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Emission trading and overlapping environmental support: installation-level evidence from the EU ETS

by Klaas Mulier, Marten Ovaere and Leo Stimpfle

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Emission Trading and Overlapping Environmental Support: Installation-level Evidence from the EU ETS

Klaas Mulier Marten Ovaere Leo Stimpfle

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We collect data on 24,000 state aid cases within the European Union to create granular measures of national environmental support and study their interactions with the European Union Emissions Trading System (EU ETS). Exploiting variation in regulated installations' exposure to carbon prices and an unexpected regulatory tightening of the EU ETS, we show that high exposed installations strongly reduced emissions relative to less exposed installations in the same industry with significant heterogeneity across countries and industries. In the power sector, emission reductions are significantly stronger in countries with more generous renewable energy support policies. In contrast, emission reductions in the manufacturing sector are significantly weaker in country-industries with more generous cost compensation for energy-intensive activities.

1. Introduction

In many countries, climate policy is a mix of various instruments and regulations to tackle the climate crisis from different angles. Economic theory supports this approach, stating that addressing multiple market failures requires a range of policy instruments (Tinbergen, 1952). For example, carbon taxes internalize the external costs of greenhouse gas emissions, while subsidies address innovation spillovers and induce economies of scale for low-carbon technologies. However, these policies can interact in complex ways, and certain combinations may reduce overall effectiveness or even have unintended negative consequences (Fischer et al., 2017; Goulder and Stavins, 2011; Perino et al., 2019; Stechemesser et al., 2024).

This paper studies the interaction between the EU Emissions Trading System (EU ETS) and member states' overlapping support policies aimed at the decarbonisation of their industries. As the cornerstone of European climate policy, the EU ETS establishes a carbon price by implementing a progressively tightening cap on emissions from electricity and heat generation, energy-intensive industry sectors, domestic aviation, and maritime transport. In parallel, member states have introduced a range of national policies, including support for renewable energy, compensation for energy-intensive industries, investment aid for energy efficiency, and funding for R&D.

To identify the effects of the EU ETS and its interaction with national support policies, we employ a difference-in-differences design. In the literature evaluating the impacts of emission trading schemes, it is common practice to construct a treatment group consisting of regulated firms and compare their outcomes against a matched sample of unregulated firms before and after the introduction of the emission trading scheme (Colmer et al., 2024; Dechezleprêtre et al., 2023; Fowlie et al., 2012). In contrast, our identification strategy exploits variation *within* the EU ETS to estimate the causal effect of carbon pricing on firms over the period 2012–2023. First, we leverage the unexpected rise in the price of EU ETS emission allowances (EUA) from around 5 EUR per tonne of carbon dioxide (tCO_2) to 60–100 EUR following the 2017 regulatory tightening of the EU ETS (De Jonghe et al., 2020; Bruninx and Ovaere, 2022; Sitarz et al., 2024) as a quasi-natural experiment. Second, we construct a novel production-based measure of emission efficiency at the installation level to compare emitters highly exposed to the carbon price to similar emitters with a relatively lower carbon price exposure.

The benefits of measuring emission efficiency at the installation-level are twofold: First, we do not have to rely on firm-level balance sheet data to approximate emission efficiency. Our sample covering around 90% of total EU ETS emissions is therefore substantially larger than many previous studies and also avoids issues of limited coverage and representativeness of cross-country firm-level data (Bajgar et al., 2020). Second, by identifying the cleanliness of installations' production technology, we are able to capture reallocation of output from the least to most efficient installations in the EU ETS, both across and within firms.

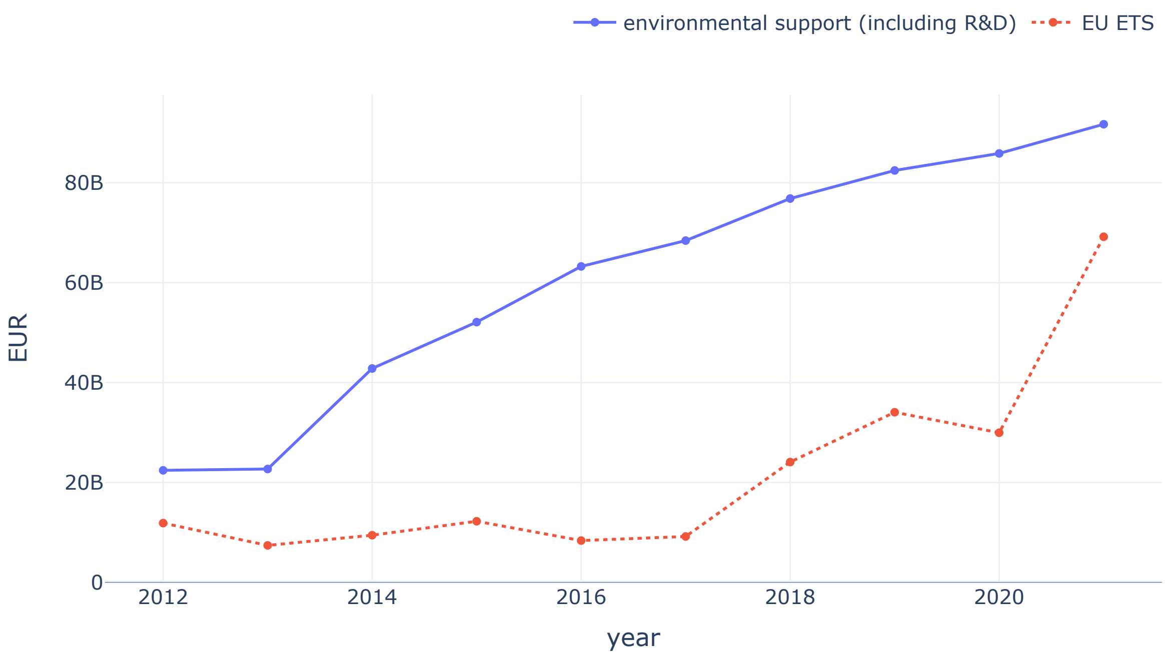


Figure 1: Annual aggregate national environmental support including R&D by EU member states (blue) versus total annual value of the EU ETS (red; aggregate emissions in tCO_2 multiplied by the annual average EUA price in EUR/tCO_2).

Leveraging transparency requirements under EU State Aid control, we construct a novel dataset documenting the highly heterogeneous national environmental support across EU member states. Over the period 2012–2021, member states' expenditures on national environmental support totalled more than EUR 650 billion over the period 2012–2021 increasing from EUR 20 billion in 2012 to more than EUR 80 billion in 2021 and exceeding the total value of the EU ETS (see Figure 1). The expenditures represented on average 4% of the total gross value added (GVA) of the industries covered by the EU ETS (or around 40 EUR per tCO_2 emitted) reaching 20% of GVA in some country-years. Among the different EU ETS sectors, support is highest for power producers, with expenditures amounting to 15% of GVA on average and reaching 50% in Czechia, Latvia, and Portugal in some years. We identify four major policy types (support for renewable energy, support for investments in energy efficiency, compensation for energy-intensive undertakings, and support for research and development) and create for each a granular measure of support intensity at the country-industry-year level. We find that national support is dominated by renewable energy support for power producers and compensation for energy-intensive manufacturing industries. We exploit the variation in support intensities between country-industries to analyse their interactions with the carbon price set by the EU ETS.

Our results indicate that the unexpected rise in the price of EUAs significantly reduced emissions amongst installations with a high exposure to the carbon price. Specifically, over the period 2017–2023 after the carbon price shock, the high-exposed (i.e., least efficient) installations reduced their emissions by almost 25% relative to low-exposed installations with notable heterogeneity across sectors. Power producers, for instance, achieved emission reductions of more than 36%, driven largely by coal-to-gas fuel switching. In contrast, the manufacturing sector saw a more modest, yet still significant reduction of almost 7%.

We also find that, among the four national support policies studied, investment aid for energy efficiency and funding for R&D do not interact significantly with the EU ETS, whereas renewable energy support and compensation for energy-intensive undertakings do. For power producers, the combination of high carbon prices and generous renewable energy support led to an additional emission reduction of almost 30%. This indicates that combining these two policies is far more effective in reducing carbon emissions than relying on carbon pricing alone. By contrast, high-exposed manufacturing installations in countries that offer generous compensation for energy-intensive activities reduce emissions by at least 7% less than similar installations in the same industry in countries with less generous levels of compensation. This means that there is a negative interaction between carbon pricing and compensation for energy-intensive activities, which has important implications for energy and climate policy. Although compensation, similar to free allocation of allowances (Naegele and Zaklan, 2019; Verde, 2020), has proven to be effective in mitigating the risk of carbon leakage (Basaglia et al., 2024), it comes with substantial costs to government revenues and leads to higher energy consumption (Basaglia et al., 2024; Gerster and Lamp, 2024). We add to this that cost compensation also weakens the carbon price signal.

Our results are robust across several dimensions, including alternative definitions of our support intensity measure, adding energy price controls, firm-level versus installation-level observations, and alternative sets of fixed effects controlling for year-industry-activity and year-industry-activity-country-specific shocks.

Our paper contributes to several literatures. First, we contribute to a growing literature that shows that EU ETS has a significant impact on firms. In particular, the EU ETS has caused emission reductions (Bayer and Aklin, 2020; Colmer et al., 2024; Dechezleprêtre et al., 2023) and increased innovation (Calel and Dechezleprêtre, 2016; Calel, 2020), without a significant contraction of economic activity (Colmer et al., 2024; Dechezleprêtre et al., 2023).

Second, some empirical papers have investigated the firm-level effects of certain national overlapping policies in Europe in isolation. For example, Gerster and Lamp (2024) find that German manufacturing firms that receive energy tax exemptions increase energy use without increasing output. Similarly, Basaglia et al. (2024) report that compensated firms increased production and electricity use relative to uncompensated firms, with no significant effect on energy intensity. Criscuolo et al. (2019) find that investment subsidies increase manufacturing employment for small firms but not for large firms.

Third, our work contributes to the economic modeling literature on the interaction between overlapping environmental policies. In the United States, federal and state-level policies often interact in complex ways. Examples include the interaction between federal fuel economy standards and state-level emissions limits (Goulder et al., 2012), the federal Clean Power Plan and state renewable portfolio standards (Bushnell et al., 2017), federal coal lease surcharges and state emissions policies (Gerarden et al., 2020), federal carbon pricing and state support for electric vehicles (Gillingham et al., 2021), and California's cap-and-trade program alongside various federal emissions reduction initiatives (Borenstein et al., 2019). In Europe, simulation-based evidence suggests that national overlapping renewable support policies can have a suppressing effect on the price of EUAs (Anke et al., 2020), can cause shifts in emission abatement between industries (Delarue and Van den Bergh, 2016), and can affect aggregate emissions within the EU ETS (Bruninx et al., 2020). To the best of our knowledge, our paper provides the first empirical estimation of the interaction of a carbon price and overlapping environmental support policies outside of economic simulation models. In particular, we provide the first installation-level empirical evidence on which and how national environmental support policies in Europe interact with the EU ETS.

The remainder of this paper is structured as follows. Section 2 our measure of national support policies and Section 3 discusses the data on emissions and carbon price exposure. In section 4, we describe our research design and empirical strategy. Section 5 presents the main results, while section 6 shows the robustness of our findings. Section 7 concludes.

2. National Environmental Support Policies

We construct a novel dataset exploiting transparency requirements under EU State Aid control to quantify national environmental policies that overlap with the EU ETS. EU State Aid control defines aid

> *"as an advantage in any form whatsoever conferred by national public authorities to undertakings on a selective basis."*[1]

The EU Commission requires "prior notification of all new aid measures" and makes data on state aid cases publicly available. While the Treaty on the Functioning of the EU (TFEU) generally prohibits State Aid, support may be deemed compatible if its expected benefits outweigh the downsides of a potentially distorted competition.[2] In practice, selective interventions by national governments are often considered compatible with the TFEU if they address market failures in the presence of externalities, for example to support the generation of low-carbon electricity from renewable energy sources. The broadness of the definition of aid in conjunction with the notion of compatibility means that EU State Aid control facilitates a comprehensive and harmonised view of targeted national support overlapping with the EU ETS.

Our data include all notified measures for which the EU Commissions has adopted a formal decision on the compatibility of the aid as well as measures that qualify for an exemption under the so-called General Block Exemption Regulation (GBER).[3] In particular, aid that does not target certain firms or industries selectively in the sense of EU State Aid control or is small and falls under the so-called de minimis rules[4] is not included.

[1] `https://competition-policy.ec.europa.eu/state-aid/overview_en`
[2] `https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv:OJ.C_.2016.262.01.0001.01.ENG`
[3] `https://eur-lex.europa.eu/EN/legal-content/summary/general-block-exemption-regulation.html`
[4] `https://eur-lex.europa.eu/eli/reg/2023/2831/oj`

2.1. Data Sources

We rely on two main data sources: the EU Commission's Competition Case Search (CCS)[5] which provides information on individual State Aid cases and the EU Transparency Award Module (TAM)[6] which provides data on aid awards to individual firms associated with State Aid cases in the CCS.

Competition Case Search (CCS) For each State Aid case, the CCS reports the case's objectives, targeted economic activities, legal basis, type of aid instrument, duration, and annual expenditures are recorded. The expenditures cover a variety of instruments, e.g., direct grants, tax exemptions, and loans, and do not have to be financed directly by member states.[7] This means that although environmental support policies cover a wide range of instruments whose strength might be hard to compare,[8] the CCS provides a harmonised measurement of support in monetary terms. While availability of harmonised data on national environmental policies has improved substantially over the past years, for example in the form of the CAPMF database (Nachtigall et al., 2022), our data is to date unique in that it avoids issues of commensurability between potentially disparate policy designs.

Transparency Award Module (TAM) The TAM reports aid awards to individual beneficiaries associated with State Aid cases recorded in the CCS. Beyond the more granular reporting of aid awards, the TAM differs in three important ways from the CCS. First, whereas the CCS reports *actual* expenditures paid, the TAM reports *planned* aid awards without requiring ex post updates after payments are made (European Commission, 2020). Second, reporting in the TAM became mandatory only from 2016 onwards. Third, the GBER transparency requirements only cover individual aid awards exceeding EUR 500,000.

[5] `https://competition-cases.ec.europa.eu/search`

[6] `https://webgate.ec.europa.eu/competition/transparency/public/search/home`

[7] Some member states appear to have believed "that State resources are involved only when aid is paid out directly from the budget or when it is paid out by a public entity". The Commission, however, clarified that "the mere fact that the advantage is not financed directly from the State budget is not sufficient to exclude that State resources are involved". See `https://ec.europa.eu/competition/state_aid/cases/252523/252523_1589754_142_2.pdf`

[8] For example, environmental support might use regulatory minimum standards (e.g., renewable energy quotas), non-market based mechanisms (e.g., fixed feed-in premiums paid by electricity consumers), or tax exemptions (e.g., reductions in energy excise taxes).

2.2. Sample Construction

We combine the Competition Case Search (CCS) and the Transparency Award Module (TAM) to create granular measures of national environmental support overlapping with the EU ETS. We proceed in four steps.

2.2.1. Identification of Environmental Support

The CCS provides details on the main objectives of a state aid case, for example "renewable energy", "environmental protection", or "energy efficiency", which we use to identify the subset of State Aid cases with environmental or R&D objectives potentially overlapping with the EU ETS. Our sample consists of more than 24,000 State Aid cases of which more 3,000 have environmental or R&D objectives. Figure 2 shows that total expenditures on environmental or R&D support increase from around EUR 20 billion in 2012 to more than EUR 80 billion in 2020 constituting up to 60% of total annual expenditures on State Aid within the EU.

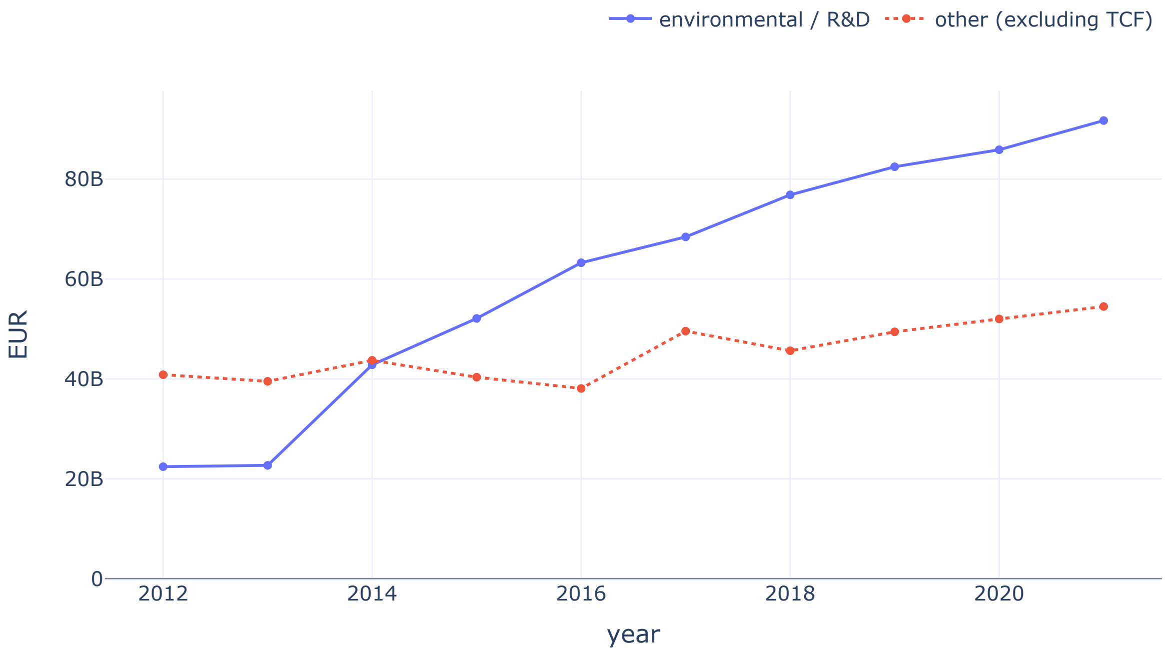


Figure 2: The chart shows annual aggregate expenditures on environmental support cases (blue) and all other cases excluding expenditures under the so-called Temporary Crisis Framework (TCF) in red. The TCF was adopted in response to the COVID-19 pandemic and Russia's invasion of Ukraine to facilitate a swifter approval of support deemed State Aid.

2.2.2. Environmental Support Policy Types

The case-level details reported in the CCS enable us to identify four distinct support categories amongst environmental State Aid cases: renewable energy support (res), compensation for energy-intensive undertakings (eiu), investment aid for energy efficiency (eff), and support for R&D (rnd). Figure 3 shows that environmental support is dominated by renewable energy support and compensation for energy-intensive undertakings which together comprise around 80% of total environmental support over the sample period.

