Does compensating firms for indirect carbon costs work? Evidence from Finnish manufacturing

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Abstract

The EU ETS indirect cost compensation subsidy scheme was introduced across 10 EU countries in the 2010s to alleviate firms' increased electricity expenses resulting from the EU Emission Trading System. Its principal goal was to bolster the competitiveness of EU-based producers and prevent the offshoring of production. This study empirically investigates the impact of this compensation subsidy on firm performance, employing detailed production plant data from Finland. Notably, there is no conclusive evidence indicating a definitive surge in electricity costs in Finland during the subsidy period. Moreover, the structure of the subsidy scheme itself seems to have suffered from inefficiencies. Consequently, my research findings do not substantiate any discernible enhancement in the competitiveness of firms benefiting from this subsidy program. The only observed effect is an increase in electricity purchases by the subsidized plants, which does not inherently translate to enhanced competitiveness.

Keywords: *firm subsidy, EU ETS, firm competitiveness*
JEL Codes: *D22, H23, Q58*

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1 Introduction

The European Union's Emissions Trading Scheme (EU ETS), initiated in 2005 as a cap-and-trade mechanism to regulate carbon emissions, has yielded encouraging outcomes. Empirical analyses indicate a reduction in emissions across the EU, with minimal adverse effects on firm competitiveness despite the regulatory stringency (Colmer et al., 2024; Dechezleprêtre et al., 2023; Bayer & Aklin, 2020; Marin et al., 2018; Arlinghaus, 2015). Nevertheless, the intensification of EU's emission reduction targets has led to concerns about potential negative impacts on industrial competitiveness. To alleviate these, the EU has instituted subsidy schemes aimed at offsetting the costs incurred by firms due to emission charges. Notably, the EU ETS indirect cost compensation has been adopted by 10 member states (Belgium, Finland, France, Germany, Greece, Lithuania, Luxembourg, the Netherlands, Slovakia, and Spain) to subsidize the increased electricity costs resulting from the ETS. The effectiveness of these types of subsidies, however, has not been thoroughly examined, underscoring the necessity for comprehensive analysis to inform the development of robust environmental and fiscal policies.

In the guidelines for the compensation subsidy, the European Commission states that its aim is "to prevent a significant risk of carbon leakage due to EUA [European Union allowance] costs passed on in electricity prices, if its competitors from third countries do not face similar CO_2 costs in their electricity prices and the beneficiary is unable to pass on those costs to product prices without losing significant market share".[1] Carbon leakage can mean either increased production in existing plants outside the regulation or relocation of production. The Commission's apprehension is thus that the increased electricity costs following the EU ETS implementation might incentivize production capacity to migrate to nations with cheaper electricity. Nevertheless, existing empirical research has not substantiated significant evidence of carbon leakage (see e.g. Dechezleprêtre et al. (2019); Koch & Basse Mama (2019); Borghesi et al. (2020)).

In this study, I analyze the effects of the EU ETS indirect cost compensation subsidy in Finland, specifically on production plant-level performance metrics such as gross production. In addition, the study incorporates the analysis of electricity purchases, employed as a proxy indicator, to assess whether the subsidy has exerted a discernible impact on the electricity consumption patterns of these production plants. To this end, a unique dataset, encompassing plant-level details, is utilized to execute a difference-in-differences analysis. This methodology enables a comparison of the competitiveness effects experienced by firms that received the subsidy against those that did not.

The contribution of this paper to existing research is twofold: to give a better understanding of the effectiveness of the compensation subsidy scheme, and to analyze how subsidies are best combined with environmental regulation. The monetary amount of energy related subsidies has been growing over the recent years in Finland, but their realized effects are still unclear (Ilmakunnas et al., 2023). Existing literature on energy-related subsidies is limited, and more evidence on their effectiveness is needed. This paper's findings will serve as a valuable resource for policymakers tasked with determining optimal fiscal strategies to support sustainable transitions. Besides subsidies, other ways of supporting the green transition also exist and could perhaps be more efficient, such as utilizing taxation and the emission trading system, as noted in a recent report on Finnish firm subsidies in Ilmakunnas et al. (2023).

The compensation subsidy in the form that is studied in this paper was given out in Finland in 2016–2020, but after this a similar but somewhat redesigned subsidy scheme still continues for 2021–2025. Between 2016–2020, the total amount of compensation subsidies given out in Finland were approximately 275 million euros.[2] The subsidy scheme was designed so that the payments would be below the income that Finland gets from selling the EU ETS emission permits. In other words, the idea appears to be that the emission permit auctions cover the costs of the subsidies.[3] The subsidy amounts

[1] *Communication from the Commission, Guidelines on certain State aid measures in the context of the greenhouse gas emission allowance trading scheme post-2012, SWD(2012) 130 final*

[2] *Amount calculated from the subsidy decisions in the Finnish Energy Authority system.*

[3] *This is noted in the draft of the original subsidy plan (in Finnish): https://www.finlex.fi/fi/esitykset/he/2016/20160147. In the redesigned subsidy, the maximum amount is not tied to the emission allowance income but instead there is a cap of 150 million euros per year.*

are also tied to the emission allowance prices, as the prices are one input in the formula that is used to calculate the maximum amount of subsidy for each plant. Nonetheless, revenue generated from the sale of emission allowances is incorporated into the nation's general budget and may be allocated for various purposes. Consequently, the formulation of optimal fiscal policy is an important consideration in this analysis.

An important question for the context of this study is whether the emission allowance costs have in fact been passed through to electricity costs, as it determines whether the subsidy compensated price increases that never materialized. This question has been the topic of many studies, although most of them have so far focused on the phase 1 and 2 when the allowances were mostly given for free. During this time, the allowances placed an opportunity cost on the installations in question regardless of how they were received, as the allowances could have been sold instead of being used by the installations (Fell, 2010). Jouvet & Solier (2013) show that during phase 1 (2005–2007), emission costs were factored into the electricity spot prices across various European markets, including Nord Pool. However, this pass-through effect was dampened in phase 2 (2008–2012), potentially as a consequence of the 2008 financial crisis. Similar findings are echoed by Sijm et al. (2008), Fell (2010), and Fabra & Reguant (2014), noting the translation of emission costs into wholesale electricity prices in the scheme's initial phase. While insights into phase 3 (2013–2020) remain sparse, the sustained low levels of emission allowance prices during this period suggest that electricity producers may have continued to incorporate emission costs into their pricing.

It can be concluded that at the outset of the 2010s, when the EU ETS indirect cost compensation subsidy was being formulated, existing evidence indicated that electricity producers were not fully absorbing the emission costs. Instead, these costs were being passed through, leading to higher electricity prices for the consumers. As a result, it was the electricity users, rather than the producers, who received the subsidy.

While extant research in the domain of environment-related subsidies remains somewhat nascent, an important contribution specifically on the indirect cost compensation subsidy has been made by Ferrara & Giua (2022), who conduct an expansive EU-wide analysis on this topic. Their findings show no significant effect on average relative competitiveness of firms, measured in terms of turnover per worker and the value of total assets per employees (Ferrara & Giua, 2022). In a related field, Laukkanen et al. (2019) evaluate the impact of energy tax refunds after a reform in 2011 on manufacturing firm performance with Finnish data. They find that the energy tax refunds had no important effect on the number of employees, wages or energy use. Similarly, Gerster & Lamp (2020) study the German energy tax exemption that has a similar goal as the compensation subsidy, i.e. subsidize firms that are considered in danger of carbon leakage because of the EU ETS. The German firms that have received the tax exemption were also eligible based on their electricity consumption. The results of Gerster & Lamp (2020) indicate that the exemption led to increased electricity consumption, while firm competitiveness metrics such as sales, employment and investment were not affected. In summary, the prevailing literature, encompassing studies on both subsidies and tax refunds designed to offset heightened energy costs, predominantly indicates a lack of significant impact on overall firm performance.

The anticipated effect of the compensation subsidy, as outlined by the European Commission, is to enhance the competitiveness of subsidized plants relative to their unsubsidized counterparts. However, as explained earlier, existing research on similar subsidies has not conclusively demonstrated significant impacts on firm competitiveness. Hence, it is imperative to empirically investigate the impacts of the compensation subsidy using real data, to ascertain its true effectiveness and efficiency.

