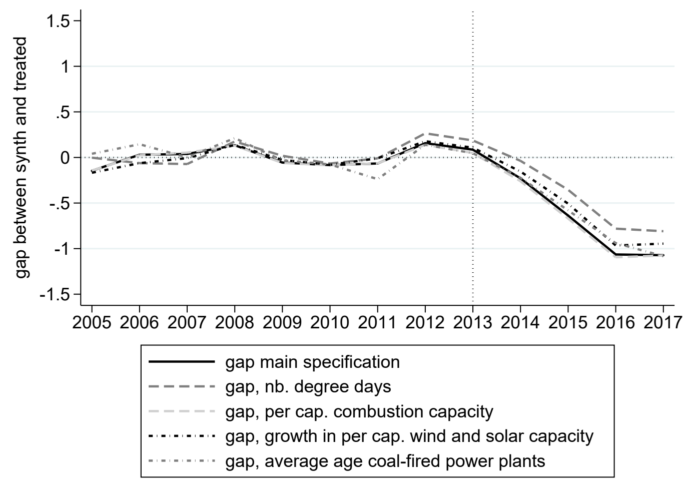
(d) Average age of operating coal-fired power plants

Figure A.6: Histograms of predictors used in the sensitivity analysis (UK: black with transparent fill; donor pool: grey fill)

Notes: Unless otherwise specified, all variables are averaged for the 2005-12 period



(a) Absolute per capita emissions



(b) Emission gap between treated and synthetic

Figure A.7: Sensitivity analysis: alternative set of predictors

Notes: The synthetic UK is composed in the following way for the different specifications: Main specification: five countries: Ireland (49.2%), Slovakia (25.6%), the Netherlands (13.7%), Finland(5.8%), the Czech Republic (5.7%). Specification with the number of heating degree days: five countries: Ireland (37.9%), Italy (31.6%), Finland (15.3%), Slovakia (12.9%) and Poland (2.4%). Specification with per capita combustion capacity: five countries: Ireland (40.8.7%), Slovakia (22.4%), the Netherlands (14.1%), Poland (6.7%) and Finland (6%). Specification with the growth in per capita renewables capacity: four countries: Italy (61.5%), Poland (20.7%), Ireland (16.1%), and Denmark (1.7%). Specification with the average age of the coal-fired power plants: six countries: Slovakia (35.2%), the Czech Republic (31.2%), Sweden (12%), Hungary (11.2%), Spain (7.5%) and Finland (3%).

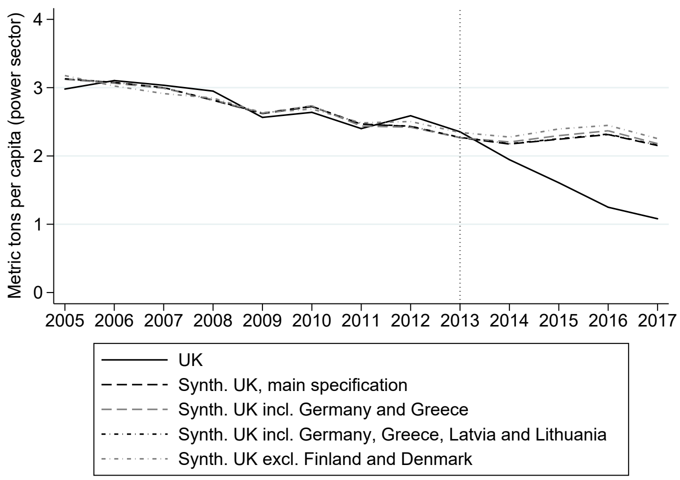
Table A.6: Predictors' values for the UK and each alternative synthetic UK