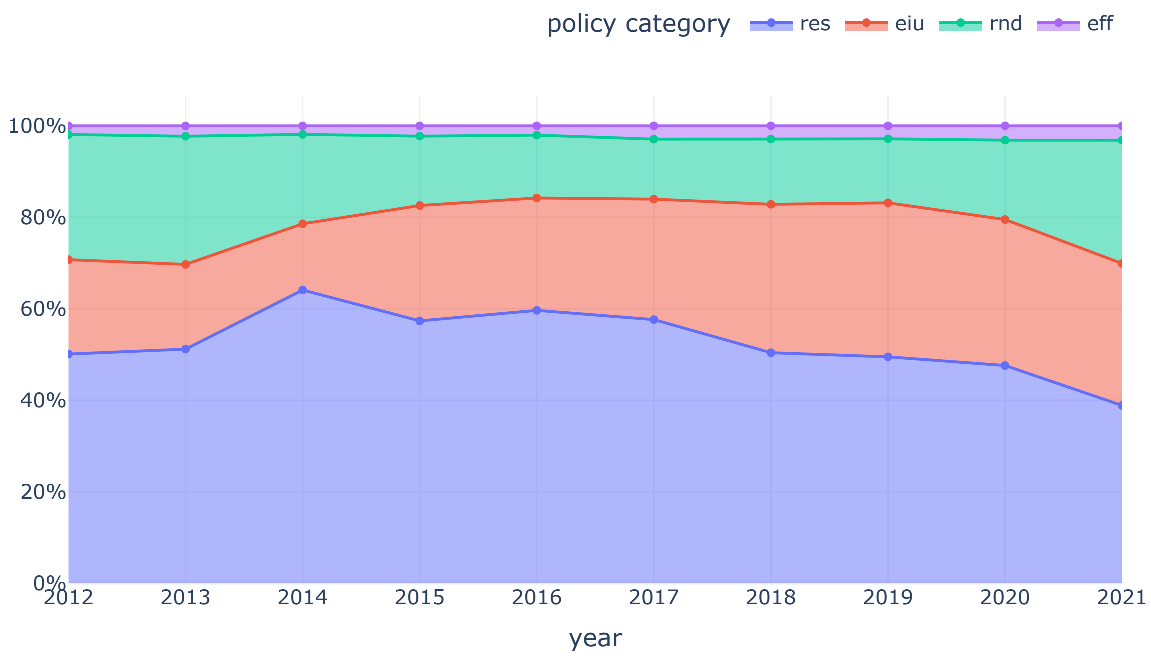


Figure 3: Breakdown of annual aggregate expenditures on state aid cases with environmental objectives. Expenditures are categorised into four distinct policy types α: renewable energy support (res), compensation for energy-intensive undertakings (eiu), R&D support (rnd), and investment aid for energy efficiency (eff).

Table 1 shows that the number of cases and average expenditures vary strongly between the four policy categories α and that environmental support is concentrated in a small number of large schemes for renewable energy support and compensation for energy-intensive industries. Average annual expenditures for renewable energy support and compensation for energy-intensive undertakings are around 500 and 360 million EUR per member state, respectively, which is 25 and 15 times larger than the average non-environmental case. (See Figure 19 in the appendix for the full distribution of annual expenditures by policy category.)

	number	annual expenditures (million EUR)					
	cases	mean	std	25%	50%	75%	max
α							
renewable energy support	98	508	2,868	3	39	140	24,449
compensation energy-intensive	92	362	828	9	58	232	5,166
investment aid energy efficiency	343	16	59	1	3	13	1,749
R&D support	2,722	11	89	0	1	4	7,745
other	21,193	20	343	0	0	3	41,916

Table 1: Number of State Aid cases and descriptive statistics of their annual expenditures in million EUR. The four policy categories α are investment aid for energy efficiency (eff), compensation for energy-intensive undertakings (eiu), renewable energy support (res), and support for R&D (rnd).

2.2.3. Disaggregation by Industry

We use beneficiary-level data obtained from the transparency award module (TAM) to disaggregate the year-case-level CCS expenditures to the NACE 4-digit level. For each case, we aggregate aid awards in the TAM for all beneficiaries in a given NACE 4-digit industry to infer an industry j's share ω_{jm} of the case's total expenditure.[9] We then use the case-industry shares ω_{jm} to disaggregate the CCS expenditures to the year-case-industry level, i.e., for each case m in policy category α

$$\text{Expenditure}^{\alpha}_{jmt} = \omega_{jm} \times \text{Expenditure}^{\alpha}_{mt}\,. \tag{1}$$

The disaggregation (1) enables us to measure the degree to which the environmental support affects industries regulated by the EU ETS. On the one hand, some industries receiving environmental support might not be covered by the EU ETS. On the other hand, environmental support can be highly concentrated in certain industries. For example, renewable energy support only targets power producers while compensation for energy-intensive undertakings targets only manufacturing firms.

2.2.4. Environmental Support Policy Intensity

To create the environmental support policy intensity, we aggregate expenditures for each policy type α by industry j, country c, and year t and normalise the total expenditures by the total EU ETS emissions in the same industry j, country c, and year t (cf. Section 3). Specifically, for each country-

[9]For cases not available in the TAM (approximately 18% of environmental State Aid cases) we impute the average industry share $\overline{\omega}_{jn}$ from cases n in the same country c and support category α.

industry-year we define the environmental support intensity $\text{ESP}^{\alpha}_{cjt}$ as

$$\text{ESP}^{\alpha}_{cjt} = \frac{\sum_{m \in M^{\alpha}_{c}} \text{Expenditure}^{\alpha}_{jmt}}{\sum_{i \in I_{cj}} \text{Emissions}_{it}}, \tag{2}$$

where m denotes a state aid case, M^{α}_{c} the set of state aid cases of type α in country c, i denotes a installation regulated by the EU ETS, and I_{cj} denotes the set of EU ETS installations in country c and industry j. Normalising expenditures by emissions enables us to capture variation of national environmental support at the NACE 4-digit level. We also explore an alternative, albeit coarser measure of environmental support intensity where we normalise expenditures by a country-industry's gross value added (GVA), i.e.,

$$\text{ESP}^{\alpha,\text{gva}}_{cjt} = \frac{\sum_{m \in M^{\alpha}_{c}} \text{Expenditure}^{\alpha}_{jmt}}{\text{GVA}_{jt}}, \tag{3}$$

Contrary to the emission-based intensity, the GVA-based measure of intensity only allows us to capture variation in national environmental support at the NACE 2-digit level. We discuss the different normalisations in more detail in Section 6.3 and show that our results are robust to the GVA-based measure of support intensity.

The environmental support intensities (2) and (3) enable us to explore the importance of the support relative to the targeted industries' size. Since 2012 countries spent on average 4% of GVA annually on environmental support in industries covered by the EU ETS corresponding to around 40 EUR/tCO_2. Figure 4 illustrates the considerable degree of variation in support intensity reaching 20% of GVA or more than 100 EUR/tCO_2 in some country-years.

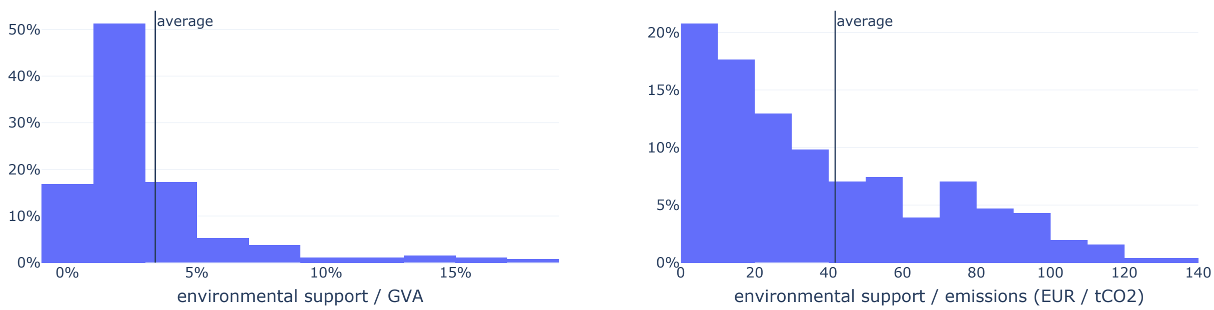
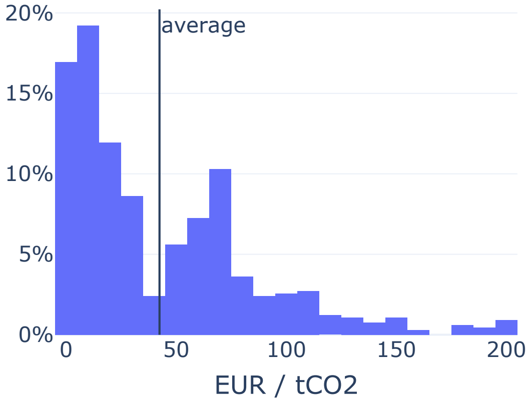
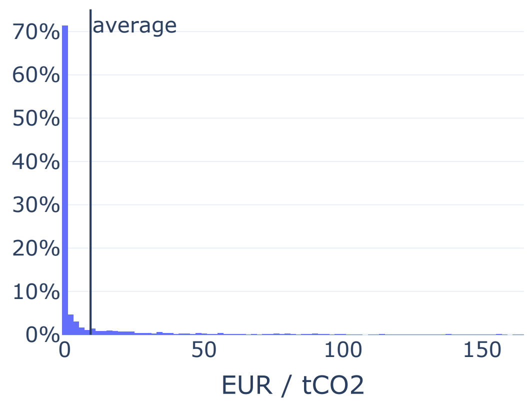


Figure 4: The chart shows the distribution of country-level annual expenditures on environmental support normalised by gross value added (left panel) and EU ETS emissions (right panel) of the NACE industries B, C, and D over the period 2012–2021. The industries' GVA is obtained from Eurostat's national accounts aggregates by industry `nama_10_a64`. To improve readability the histograms' x-axes are truncated at the 99%-tile.

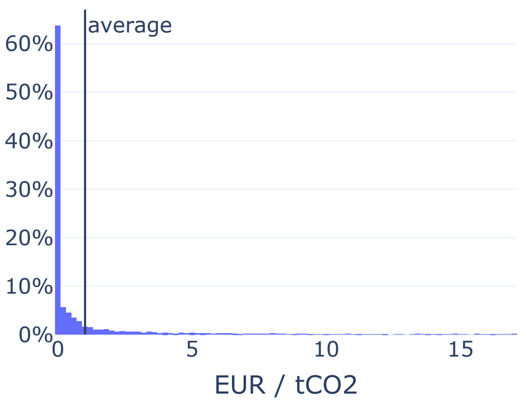
The variation in support intensity is also large between policy types and industries. Figure 5 shows the distribution of environmental support relative to carbon emissions at the NACE 4-digit level. We find that renewable energy support for the power sector reached on average almost 50 EUR/tCO_2 or 15% of the sector's GVA with some countries providing support in excess of 100 EUR/tCO_2 or as little as 10 EUR/tCO_2.(For the distribution in terms of GVA see Figure 21 in the appendix). Figure 5b shows that compensation for energy-intensive undertakings is lower on average, but highly concentrated in a small number of country-industries where the support can also be in excess of 50 EUR/tCO_2 or 5% of GVA. This suggests that many countries choose not to provide selective support for energy-intensive activities but that the support is strong if it is given. Finally, support for R&D and investment aid for energy efficiency are relatively less important with expenditures staying well below 5 EUR/tCO_2 or 1% of GVA in most country-industries (see Figures 5c and 5d).



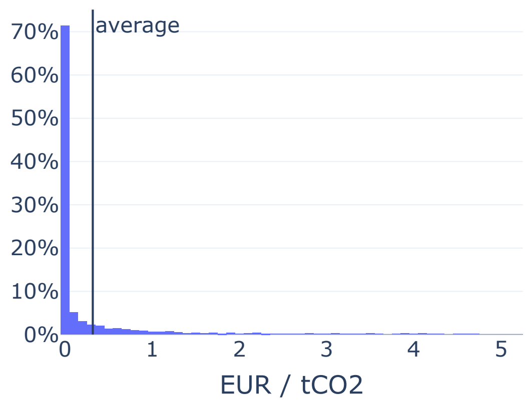
(a) renewable energy support



(b) Compensation for energy-intensive industries



(c) R&D support



(d) investment aid for energy efficiency

Figure 5: The histograms show the distribution of annual country-industry expenditures on environmental support normalised by the country-industry's total EU ETS emissions over the period 2012–2021. Expenditures are aggregated at the NACE 4-digit. To improve readability the histograms' x-axes are truncated at the 95%-tile.

2.2.5. Environmental Support Policy Indicator

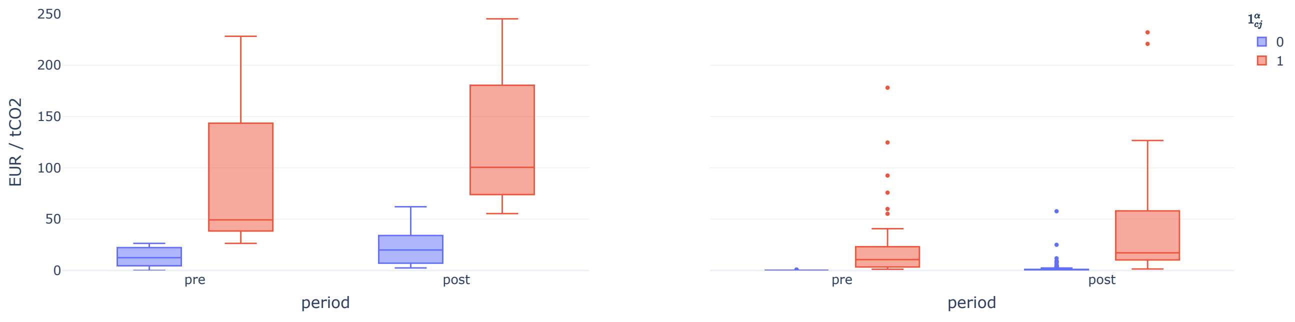
The national support policy intensity is in general not exogenous to the EU ETS, as member states could endogenously respond to increased carbon prices at the European level and provide more support to their local industries.[10] To mitigate potential endogeneity concerns in our identification strategy, we focus on the national support policy intensity in the pre-period 2012–2016 before tightening of the EU ETS (see Section 4.1). More precisely, we define a country-industry as having a high availability of support if the average policy intensity over 2012–2016 is higher than the median intensity in its NACE 4-digit industry across all countries, i.e.,

$$\mathbb{1}^{\alpha}_{cj} = \begin{cases} 1, & \text{if } \overline{\text{ESP}}^{\alpha}_{cj} > \text{median}^{\alpha}_{j} \\ 0, & \text{else,} \end{cases} \tag{4}$$

where $\overline{\text{ESP}}^{\alpha}_{cj}$ is the average annual intensity over the period 2012–2016 and $\text{median}^{\alpha}_{j}$ denotes the median average annual intensity of type α in industry j over the period 2012–2016. The dummy variables $\mathbb{1}^{\alpha}_{cj}$ enable us to compare emitters in the same industry producing the same product, facing the same product demand, and which mainly differ in the availability of national support α based on the country where they are located.

Figure 6 illustrates the environmental support intensity for low-intensity country-industries $\mathbb{1}^{\alpha}_{cj} = 0$ and high-intensity country-industries $\mathbb{1}^{\alpha}_{cj} = 1$ before and after the regulatory tightening of the EU ETS in 2017. We find that support tends to be sticky and country-industries with high levels of support in the period 2012–2016 also tend to give higher levels of support after 2016 (also see Figure 20 in the appendix). Moreover, the support intensity tends to increase for all country-industries over time. The median renewable energy support for high-intensity country-industries increases from around 50 EUR/tCO_2 in the pre-period to around 90 EUR/tCO_2 in the post-period after 2016 (Figure 6a). In contrast, in most low-intensity country-industries the renewable support intensity stays below 50 EUR/tCO_2 even in the post-period. While the general patterns are comparable for compensation for energy-intensive undertakings, support is notably more concentrated in high-intensity country-industries (Figure 6b).

[10] For example, the category "compensation for energy-intensive undertakings" includes measures for the compensation of indirect emission costs which are linked to the EU ETS allowance price, see: `https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52012XC0605(01)`



(a) Renewable energy support

(b) Compensation for energy-intensive undertakings

Figure 6: The chart shows the average annual environmental support intensity $\overline{\mathrm{ESP}}^{\alpha}_{cj}$ in the pre-period (2012–2016) and the post-period (2017–2023). The colour indicates if a country's pre-period average intensity is above the median $\mathbb{1}^{\alpha}_{cj} = 1$ (red) or below $\mathbb{1}^{\alpha}_{cj} = 0$ (blue).

3. Emission Data

3.1. EU Transaction Log

The EU ETS regulates greenhouse gas emissions at the level of individual installations, e.g., power or steel plants. An installation is covered by the EU ETS if it performs a regulated activity and surpasses an activity-specific capacity threshold as defined by EU Directive 2003/87/EC. Installations regulated by the EU ETS are recorded in the European Union Transaction Log (EUTL)[11] which reports installation-level data on annual verified emissions, emission allowances allocated for free, industry, main activity, and owner. Regulated installations are linked to a unique Operator Holding Account which in turn can be linked to a firm. The EUTL has been used extensively in the empirical literature on the EU ETS and for more details we refer to existing studies, for example by Dechezleprêtre et al. (2023), Abrell et al. (2022a), or Zaklan (2023). Figure 7 illustrates the total annual verified emissions recorded in the EUTL over the four Phases of the EU ETS since its inception in 2005.

3.2. Emission Intensity and Carbon Price Exposure

To estimate the causal effect of the EU ETS, we exploit variation in the efficiency of regulated installations. The basic idea is that because less efficient installations have to surrender more EUAs per unit of output, they are, all else being equal, more exposed to rising carbon prices than more efficient

[11] Available at `https://ec.europa.eu/clima/ets/`; we use the pre-processed version provided by Jan Abrell at `https://www.euets.info`.

Figure 7: Aggregate annual EU ETS emissions of power producers and installations in the manufacturing sector (including mining and quarrying).

installation. Although the EUTL only reports emissions but not output, it is possible construct an installation-level measure of emission intensity by exploiting the benchmark-based harmonised free allocation methodology of the EU ETS (Section 3.2.1). Because free allocation to power producers was phased out with the start of Phase III of the EU ETS, we match power producers with data on their production technology to directly infer their emission intensity as explained in Section 3.2.2.

3.2.1. Emission Intensity in the Manufacturing Sample

For the manufacturing sample, we exploit the harmonised free allocation methodology introduced in Phase III of the EU ETS to construct an installation-level measure of emission intensity.[12] In the EU ETS, emission permits—so-called EU allowances (EUAs)—are auctioned in competitive bidding or, motivated by concerns about competitiveness and carbon leakage, allocated for free (Sato et al., 2022).[13] In Phase I and II, free allocation of allowances was decentralized and largely based on "grandfathering" allowances to installations based on their historical emissions. In contrast, Phase III

[12]Cameron and Garrone (2024) and Belloc and Valentini (2024) use the free allocation methodology in a similar way to construct measures of environmental efficiency.

[13]The use of free allocation is often justified by the so-called Coasean independence property (Coase, 1960): Under certain conditions, the initial allocation of emission permits in a cap-and-trade system is independent of the optimal allocation (Montgomery, 1972). If the Coasean independence property holds, the cap-and-trade system will achieve lowest cost emission abatements regardless of whether permits are auctioned or allocated for free. To date, empirical studies failed to reject the Coasean independence property property (Fowlie and Perloff, 2013; Zaklan, 2023).

harmonised the free allocation methodology across member states moving from grandfathering towards an allocation according to efficiency benchmarks (Fowlie et al., 2016). The efficiency benchmarks are designed to represent the "average performance of the 10% most efficient installations in a sector or sub-sector" with the goal "that the free allocation of emission allowances takes place in a manner that provides incentives for reductions in greenhouse gas emissions."[14] More precisely, the initial free allocation F_i of an installation i that performs activity a to produce product p is given by

$$F_i = \text{Benchmark}_p^a \times \text{CLEF}_p^a \times \text{HAL}_i, \tag{5}$$

where Benchmark_p^a is the efficiency benchmark of activity a expressed as tCO_2 per unit of product p, CLEF_p^a is the carbon leakage exposure factor for activity a, and HAL_i is the historical activity level defined as the median output in units of product p between 2005–2008 or, where higher, 2009–2010. Because F_i is recorded in the EUTL and Benchmark_p^a and CLEF_p^a are publicly available, we can solve (5) for the historical activity level HAL_i to approximate installation i's emission intensity as

$$\text{CPE}_i = \frac{\text{HEL}_i}{\text{HAL}_i}, \tag{6}$$

where HEL_i is the installation's historical emission level defined as the median emissions in tCO_2 between 2005–2008 or, where higher, 2009–2010. We discuss further details and limitations of this approach in Section B in the appendix.