This paper is organized as follows. Section 2 outlines the institutional background of the subsidy scheme. Section 3 details the data that is used in the empirical analysis, and Section 4 then explains the empirical strategy. Section 5 discusses the results and checks their robustness. Section 6 concludes.

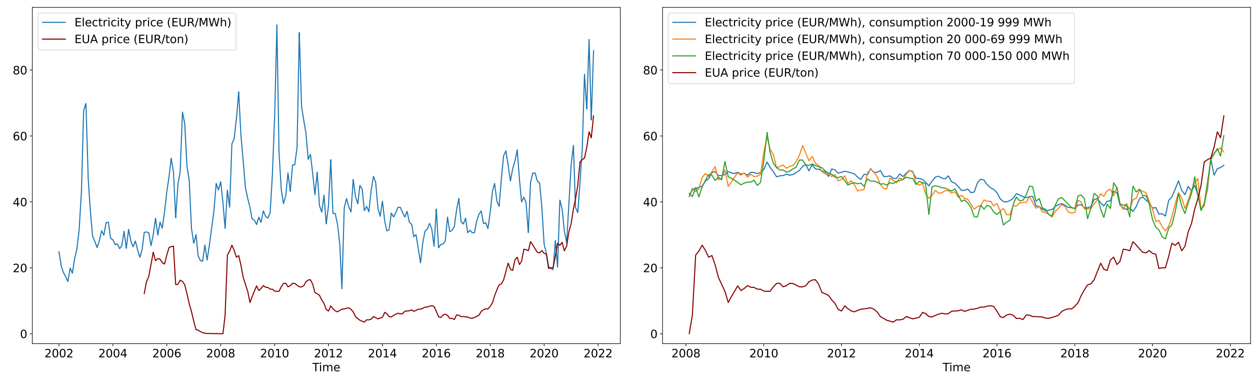
2 Institutional setting

2.1 Electricity price formation in the Nordic market

The EU ETS is currently in its fourth phase, marked by increasingly stringent regulations. This phase is characterized by a reduction in the allocation of free emission permits and a decrease in the total number of permits available. The scheme encompasses power stations and other combustion plants with a capacity exceeding 20 MWh. Consequently, as these plants are required to purchase more emission permits from the market, the cost of energy generation is expected to rise. This increase in costs is presumed to indirectly affect firms through higher electricity prices. Many EU countries have addressed these assumed indirect costs by providing firms with the EU ETS indirect cost compensation subsidy throughout the 2010s, a mechanism detailed in the preceding section.

While the pass-through rate of emission allowance costs to electricity market prices has been found to be high, firms do not necessarily pay the full market price. In Finland, there are various options for firms' electricity procurement. Firstly, firms can acquire electricity from retailers sourcing it from the Nord Pool, the Nordic power exchange market. Additionally, larger industrial plants have the capability to purchase electricity directly from this power exchange. Secondly, a portion of plants, particularly some major subsidy recipients in the paper production sector, generate their own electricity as part of their production processes. Thirdly, firms have the option of entering into power purchase agreements (PPAs) with electricity producers. These PPAs, typically spanning 10 to 20 years, offer a long-term electricity purchasing solution. Lastly, the unique Mankala principle enables multiple corporations to collectively finance a non-profit limited liability company for energy plant construction, subsequently allowing them to purchase energy at production cost.[4] These varied methods underscore that manufacturing plants in Finland are not uniformly subject to general market electricity prices.

Figure 1: *Evolution of EUA and Finnish electricity prices*



Notes: The left panel shows the day-ahead prices in the Nord Pool market for Finland, and the right panel shows the prices that firms have paid for electricity on average.
Sources: The electricity prices are obtained from Statistics Finland and EUA prices from International Carbon Partnership (ICAP) allowance price explorer. The Statistics Finland data is in the total country and month level. The average electricity prices for firms were only available from 2008 onward.

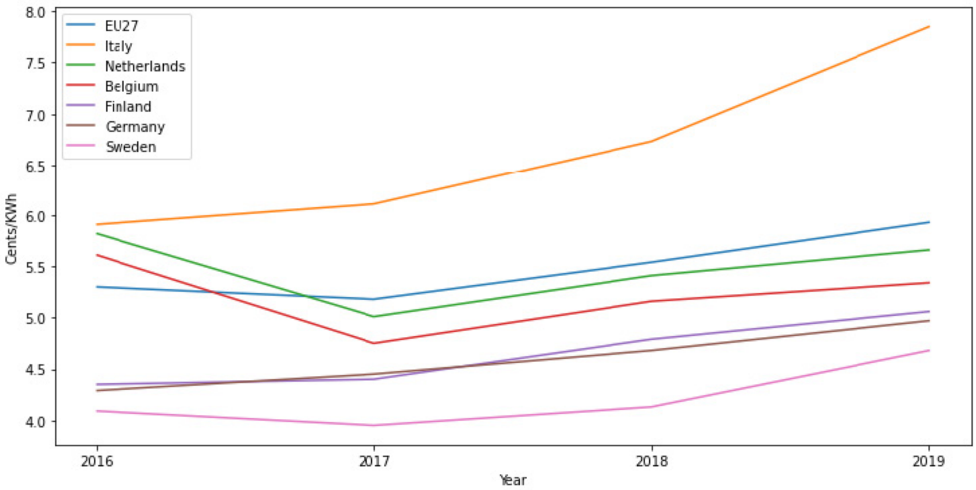
Figure 1 presents a comparative analysis of electricity pricing trends in Finland. The left panel of the figure delineates the monthly average day-ahead electricity prices in the Nord Pool market, juxtaposed with the emission allowance (EUA) prices. This panel reveals that while EUA prices have generally remained low during the study period, electricity spot prices have exhibited more variability, including notable spikes. A degree of correlation between rising EUA prices and

[4] *Information on the different kinds of electricity purchase methods from sources other than Finnish newspapers and blogs is limited, but a summary on the PPA is found at https://tuulivoimayhdistys.fi/en/wind-power-in-finland-2/ppa-power-purchase-agreement/what-is-ppa and on the Mankala principle at https://www.borenius.com/insights/2022/10/17/what-is-the-mankala-modelfound-in-finnish-power-production/.*

concurrent increases in electricity spot prices is observable, suggesting some influence of emission allowances on electricity market dynamics.

Conversely, the right panel of Figure 1 showcases the trajectory of average electricity prices paid by firms, excluding taxes, from 2008 to 2019. This data, derived directly from the firms and aggregated to country level, ostensibly reflects the actual prices they incurred. A notable feature of this data is the relative stability of electricity prices paid by firms over the observed period, in contrast to the fluctuations in the electricity spot market. The lack of a clear correlation between firm-specific electricity prices and emission allowance prices, as depicted in this panel, may be attributable to the diverse electricity procurement strategies utilized by firms, as previously discussed. These strategies potentially buffer firms from the direct impacts of market price volatilities, underscoring the complexities in assessing the true cost implications of emission trading schemes on firm-level electricity expenditures.

Figure 2: *Average electricity prices (cents/kWh) for large industrial producers (70–150 GWh consumption)*



Year	EU27	Italy	Netherlands	Belgium	Finland	Germany	Sweden
2016	5.3	5.91	5.82	5.61	4.35	4.29	4.09
2017	5.18	5.11	5.01	4.75	4.4	4.45	3.95
2018	5.54	5.73	5.41	5.16	4.79	4.68	4.13
2019	5.93	7.85	5.66	5.34	5.06	4.97	4.68

Source: Eurostat

Finland's electricity generation is characterized by a relatively low CO_2 intensity (gCO_2/kWh) compared to the EU average, as per the European Environment Agency (EEA) statistics.[5] In 2021, Finland had the fourth lowest CO_2 intensity among the EU27 countries. Sweden had the lowest number at only 9 gCO_2/kWh vs. Finland's 77 gCO_2/kWh and the EU27 average 275 gCO_2/kWh. This indicates that electricity is produced in Finland with relatively clean methods. However, the rationale behind the EU ETS indirect cost compensation subsidy scheme is predicated on the assumption that electricity producers, particularly those with higher carbon emissions, incur additional costs from purchasing emission allowances, consequently elevating electricity prices. In scenarios where electricity is generated via low-emission methods, such as hydroelectric power, the absence of emission costs implies that such electricity production would not lead to increased prices under the EU ETS framework.