Variable	UK	Synth.UK				
		Original	Alt.1	Alt.2	Alt.3	Alt.4
Per cap. Residual load	4.29	4.30	X	4.44	4.27	2.01
Coal-gas price ratio	0.52	0.51	0.48	0.50	0.51	0.52
Per cap. LCP opt-out emissions 2009	0.29	0.24	0.29	0.29	0.36	0.31
Lignite dummy	0.00	0.06	0.024	0.07	0.21	0.42
Per cap. emissions 2005	2.98	3.13	2.98	3.12	3.06	2.94
Per cap. emissions 2012	2.59	2.43	2.32	2.45	2.49	2.45
Nb. of degree days	3020.30	X	3024.32	X	X	X
Per cap. combustible fuels capacity	1.10	X	X	1.15	X	X
Growth in per cap. renewable capacity	0.23	X	X	X	0.21	X
Avg. age of coal-fired power plants	36.04	X	X	X	X	36.07

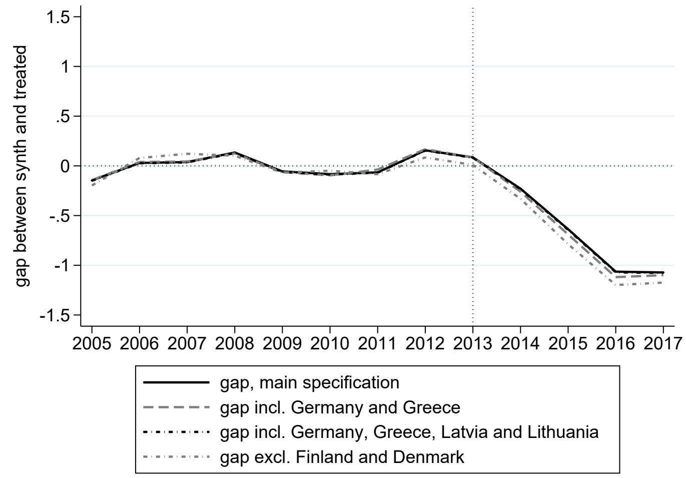
Notes: The per capita residual load, number of degree-days, per capita combustible fuels capacity and the average age of coal-fired power plants variables are averaged for the period 2005-2012. The coal-to-gas price ratio variable is averaged for the period 2007-2012. The growth in per capita renewable capacity is averaged for the period 2010-2012. LCP per capita opt-out emissions are taken in 2009, the lignite dummy is time-invariant. The outcome lags (per capita power sector emissions) are taken in 2005 and 2012.

A.10 Sensitivity of the results to the choice of the donor pool

Figure A.8 shows the sensitivity of the upper bound results to a different composition of the donor pool. Note that the results would be the same if applied on the lower bound from part 4.2, since the composition of the synthetic UK is the same. In a first test, I include Greece and Germany back in the donor pool, two countries that were previously excluded because of a shock affecting their power sector at the period of interest. In a second test, I include Germany, Greece, Latvia and Lithuania, all the countries that were previously excluded except Estonia (Adding Estonia makes it impossible to find a convex combination of countries replicating the trajectory of the UK, probably due to the too large discrepancy in emissions between Estonia and the other countries). In a third test, I exclude Denmark and Finland from the original donor pool. These two countries may be influencing the results substantially since they have large variations in per capita emissions and have a non-zero weight in the initial synthetic UK. The composition of the synthetic UK barely changes with different compositions of the donor pool. Figure A.8b shows that the emission reduction estimate obtained with the main specification is close to the estimates obtained with different compositions of the donor pool.



(a) Absolute per capita emissions



(b) Emission gap between treated and synthetic

Figure A.8: Sensitivity analysis: alternative donor pool

Notes: The synthetic UK is composed in the following way for the different specifications: Main specification: five countries: Ireland (49.2%), Slovakia (25.6%), the Netherlands (13.7%), Finland(5.8%), the Czech Republic (5.7%). Specification including Greece and Germany in the donor pool: four countries: Ireland (54.2%), the Netherlands (22.5%), Slovakia (16.6%), and Finland(6.6%). Specification including Greece, Germany, Latvia, Lithuania (entire donor pool except Estonia): five countries: Ireland (49.4%), Slovakia (25.2%), the Netherlands (14.2%), Finland(5.8%), the Czech Republic (5.5%). Specification excluding Finland and Denmark: four countries: Ireland (51%), Slovakia (20.6%), the Netherlands (18.1%), Poland (10.3%).