3.2.2. Emission Intensity of Power Producers

Because free allocation was phased out for power producers at the beginning of Phase III,[15] it is not possible to infer power producers' emission intensity from the harmonised benchmarking decision. We therefore match the EUTL with the Global Energy Monitor (GEM)[16] which provides data on age, production technology and fuel type for coal, oil, gas, and bioenergy plants. We match installations on longitude and latitude and validate our matches manually against other plant details such as name, address, and age. We identify more than 1,200 power plants covering approximately 98% of total EU ETS emissions in the NACE 4-digit sector 35.11 (see Figure 17 in the appendix). We infer the emission

[14] https://eur-lex.europa.eu/eli/dec/2011/278/oj

[15] While allocation to power producers was phased out in principle, Article 10c of the EU ETS directive granted certain member states the right to grant free allocation to "modernise the energy sector". https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/free-allocation/allocation-modernise-energy-sector_en

[16] https://globalenergymonitor.org

intensity of power producers by means of its emission factor expressed in gCO_2/kWh as determined by its technology and fuel type (Nicholson and Heath, 2021).[17]

3.2.3. Carbon Price Exposure

Regulated installations have to surrender one EUA for each tCO_2 emitted on an annual basis. The higher an installation's emission intensity, the more EUAs it has to surrender for the same output. We therefore approximate an installation's carbon price exposure by its emission intensity and define an installation i as high-exposed if its emission intensity CPE_i is above the median emission intensity of installations performing the same activity a within its NACE 4-digit industry j, i.e.,

$$\mathbb{1}^{\mathrm{CPE}_i} = \begin{cases} 1, & \text{if } \mathrm{CPE}_i > \mathrm{median}_{ja}, \\ 0, & \text{otherwise}, \end{cases} \tag{7}$$

where median_{ja} denotes the median emission intensity of installations in NACE 4-digit industry j performing activity a.

3.3. Sample Description

As can be seen in Table 2, our sample covers more than 3,000 firms owning more than 4,500 installations that were active over the period 2012–2023 in 27 countries[18] representing approximately 90% of total EU ETS emissions (for more details see Figure 18 in the appendix). Our sample starts in 2012, the first year of availability of data on national support policies, and includes all installations for which we are able to determine the carbon price exposure according to our methodology described in Section 3.2.

We split our main sample into two subsamples with distinct characteristics: the power sample and the

[17] The GEM records details at the level of *units*. A single installation can consist of multiple units which in rare cases can use multiple technologies or fuels. We use a capacity-weighted average emission factor for installations with multiple units.

[18] We exclude the United Kingdom for two reasons: First, following the UK's exit from the EU, it has set up a national emission trading system and left the EU ETS at the end of 2020. Second and more importantly, in 2013 the UK introduced the so-called Carbon Price Support (CPS). The CPS effectively increased the EUA price for installations in the UK to levels installations outside the UK only experienced years later after the MSR reform (Leroutier, 2022; Abrell et al., 2022b).

Sample	Full	Power	Manufacturing
Observations	53,662	15,131	38,531
Firms	3,033	727	2,356
Installations	4,609	1,283	3,326
NACE 4-digit industries	70	1	69
Activities	24	1	23
Countries	27	27	26
Annual installation-level emissions (tCO_2)			
Average	289,099	656,414	144,855
Median	26,845	115,610	19,209
Standard deviation	1,182,877	2,023,869	516,179
Annual firm-level emissions (tCO_2)			
Average	439,392	1,154,370	204,552
Median	27,103	148,284	19,054
Standard deviation	2,490,333	4,762,762	719,143

Table 2: Descriptive statistics of the three samples studied: the full sample, the power sample, and the manufacturing sample. The sample covers the period 2012–2023. The unit of observation is installation-years. Installations are associated to firms via the company registration number of its Operator Holding Account in the EUTL. An installation's NACE 4-digit industry is inferred from the EU Commission's carbon leakage assessment. An installation's activity corresponds to its main activity regulated EU ETS in accordance with Annex II of the EU ETS Directive 2003/87/EC. See `https://www.euets.info/download` for more details.

manufacturing sample. While the power sample consists of fewer installations and firms, it contains the larger emitters and is responsible for the majority of emissions during the sample period. Figure 7 shows that until the second half of Phase III power producers emitted almost twice as much as all other installations combined and that in aggregate power producers reduced emissions significantly more compared to other industries.

3.3.1. Power

There is a large difference in average emissions between high-exposed and low-exposed power producers (see Figure 8). Because producing electricity from coal is two to three times more emission intensive than gas-firing (Nicholson and Heath, 2021), high-exposed power producers are generally coal-fired. Some of the difference in average emissions between high-exposed and low-exposed installations is therefore caused by the difference in emission efficiency of the different production technologies. We note that because until 2016 the average emissions from high-exposed installations were around five times higher, coal-fired installations also appear to have on average a higher production capacity.

The normalised average outcomes in the right panel of Figure 8 illustrate that average emissions of high-exposed installations steadily decrease over the sample period but at an increasing rate from 2017 onwards. In contrast, average emissions of low-exposed installations decrease from 2012 to 2014 before increasing beyond 2012 levels in 2019. This increase in emissions of low-exposed installations over the period 2014–2019 coincides with decreasing European gas prices and illustrates the importance relative gas and coal prices for emissions abatement decisions in the power sector: power producers can respond to a relative change in fuel prices by switching production to power plants using less expensive fuels (Cullen and Mansur, 2017). When controlling for relative fuel prices, our granular data on power producer's production technologies enable us to disentangle the effect of fuel prices from the effect of carbon prices.

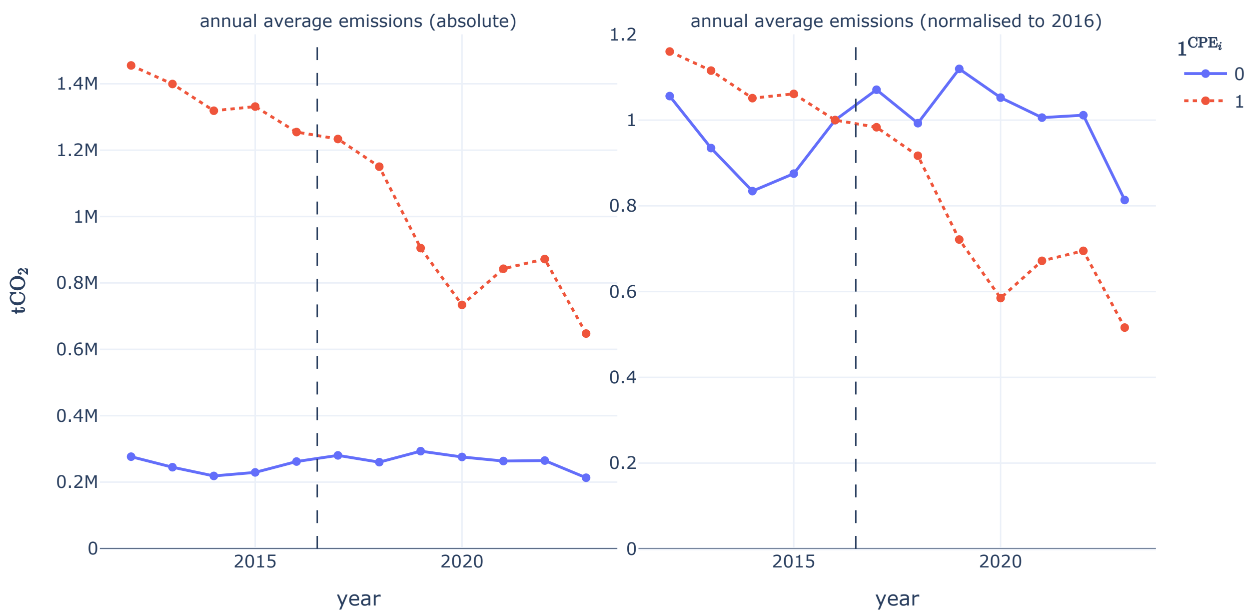


Figure 8: Annual average emissions of installations in the power sample. The left-hand side shows absolute values, while the right-hand side is normalised to 2016.

3.3.2. Manufacturing

Figure 9 shows the annual average emissions of high-exposed and low-exposed installations in the manufacturing sample. While the difference is smaller than in the power sample, high-exposed installations on average still emit more than 50% more each year. Similarly to the power sample, an important driver is the difference in emission efficiency between high-exposed and low-exposed installations. For example, according to the free allocation methodology's benchmarks, blast furnaces emit more than four times more carbon dioxide per tonne of steel than electric arc furnaces. Normalising the average outcomes suggests that high-exposed and low-exposed installations were on common trends before the 2017 carbon price shock (see right panel in Figure 9). We will assess the difference in trends between the two groups more rigorously in Section 5.

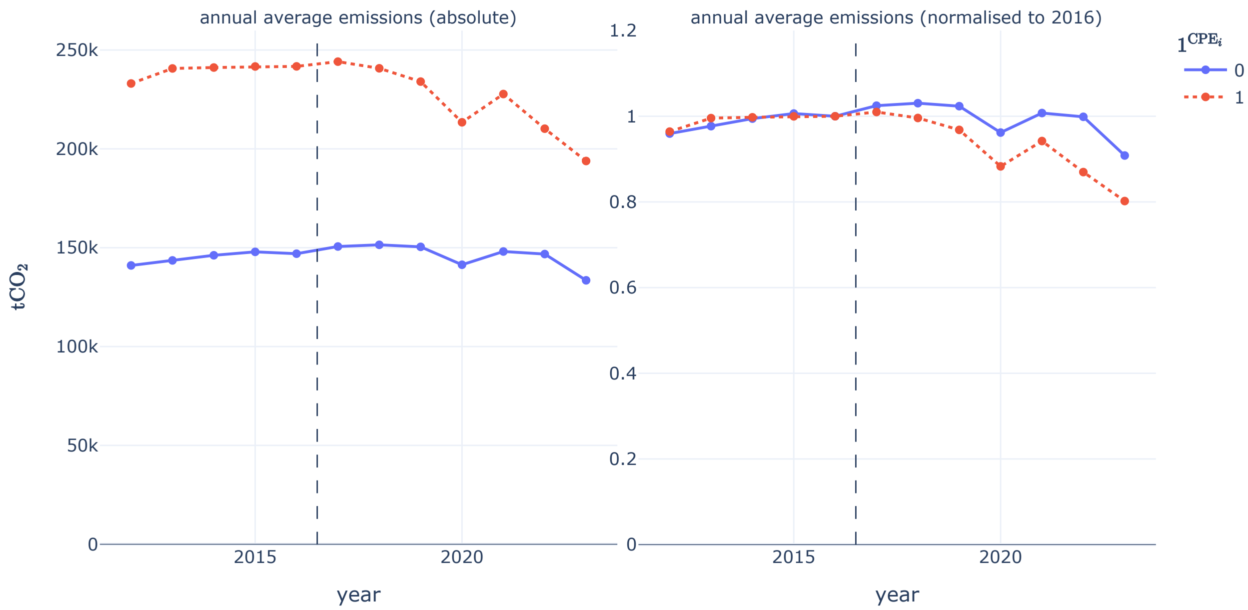


Figure 9: Annual average emissions of installations in the manufacturing sample. The left-hand side shows absolute values, while the right-hand side is normalised to 2016.

4. Research Design and Methods

4.1. Identification Strategy

We follow De Jonghe et al. (2020) and exploit the unexpected regulatory tightening of the EU ETS as a natural experiment. At the beginning of its third trading phase, EU allowance (EUA) prices remained at depressed levels of around 5 EUR/tCO_2 due to a structural oversupply of allowances (Sato et al., 2022) and a lack of long-term credibility of the EU ETS (Sitarz et al., 2024). While the EU Commission proposed a mechanism to manage the supply of EUAs, the so-called market stability reserve (MSR), as early as 2015, market participants remained skeptical that the proposed adjustments would succeed in reducing the structural oversupply.

In 2017 the MSR proposal was strengthened significantly with the inclusion of an invalidation policy that updated the MSR from a tool to merely adjust the short-term supply of allowances to managing their long-term availability by cancelling excess allowances (Bruninx et al., 2020): Under the invalidation policy "allowances held in the reserve above the total number of allowances auctioned during the previous year should no longer be valid."[19] The invalidation mechanism was proposed for the first time by the European Council on March 24, 2017[20] and agreed informally after six trilogues in November 2017,[21] triggering an unprecedented increase in the price of EUAs to around 25 EUR/tCO_2 after 2018 (see Figure 10). Subsequently, the adjustments in the context of the "Fit for 55 Package" caused further price increases to 60–100 EUR/tCO_2 after 2021.

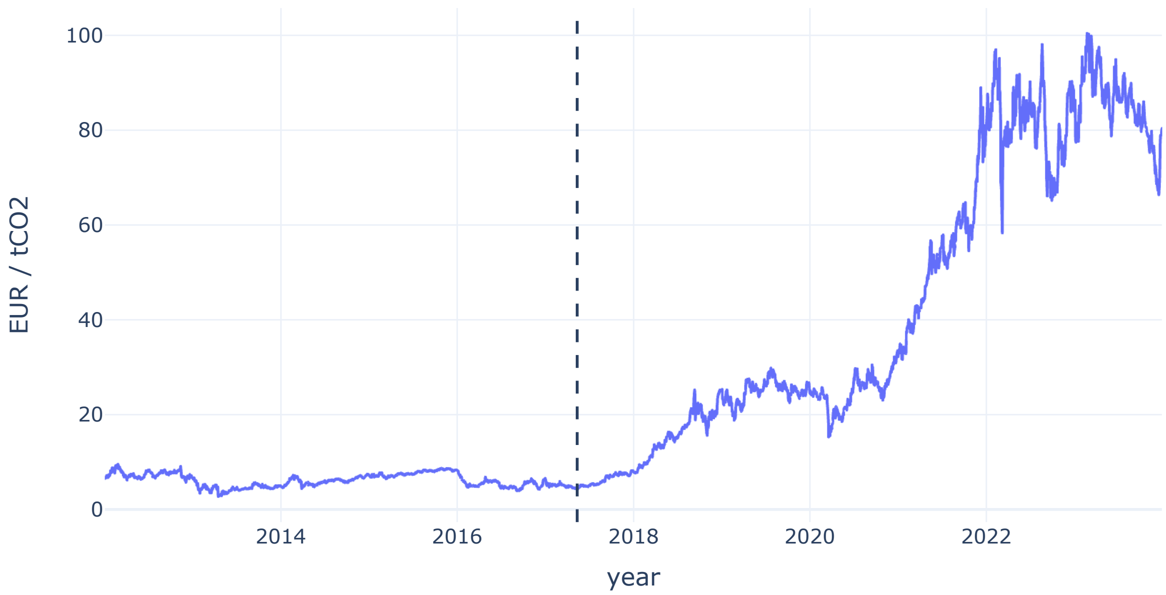


Figure 10: The figure shows the evolution of the EU allowance (EUA) price over the period 2012–2023. The EU Commission launched a proposal for the so-called Market Stability Reform (MSR) initially in 2015 but the market did not meaningfully react until the strengthening of the MSR by the invalidation mechanism in 2017.

Our identification strategy exploits this unexpected increase in the EUA price as an exogenous shock. Using a difference-in-differences strategy, we compare installations with a relatively high carbon price exposure (treated) to similar installations with a relatively low carbon price exposure (control) before and after the carbon price shock. The main identifying assumption is that treatment and control groups would have followed parallel trends in the absence of the exogenous event, the so-called the parallel trends assumption. In a second step, we use variation in the environmental support intensities

[19]https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32018L0410
[20]https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=consil:ST_7607_2017_INIT
[21]https://data.consilium.europa.eu/doc/document/ST-14395-2017-INIT/en/pdf

at the country-industry level to investigate whether the effect of the carbon price shock differs between installations with relatively high and low availability of national support in their industry.

4.2. Empirical Specification

Our empirical strategy proceeds in two steps. First, we use a difference-in-differences strategy to estimate the effect of the carbon price shock between high-exposed and low-exposed firms or installations. Second, we use a triple difference strategy to investigate the joint effect of the carbon price shock and overlapping national support policies. We denote by Post_t the dummy variable that indicates the period after the carbon price shock, i.e.,

$$\text{Post}_t = \begin{cases} 1, & \text{if } t > 2016, \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

Baseline Difference-in-Differences In our baseline difference-in-differences strategy we use the canonical two-way fixed effects estimator

$$Y_{it} = \beta_0 + \beta_1 \times \text{Post}_t \times \mathbb{1}^{\text{CPE}_i} + X_{it} + \lambda_i + \tau_t + \epsilon_{it}, \tag{9}$$

where X_{it} is a (potentially empty) set of control variables, λ_i are installation fixed effects, τ_t are year fixed effects and ϵ_{it} is the error term clustered at the installation level. Our outcome variable Y_{it} are the emissions of installation i in year t.

Triple Difference To investigate the interaction of the carbon price shock with overlapping national policies, we use the triple difference specification (Olden and Møen, 2022) given by

$$\begin{aligned} Y_{it} = \beta_0 + X_{it} + \lambda_i + \tau_t + \epsilon_{it} \\ + \beta_1 \times \text{Post}_t \times \mathbb{1}^{\text{CPE}_i} \\ + \beta_2 \times \text{Post}_t \times \mathbb{1}^{\alpha}_{cj} \\ + \beta_3 \times \text{Post}_t \times \mathbb{1}^{\text{CPE}_i} \times \mathbb{1}^{\alpha}_{cj}. \end{aligned} \tag{10}$$

Alternative Fixed Effects Due to the EU ETS's broad geographical and sectoral scope, time-varying shocks affecting only certain industries or countries pose a threat to our identification strategy. We check the robustness of our results to alternative specifications where we replace the year fixed effects τ_t with more restrictive sets of fixed effects to flexibly account for these potential time-varying confounders. We use year-industry-activity fixed effects τ^1_{tja} to account for time-varying industry-activity-specific shocks and compare installations in the same industry performing the same activities. In alternative specifications we additionally control for time-varying country-specific shocks by adding year-country fixed effects τ^2_{tc} or year-industry-activity-country fixed effects τ^3_{tjac}.

Model Coefficients The main coefficients of interest are β_1, the effect of the carbon price shock on high-exposed compared to low-exposed installations, and β_3, the difference in the effect of the carbon price shock conditional on the availability and generosity of national environmental support policies of type α. We note that our empirical strategy does not enable us to identify the pure effect of national support policies. Because our measure $\mathbb{1}^{\alpha}_{cj}$ exploits variation in environmental support at the country-industry level, a potential threat to the identification of β_2 are time-varying country-industry-specific shocks. However, controlling for these shocks by means of year-industry-country fixed effects τ^3_{tcja} absorbs all variation that could be used for the identification of β_2. We therefore focus on β_1 and β_3 in our analysis.