[5] *https://www.eea.europa.eu/data-and-maps/daviz/co2-emission-intensity-12*

Furthermore, Figure 2 illustrates that the average electricity prices for large industrial producers in Finland have consistently been lower than the EU average. This figure presents a comparative analysis of average annual electricity prices for large industrial producers in Finland and its primary EU export competitors, exclusive of taxes and levies. Notably, Sweden registers the lowest prices in this comparison. Finland's electricity prices also fall below the EU average, suggesting that the prevalence of clean electricity production methods, devoid of associated emission costs, may have contributed to this favorable pricing structure.

2.2 The institutional context of the subsidy

There were two requirements for receiving the compensation subsidy in Finland during 2016– 2020: first, the plant manufactured products in specifically defined industries, and second, it used at least 1 GWh (1000 MWh) of electricity per year during the baseline period that was used when calculating the subsidy. The subsidy was granted only for electricity consumption exceeding this 1 GWh threshold. Moreover, according to the Finnish Energy Authority's guidelines, one of three conditions had to be met: (1) the electricity was purchased from a third party, (2) the electricity was produced in a plant under the EU ETS, or (3) the electricity could potentially be sold to a third party at market price instead of being consumed internally. The guidelines do not provide further specifics on these requirements, suggesting that firms generating their own electricity could still qualify for the subsidy if this electricity is sellable to third parties. Thus, none of the observed electricity procurement methods used by Finnish firms seem to be excluded from the subsidy scheme.

The maximum amount of compensation subsidy per installation was calculated with the following formula, as instructed by the European Commission[6]:

$$A_{max,t} = I_t * C_t * P_{t-1} * E * BO \text{ if } E \text{ was available,}$$

$$A_{max,t} = I_t * C_t * P_{t-1} * EF * BEC \text{ if } E \text{ was not available}$$

where I_t is a percentage of the eligible costs at year t, i.e. a policy variable that is defined so that the total amount of subsidies given out in a specific year will be below a specific amount, C_t is the applicable CO_2 emission factor (tCO_2/MWh) at year t, and P_{t-1} is the EUA forward price at year $t - 1$ (EUR/tCO_2). These three variables were the same for all subsidy applicants. For the plant-specific metrics, E is the applicable product-specific electricity consumption efficiency benchmark, and BO is the baseline output. If E was not available, a fall-back electricity consumption efficiency benchmark, EF, was used together with BEC, the baseline electricity consumption (MWh).

The baseline period for determining subsidy eligibility in Finland spanned from 2005 to 2011, provided the plant was operational throughout these years. Otherwise, there was an alternative reference period based on when the operations have started.[7] As such, there is no endogeneity problem in which the plants would have an incentive to adjust their current production to receive a higher subsidy. Moreover, the proposal for adopting this compensation subsidy scheme in Finland was first announced in May 2015, with the relevant law enacted in 2016.[8] This timeline rules out the possibility of plants anticipating and adjusting to the subsidy during the baseline period.

6 *Communication from the Commission – Guidelines on certain State aid measures in the context of the greenhouse gas emission allowance trading scheme post-2012 (SWD(2012) 130 final) (SWD(2012) 131 final)*

7 *For plants that commenced operations after 2005 but before 2012, the subsidy calculation was based on the average output over seven continuous years starting from the year of operation onset. For those starting after 2011, the subsidy was initially based on the current year's output, shifting to the average of the past three years after four continuous years of operation.*

8 *The proposal for the law (only available in Finnish): https://www.finlex.fi/fi/esitykset/he/2016/20160147.*

Table 1 lists the industries eligible for the compensation subsidy, encompassing two mining sectors and various manufacturing industries. These sectors are identified by the European Commission as being most susceptible to the economic impacts of increased electricity costs. In the Finnish context, paper production is the predominant industry among these categories, and subsequent analysis will demonstrate that a majority of the subsidy recipients are indeed in this sector.

Table 1: *Eligible industries*

	Industries and sub-industries	NACE Rev. 1.1	NACE Rev. 2
1	Mining of iron ore	1310	0710
2	Mining of chemical and fertiliser minerals	1430	0891
3	Preparation and spinning of cotton-type fibres	1711	1310
4	Manufacture of leather clothes	1810	1411
5	Manufacture of paper and paperboard	2112	1712
6	Manufacture of other inorganic basic chemicals	2413	2013
7	Manufacture of other organic basic chemicals	2414	2014
8	Manufacture of fertilizers and nitrogen compounds	2415	2015
9	Manufacture of man-made fibres	2470	2060
10	Manufacture of basic iron and steel and of ferro-alloys, incl. seamless steel tubes	2710	2410, 2420
11	Aluminium production	2742	2442
12	Lead, zinc and tin production	2743	2443
13	Copper production	2744	2444
14	Following subsection of Manufacture of pulp:	2111	1711
	Mechanical pulp	21111400	
15	Following subsections of Manufacture of plastics in primary forms:	2416	2016
	Linear high-density polyethylene	24161035	
	High-density polyethylene	24161039	
	Low-density polyethylene	24161050	
	Polyvinyl chloride	24163010	
	Polycarbonate	24164040	
	Polypropylene	24165130	

Notes: The table with NACE Rev. 1.1 codes is sourced from the Finnish Energy Authority. The NACE Rev. 2 codes have been added by the author of this paper.

3 Data and descriptive statistics

3.1 Data sources

The subsidy recipients

The Finnish Energy Authority has publicly disclosed the recipients of the compensation subsidy. Between 2016 and 2020, 62 production plants, owned by 39 different firms, have benefited from this subsidy. A large share of these recipients were in the paper and pulp sector. For the purpose of this analysis, a comprehensive list was compiled, detailing the installations that received the subsidy, along with the respective subsidy amounts for each year. This compilation was enriched with firm IDs sourced from the Finnish Patent and Registration Office.

It is important to note that the subsidy recipients are identified at the installation level, with an 'installation' potentially comprising multiple production plants located in proximity, as is commonly the case with e.g. paper and pulp plants. The public list specifies the name of each installation. However, given that the subsidies target specific industrial sectors, such as paper production, it is feasible to ascertain which specific plant within an installation was the actual recipient of the subsidy.

Emission data

Emission and allowance data at the installation level were sourced from the EU Transaction Log (EUTL), focusing on Finnish manufacturing sector installations. This data was supplemented with average emission allowance prices to compute the final emission costs for each installation.

Financial data

The financial performance metric data are provided by Statistics Finland which collects this data with surveys (mandatory for respondents) together with information from the Finnish Tax Administration. Unlike the subsidy recipient and emission data, these financial metrics are available at a more granular, plant-level detail. The Statistics Finland data are not publicly available, and can only be accessed in a closed online portal in a pseudonymized format. The dataset adheres to the Finnish TOL2008 classification system, compatible with the NACE Rev. 2 at the 4-digit level, with an added digit for national specificity.

The financial dataset encompasses a broad spectrum of variables pertinent to plant profits and costs. For my analysis, I focus on several key plant performance metrics: gross value of production, number of full-time employees, and total wage amounts (inclusive of bonuses), as they are broadly representative and consistently available. Additionally, I examine electricity purchase data as a proxy to assess the impact of the subsidy on plants' electricity consumption. Despite some inconsistencies and missing observations in this variable, efforts have been made to rectify obvious errors and ensure its reliability for analysis.[9] In the initial phase of the analysis, plant expenditure data are also utilized for calculating propensity scores. Key financial figures, including gross production, salaries, expenses, and electricity purchases, are measured in euros.

[9] *With all outcome variables, I take the specific plant's all observations and mark the ones that either 5 times larger or smaller than the plant average. Then, I manually check if the observations appear like they might have errors in recording, such as if the number of employees is about 50 for all years except 100 for one year, and change those observations to missing.*

The final dataset

In constructing the final dataset, financial data were merged with information on compensation subsidy recipients and their emission allowance costs. As noted, there is a difference in data levels: financial metrics are plant-level, whereas subsidy and emission data are installation-level. Therefore, the data were matched so that the subsidy recipient plants were identified based on first the installation and then the specific sector of operation. For instance, in installations combining paper and pulp production, the subsidy was allocated to the paper production plant.

The analysis is confined to plants classified under NACE Rev. 2 industries 17, 20, and 24, aligning with the industries of the subsidy recipients. The dataset covers the period from 2013 to 2019. Given that the subsidy is aimed at larger plants, the dataset includes only those with a minimum of 10 employees and a revenue exceeding 1,000,000 euros over the observed period. Additionally, eligible plants are required to have data available for at least one year both before and after the subsidy's commencement in 2016. The resulting dataset comprises 333 plants, out of which 61 received the subsidy between 2016 and 2019[10], with most receiving it throughout the entire period.