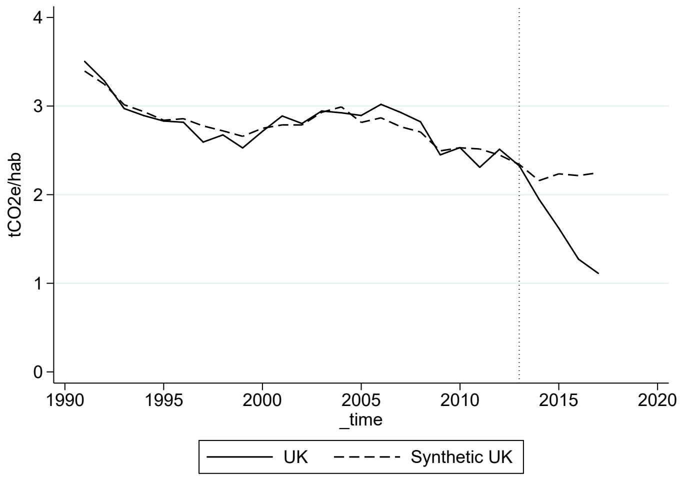
A.11 Sensitivity of the results to a longer pre-treatment period

The emission data used in the main analysis are only available from 2005, which means that only eight years of pre-treatment data can be used to generate the synthetic UK and assess the validity of the method. Although there is no rule of the thumb for the minimum number of pre-treatment periods that can be deemed "safe" to apply the synthetic control method, Abadie et al. (2015) al mention that "the applicability of the method requires a sizeable number of pre-intervention periods" (p500). I test whether having a relatively short time period is likely to bias my estimate by applying the synthetic control method to aggregate emission data for the electricity and heat generation sector available since 1990. This emission data is directly available at the country level on the European Environmental Agency (EEA)'s website, and includes all greenhouse gas emissions from the public electricity and heat production sector. I divide the variable by annual country population to obtain per capita emissions, and I apply the synthetic control method to the 1990-2012 pre-treatment period, keeping the same predictors as in the main specification. A drawback of this aggregate variable is that I can not identify emissions from individual plants and isolate confounding factors like I do in the main analysis. But it would be reassuring to find an emission reduction close to the main result.

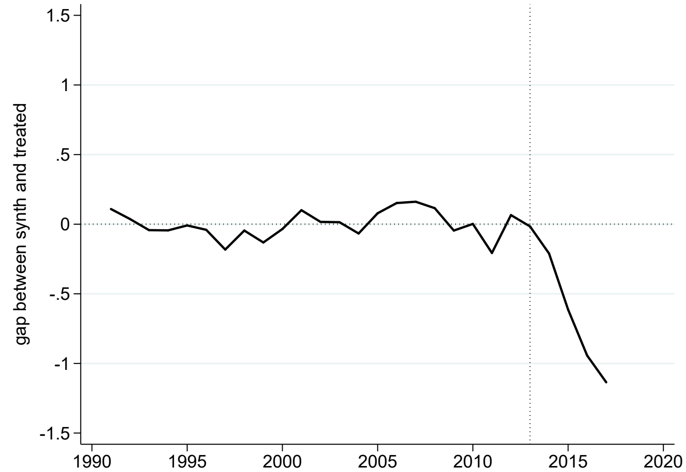
Figure A.9 shows the results. The composition of the synthetic UK changes compared to the main result, with the new synthetic UK made of three countries: Poland (36.0%), Italy (44.2%), and Slovakia (19.7%). It means that the combination of countries best mimicking the evolution of UK emissions over the 1990-2012 period is not the same as the combination of countries best mimicking the evolution of UK emissions over the 2005-2012 period. I calculate the cumulative abatement over the 2013-2017 period by adding up the annual differences in emissions between the UK and synthetic UK over these 5 years. I find the same cumulative abatement as the estimate for the upper bound using a shorter pre-treatment period: 191 MtCO_2e over the 2013-2017 period.