Event Study Specification To assess the plausibility of the parallel trends assumption and investigate temporal dynamics, we also use event study versions of (9) and (10) where Post_t is replaced by year dummies, i.e.,

$$Y_{it} = \beta_0 + \sum_{s=2012}^{2023} \beta_1^s \times \mathbb{1}_{t=s} \times \mathbb{1}^{\text{CPE}_i} + \lambda_i + \tau_t + \epsilon_{it}, \tag{11}$$

and

$$\begin{aligned} Y_{it} = \beta_0 &+ \lambda_i + \tau_t + \epsilon_{it} \\ &+ \sum_{s=2012}^{2023} \beta_1^s \times \mathbb{1}_{t=s} \times \mathbb{1}^{\text{CPE}_i} \\ &+ \sum_{s=2012}^{2023} \beta_2^s \times \mathbb{1}_{t=s} \times \mathbb{1}^{\alpha}_{cj} \\ &+ \sum_{s=2012}^{2023} \beta_3^s \times \mathbb{1}_{t=s} \times \mathbb{1}^{\text{CPE}_i} \times \mathbb{1}^{\alpha}_{cj}, \end{aligned} \tag{12}$$

where $\mathbb{1}_{t=s}$ is a dummy variable equal to one if the year t is equal to s.

Estimation We are interested in estimating the average proportional treatment effect (Chen and Roth, 2024) of the carbon price shock, i.e.,

$$\text{ATT}_{\%} = \frac{\mathbb{E}[Y_{it}(1)]}{\mathbb{E}[Y_{it}(0)]} - 1, \tag{13}$$

where $Y_{it}(a)$ denotes the potential outcome of installation i in year t for treatment status $a = 0, 1$. Because our main outcome of interest $Y_{it} = \text{Emissions}_{it}$ is non-negative and bounded by zero, it is natural to assume an exponential conditional mean function and estimate specification (9) by means of Poisson quasi-maximum likelihood (QML) (Correia et al., 2020) which approximates the average proportional treatment effect $\text{ATT}_{\%}$ (Wooldridge, 2023).[22] To see this, we note that the exponential conditional mean function

$$\mathbb{E}\left[Y_{it} \mid \text{Post}_t, \mathbb{1}^{\text{CPE}_i}\right] = \exp\left[\beta_0 + \beta_1 \times \text{Post}_t \times \mathbb{1}^{\text{CPE}_i} + \lambda_i + \tau_t\right] \tag{14}$$

implies that β_1 is given

$$\begin{aligned} \beta_1 &= \ln \mathbb{E}[Y_{it} \mid \text{Post}_t = 1, \mathbb{1}^{\text{CPE}_i} = 1] - \ln \mathbb{E}[Y_{it} \mid \text{Post}_t = 0, \mathbb{1}^{\text{CPE}_i} = 1] \\ &\quad - \ln \mathbb{E}[Y_{it} \mid \text{Post}_t = 1, \mathbb{1}^{\text{CPE}_i} = 0] + \ln \mathbb{E}[Y_{it} \mid \text{Post}_t = 0, \mathbb{1}^{\text{CPE}_i} = 0] \\ &= \ln \frac{\mathbb{E}[Y_{it} \mid \text{Post}_t = 1, \mathbb{1}^{\text{CPE}_i} = 1]}{\mathbb{E}[Y_{it} \mid \text{Post}_t = 0, \mathbb{1}^{\text{CPE}_i} = 1]} - \ln \frac{\mathbb{E}[Y_{it} \mid \text{Post}_t = 1, \mathbb{1}^{\text{CPE}_i} = 0]}{\mathbb{E}[Y_{it} \mid \text{Post}_t = 0, \mathbb{1}^{\text{CPE}_i} = 0]} \\ &= \ln \frac{\Delta(1)}{\Delta(0)}, \end{aligned} \tag{15}$$

where $\Delta(a)$ denotes the ratio in average outcomes before and after the carbon price shock for treatment status $a = 0, 1$, i.e.,

$$\Delta(a) = \frac{\mathbb{E}[Y_{it} \mid \text{Post}_t = 1, \mathbb{1}^{\text{CPE}_i} = a]}{\mathbb{E}[Y_{it} \mid \text{Post}_t = 0, \mathbb{1}^{\text{CPE}_i} = a]}. \tag{16}$$

In other words, the coefficient β_1 captures the log-difference between high-exposed and low-exposed installations in the ratio of average emissions before and after the carbon price shock $\Delta(a)$. We can

[22] Although Poisson QML with fixed effects is potentially affected by the so-called incidental parameter problem (Lancaster, 2000), it is consistent for one, two, and three sets of fixed effects (Fernández-Val and Weidner, 2016; Weidner and Zylkin, 2021).

therefore estimate the average proportional treatment effect $\text{ATT}_{\%}$ by rearranging (15) as

$$\text{ATT}_{\%} = e^{\beta_1} - 1. \tag{17}$$

Another useful feature of this approach is that while parallel trends can be sensitive to the specification's functional form (Roth and Sant'Anna, 2023), the exponential conditional mean function implies that parallel trends must hold in the ratio of means (Wooldridge, 2023). The parallel trends assumption in the ratio of means reflects that changes in emission levels are likely larger for larger installations and is therefore preferable to parallel trends in levels.

A commonly used alternative for the estimation of a proportional treatment effect is to log-linearise (14) and apply OLS to the log-transformed outcome $Y_{it} = \ln \text{Emissions}_{it}$. We prefer estimation by Poisson QML for two reasons: First, because installations can temporarily cease production or permanently close, Emisions_{it} can be zero-valued in which case log-linearisation is not well-defined and other commonly applied log-like transformations should not be interpreted as approximating proportional treatment effects (Chen and Roth, 2024). Second, even in the absence of zeros, OLS applied to a log-linearised model is in general inconsistent in the presence of heteroskedasticity (Silva and Tenreyro, 2006; Blackburn, 2007). Nevertheless, we show in Section 6.4 that the OLS estimates of the log-linearised specification are qualitatively similar to the Poisson QML estimates.

5. Results

In this section, we present our treatment effects estimates. We first investigate the baseline effect of the carbon price shock and discuss results for the simple difference-in-differences strategy (9) in Section 5.1. In the following Section 5.2 we present results for the triple difference strategy (10) where we focus on the two main overlapping national policies: renewable energy support for power producers and compensation for energy-intensive undertakings.

5.1. The Effect of the Carbon Price Shock

Table 3 shows the Poisson QML estimates of the effect of the carbon price shock for the full sample, the manufacturing sample and the power sample. We find that after the carbon price shock, high-exposed installations reduce their emissions by approximately $24\% \approx 1 - e^{-0.279}$ relative to cleaner, low-exposed installations in the same industry. We show that our results are robust when flexibly accounting for unobserved time-varying heterogeneity by means of alternative sets of fixed effects in Section 6.1.

	(1)	(2)	(3)
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i}$	-0.279***	-0.067***	-0.449***
	(0.031)	(0.017)	(0.051)
Sample	Full	Manufacturing	Power
Fixed effects	λ_i, τ^1_{tja}	λ_i, τ^1_{tja}	λ_i, τ^1_{tja}
Energy price controls	Yes	Yes	Yes
Cluster variable	Installation	Installation	Installation
Clusters	4,967	3,050	1,247
Observations	57,986	35,366	14,732
Pseudo R^2	0.962	0.981	0.939
RMSE	0.386	0.276	0.419

Table 3: Poisson QML estimates of specification (9) for the full sample and the power and manufacturing subsamples using installation fixed effects λ_i and year-industry-activity fixed effects τ^1_{tja}. The dependent variable is Emissions_{it}. The unit of observation is installation-years. Standard errors are clustered at the installation level. Significance levels: $* < 0.1$, $** < 0.05$, $*** < 0.01$.

The effect size varies strongly between the power sample and the manufacturing sample. We find that high-exposed installations reduced their emissions by more than $36\% \approx 1 - e^{-0.449}$ in the power sample (column 3) compared to around $6.5\% \approx 1 - e^{-0.067}$ in the manufacturing sample (column 2). This heterogeneity is consistent with estimates of marginal abatement costs for different industries and technologies. For example, Duscha et al. (2022) estimate that until 2030 the power sector will dominate emission reductions in the EU ETS for any price level below 90 EUR/tCO_2 largely driven by low-cost abatement strategies such as coal-to-gas fuel switching (Cullen and Mansur, 2017).

As discussed in Section 4.1 our identification strategy requires the parallel trends assumption. To assess its plausibility, we estimate the event study coefficients β^s_1 in specification (11). Figure 11 shows that prior to 2017 the coefficients are small and statistically indistinguishable from zero and that high-exposed installations start to reduce emissions relative to low-exposed installations only after the carbon price shock.

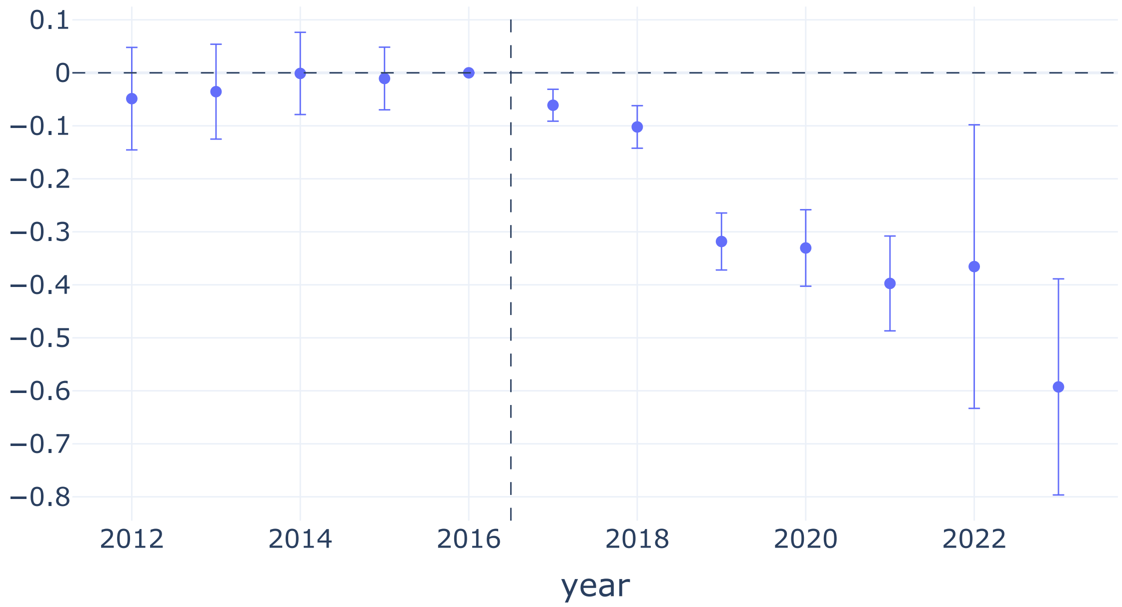


Figure 11: Estimates of the event study specification (11). Each dot represents the point estimate of β_1^s for a given year s. The coefficient β_1^{2016} is normalised to zero. Standard errors are clustered at the installation level and vertical bars show 95% confidence intervals.

We also find considerable temporal heterogeneity in the effect of the carbon price shock. While high-exposed installations start to significantly reduce emissions as early as 2017, we observe the largest reductions in later years consistent with further strong increases in the EUA price between 2020 and 2022 (see Figure 10). While the point estimates in 2022 and 2023 remain statistically highly significant, they are considerably less precisely estimated than in prior years. The increased variance is likely caused by heterogenous responses to the energy crisis following Russia's invasion of Ukraine when some high-exposed coal-fired installations were brought back online to soften the increase in gas prices.

Estimating the event study separately for the power and manufacturing subsamples we confirm the absence of pre-trends and observe quantitatively similar temporal effect dynamics (see Figure 23 and Figure 24 in the appendix).

5.2. Interactions with Overlapping National Policies

We now turn to our analysis of national environmental policies overlapping with the EU ETS. Our descriptive analysis of national environmental support in Section 2.2.5 suggests that renewable energy for power producers and compensation for energy-intensive manufacturing industries are the most generous support policies. We formally assess the importance of the different support policies by including all support categories α in the triple difference (10) to run a horse race. Table 4 confirms that the only significant interactions between the carbon price shock and national support policies is renewable energy support for the power sample and compensation for energy-intensive undertakings for the manufacturing sample. We therefore focus our analysis on the triple difference with $\mathrm{ESP}_{cj}^{\mathrm{res}}$ for the power sample and $\mathrm{ESP}_{cj}^{\mathrm{eiu}}$ for the manufacturing sample.

	(1)	(2)
$\mathrm{Post}_t \times \mathbb{1}^{\mathrm{CPE}_i}$	-0.086***	-0.416***
	(0.026)	(0.060)
$\mathrm{Post}_t \times \mathbb{1}^{\mathrm{CPE}_i} \times \mathbb{1}_{cj}^{\mathrm{eff}}$	-0.017	-0.246
	(0.048)	(0.229)
$\mathrm{Post}_t \times \mathbb{1}^{\mathrm{CPE}_i} \times \mathbb{1}_{cj}^{\mathrm{eiu}}$	0.086***	
	(0.033)	
$\mathrm{Post}_t \times \mathbb{1}^{\mathrm{CPE}_i} \times \mathbb{1}_{cj}^{\mathrm{res}}$		-0.448***
		(0.100)
$\mathrm{Post}_t \times \mathbb{1}^{\mathrm{CPE}_i} \times \mathbb{1}_{cj}^{\mathrm{rnd}}$	-0.089	0.227
	(0.069)	(0.260)
Sample	Manufacturing	Power
Fixed effects	λ_i, τ_{tjac}^3	λ_i, τ_{tjac}^3
Energy price controls	Yes	Yes
Cluster variable	Installation	Installation
Clusters	2,872	1,247
Observations	33,200	14,727
Pseudo R^2	0.985	0.945
RMSE	0.251	0.402

Table 4: Poisson QML estimates of specification (10) using installation fixed effects λ_i and year-industry-activity-country fixed effects τ_{tjac}^3. The dependent variable is $\mathrm{Emissions}_{it}$. The unit of observation is installation-years. Standard errors are clustered at the installation level. We include all four national support policies $\mathbb{1}_{cj}^{\mathrm{res}}$, $\mathbb{1}_{cj}^{\mathrm{eiu}}$, $\mathbb{1}_{cj}^{\mathrm{eff}}$, $\mathbb{1}_{cj}^{\mathrm{rnd}}$. Note that $\mathbb{1}_{cj}^{\mathrm{res}}$ only applies to the power sample and $\mathbb{1}_{cj}^{\mathrm{eiu}}$ only to the manufacturing sample. Significance levels: $* < 0.1$, $** < 0.05$, $*** < 0.01$.

5.2.1. Renewable Energy Support for Power Producers

In this section, we discuss the effect of the carbon price shock and its interaction with national renewable support policies for power producers. Column 1 in Table 5 shows that we find a smaller effect of the carbon price shock of around $28\% \approx 1 - e^{-0.324}$ in countries with low levels of renewable energy support compared to our baseline result of $36\% \approx 1 - e^{-0.449}$ in Table 3. There is, however, a strong and significant interaction between the carbon price shock and renewable energy support: High-exposed power producing installations reduce their emissions by more than $55\% \approx 1 - e^{-0.324-0.485}$, i.e., almost twice as much, in countries with high levels of renewable energy support.

Our estimates are robust to controlling for time-varying country-specific heterogeneity by means of year-country fixed effects τ^2_{tc}. Column 2 in Table 5 shows that we find a stronger effect of the carbon price shock of around $38\% \approx 1-e^{-0.472}$ and a somewhat smaller although highly significant interaction with high levels of renewable support.

	(1)	(2)
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i}$	-0.324***	-0.472***
	(0.057)	(0.069)
$\text{Post}_t \times \mathbb{1}^{\text{res}}_{cj}$	0.086	
	(0.070)	
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i} \times \mathbb{1}^{\text{res}}_{cj}$	-0.485***	-0.395***
	(0.096)	(0.105)
Fixed effects	λ_i, τ^1_{tja}	λ_i, τ^1_{tja}, τ^2_{tc}
Energy price controls	Yes	Yes
Cluster variable	Installation	Installation
Clusters	1,247	1,247
Observations	14,732	14,727
Pseudo R^2	0.941	0.945
RMSE	0.414	0.402

Table 5: Poisson QML estimates of specification (10) for the power sample and renewable energy support. The dependent variable is Emissions_{it}. The unit of observation is installation-years. Standard errors are clustered at the installation level. Column 1 shows estimates using installation fixed effects λ_i and year-industry-activity fixed effects τ^1_{tja}. Column 2 shows estimates including year-country fixed effects τ^2_{tc}. The coefficient β_2 is absorbed by the year-country fixed effects τ^2_{tc} because the power sample consists of exactly one NACE 4-digit industry and activity. Significance levels: $* < 0.1$, $** < 0.05$, $*** < 0.01$.

To assess the plausibility of the parallel trends assumption we estimate the event study version of the triple difference specification (12). Compared to the simple difference-in-differences (9) there is a slight nuance in the parallel trends assumption for the triple difference specification (10). The triple interaction coefficient β_3 can be thought of as the difference between two simple difference-in-differences (Olden and Møen, 2022). In our case, β_3 captures the difference between β_1 for the subsamples of country-industries with high levels of renewable energy support $\mathbb{1}_{cj}^{\text{res}} = 1$ and low levels support $\mathbb{1}_{cj}^{\text{res}} = 0$. To draw valid inferences about the interaction of carbon pricing and national support policies, the difference between these two difference-in-differences needs to follow parallel trends. While this is the only parallel trends assumption needed for the triple difference β_3 (Olden and Møen, 2022), we are also interested in the effect of the carbon price shock and therefore require two parallel trend assumptions.

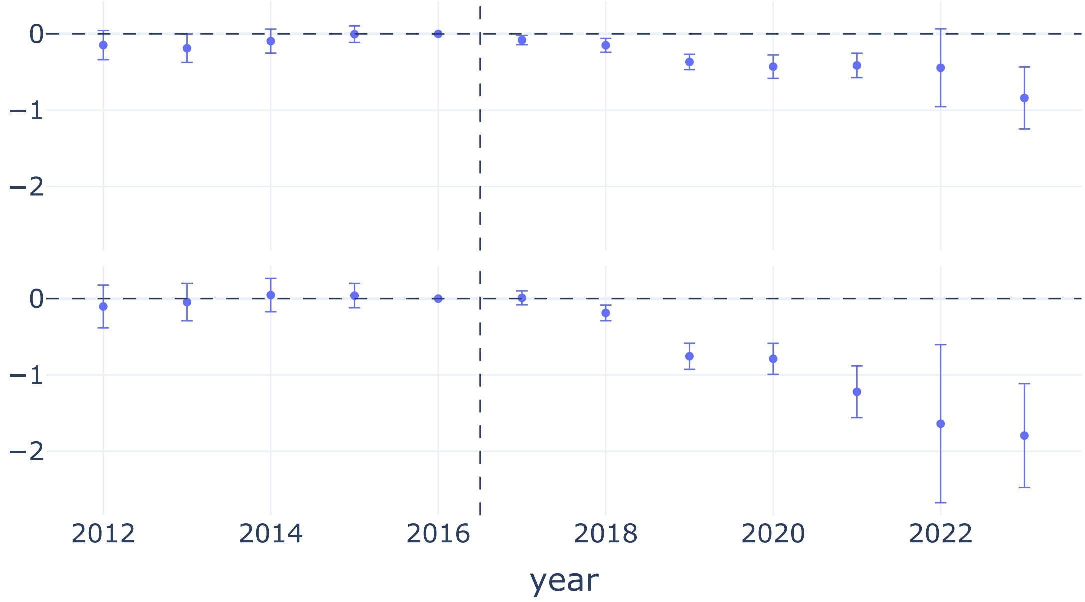


Figure 12: Estimates of the event study specification (11) for the two subsamples of low-intensity countries $\mathbb{1}_{cj}^{\text{res}} = 0$ (top panel) and high-intensity countries $\mathbb{1}_{cj}^{\text{res}} = 1$ (bottom panel). The specification includes installation fixed effects λ_i and year-industry-activity fixed effects τ_{tja}^{1}. Each dot represents the point estimate of β_1^s for the corresponding year s. The coefficient β_1^{2016} is normalised to zero. Standard errors are clustered at the installation level and vertical bars show 95% confidence intervals.