3.2 Descriptive statistics

Table 2 presents the distribution of the subsidized plants across various industries. The prevalence of the paper industry is clear, as almost half of the subsidy recipient plants operate in this industry.

Table 2: *Distribution of industries in Finnish subsidy recipients*

Industries	NACE Rev. 2	Freq
Manufacture of paper and paper products	17	29
Manufacture of chemicals and chemical products	20	21
Manufacture of basic metals	24	11
Total		61

Next, Table 3 showcases more statistics from my final dataset. More precisely, it shows the mean value of the subsidy per installation divided by its gross production for 2016–2019, the amount of total subsidies that were granted each year and the mean gross production of subsidized plants. For comparison, mean gross production values of non-subsidized plants are added, as well as the numbers of subsidized and non-subsidized plants.

Table 3: *Compensation subsidy statistics*

Year	Number of subsidized plants	Mean subsidy/ output	Total of subsidy granted	Mean production, subsidized	Mean production, non-subsidized	Number of non-subsidized plants
2016	61	2.86 %	37.91	246.40	43.51	272
2017	61	2.11 %	26.75	269.86	45.18	266
2018	61	2.38 %	29.12	287.30	49.38	262
2019	61	6.45 %	74.73	266.16	50.34	254

Notes: The monetary values are shown in millions of euros.

[10] *One subsidized plant had to be dropped due to it not being identified in the Statistics Finland data.*

The amount of subsidy varies based on the different production and electricity consumption efficiency of the products, so there is a great variation in the subsidy amounts granted. Notably, there was a significant increase in the total subsidy amount in 2019. Since the recipient installations largely remained consistent over this period, this rise can be attributed to larger individual subsidies rather than an increase in the number of recipients. This escalation is likely linked to the rise in EUA prices, a key factor in the subsidy calculation formula. Another factor to note is the difference in the size of the mean gross production between the subsidy recipients and non-recipients. In the final analysis, I balance this discrepancy by utilizing regression weights.

Previous studies related to the effects of the EU ETS predominantly conduct the analyses on the aggregated firm level (see e.g. Colmer et al. (2024); Dechezleprêtre et al. (2023); Ferrara & Giua (2022)), as financial statement variables are generally only available for firms and not plants. However, both the ETS participation and the indirect cost compensation subsidy eligibility are defined on the plant level. This distinction presents a unique opportunity with the Finnish data to analyze subsidy effects with finer granularity than is possible with firm-level aggregation.

4 Empirical strategy

In my empirical analysis, I employ the difference-in-difference (DiD) methodology to compare the performance of plants that received the subsidy against those that did not, both before and after the subsidy was implemented. This approach incorporates two-way fixed effects for both plant (unit) and time, capturing common effects specific to each plant and year. The basic DiD model is represented as:

$$ln(y_{it}) = \beta_0 + \beta_1 Subs_{it} + \beta_2 Permit_{it} + \nu_i + \nu_t + \epsilon_{it}, \tag{1}$$

where y_{it} denotes various plant-level performance metrics, such as gross production and employment, for plant i at time t. The term $Subs_{it}$, the main variable of interest in this analysis, is a binary indicator of whether a plant received the compensation subsidy.

The variable $Permit_{it}$ represents the cost of emission permits for plants within the EU ETS. This is calculated as the difference between freely allocated allowances and the plant's emissions, multiplied by the average annual price of emission permits. Depending on whether a plant received more allowances than its emissions, $Permit_{it}$ can be either positive or negative. The inclusion of emission permit costs is included because of the participation of many subsidy recipients in the EU ETS, impacting their operational expenses and, consequently, their competitive positioning. It is important to note, however, that participation in the EU ETS is independent of eligibility for the compensation subsidy, resulting in the presence of ETS plants within both the treated and control groups.

The fixed effects are given by ν_i for the plant and ν_t for the year. An alternative approach is to use industry-year fixed effects at the 2-digit level, which account for any time-varying shocks impacting entire industries. Given that my dataset encompasses only three 2-digit level industries, the variation is limited, but I test both specifications for robustness. In all estimations, standard errors are clustered at the plant level.

It should be noted that there are firms in the dataset that own both subsidy-recipient and non-recipient plants. In such cases, only plants that actually received subsidies are categorized as treated in the main analysis, while their non-recipient counterparts may be part of the control group. This distinction is important for firms such as large paper producers, where subsidy receipt can vary between plants. While this setup raises the potential for intra-firm spillover effects, robustness checks indicate that such effects do not significantly alter the results. Thus, the main analysis focuses exclusively on actual subsidy recipients as the treated group, ensuring greater precision in identifying treatment effects.

The objective of the DiD approach in this study is to estimate the Average Treatment Effect on the Treated (ATT), denoted as $E[Y^1 - Y^0 | D = 1]$. Here, Y^1 represents the outcome for the subsidy recipient group with the treatment, Y^0 the outcome for the same group without the treatment, and D indicates the treatment status. Essentially, the ATT quantifies the average impact of the subsidy on its recipients. However, the specific targeting of the subsidy, based on industry participation or output levels, may introduce bias in the estimation since selection into treatment is not random. One indicator of this is that the subsidy recipient plants are much larger in production than their non-recipient counterparts, as noted earlier. To address this, I employ inverse propensity score weighting in the regressions, following the methodology originally outlined by Rosenbaum & Rubin (1983). These propensity scores (p^) estimate the probability of receiving the subsidy based on various installation characteristics, aiming to simulate a randomized treatment scenario.

When calculating the ATT, treated units are assigned weights of 1, while control units are weighted by $\hat{p}/(1 - \hat{p})$, where $\hat{p}$ is the propensity score. In other words, the treated plants are being used as the reference to which the treated and control plants are being standardized (Austin & Stuart, 2015).

In the estimation of propensity scores, I employ logistic regression, utilizing pre-treatment averages of financial variables to predict the likelihood of receiving treatment. Specifically, this includes the average gross production, number of employees, and total expenditure of plants from 2013 to 2015. The decision on which variables to include in calculating propensity scores aligns with the evolving recommendations in the literature. Initially, Rubin & Thomas (1996) advocated for including all variables related to the outcome, irrespective of their connection to treatment assignment. However, Rubin (2001) later suggested prioritizing variables strongly related to assignment, to avoid potential bias even at the cost of some efficiency loss. The most current guidance recommends selecting variables that are pertinent to both the assignment and the outcome (Adelson et al., 2017).

In my dataset, gross production is presumed to have the highest correlation with treatment assignment, given that the subsidy's formula considers either past average output or electricity consumption. Consequently, the pre-treatment mean of gross production is a key variable in my analysis. Additionally, the number of employees is included as a proxy for plant size and, by extension, production capacity. Plant-level expenditure is also factored in, encompassing electricity expenses, thereby serving as another relevant explanatory variable. In the propensity score estimation process, the dataset is pooled, designating subsidy recipients as the treatment group for all years. To account for industry-specific characteristics, categorical variables representing 2-digit level NACE industries are included in the logistic regression models. This approach is necessitated by the limited number of observations within each industry, which precludes separate estimations for each industry group. In addition, to address the potential variability in logistic regression outcomes, I employ a repeated sampling method. Specifically, the logistic regression is executed 1,000 times, generating mean propensity scores for each plant.[11]