While predictors' values were closely aligned between the UK and synthetic UK in the main analysis, this is no longer the case with the new synthetic UK: table A.7 shows that the predictors' values of the synthetic UK are further away from the UK than that of the average donor pool. This may indicate that averaging the predictors for the end of the pre-treatment period only is not appropriate to predict emission values from before 2005[80]. I run a permutation test similar to the one performed in section 4.3. Figure A.10 shows that the decrease in emissions seen in the UK is not found with the same magnitude in other European countries. Overall, this test suggests that using a relatively short time period in my main results should not come at the cost of a large bias in the estimation.

[80]The other way around, keeping the original weighting and synthetic UK obtained in the main specification yields an emission trajectory which does not mimic well the emission trajectory for the UK before 2005. Applying the synthetic control method before 2005 could be inherently difficult in the case of power sector emissions compared to other sectors such as transport, due to the important change in European electricity markets over the 1990s and 2000s from heavily regulated industries to more liberalized and interconnected markets subject to a single carbon market.



(a) Absolute per capita emissions

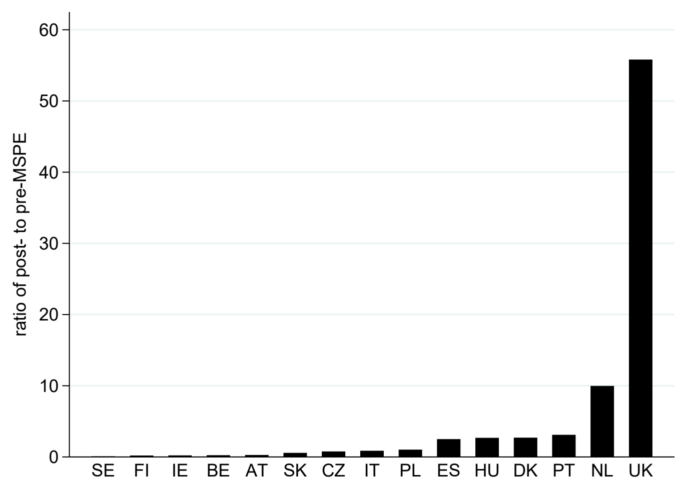


(b) Emission gap between treated and synthetic

Figure A.9: Sensitivity analysis: extended pre-treatment period with Eurostat greenhouse gas emissions by sector

Notes: The synthetic UK comprises three countries: Poland (36.1%), Italy (44.2%), Slovakia (19.7%).

(a) Permutation test with longer pre-treatment period



(b) Ratio of MSPEs with longer pre-treatment period

Figure A.10: Sensitivity analysis: extended pre-treatment period with Eurostat greenhouse gas emissions by sector, permutation test

Notes: In both figures, France is not included: for this country it is impossible to find a stable diagonal V matrix