Figure 12 shows estimates of the simple difference-in-differences event study specification (11) for the two subsamples $\mathbb{1}_{cj}^{\text{res}} = 0$ (top panel) and $\mathbb{1}_{cj}^{\text{res}} = 1$ (bottom panel). Reassuringly, we do not find any pre-trends in either sample. Consistent with the negative triple interaction between the carbon price shock and renewable energy support in Table 5, we find a stronger effect of the carbon price shock in the subsample with high renewable support intensity $\mathbb{1}_{cj}^{\text{res}} = 1$. Equivalently, Figure 13 shows estimates of the triple difference event study specification (12) confirming the absence of pre-trends in the event study coefficients β_1^s and β_3^s as well as a negative interaction between the carbon price shock and renewable support.

We have discussed the temporal heterogeneity of the carbon price shock in Section 5.1. The triple difference event study estimates in Figure 13 also show considerable temporal hetereogeneity in the interaction between the carbon price and renewable support. High-exposed power producers in countries with low levels of renewable support increasingly reduce emissions until 2020 but reverse some of their emission reductions in 2021 and 2022. This is likely driven by coal-fired plants increasing output as a response to very high gas prices following Russia's invasion of Ukraine. In contrast, similar high-exposed installations in countries with high levels of renewable support keep reducing emissions beyond 2020 resulting in larger coefficient estimates for the triple interaction β_3^s. This suggests that in the absence of high levels of renewable support the carbon price alone was insufficient to prevent a switch back to coal in response to the unprecedented increase in natural gas prices.

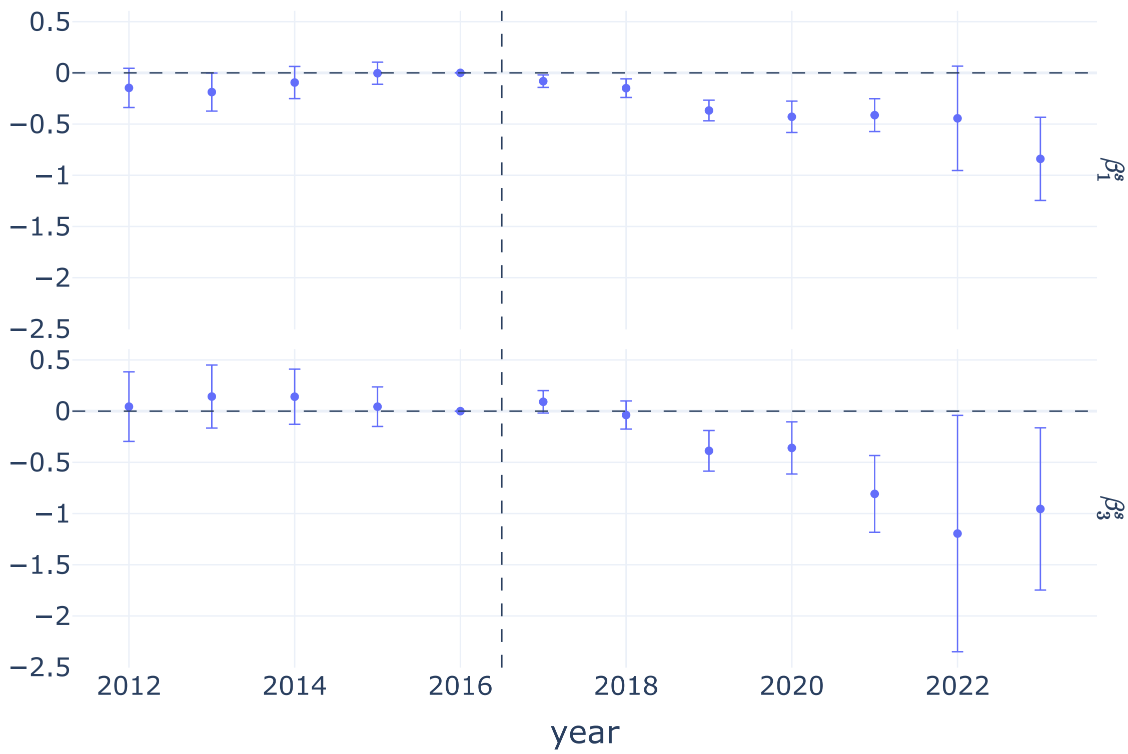


Figure 13: Estimates of the event study specification (12) for β_1^s (top panel) and β_3^s (bottom panel) with installation fixed effects λ_i and year-industry-activity fixed effects τ_{tja}^1. Each dot represents the point estimate of β_k^s for a given year s. The coefficient β_k^{2016} is normalised to zero. Note that the coefficients β_2^s are absorbed by the year-country fixed effects τ_{tc}^2 because the power sample consists of exactly one NACE 4-digit industry and activity. Standard errors are clustered at the installation level and vertical bars show 95% confidence intervals.

5.2.2. Compensation for Energy-Intensive Undertakings

We next discuss the effect of the carbon price shock and its interaction with national compensation for energy-intensive undertakings. Table 6 shows estimates of the triple difference specification (10) for the manufacturing sample and four progressively more restrictive sets of fixed effects. Across the four different specifications we find that the carbon price shock causes emission reductions of between 9–11% in high-exposed installations relative to low-exposed installations in country-industries with low levels of compensation. Moreover, there is an economically and statistically significant interaction between the carbon price shock and high levels of compensation: Across all four specifications the effect of the carbon price shock is strongly attenuated by at least $8\% \approx e^{0.077} - 1$ and almost entirely offset in country-industries with high levels of compensation. Gerster and Lamp (2024) and Basaglia et al. (2024) find that compensation for energy-intensive undertakings causes compensated firms to increase their energy use without a concurrent increase in output. Our findings provide complementary evidence that the EU ETS carbon price signal is attenuated in country-industries with high levels of compensation.

	(1)	(2)	(3)	(4)
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i}$	-0.106***	-0.107***	-0.115***	-0.096***
	(0.025)	(0.025)	(0.023)	(0.026)
$\text{Post}_t \times \mathbb{1}^{\text{eiu}}_{cj}$	-0.051**	-0.049**	-0.031	
	(0.024)	(0.023)	(0.043)	
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i} \times \mathbb{1}^{\text{eiu}}_{cj}$	0.101***	0.115***	0.133***	0.077**
	(0.037)	(0.037)	(0.030)	(0.032)
Fixed effects	λ_i, τ_t	λ_i, τ^1_{tja}	λ_i, τ^1_{tja}, τ^2_{tc}	λ_i, τ^3_{tjac}
Energy price controls	No	No	No	No
Cluster variable	Installation	Installation	Installation	Installation
Clusters	3,109	3,047	3,047	2,879
Observations	36,059	35,339	35,339	33,273
Pseudo R^2	0.979	0.981	0.982	0.985
RMSE	0.283	0.275	0.266	0.251

Table 6: Poisson QML estimates of specification (10) for the manufacturing sample and compensation for energy-intensive undertakings. Each column corresponds to a different set of fixed effects: λ_i are installation fixed effects, τ_t year fixed effects, τ^1_{tja} year-industry-activity fixed effects, τ^2_{tc} year-country fixed effects, and τ^3_{tjac} year-industry-activity-country fixed effects. The dependent variable is Emissions_{it}. The unit of observation is installation-years. Standard errors are clustered at the installation level. Significance levels: $* < 0.1$, $** < 0.05$, $*** < 0.01$.

Our estimates for the specifications with with year fixed effects τ_t (column 1) and year-industry-activity fixed effects τ^1_{tja} (column 2) show a negative and significant coefficient β_2 suggesting that low-exposed installations in country-industries with high levels of compensation reduce more compared to similar installations in country-industries with low levels of compensation (see columns 1 and 4 in Table 6). However, when including year-country fixed effects τ^2_{tc} to control for time-varying country-specific heterogeneity β_2 becomes small and statistically insignificant (column 3). Moreover, as discussed in Section 4.2, we are in principle unable disentangle the pure effect of environmental support from time-varying industry-country-specific shocks as τ^3_{tjac} absorbs the variation in our environmental support measure $\mathbb{1}^{\text{eiu}}_{cj}$ (column 4).

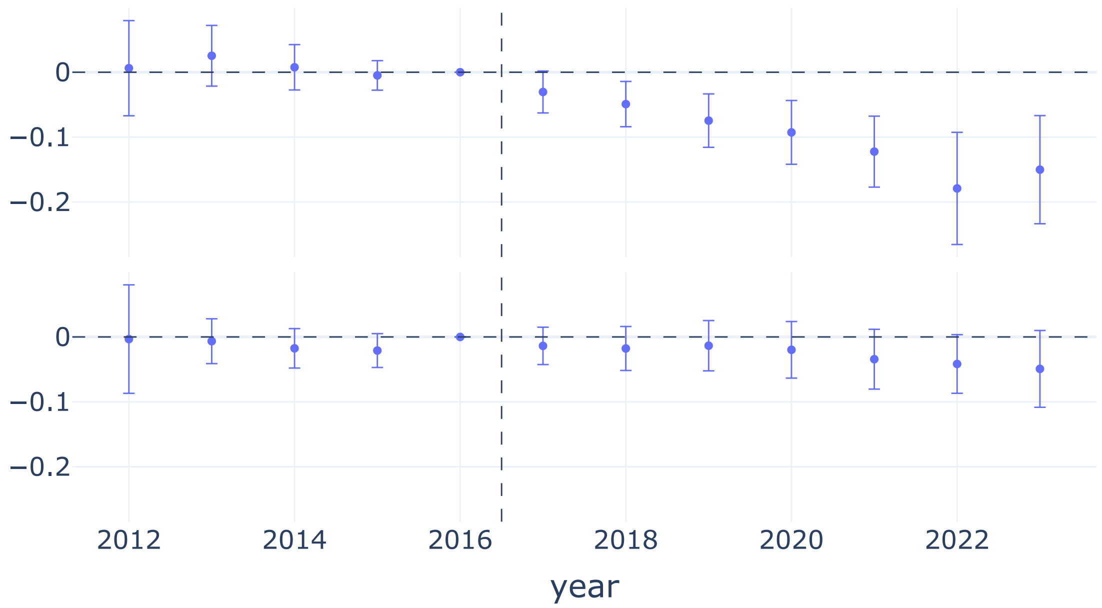


Figure 14: Estimates of the event study specification (11) for the two subsamples of low-intensity countries $\mathbb{1}^{\text{eiu}}_{cj} = 0$ (top panel) and high-intensity countries $\mathbb{1}^{\text{eiu}}_{cj} = 1$ (bottom panel). The specification includes installation fixed effects λ_i, year-industry-activity fixed effects τ^1_{tja}. Each dot represents the point estimate of β^s_1 for the corresponding year s. The coefficient β^{2016}_1 is normalised to zero. Standard errors are clustered at the installation level and vertical bars show 95% confidence intervals.

Our estimates of the event study specification (11) do not indicate a violation of the parallel trends assumptions. Figure 14 shows that before the carbon price shock low-exposed and high-exposed installations were on common trends in both low-intensity country-industries (top panel) and high-intensity country industries (bottom panel). Equivalently, the estimates of the triple difference event study (12) suggest that the coefficients β^s_k in the pre-period are close to zero and statistically insignificant (Figure 15). We find that after the carbon price shock the least efficient, high-exposed installations reduce their emissions relative to cleaner installations in country-industries with low levels of compensation.

In contrast, the effect of the carbon price is almost entirely offset in country-industries with high levels of compensation as the triple interaction β_3^s becomes larger with increases in the absolute value of β_1^s.

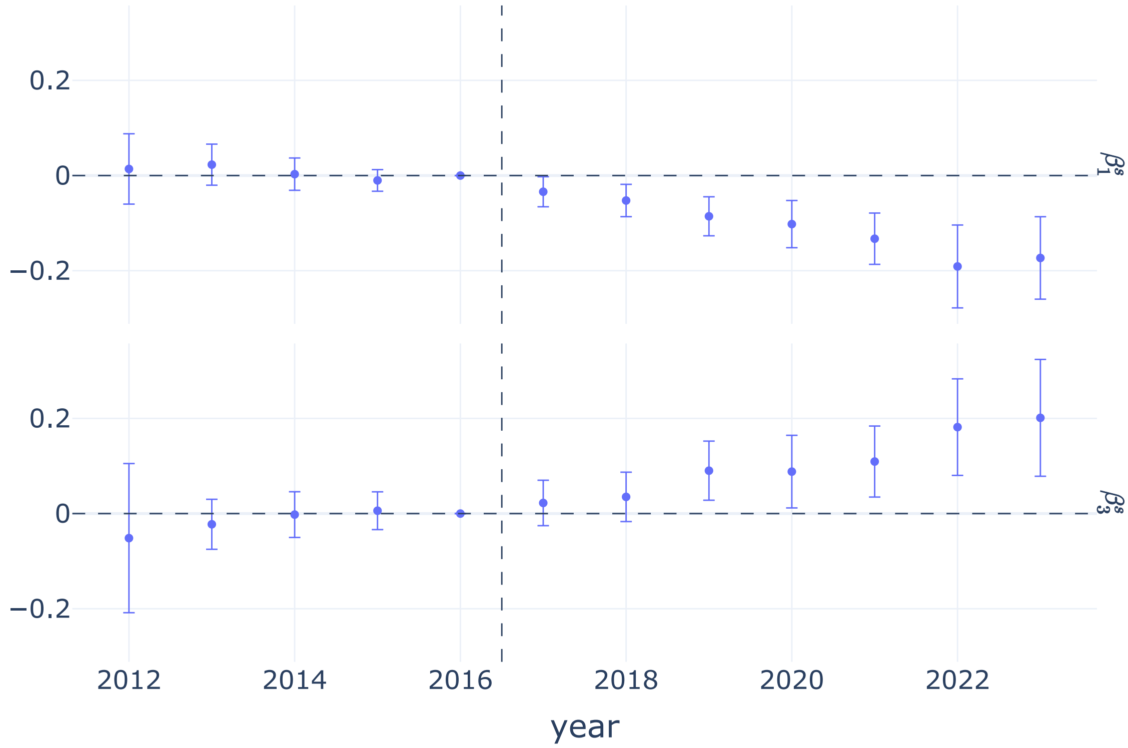


Figure 15: Estimates of the event study specification (12) for β_1^s (top panel), β_2^s (middle panel), and β_3^s (bottom panel) with installation fixed effects λ_i and year-industry-activity fixed effects τ_{tja}^1. Each dot represents the point estimate of β_k^s for a given year s. The coefficient β_k^{2016} is normalised to zero. Standard errors are clustered at the installation-level and vertical bars show 95% confidence intervals.

6. Robustness

6.1. Alternative Fixed Effects

We discuss the robustness of our baseline estimates to alternative sets of fixed effects. First, we replace installation fixed effects λ_i with firm fixed effects λ_f and adjust the level of clustering accordingly. Table 7 shows that the point estimates are quantitatively similar but that the estimates are more precise and that the model's goodness-of-fit measures improve with installation fixed effects λ_i. This is because contrary to firm fixed effects λ_f, installation fixed effects λ_i capture within-firm differences between installations, for example, different activities or production technologies which can be responsible for large differences in emissions.

Second, our estimates presented in Section 5.1 control for year-industry-activity-specific shocks by means of year-industry-activity fixed effects τ^1_{tja}. Table 7 shows that our estimates are also quantitatively similar when using the two-way fixed effects estimator where τ^1_{tja} is by year fixed effects τ_t.

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i}$	-0.312***	-0.313***	-0.071***	-0.066***	-0.480***	-0.449***
	(0.049)	(0.030)	(0.019)	(0.018)	(0.072)	(0.051)
Sample	Full	Full	Manufacturing	Manufacturing	Power	Power
Fixed effects	λ_f, τ_t	λ_i, τ_t	λ_f, τ_t	λ_i, τ_t	λ_f, τ_t	λ_i, τ_t
Energy price controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster variable	Firm	Installation	Firm	Installation	Firm	Installation
Clusters	3,284	5,035	2,201	3,118	713	1,247
Observations	61,682	58,775	36,757	36,155	14,973	14,732
Pseudo R^2	0.793	0.961	0.880	0.979	0.726	0.939
RMSE	1.007	0.391	0.651	0.283	0.988	0.419

Table 7: Poisson QML estimates of specification (9) including year-country fixed effects τ^2_{tc}. Each column corresponds to a different sample (full, manufacturing, power) and uses a different combination of fixed effects and clustering variable. The dependent variable is Emissions_{it}. The unit of observation is installation-years. Significance levels: $* < 0.1$, $** < 0.05$, $*** < 0.01$.

A potential concern is that our estimates could be biased by time-varying country-specific shocks. To address this concern we estimate a more restrictive specification including year-country fixed effects τ^2_{tc}. Table 8 shows that our estimates are qualitatively similar when controlling for time-varying country-specific shocks. One might also be worried about time-varying shocks affecting only certain industries in certain countries. We address this concern by replacing year-industry-activity fixed effects τ^1_{tja} with event tighter year-industry-activity-country fixed effects τ^3_{tjac}. Table 9 shows that our estimates are robust and quantitatively similar.