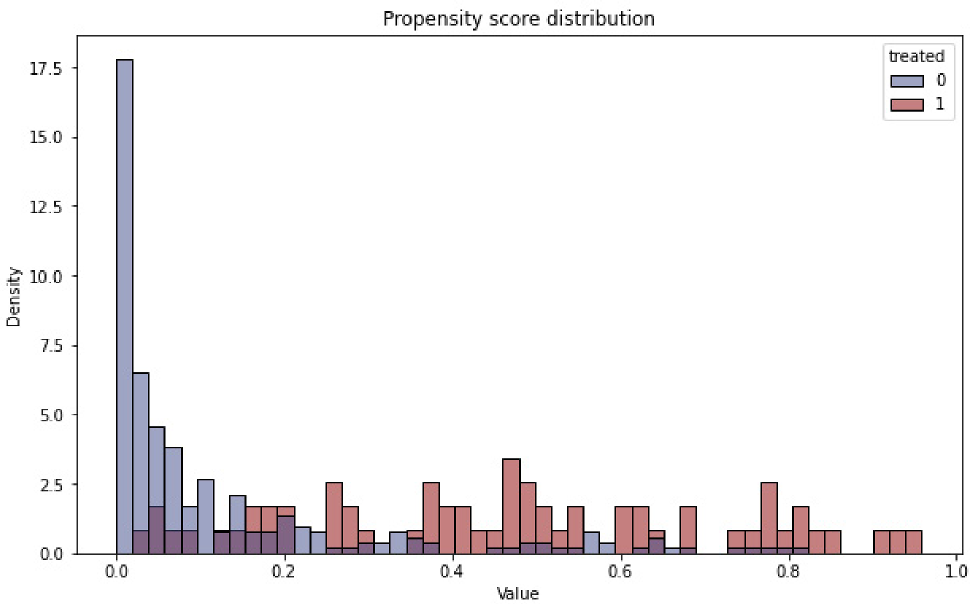
Logistic regression has been the prevalent method for estimating propensity scores in prior research. In an effort to explore advanced methodologies, I also experimented with machine learning techniques, specifically the random forests algorithm, for data classification. However, this approach encountered a limitation in the context of inverse propensity score weighting, as the random forests algorithm tended to yield extremely low propensity scores for non-recipients of the subsidy. Using the inverse propensity score weighting method requires that there is an overlap between the scores for the two groups (Desai & Franklin, 2019), and as such this method was deemed unsuitable for the current analysis. Additional details on the testing of the random forests algorithm and its outcomes in estimating propensity scores are discussed in Appendix B.

[11] *This repetition helps mitigate the effects of random variations in the model's training and testing splits. For each iteration, the logistic regression classifier is trained on 70 percent of the data and tested on the remaining 30 percent.*

The logistic regression approach, while providing a classification accuracy of approximately 86 %, offered a more balanced distribution of calculated probabilities for treatment across both treatment and control groups. This distribution is crucial for the validity of the inverse propensity score weighting method. Figure 3 illustrates the distributions of the calculated propensity scores by treatment status, offering a comparative perspective.

In line with standard methodology recommendations for propensity score analysis (see e.g. Cunningham (2021), Lee et al. (2011)), I have implemented a trimming process to address the potential distortion caused by units with very low propensity scores. This method, following the approach used by Guadalupe et al. (2012), involves retaining only those observations within the range of score overlap. Specifically, I exclude subsidy non-recipient plants with propensity scores below 0.02. This trimming results in a final dataset comprising 240 plants, including the 61 subsidy recipients. Table 4 provides a comparative overview of various financial metrics between the subsidy recipients and non-recipients in this refined sample. The table displays both actual and inverse propensity score weighted values, highlighting how the weighting procedure enhances the comparability between the treated and control groups.

Figure 3: *Distributions of the propensity scores*



Notes: The propensity scores were obtained by estimating a logistic regression 1,000 times with pre-treatment means of gross production, number of employees and total expenditure of the plants as the predictors, and then calculating the mean propensity score for each plant.

The core identifying assumption in DiD analysis is the parallel trend assumption, which posits that, in the absence of treatment, outcome variables would have followed similar trends in both treatment and control groups. Achieving balance between these groups on relevant covariates is essential for this assumption to hold. In my analysis, focusing on specific industries and employing propensity score weighting aids in achieving this balance. However, the potential influence of concurrent energy-related policies on the groups is a consideration.

Table 4: *Financial statistics for the matched data (standard deviations in parentheses)*

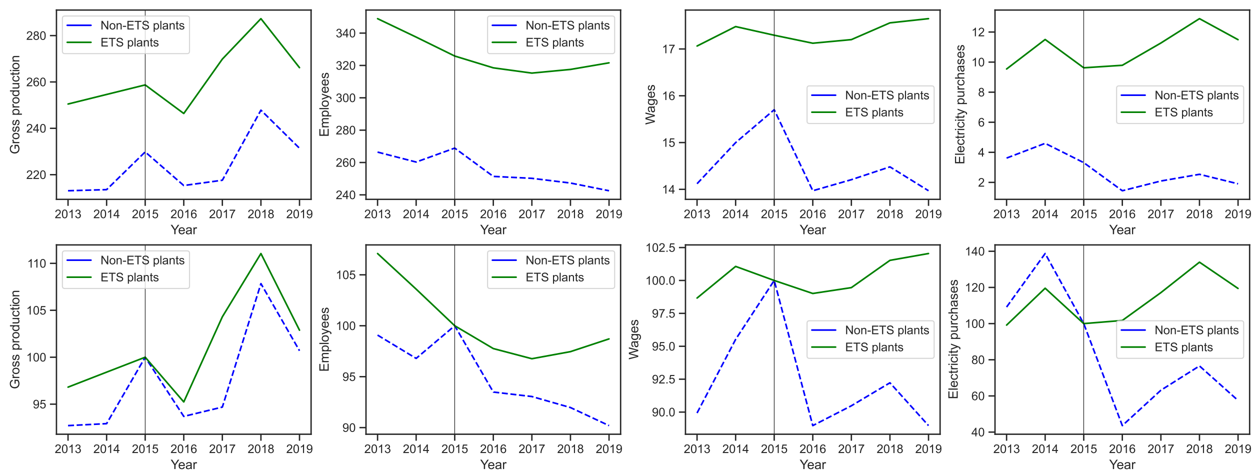
Category	Recipients	Non-recipients	Weighted non-recipients
Number of plants	61	179	179
Mean gross production, million euros	262.58 (420.57)	68.84 (129.10)	224.09 (212.66)
Mean number of employees	328 (411)	104 (110)	255 (171)
Mean total wages, million euros	17.5 (22.02)	5.79 (6.78)	14.49 (9.62)
Mean electricity purchases, million euros	11.35 (16.43)	1.18 (2.53)	2.79 (4.33)

Notes: The weighted means are calculated as $x_{\text{weight}} = \frac{\sum w_i x_i}{\sum w_i}$.
The weighted standard deviations are derived from the variance $s^2_{\text{weight}} = \frac{\sum w_i}{(\sum w_i)^2 - \sum w_i^2} \sum w_i (x_i - \bar{x}_{\text{weight}})^2$ *, following Austin & Stuart (2015).*

In the Finnish context, while there are other policies like investment subsidies for renewable energy projects and energy tax refunds for energy-intensive firms, these were established prior to my observation period (2013–2019) and remained unchanged during this timeframe. The impact of the EU ETS is directly addressed by including emission permit costs in the regression models. Importantly, no other significant energy-related policy changes affecting the industries in focus occurred during the observation period, supporting the validity of the parallel trend assumption in this context.

One test of the parallel trends assumption is to check the pre-treatment trends. In my analysis, a simple plot of raw data is insufficient due to the use of inverse propensity score weighting in the regressions. Consequently, Figure 4 illustrates these trends with the applied weights. The figure's top row depicts the weighted means of the data, while the bottom row transforms these means into indices, using 2015 as the base year (set to 100). While the pre-treatment trends are almost but not exactly aligned, the influence of the weights on these findings necessitates additional analyses to confirm the assumption.