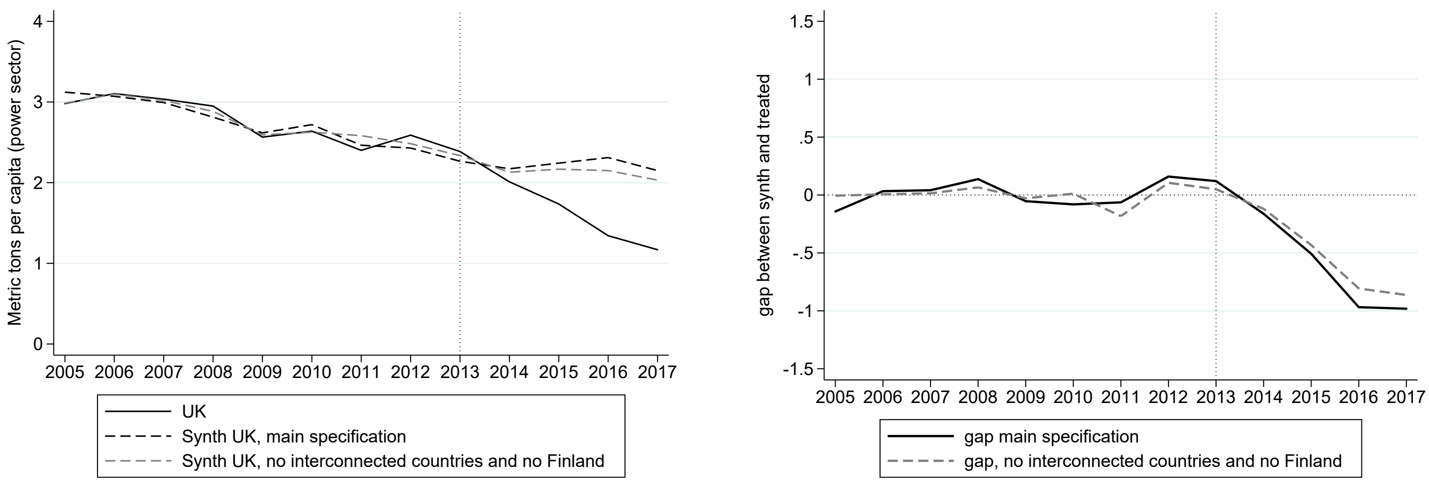
Table A.7: Predictors' values for the UK, synthetic UK and average of the donor pool, longer panel dataset

Variable	**UK**	**Synth. UK**	**Avg. Donor pool**
Per capita residual load	4.29	3.34	3.37
Coal-gas price ratio	0.52	0.44	0.71
Per cap. LCP opt-out emissions 2009	0.29	0.64	0.22
Lignite dummy	0	0.36	0.20
Per cap. emissions 1990	3.57	3.57	2.70
Per cap. emissions 1998	2.67	2.72	2.77
Per cap. emissions 2012	2.51	2.45	2.14

Notes: The per capita residual load is averaged for the period 2005-12, and the coal-to-gas price ratio for the period 2007-12. Per capita opt-out emissions are taken in 2009, the lignite dummy is time-invariant. Outcome lags are taken in 1990, 1998 and 2012.

A.12 Estimation of the spillovers removing all interconnected countries from the donor pool

I run the synthetic control method again, after removing the countries interconnected to Ireland from the donor pool. When I do so, the pre-treatment fit becomes quite poor due to the hight weight taken by Finland. I thus also run a specification where I also remove Finland from the donor pool. Figure A.11 shows the trajectory of these two alternative synthetic UK compared to the trajectory of UK emissions. For the synthetic UK without the interconnected countries nor Finland, the gap in emissions is smaller and results in a cumulative abatement 22 $MtCO_2e$ lower, of 142 $MtCO_2e$, 14% less than the lower bound estimate. Predictor balance is however less good, suggesting a trade-off, also pointed by Abadie (2021), between keeping in the donor pool countries sufficiently close to the treated unit, and having countries "too close" geographically and hence subject to spillovers from the treated unit. In particular, the amount of LCP opt-out emissions is not anymore aligned with the UK value and is greater in this new synthetic UK than in the original synthetic UK, which may partly explain why the emission gap is smaller than in the main specification.



(a) UK and synthetic UK

(b) gap between UK and synthetic UK

Figure A.11: UK (incl. counterfactual emissions from biomass converted plants) and synthetic UK - no interconnected countries

Notes: The initial synthetic UK comprises five countries: Ireland (49.2%), Slovakia (25.6%), the Netherlands (13.7%), Finland(5.8%), the Czech Republic (5.7%). The synthetic UK with Ireland, the Netherlands and France removed from the donor pool comprises five countries: Spain (58.9%), Finland (25.4%), Slovakia (7.6%), the Czech Republic (6.5%) and Denmark (1.7%). The synthetic UK with Ireland, the Netherlands, France and Finland removed from the donor pool comprises four countries: Italy (72%), Poland (23.4%), Denmark (2.5%), and the Czech republic (2.1%). UK emission values include estimated counterfactual emissions in the absence of biomass conversion for Lynemouth and Drax plants.