6.2. Energy Price Controls

As discussed in Section 3.3.1 to account for fuel switching between coal-fired and gas-fired installations, we control for energy prices throughout our analysis of the power sample. Although fuel

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i}$	-0.366***	-0.358***	-0.075***	-0.072***	-0.678***	-0.669***
	(0.048)	(0.031)	(0.017)	(0.016)	(0.081)	(0.053)
Sample	Full	Full	Manufacturing	Manufacturing	Power	Power
Fixed effects	λ_f, τ^1_{tja}, τ^2_{tc}	λ_i, τ^1_{tja}, τ^2_{tc}	λ_f, τ^1_{tja}, τ^2_{tc}	λ_i, τ^1_{tja}, τ^2_{tc}	λ_f, τ^1_{tja}, τ^2_{tc}	λ_i, τ^1_{tja}, τ^2_{tc}
Energy price controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster variable	Firm	Installation	Firm	Installation	Firm	Installation
Clusters	2,715	4,210	1,827	2,636	714	1,248
Observations	49,895	49,642	31,029	31,029	14,980	14,739
Pseudo R^2	0.810	0.961	0.905	0.978	0.736	0.945
RMSE	0.909	0.373	0.516	0.253	0.978	0.401

Table 8: Poisson QML estimates of specification (9) including year-country fixed effects τ^2_{tc}. Each column corresponds to a different sample (full, manufacturing, power) and uses a different combination of fixed effects and clustering variable. The dependent variable is Emissions_{it}. The unit of observation is installation-years. Significance levels: $* < 0.1$, $** < 0.05$, $*** < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i}$	-0.440***	-0.440***	-0.056***	-0.057***	-0.678***	-0.669***
	(0.060)	(0.037)	(0.018)	(0.018)	(0.081)	(0.053)
Sample	Full	Full	Manufacturing	Manufacturing	Power	Power
Fixed effects	λ_f, τ^3_{tjac}	λ_i, τ^3_{tjac}	λ_f, τ^3_{tjac}	λ_i, τ^3_{tjac}	λ_f, τ^3_{tjac}	λ_i, τ^3_{tjac}
Energy price controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster variable	Firm	Installation	Firm	Installation	Firm	Installation
Clusters	2,573	4,050	1,682	2,476	714	1,248
Observations	47,950	47,697	29,084	29,084	14,980	14,739
Pseudo R^2	0.811	0.963	0.900	0.980	0.736	0.945
RMSE	0.934	0.378	0.544	0.248	0.978	0.401

Table 9: Poisson QML estimates of specification (9) including year-industry-activity-country fixed effects τ^3_{tjac}. Each column corresponds to a different sample (full, manufacturing, power) and uses a different combination of fixed effects and clustering variable. The dependent variable is Emissions_{it}. The unit of observation is installation-years. Significance levels: $* < 0.1$, $** < 0.05$, $*** < 0.01$.

switching is not a first order concern for the manufacturing sample, it is well-known that industrial energy consumers within the EU face heterogeneous energy prices (Sato et al., 2019) which can affect firm behaviour (Fontagné et al., 2024; Saussay and Sato, 2024; Gerster and Lamp, 2024). Because the difference-in-differences strategy combined with year-country fixed effects absorbs year-country variation in energy prices, we do not directly control for energy prices in our analysis of the manufacturing sample in Section 5.2.2. A potential concern is that installations could be differentially impacted by energy prices depending on their carbon price exposure. To directly address this concern, we control for country-level electricity prices for industrial consumers. Table 10 shows that our estimates for the manufacturing sample are qualitatively and quantitatively similar when controlling for electricity prices.

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i}$	-0.100***	-0.104***	-0.086***	-0.097***	-0.105***	-0.090***
	(0.024)	(0.021)	(0.025)	(0.023)	(0.021)	(0.026)
$\text{Post}_t \times \mathbb{1}^{\text{eiu}}_{cj}$	-0.064***	-0.024		-0.044**	-0.027	
	(0.024)	(0.037)		(0.021)	(0.041)	
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i} \times \mathbb{1}^{\text{eiu}}_{cj}$	0.113***	0.121***	0.092***	0.105***	0.119***	0.074**
	(0.037)	(0.031)	(0.033)	(0.034)	(0.028)	(0.032)
Fixed effects	λ_f, τ^1_{tja}	λ_f, τ^1_{tja}, τ^2_{tc}	λ_f, τ^3_{tjac}	λ_i, τ^1_{tja}	λ_i, τ^1_{tja}, τ^2_{tc}	λ_i, τ^3_{tjac}
Energy price controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster variable	Firm	Firm	Firm	Installation	Installation	Installation
Clusters	2,143	2,143	1,991	3,047	3,047	2,879
Observations	35,845	35,845	33,335	35,339	35,339	33,273
Pseudo R^2	0.902	0.903	0.899	0.981	0.982	0.985
RMSE	0.567	0.564	0.592	0.275	0.266	0.251

Table 10: Poisson QML estimates of specification (10) for the manufacturing sample and compensation for energy-intensive undertakings including controls for the price of electricity. Each column corresponds to a different combination of fixed effects and clustering variable. The dependent variable is Emissions_{it}. The unit of observation is installation-years. Electricity prices are obtained from Eurostat's electricity prices for non-household consumers `nrg_pc_205`. Significance levels: $* < 0.1$, $** < 0.05$, $*** < 0.01$.

6.3. GVA Support Intensity

We check the robustness of our results to an alternative measure of support intensity. A potential concern regarding the environmental support intensity (2) where we measure expenditures relative to emissions is bias arising from differences in emission efficiency between country-industries. For example, all else equal the emission-based support intensity is higher for a country-industry that emits less per unit of output. Moreover, the support intensity could be inflated if only a small fraction of carbon emitting activities in country-industries are regulated by the EU ETS.[23]

To address these concerns, we create an alternative measure of support intensity for which we do not rely on EU ETS emissions in the numerator of the support intensity (2). Instead, we replace emissions with a country-industry's gross value added (GVA) at the NACE 2-digit level. Specifically, we define the GVA-based environmental support intensity as

$$\text{ESP}^{\alpha}_{cjt} = \frac{\sum_{m \in M^{\alpha}_{cj}} \text{Expenditure}^{\alpha}_{mt}}{\text{GVA}_{cj}}, \tag{18}$$

[23]Because the EU ETS only regulates an installation if it is above an activity-specific capacity threshold, it does not cover all national emissions of the regulated activities. However, comparing Eurostat's national emission accounts at the NACE 2-digit industry against EU ETS NACE 2-digit aggregates, we find that both sources are highly correlated (> 98% Pearson correlation, > 85% Spearman rank correlation) and that the EU ETS covers on average 83% (median 88%) of annual national emissions at the NACE 2-digit level (for more details see Figure 25 and Figure 26 in the appendix).

	(1)	(2)	(3)	(4)
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i}$	-0.344***	-0.475***	-0.339***	-0.512***
	(0.068)	(0.074)	(0.061)	(0.066)
$\text{Post}_t \times \mathbb{1}^{\text{res}}_{cj}$	0.161*		0.117	
	(0.085)		(0.071)	
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i} \times \mathbb{1}^{\text{res}}_{cj}$	-0.381***	-0.510***	-0.305***	-0.345***
	(0.142)	(0.153)	(0.099)	(0.107)
Fixed effects	λ_f, τ^1_{tja}	λ_f, τ^1_{tja}, τ^2_{tc}	λ_i, τ^1_{tja}	λ_i, τ^1_{tja}, τ^2_{tc}
Energy price controls	Yes	Yes	Yes	Yes
Cluster variable	Firm	Firm	Installation	Installation
Clusters	713	713	1,247	1,247
Observations	14,961	14,968	14,732	14,727
Pseudo R^2	0.728	0.733	0.939	0.945
RMSE	0.988	0.986	0.418	0.402

Table 11: Poisson QML estimates of specification (10) for the power sample and renewable energy support using the GVA-based support intensity. Each column corresponds to a different combination of fixed effects and clustering variable. The dependent variable is Emissions_{it}. The coefficient for $\text{Post}_t \times \mathbb{1}^{\text{res}}_{cj}$ is absorbed by the year-country fixed effects τ^2_{tc} because the power sample consists of exactly one NACE 4-digit industry and activity. The unit of observation is installation-years. Significance levels: $* < 0.1$, $** < 0.05$, $*** < 0.01$.

and the high-intensity dummy $\mathbb{1}^{\text{ESP}^{\alpha}_{cjt}}$ analogously to (4) in the case of the emission-based support intensity. Because the GVA-based support intensity is measured at the NACE 2-digit level, it is less granular than the emission-based support intensity at the NACE 4-digit level and, consequently, exploits less variation in national environmental support.

Table 11 shows that our results for renewable energy support are robust to the GVA-based measure of support intensity. The estimates of β_1 and β_3 are qualitatively similar to our baseline estimates in Table 5 across the four specifications.

Table 12 shows that the results for compensation for energy-intensive undertakings are qualitatively and across most specifications also quantitatively similar. The triple interaction β_3 becomes smaller and statistically insignificant in the specification with year-industry-activity-activity fixed effects τ^3_{tjca}. Because environmental support tends to be highly concentrated in a small number of NACE 4-digit industries, the GVA-based support intensity can introduce downward bias. Indeed, because support expenditures are aggregated to the NACE 2-digit level, some NACE 4-digit industries are considered high-intensity in the GVA-based approach although the support is directed at other NACE 4-digit industries within the same NACE 2-digit code. The more granular emission-based approach does not

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i}$	-0.113***	-0.121***	-0.100***	-0.120***	-0.131***	-0.107***
	(0.037)	(0.034)	(0.037)	(0.036)	(0.032)	(0.037)
$\text{Post}_t \times \mathbb{1}^{\text{eiu}}_{cj}$	-0.043	0.035		-0.038	0.020	
	(0.031)	(0.058)		(0.031)	(0.059)	
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i} \times \mathbb{1}^{\text{eiu}}_{cj}$	0.075*	0.083**	0.066	0.076*	0.087**	0.054
	(0.043)	(0.039)	(0.043)	(0.042)	(0.037)	(0.043)
Fixed effects	$\lambda_f,\ \tau^1_{tja}$	$\lambda_f,\ \tau^1_{tja},\ \tau^2_{tc}$	$\lambda_f,\ \tau^3_{tjac}$	$\lambda_i,\ \tau^1_{tja}$	$\lambda_i,\ \tau^1_{tja},\ \tau^2_{tc}$	$\lambda_i,\ \tau^3_{tjac}$
Energy price controls	No	No	No	No	No	No
Cluster variable	Firm	Firm	Firm	Installation	Installation	Installation
Clusters	2,138	2,137	1,988	3,040	3,040	2,875
Observations	35,798	35,776	33,293	35,270	35,270	33,231
Pseudo R^2	0.902	0.903	0.899	0.981	0.982	0.985
RMSE	0.567	0.564	0.592	0.276	0.266	0.251

Table 12: Poisson QML estimates of specification (10) for the manufacturing sample and compensation for energy-intensive undertakings using the GVA-based support intensity. Each column corresponds to a different combination of fixed effects and clustering variable. The dependent variable is Emissions_{it}. The unit of observation is installation-years. Significance levels: $* < 0.1$, $** < 0.05$, $*** < 0.01$.

suffer from this source of downward bias.

6.4. Estimation by OLS

As discussed in Section 4.2 our preferred estimation method of the average proportional treatment effect is Poisson QML. Table 13 reports estimates of specification (9) when log-transforming the outcome $Y_{it} = \ln \text{Emissions}_{it}$ and using OLS. We find quantitatively similar estimates in the manufacturing and power subsamples. We note that in the full sample the coefficient estimate's absolute value is almost halved from -0.279 using Poisson QML (column 1 in Table 3) to -0.161 using OLS (column 1 in Table 13). This difference is driven by the fact that the proportional treatment effect (17) estimated by Poisson QML captures the average emission reductions of high-exposed installations in the aggregate whereas the OLS coefficient corresponds approximately to an individual-level average proportional treatment effect (Chen and Roth, 2024). Because high-exposed power producers are on average larger emitters (see Figure 8, their emission reductions contribute more to the aggregate reductions in the full sample resulting in a larger Poisson QML estimate. In other words, the OLS estimate is smaller because there are more manufacturing installations that on average have achieved smaller emission reductions than a smaller number of high-exposed power producers (Dechezleprêtre et al., 2023).

	(1)	(2)	(3)
$\text{Post}_t \times \mathbb{1}^{\text{CPE}_i}$	-0.161***	-0.071***	-0.438***
	(0.028)	(0.021)	(0.068)
Sample	Full	Manufacturing	Power
Fixed effects	λ_i, τ^1_{tja}	λ_i, τ^1_{tja}	λ_i, τ^1_{tja}
Energy price controls	Yes	Yes	Yes
Cluster variable	Installation	Installation	Installation
Clusters	4,599	2,858	1,230
Observations	48,384	30,153	13,548
Pseudo R^2	0.889	0.910	0.846
RMSE	0.748	0.542	0.998

Table 13: OLS estimates of specification (9) for the full sample and the power and manufacturing subsamples using installation fixed effects λ_i and year-industry-activity fixed effects τ^1_{tja}. The dependent variable is $\ln \text{Emissions}_{it}$. The unit of observation is installation-years. Standard errors are clustered at the installation level. Significance levels: $* < 0.1$, $** < 0.05$, $*** < 0.01$.

7. Conclusion

We have analysed the joint impact of the EU ETS and overlapping national support policies on emissions of regulated installations. Our findings show that the EU ETS contributed significantly to emission reductions, particularly after the 2017 regulatory tightening. The least efficient installations highly exposed to the carbon price reduced their emissions on average by 25% compared to more efficient installations over the period 2017–2023. The effect is particularly pronounced in the power sector, where emission reductions exceeded 36%. In contrast, high-exposed installations in the manufacturing sector experienced a more modest reduction of around 7%, reflecting differences in abatement costs across industries.

Our results show that national environmental support policies interact with the EU ETS in important ways. First, the combination of high carbon prices and national support for renewable energy led to an additional emission reduction of almost 30% among power producers. This indicates that combining these two policies is far more effective in reducing carbon emissions than relying on carbon pricing alone. Looking at this effect over time, we find that countries with less than median renewable support saw its emissions increase again during the energy crisis of 2021–2022 as coal plants were brought back online. In countries with more than median renewable support, on the other hand, the coal-to-gas shift continued during the energy crisis. As a result, countries with less support for renewables increased their emissions, which might have contributed to increased EUA prices, and even to increased EU ETS emissions – given the existence of the EU ETS invalidation rule (Perino, 2018; Bruninx and Ovaere, 2022).

Second, in manufacturing industries receiving high levels of compensation for energy-intensive activities, the impact of the carbon price was significantly attenuated, preventing a shift away from the least efficient installations. This indicates that, compared to country-industries without compensation, cost-effective efficiency gains were not achieved, potentially harming the long-term competitiveness of the compensated industries. Moreover, because aggregate emissions have to decrease in line with the EU ETS's annual cap, abatement has to occur elsewhere at a potentially higher cost, which undermines the system's overall cost-effectiveness. Policymakers may need to reconsider the extent and design of such compensation mechanisms to better balance the benefits of reducing leakage with the costs of increased government spending and the cost of weakening the effect of carbon pricing on industrial decarbonization.

Our findings raise important questions for future research. First, our analysis is restricted to national environmental support covered by EU State Aid control but excludes potentially important other forms of national support. Second, while we document significant interactions, our data does not allow us to directly investigate the mechanisms via which the effect of carbon pricing is reinforced or attenuated. Uncovering these is crucial to improve the compatibility of national environmental policies overlapping with the EU ETS.

Appendix

A. State Aid Data

We use data obtained from the Competition Case Search (CCS) to identify state aid overlapping with the EU ETS. We identify state aid cases with environmental or R&D objectives by means of the fields "primary objective(s)" and "objective(s)" in the CCS. We categorise the identified state aid cases overlapping with the EU ETS into one of four disjoint subcategories: renewable energy support, compensation for energy-intensive undertakings, investment aid for energy efficiency, and support for research and development.

A.1. Renewable Energy Support

Renewable energy support encompasses a wide variety of measures supporting the generation of electricity from renewable energy sources including feed-in tariffs (for example Netherlands' SDE+[24]), renewable energy certificates (for example Romania's green certificates scheme[25]), and renewable energy auctions (for example Denmark's multi-technology tender[26]).

Some measures are designed to provide support regardless of the producer's size. For example, Germany's feed-in-tariff[27] provides notched premia for large- and small-scale production technologies. We therefore collect data from national sources to adjust the CCS expenditures for support directed at small-scale technologies not regulated by the EU ETS, e.g., rooftop solar. The adjustments for residential support concern the following countries: Austria, Czech Republic, Croatia, France, Germany, Lithuania, Portugal.

[24] https://competition-cases.ec.europa.eu/cases/SA.34411
[25] https://competition-cases.ec.europa.eu/cases/SA.33134
[26] https://competition-cases.ec.europa.eu/cases/SA.49918
[27] https://competition-cases.ec.europa.eu/cases/SA.38632

A.2. Compensation for Energy-Intensive Undertakings

Compensation for energy-intensive undertakings includes support measures to ease the cost of energy consumption for energy-intensive activities. The measures include exemptions from electricity taxes (for example in Denmark[28]), reductions for renewable surcharges (for example in Germany[29]) or compensation of indirect CO_2 costs (for example in Lithuania[30]).

A.3. Investment Aid for Energy Efficiency

Investment aid for energy efficiency includes measures in the form of loans or direct grants for investments in improved energy efficiency. State aid cases in this category include both large national schemes (for example by the French Agency for the Ecological Transition (ADEME)[31] or Italy's development contracts[32]) and smaller short-term measures (for example loan programs by Germany's development bank KfW[33]).

A.4. Support for Research & Development

Support for Research & Development includes direct grants and tax subsidies for research and development activities. Note that the data does not enable us to identify if the support is primarily directed at environmentally related R&D. This category therefore is the only national support policy category that does not have an exclusive environmental objective. Similarly to investment aid for energy efficiency, state aid cases in this category can be both larger national schemes (for example Germany's energy research program[34]) and smaller or short-term measures (for example a technology and innovation program in Austria[35]).

[28] https://competition-cases.ec.europa.eu/cases/SA.34287
[29] https://competition-cases.ec.europa.eu/cases/SA.41381
[30] https://competition-cases.ec.europa.eu/cases/SA.41981
[31] https://competition-cases.ec.europa.eu/cases/SA.40266
[32] https://competition-cases.ec.europa.eu/cases/SA.48248
[33] https://competition-cases.ec.europa.eu/cases/SA.34164
[34] https://competition-cases.ec.europa.eu/cases/SA.39097
[35] https://competition-cases.ec.europa.eu/cases/SA.36050

B. Installation-level Emissions Intensity

There are two important limitations to the approximation of emission intensity (6). First, the activity type "combustion" includes installations "where deriving a product benchmark was not feasible" in which case free allocation is determined "on the basis of generic fallback approaches".[36] Because potentially very different activities can be grouped under "combustion", it is unlikely that the free allocation methodology enables reliable inference on the installation's historical output level, and consequently also its carbon price exposure. We therefore exclude combustion installations from the manufacturing sample, which corresponds to approximately 16% of regulated emissions.

Second, there is in general no unique mapping of benchmarks to installations. The EUTL records an installation's main activity a but a single activity can potentially relate to multiple products $p_1, \ldots, p_n$ each with a distinct efficiency benchmark $\text{Benchmark}^a_{p_k}$. It is therefore in general not possible to exactly calculate the historical activity level HAL_i unless the activity a is associated with exactly one product p. Fortunately, 13 out of 24 activities are associated with exactly one product and the variation in benchmark values tends to be small for the other activities.[37] We therefore make the simplifying assumption that Benchmark^a_p and CLEF^a_p are constant and given by the average value of all products p of activity a.

Manufacturing of basic metals Our simplifying assumption does not provide valid approximations for installations in the industry "manufacturing of basic metals" (NACE 2-digit code 24). This is because the activity "production of steel" is associated with distinct benchmarks for the two main production technologies: blast furnace and electric arc furnace. While electric arc furnaces are significantly more efficient than blast furnaces, the free allocation methodology uses distinct benchmarks for the two technologies, hence shifting free allocation in favour of the less efficient blast furnaces.[38] Consequently, without knowledge of the underlying technology it is not possible to infer the emission efficiency of installations manufacturing steel from the free allocation methodology (5).

[36] https://eur-lex.europa.eu/eli/dec/2011/278/oj

[37] For example, the activity "Production of paper or cardboard" is associated with seven products with efficiency benchmarks ranging from 0.24 to 0.32 tCO_2 per unit of product. A notable exception concerns activities associated with the manufacture of basic metals which we discuss separately in the following paragraph.