Figure 4: *Trends of the dependent variables*

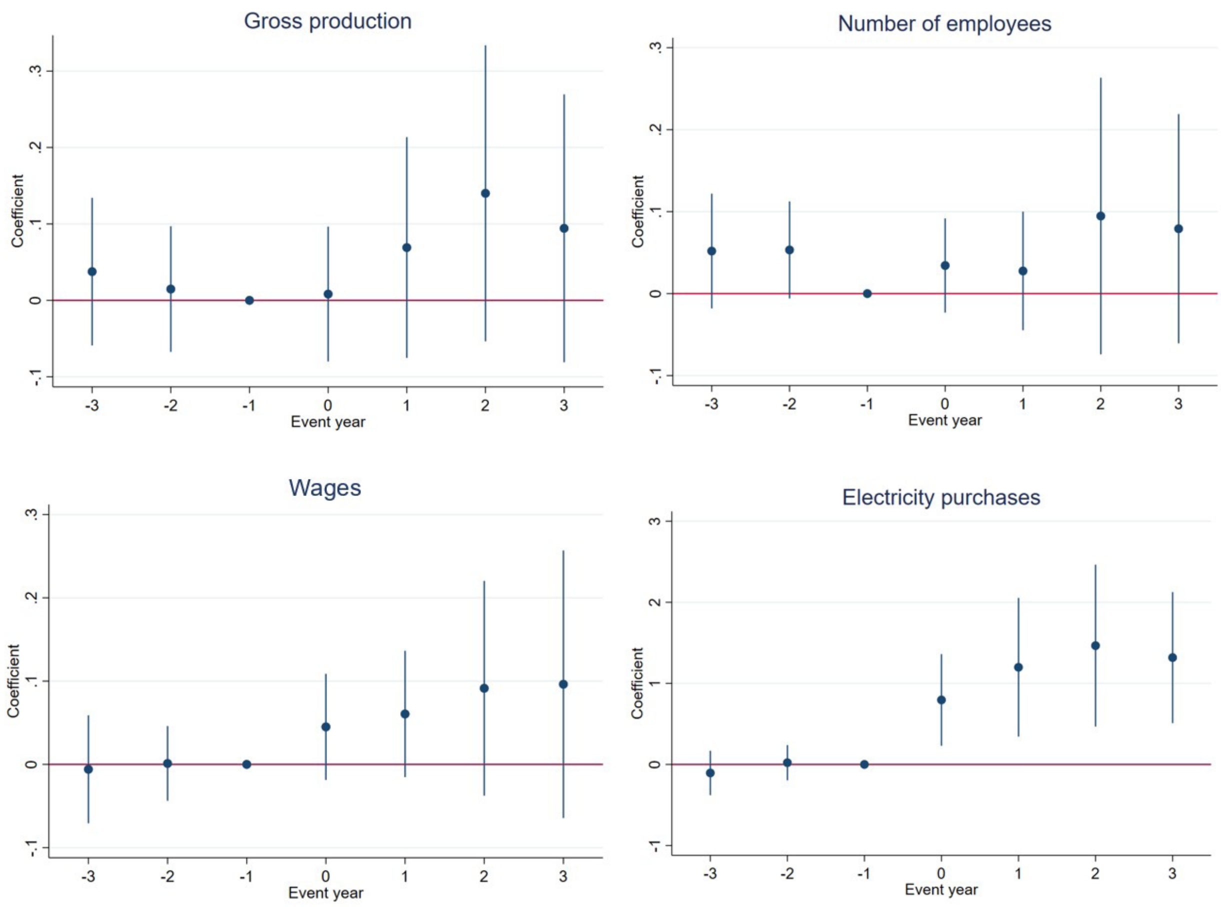


Notes: In the first line of figures, the trends are drawn by calculating the means for each year as $\bar{x}_{\text{weight}} = \frac{\sum w_i x_i}{\sum w_i}$ *separately for the treated and control groups. In the bottom figures, the means are transformed into indices with base year 2015 as 100.*
"Wages" refers to total wages, i.e. payroll expenses.

Figure 5 showcases an event study graph, a method recommended for evaluating parallel trends, as suggested by Cunningham (2021). This graph depicts regression coefficients, calculated separately for each time period leading up to and following the implementation of the treatment. The parallel trends assumption is substantiated if the coefficients for pre-treatment periods (lags) are approximately zero. Such a result would indicate a lack of significant differences between the treatment and control groups before the introduction of the treatment.

In Figure 5, the analysis includes three years before and after the initial year of subsidy receipt, with 2015 as the reference year. The lags (pre-treatment years) show coefficients close to zero, and their confidence intervals include zero, suggesting no significant pre-treatment differences between the groups. This supports the parallel trends assumption. While the leads (post-treatment years) deviate slightly more, their wide confidence intervals still encompass zero, indicating no substantial impact from the subsidy on most outcome variables. An exception is noted in the electricity purchases variable, which shows a more pronounced increase post-treatment, suggesting a possible effect of the subsidy.

Figure 5: *Event study*



Notes: The event time figures are created from regressions of otherwise same form as Equation 1, but in this case the subsidy variable is separate for each year. There are thus three lagged subsidy variables for the time before the subsidy period started, one variable for the start of the subsidy period (2016), and three lead subsidy variables for the three years after the start of the subsidy period. The year before the subsidy period started is used as the reference year. The standard errors are clustered at plant level. The error bars indicate the confidence intervals for each lag and lead subsidy variable. "Wages" refers to total wages, i.e. payroll expenses.

After balancing the data, the plants should be similar except for receiving the subsidy or not. If the electricity prices for firms have increased, it is expected that all plants in the data faced similar trends. As such, the hypothesis is that the subsidized plants should be more competitive than the non-subsidized ones due to the extra support they got. The goal of the compensation subsidy was to boost the competitiveness of the subsidized plants, so some positive effects should be visible in the recipient group if the subsidy has been successful.

As the probability of receiving the subsidy is based on strictly the industry and past electricity consumption of the plant, another empirical approach would have been to use a regression discontinuity design with a cutoff at 1 GWh of average electricity consumption per year during the baseline period for plants in the eligible industries. However, data on exact electricity consumption for the plants is not available, as the electricity purchases variable only serves as a proxy. As such, using a DiD design with the subsidy eligibility rules that induce variation in treatment status across plants with similar production levels is a more feasible strategy for this analysis.

5 Results

Table 5 presents the results from regressions with the different fixed effects specifications. As the compensation subsidy is a binary variable, the estimated coefficients tell us what would happen to the dependent variables if the plant got the subsidy vs. if it did not. For example, the gross production in column (1) would be $(e^{0.050} - 1) * 100 = 5$ percent higher when receiving the subsidy. However, none of the performance-related estimated coefficients in Table 5 are statistically significant at the 5 % level. These results are similar with both fixed effects specifications. Only the electricity purchases show statistically significant and large coefficients in columns (4) and (8). These values would translate to 194 % and 228 % higher electricity purchases due to treatment, respectively.

Table 5: *Regression results*

	Ln gross production	**Ln employees**	**Ln wage**	**Ln electricity purchases**	**Ln gross production**	**Ln employees**	**Ln wage**	**Ln electricity purchases**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Compensation subsidy	0.050 (0.053)	0.021 (0.051)	0.072 (0.044)	1.077** (0.380)	0.056 (0.054)	0.022 (0.052)	0.071 (0.043)	1.188** (0.399)
Permit costs	0.000 (0.001)	-0.001 (0.001)	0.000 (0.001)	-0.017 (0.018)	0.000 (0.001)	0.000 (0.001)	0.002 (0.001)	-0.016 (0.016)
Plant fixed effect	X	X	X	X	X	X	X	X
Year fixed effect	X	X	X	X				
Industry-year fixed effect					X	X	X	X
Observations	1,618	1,638	1,621	1,482	1,618	1,638	1,621	1,482

*Robust standard errors in parentheses, clustered at plant level. All regressions are weighted with the inverse propensity scores. The "permit costs" variable is defined as the difference between the allowances that were allocated free of charge and the emissions of the plant, multiplied by the average annual price of emission permits. The permit cost variable is divided by 100,000 for a better scale. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

The estimated impact of the subsidy on electricity purchases, as shown in the regression results, appears notably high. A closer examination of the data revealed a potential explanation. Specifically, some subsidy recipient plants exhibit a marked increase in electricity purchases coinciding with the onset of the subsidy period. For instance, one such plant displayed a drastic escalation in electricity purchases from 2013–2015 to 2016–2019, increasing by up to 100-fold. While it's challenging to ascertain whether these figures represent actual consumption changes or recording errors, the pattern is predominantly observed among subsidy recipients. This suggests that these plants might indeed have increased their electricity purchases post-treatment.

The results show that the coefficients for emission permit costs are minimal and not statistically significant. This finding aligns with expectations, given that during the study period, emission permit costs were relatively low compared to the firms' revenues. Additionally, excluding these permit costs from the regression does not materially alter the results related to the compensation subsidy variable.

The analysis indicates that the compensation subsidy, during 2016–2019, did not significantly affect plant-level gross production, employment numbers, or salaries. This suggests that the subsidy had negligible influence on key competitiveness indicators of the recipient plants. One factor to note, however, is that the confidence intervals of the estimated coefficients for the financial variables predominantly fall within a [-0.05, 0.10] range, and as such the data may not be sufficiently sensitive to detect small effect sizes. Nevertheless, the results in Table 5 are not statistically significant even at the 10 % level.