[38] The efficiency benchmark for blast furnaces is 1.328 tCO_2 per tonne of steel compared to 0.283 tCO_2 per tonne of steel for electric arc furnaces. See https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/free-allocation_en

We therefore enrich the EUTL with data on the main production technology of steel plants monitored by the Global Energy Monitor (GEM)[39]. We successfully identify 147 installations corresponding to approximately 90% of verified emissions in the NACE 4-digit industry "24.10—manufacture of basic iron and steel and of ferro-alloys" (cf. Figure 16 in the appendix). We then use an installation's production technology to infer its benchmark value Benchmark_p^a used in the free allocation methodology (5) and determine its carbon price exposure CPE_i according to (6).

[39] https://globalenergymonitor.org

C. Supplementary Figures

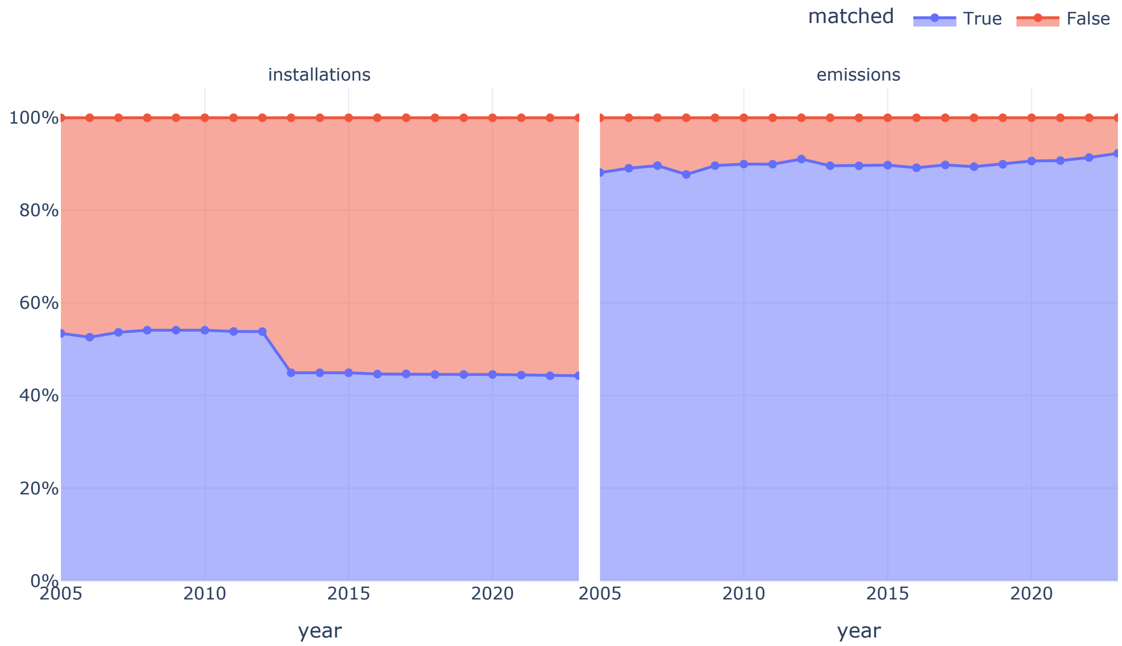


Figure 16: Share of installations (left-hand side) and emissions (right-hand side) in the NACE 4-digit industry 24.10 that are successfully matched to the Global Energy Monitor's *Global Steel Plant Tracker*.

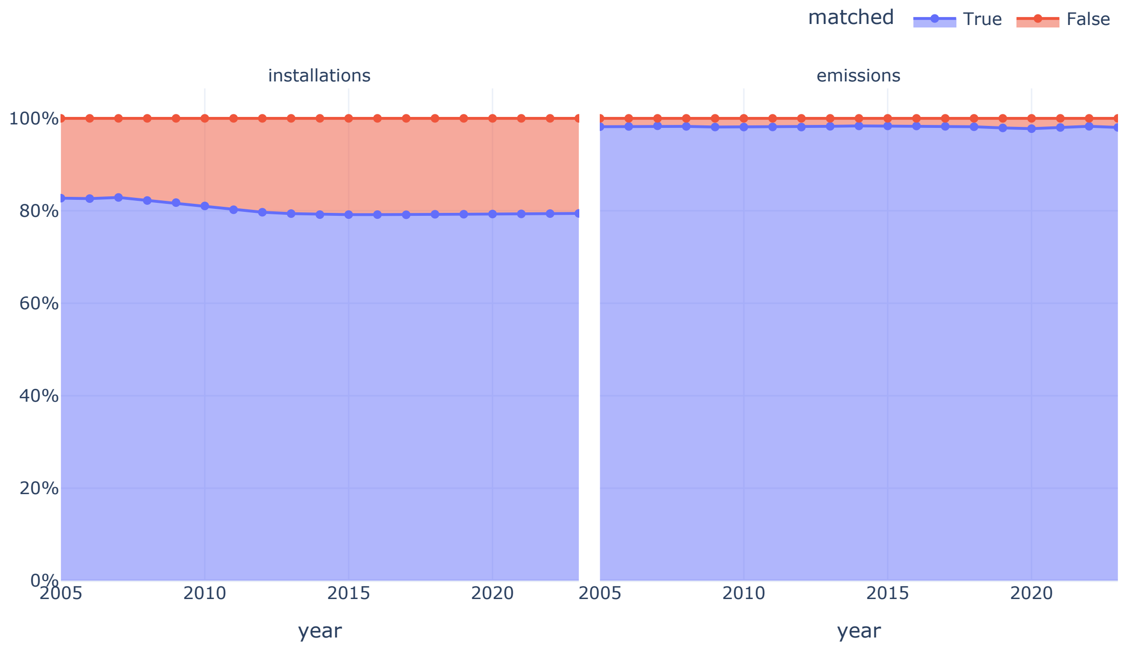


Figure 17: Share of installations (left-hand side) and emissions (right-hand side) in the NACE 4-digit industry 35.11 that are successfully matched to the Global Energy Monitor databases.

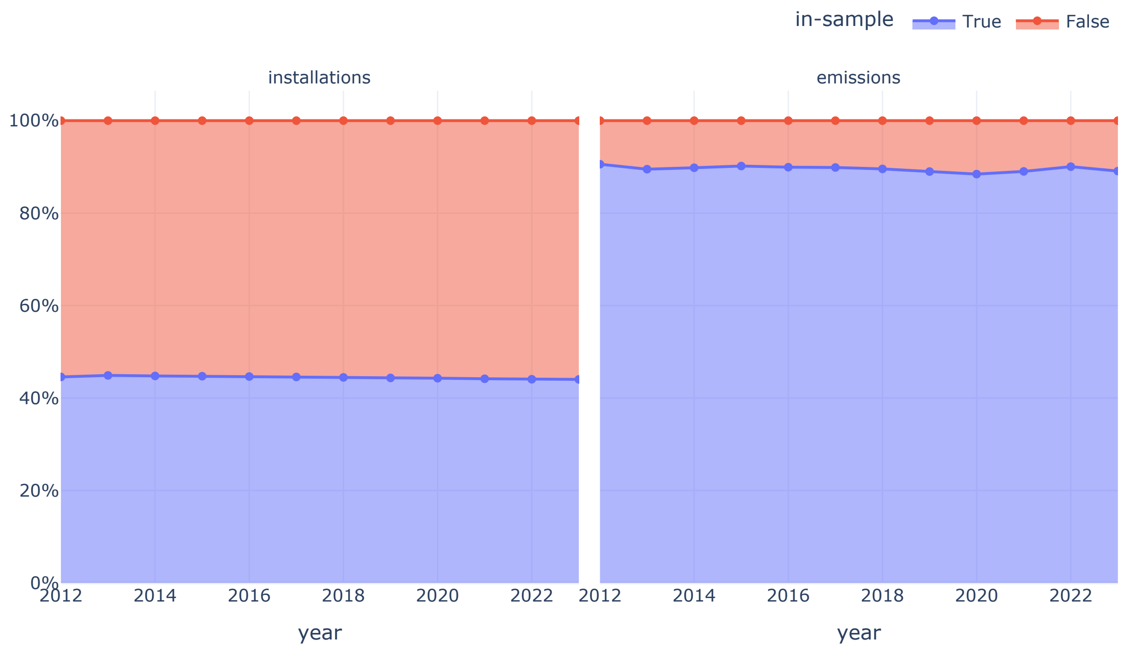


Figure 18: Share of installations (left-hand side) and emissions (right-hand side) covered by the main sample.

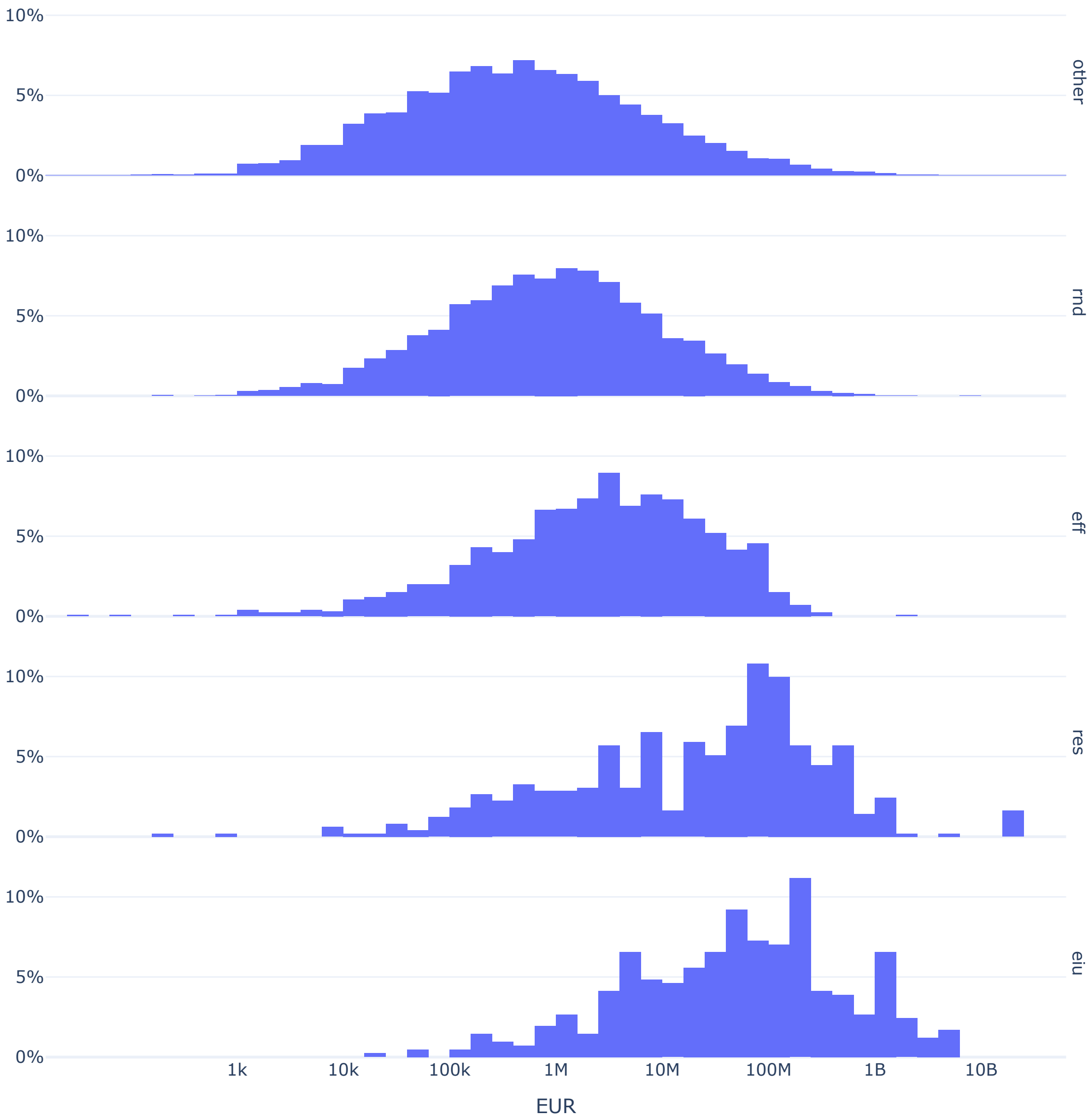
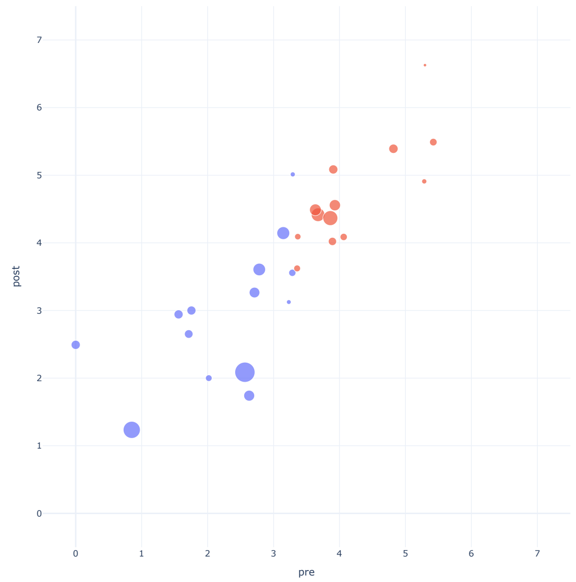
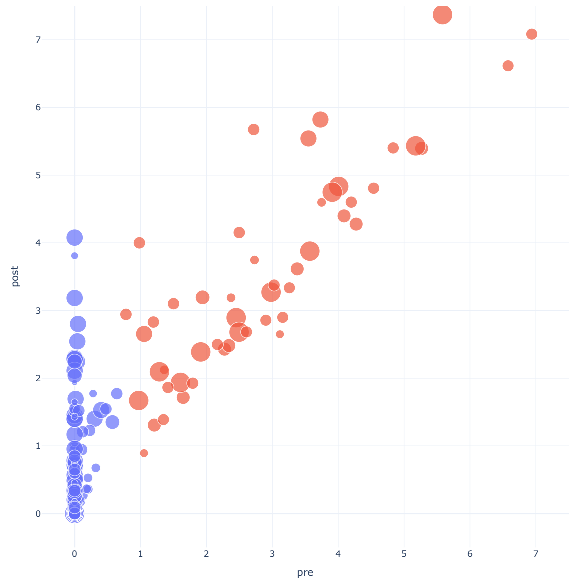


Figure 19: The chart shows the distribution of annual case-level expenditures $\text{Expenditure}_{mt}^{\alpha}$ as defined in (2). Each row corresponds to a distinct policy category α: support for R&D, investment aid for energy efficiency (eff), renewable energy support (res), and compensation for energy-intensive industries (eiu). Other refers to all other state aid cases not part of one of the four categories α.

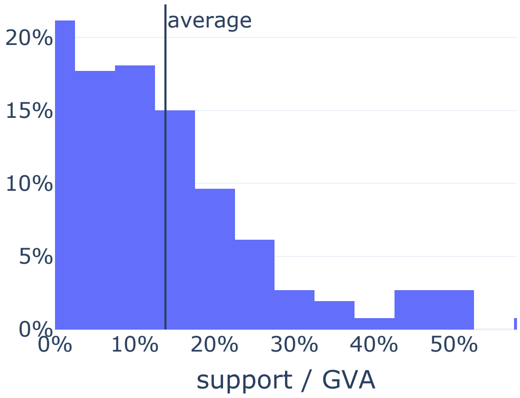


(a) renewable energy support

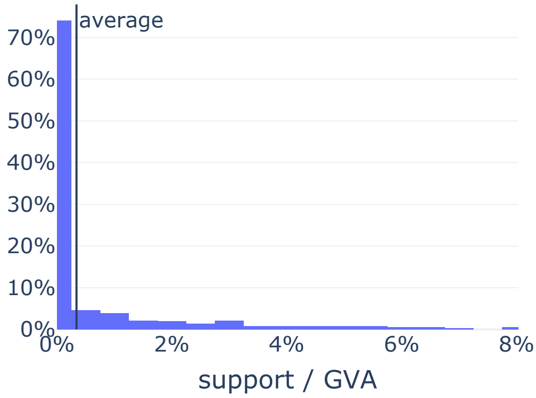


(b) compensation energy-intensive undertakings

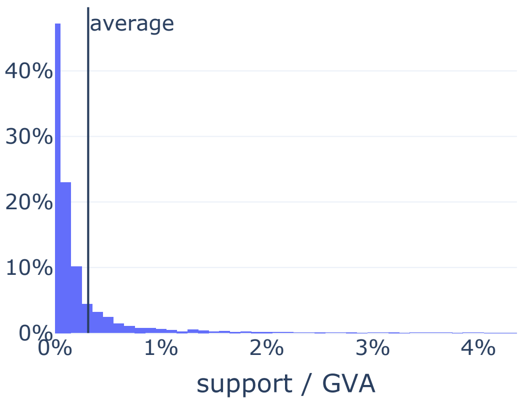
Figure 20: The chart shows the average annual environmental support intensity $\overline{\mathrm{ESP}}^{\alpha}_{cj}$ in the pre-period before 2017 (x-axis) and the post-period (y-axis). The colour indicates if a country's pre-period average intensity is above the median $\mathbb{1}^{\alpha}_{cj} = 1$ (red) or below $\mathbb{1}^{\alpha}_{cj} = 0$ (blue). The marker size corresponds to total emissions in the country-industry. The environmental support intensity is log-transformed to improve the charts' readability.



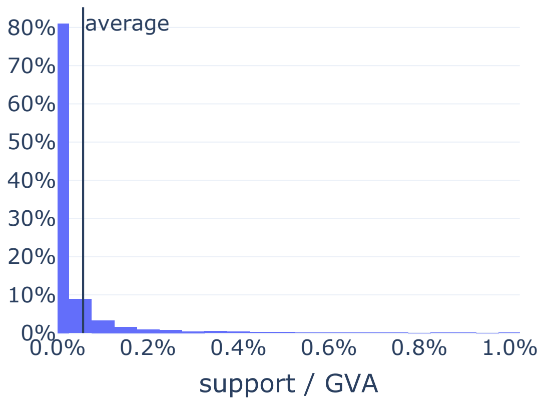
(a) renewable energy support



(b) Compensation for energy-intensive industries



(c) R&D support



(d) investment aid for energy efficiency

Figure 21: The histograms show the distribution of annual country-industry expenditures on environmental support normalised by the country-industry's gross value added (GVA) over the period 2012–2021. Expenditures are aggregated at the NACE 2-digit industry level and the corresponding GVA is obtained from Eurostat's national accounts aggregates by industry `nama_10_a64`. To improve readability the histograms' x-axes are truncated at the 99%-tile.

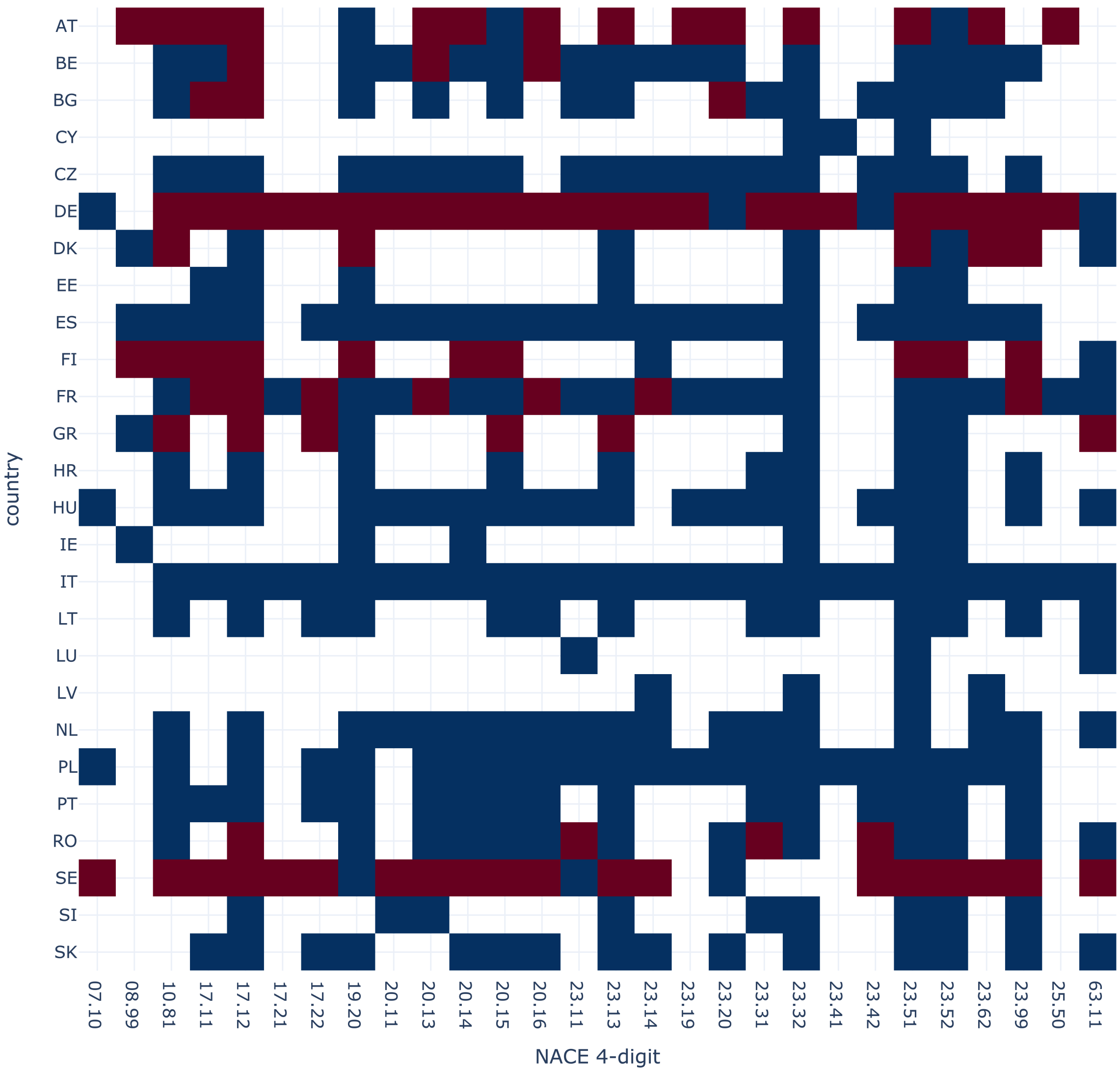


Figure 22: The chart illustrates the distribution of country-industries with high levels of compensation for energy-intensive undertakings. The chart includes NACE 4-digit industries with at least five installations. Each cell represents a country-industry. A cell is marked red if $\mathbb{1}^{\mathrm{ESP}_{cj}^{\mathrm{eiu}}} = 1$ and blue if $\mathbb{1}^{\mathrm{ESP}_{cj}^{\mathrm{eiu}}} = 0$. Non-coloured cells indicate that there are no installations in this country-industry.

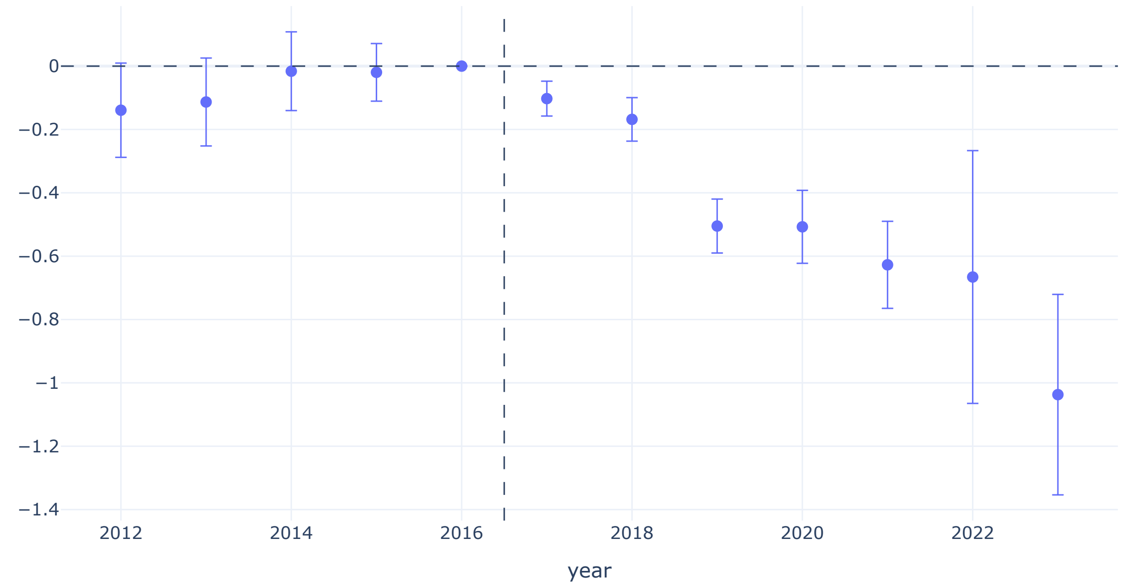


Figure 23: Estimates of the event study specification (11) for the power sample. Each dot represents the point estimate of β_1^s for a given year s. The coefficient β_1^{2016} is normalised to zero. Standard errors are clustered at the installation-level and vertical bars show 95% confidence intervals.

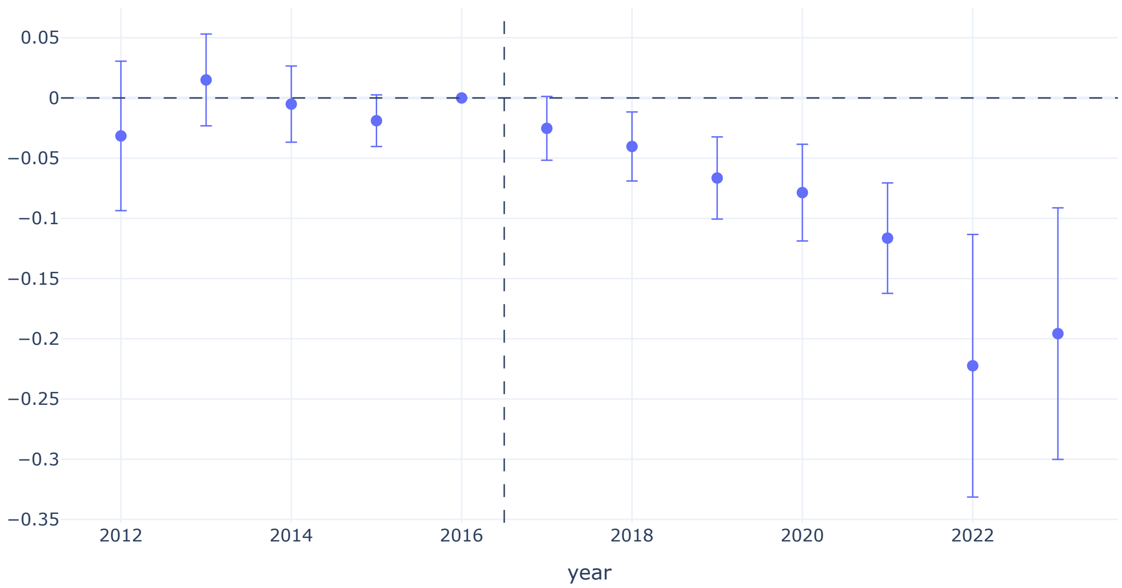


Figure 24: Estimates of the event study specification (11) for the manufacturing sample. Each dot represents the point estimate of β_1^s for a given year s. The coefficient β_1^{2016} is normalised to zero. Standard errors are clustered at the installation-level and vertical bars show 95% confidence intervals.

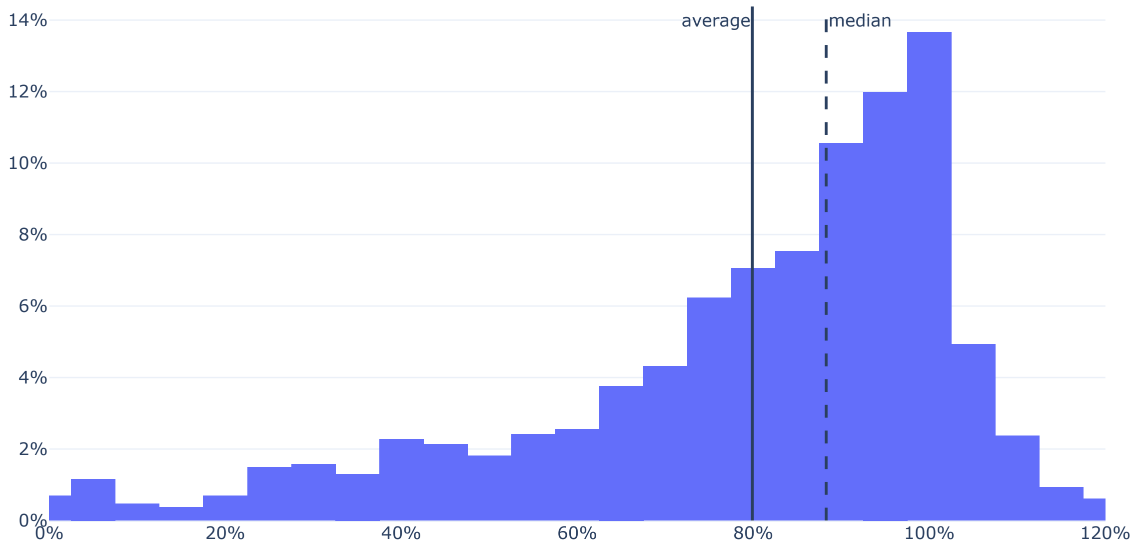


Figure 25: Distribution of the share of annual national NACE 2-digit emissions covered by the EU ETS for the six largest NACE 2-digit industries 17, 19, 20, 23, 24, 35 over the period 2005–2022. The NACE 2-digit industries 17, 19, 20, 23, 24, 35 account for more than 97% of overall EU ETS emissions. The unit of observation is year-country-industry. National NACE 2-digit emissions are obtained from Eurostat's air emissions accounts by NACE Rev. 2 activity `env_ac_ainah_r2`.

Figure 26: Average annual share of national NACE 2-digit emissions covered by the EU ETS for the six largest NACE 2-digit industries 17, 19, 20, 23, 24, 35 over the period 2005–2022. The x-axis shows annual average national emissions in each NACE 2-digit industry. The y-axis shows the average annual share of emissions covered by the EU ETS. The NACE 2-digit industries 17, 19, 20, 23, 24, 35 account for more than 97% of overall EU ETS emissions. National NACE 2-digit emissions are obtained from Eurostat's air emissions accounts by NACE Rev. 2 activity `env_ac_ainah_r2`.

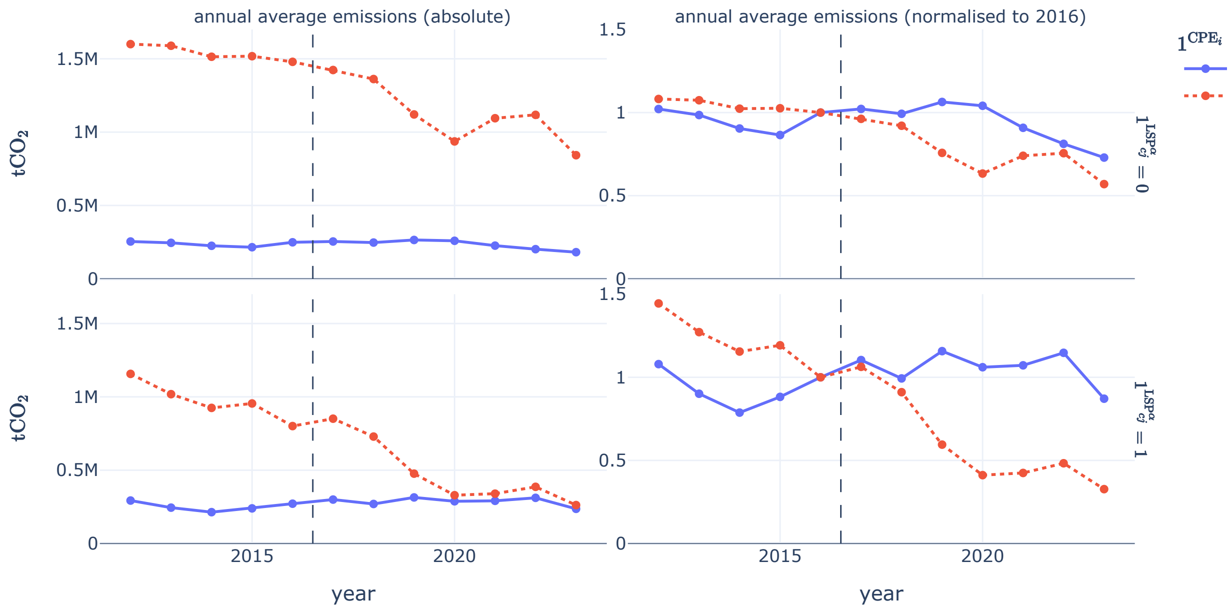


Figure 27: The chart compares the annual average emissions in the power sample for high-exposed (dashed, red) and low-exposed (solid, blue) installations between countries with low levels of renewable energy support (top panel) and high level of renewable energy support (bottom panel). The left-hand side shows absolute values, while the right-hand side is normalised to 2016.

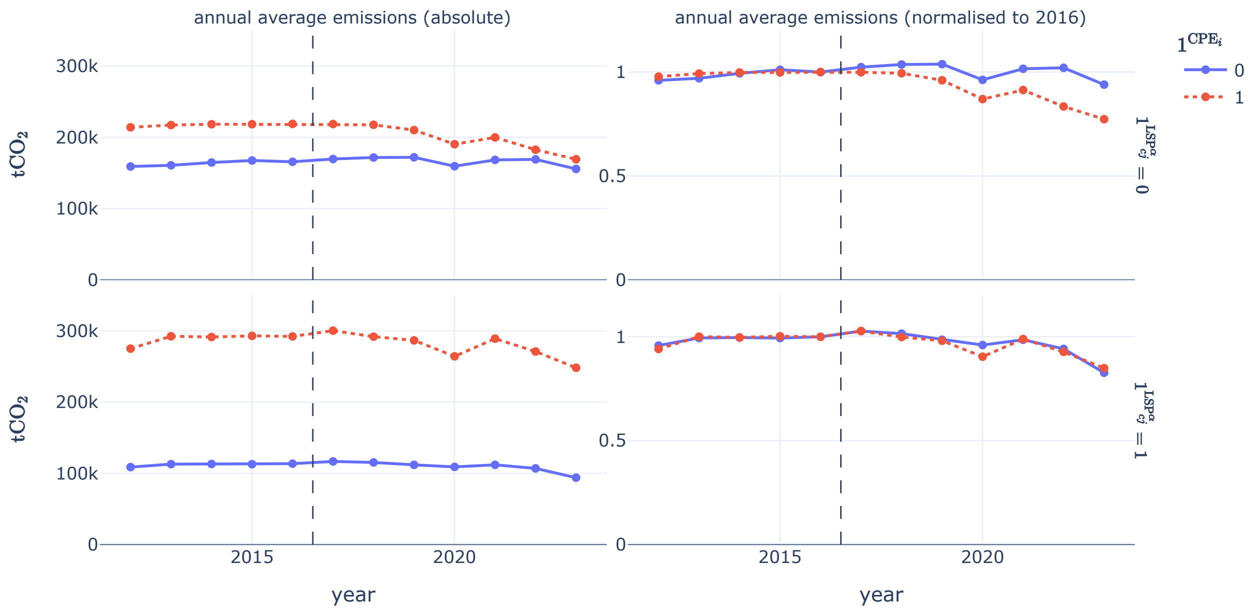


Figure 28: The chart compares the annual average emissions in the manufacturing sample for high-exposed (dashed, red) and low-exposed (solid, blue) installations between country-industries with low levels of compensation for energy-intensive activities (top panel) and high levels of compensation for energy-intensive activities (bottom panel). The left-hand side shows absolute values, while the right-hand side is normalised to 2016.

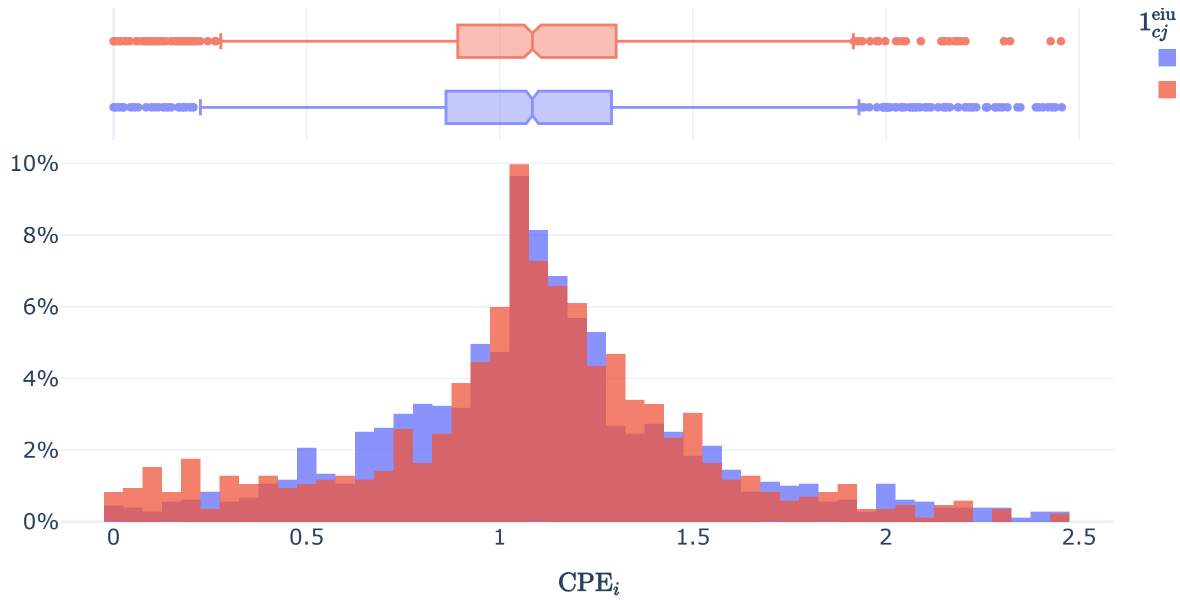


Figure 29: The chart shows the distribution of the carbon price exposure CPE_i for the manufacturing sample for high-intensity and low-intensity country-industries for compensation for energy-intensive industries. The carbon price exposure CPE_i is scaled by $\mathrm{Benchmark}^a_p \times \mathrm{CLEF}^a_p$ to facilitate comparability across different activities a (cf. (5)). The x-axis is truncated at the 95%-tile.

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Pierre Wunsch
Governor of the National Bank of Belgium

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