The notable exception regarding the subsidy effects is electricity purchases, which increased among subsidy recipients, implying that the subsidy may have been partially used to offset electricity costs. Given Finland's low CO_2 intensity in electricity generation, as discussed in section 2, this increased electricity usage could be seen as environmentally beneficial. However, since the subsidy's primary goal was to enhance firm competitiveness, not energy usage patterns, it did not achieve its intended objective in this regard.

These findings are robust to the application of propensity score weighting. Analysis without these weights yields similar results, confirming the non-significant impact on most performance metrics and the significant increase in electricity purchases. However, the size of the increase in electricity purchases would not be quite as large without the regression weights.[12]

An examination of plant exits could potentially offer insights into the impact of the subsidy on competitiveness and operational sustainability. However, the relatively low overall number of plant exits in my dataset precludes any definitive conclusions in this area. Throughout the study period, the count of subsidy recipient plants remained constant, while the control group experienced slight variations. Specifically, the control group (before trimming) decreased from 272 plants in 2016 to 256 in 2019, indicating that 16 plants either ceased operations or were not reported in 2019. The latter scenario is unlikely, given the mandatory nature of reporting and multiple data sources. This number is not significant enough to draw conclusions in either direction.

In the broader context, these results align with Ferrara & Giua (2022) and other studies, which also found no significant competitive advantage from similar subsidies. This raises questions about the effectiveness of current energy-related subsidy designs, especially as environmental regulations in the EU become more stringent. While government support for EU producers is understandable, the actual utility of such subsidies in preventing the relocation of firms remains uncertain.

[12] The results without propensity score weights are not shown here, as the conclusions are similar to the base estimations, but they are available upon request.

5.1 Robustness checks

Table 6 outlines six robustness checks conducted to validate the findings of this study:

(A) A placebo subsidy dummy is introduced for the period preceding the actual subsidy to verify the absence of divergent events between the groups prior to the treatment.

(B) The analysis includes a delayed subsidy dummy, activated a year after the main estimation's subsidy dummy. This adjustment accounts for the delay between subsidy application and receipt.

(C) The dataset is refined to include only observations with complete electricity purchase data, addressing the potential bias from missing values.

(D) The impact of using a Poisson pseudo-maximum likelihood (PPML) estimator, as opposed to OLS, on the results is examined.

(E) Explanatory variables are normalized by the number of workers, removing the influence of firm size from the analysis.

(F) The compensation subsidy dummy is redefined so that any firm with at least one treated plant is marked as treated. This addresses potential spillover effects within firms using the subsidy for broader purposes.

Table 6: *Robustness checks*

	(A) Placebo subsidy			
	Ln gross production	Ln employees	Ln wage	Ln electricity purchases
	(A1)	(A2)	(A3)	(A4)
Placebo compensation subsidy (2013–2015)	-0.060 (0.060)	-0.026 (0.052)	-0.018 (0.037)	0.008 (0.126)
Permit costs	-0.004 (0.005)	0.023 (0.012)	0.000 (0.003)	0.001 (0.011)
Observations	1,533	1,546	1,537	956
	B) Delayed subsidy			
	Ln gross production	Ln employees	Ln wage	Ln electricity purchases
	(B1)	(B2)	(B3)	(B4)
Compensation subsidy t+1	0.074 (0.059)	0.027 (0.052)	0.064 (0.048)	1.017** (0.351)
Permit costs	0.000 (0.001)	-0.001 (0.001)	0.000 (0.001)	-0.018 (0.017)
Observations	1,618	1,638	1,621	1,482

	(C) No missing electricity variables			
	Ln gross production	Ln employees	Ln wage	Ln electricity purchases
	(C1)	(C2)	(C3)	(C4)
Compensation subsidy	0.022 (0.058)	-0.016 (0.050)	0.032 (0.039)	1.077** (0.380)
Permit costs	-0.001 (0.001)	-0.002 (0.001)	0.000 (0.001)	-0.017 (0.018)
Observations	1,471	1,481	1,470	1,482
	(D) PPML			
	Gross production	Employees	Wage	Electricity purchases
	(D1)	(D2)	(D3)	(D4)
Compensation subsidy	0.001 (0.064)	0.003 (0.052)	0.062 (0.051)	0.588 (0.310)
Permit costs	-0.001 (0.001)	-0.001* (0.000)	0.000 (0.000)	0.005 (0.004)
Observations	1,618	1,638	1,621	1,482
	(E) Per worker variables			
	Ln gross / worker	Ln wage / worker	Ln elec. purch. / worker	
	(E1)	(E2)	(E3)	
Compensation subsidy	0.028 (0.042)	0.051 (0.028)	1.094** (0.390)	
Permit costs	0.001 (0.001)	0.001* (0.001)	-0.015 (0.018)	
Observations	1,617	1,620	1,481	
	(F) Spillover effects			
	Ln gross production	Ln employees	Ln wage	Ln electricity purchases
	(F1)	(F2)	(F3)	(F4)
Compensation subsidy	0.033 (0.056)	-0.005 (0.044)	0.032 (0.044)	0.428* (0.167)
Permit costs	-0.002* (0.001)	-0.002 (0.001)	0.000 (0.001)	-0.002 (0.007)
Observations	2,242	2,265	2,242	2,026

*Robust standard errors in parentheses, clustered at plant level. All regressions include fixed effects for the year and plant, and are weighted with the inverse propensity scores. The permit cost variable is divided by 100,000 for a better scale. * p < 0.05, ** p < 0.01, *** p < 0.001*

In Table 6, results are shown with plant and year fixed effects. Appendix C also includes results with industry-year fixed effects, which did not significantly alter the coefficients' significance or magnitude. In addition, the Appendix C provides a detailed discussion of the robustness checks.

The overarching conclusion from these checks is that they largely corroborate the main results. Specifically, coefficients that were not statistically significant in the baseline analysis continue to exhibit no significant effects. Similarly, the findings related to the electricity purchases variable are mostly robust to the different checks. The only exception is the PPML estimator test, which yields estimates that are not statistically significant. However, when using industry-year fixed effects, as shown in Appendix C, the effect is again statistically significant, albeit smaller than with OLS. Additionally, the spillover test shows smaller estimates for the electricity purchases than the baseline. This discrepancy warrants a degree of caution when interpreting the results concerning this variable.

6 Discussion and conclusions

This paper examined the impact of the indirect cost compensation of the EU ETS on firm performance with data from Finnish manufacturing industry. Aimed at compensating firms for increased electricity costs and enhancing competitiveness, the subsidy was also intended to prevent firms from relocating production. Utilizing a difference-in-difference model with plant-level data from both subsidy recipients and non-recipients, the study found no significant effects of the subsidy on plant gross production, employment, or worker compensation. While there is evidence of increased electricity purchases attributable to the subsidy, this does not directly relate to improved competitiveness.

One possible explanation for these findings is that major subsidy recipients (see Table A1) are paper and pulp producers that generate all the electricity they need alongside their production. Therefore, the subsidies are not necessary to keep the firms competitive and can be used for any other purpose. For example, the top second subsidy recipient, Metsä Group, announces on their website: "Pulp mills utilise energy in their own production, but they do not need all that they generate. In other words, the mills are more than self-sufficient in energy."[13] In addition, the top one subsidy recipient, UPM, has in fact been the second largest electricity producer in Finland for many years now. This fact was already stated in UPM's financial statement of 2016[14] when the subsidy scheme started, and it is still the case now in 2023 according to UPM's website[15]. UPM owns many hydroelectric power plants, in addition to a share of the nuclear power plants in Olkiluoto. For UPM, the electricity it generates is already a large business, and it can actually benefit from increased electricity prices. Many of UPM's plants (both the paper and power generation ones) are included in the ETS and have to acquire emission permits, but as these are direct costs, this should not have an impact on the indirect compensation subsidy scheme.

The rationale behind subsidizing plants that are self-sufficient in electricity generation and even sell excess energy warrants scrutiny. The current subsidy criteria, based solely on industry participation and production levels, lack efficiency. This approach predominantly benefits larger firms with greater revenues, leading to higher subsidy amounts without ensuring their effective use. Since these subsidies are not designated for specific purposes, there is no guarantee they are being utilized to enhance the performance metrics analyzed in this study. For instance, the additional profits could be allocated as dividends to shareholders.

The plant-level dataset used in this research does not provide detailed insights into how these subsidies are expended, unlike firm-level financial statements. Consequently, this study cannot conclusively determine the actual utilization of the subsidies. However, a potential improvement to the subsidy scheme could involve requiring applicants to disclose the anticipated impact of higher electricity costs and their methods of electricity procurement. This additional information could lead to a more targeted and efficient allocation of subsidies.

[13] *https://www.metsagroup.com/metsafibre/news-and-publications/news-and-releases/stories/2021/energy-from-pulp-mills-to-the-nation/*

[14] *https://www.upm.com/siteassets/asset/investors/2016/upm-results-2016-en.pdf*

[15] *https://www.upmenergy.com/*

The central question arising from this analysis is the justification of granting the compensation subsidy to Finnish plants. Doubts arise due to the uncertain increase in electricity costs, given the general price stability and the plants' own electricity generation and procurement methods. The lack of observed effects on the subsidized plants' competitiveness in this study suggests that the subsidy may not be an efficient tool for enhancing firm performance. While data limitations and the small sample size of subsidy recipients in Finland should be considered, the findings prompt a reevaluation of the subsidy's design. Currently, it is allocated based on industry and past production levels, predominantly benefiting large paper and pulp plants without necessitating a justification of need or potential impact on competitiveness.

While this study focused on competitiveness, future research could explore other additional factors. That is, the technological choices of the subsidized vs. non-subsidized plants could be studied. It is possible that the subsidy has incentivized the recipients to use more electricity-intensive technologies than the non-recipients, as the electricity purchases showed evidence of increases. If the new technologies are more efficient and environmentally friendly, it is still possible that the subsidy has had positive effects.

Public criticism contributed to the termination of this subsidy scheme in Finland after 2020, replaced in 2021 by a redesigned subsidy without a minimum electricity usage requirement and mandating 50 % of the subsidy be used for emission reduction, energy efficiency, or renewable energy. Despite these changes, the new subsidy's recipient list and fundamental formula remain similar to its predecessor, suggesting ongoing relevance of the concerns and conclusions drawn from this study. Thus, as environmental policies evolve, it becomes increasingly imperative to assess the efficacy of such fiscal tools in achieving their intended goals.

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A The subsidy recipients

Table A1 lists the compensation subsidy recipients on firm level and in descending order based on the total amount of subsidy the firms received in 2016–2019. As can be seen, UPM has received the largest amount of subsidies. About 29 % of the total subsidies granted in 2016–2019 have gone to UPM. UPM and the second top recipient, Metsä Board, do have the highest number of plants that have applied for the subsidy. However, giving such a high share of the subsidy to large companies that also produce all of their electricity consumption alongside paper production does not appear efficient.

Table A1: *Subsidy recipient firms*

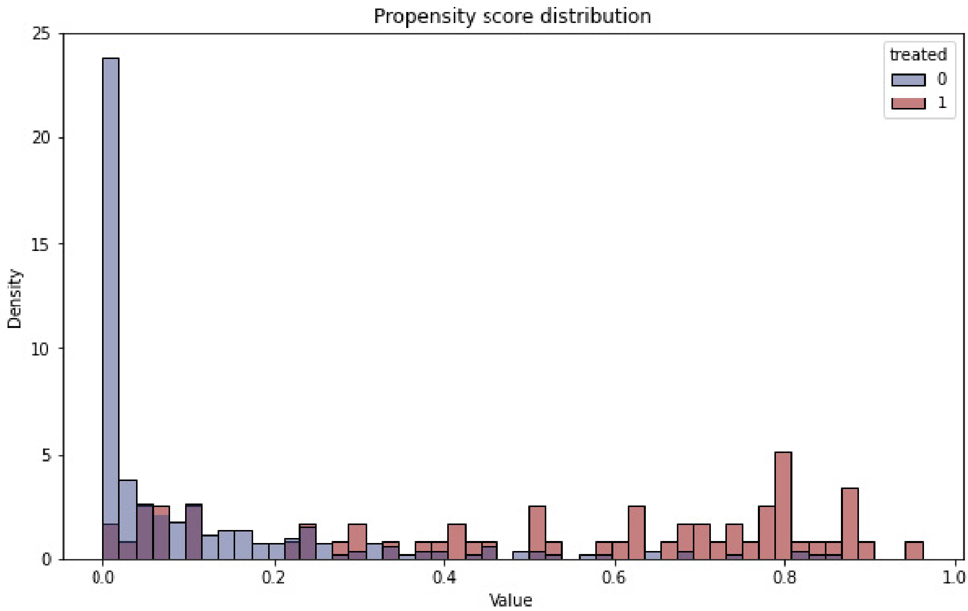
Company name	Subsidy 2016	Subsidy 2017	Subsidy 2018	Subsidy 2019	Subsidy total 2016–2019	Number of plants
UPM	11,204,675	7,779,412	8,476,075	21,716,314	49,176,472	6
Metsä Board	3,316,974	2,160,015	2,353,449	6,029,706	13,860,144	7
Boliden Kokkola	2,631,432	1,827,005	1,990,617	5,100,104	11,549,158	1
Outokumpu Chrome	2,491,015	1,729,513	1,884,395	4,827,955	10,932,878	1
Kemira Chemicals	2,103,134	1,690,637	1,842,038	4,719,433	10,355,242	4
Stora Enso	2,202,912	1,529,483	1,666,451	4,452,082	9,850,928	4
Outokumpu Stainless	2,086,901	1,448,937	1,578,692	4,044,723	9,159,252	1
Stora Enso Publication Papers	1,569,281	1,089,553	1,187,124	3,041,498	6,887,456	1
Sappi Finland Operations	1,478,876	1,064,428	1,159,750	2,971,363	6,674,417	1
SSAB Europe	1,490,022	1,034,523	1,127,167	2,887,883	6,539,596	3
Stora Enso Veitsiluoto	1,245,479	864,737	942,176	2,413,922	5,466,314	1
Stora Enso Oulu	1,044,961	725,517	790,489	2,025,289	4,586,257	1
Borealis Polymers	848,542	589,143	641,902	1,644,599	3,724,186	1
Yara Suomi	767,578	532,930	571,389	1,480,610	3,352,506	3
Kotkamills	317,860	410,126	446,854	1,053,616	2,228,456	2
Ovako Imatra	393,280	273,055	297,507	762,235	1,726,077	1
Nouryon Finland	454,072	279,935	266,513	682,826	1,683,346	1
Metsä Tissue	322,917	222,858	243,690	624,351	1,413,817	1
Boliden Harjavalta	294,316	204,343	222,643	570,427	1,291,729	1
Mondi Powerflute	247,501	171,840	187,229	479,693	1,086,263	1
Tervakoski	239,844	166,524	181,437	464,854	1,052,659	1
Stora Enso Ingerois	198,374	137,731	150,065	384,477	870,647	1
Essity Finland	192,550	133,757	145,735	373,383	845,425	1
Pankakoski Mill	186,765	129,671	141,283	361,977	819,696	1
Jujo Thermal	-	100,875	109,909	281,594	492,378	1
Taminco Finland	97,843	67,932	74,016	189,634	429,426	1

Company name	Subsidy 2016	Subsidy 2017	Subsidy 2018	Subsidy 2019	Subsidy total 2016–2019	Number of plants
Luvata Pori	94,222	65,418	71,277	182,616	413,533	1
Umicore Finland	93,284	64,767	70,568	180,799	409,418	1
Corenso United	66,087	45,884	49,993	128,086	290,051	1
Solvay Chemicals Finland	59,281	41,159	44,844	114,895	260,178	1
Cupori	46,564	32,329	35,224	90,247	204,364	1
Genencor International	-	35,444	38,618	98,942	173,003	1
Kraton Chemical	37,533	26,059	28,393	72,744	164,728	1
Aurubis Finland	37,056	25,728	28,032	71,820	162,636	1
Roal	25,003	21,567	23,498	60,204	130,273	1
Finnfeeds Finland	19,850	13,782	15,016	38,472	87,119	1
Prefere Resins Finland	-	15,588	16,984	43,514	76,087	1
Evonik Silica Finland	-	-	14,268	36,556	50,824	2
Danisco Sweeteners	-	-	8,910	22,828	31,738	1
Total	37,905,982	26,752,204	29,124,219	74,726,271	168,508,674	62

B Random forests

Random forests is a commonly used machine learning ensemble method that combines multiple regression trees to predict the correct classification of data. The decision trees partition the data into regions so that observations are as homogeneous as possible within the regions (Lee et al., 2010). Within each node of the tree, observations will have similar probabilities for class membership (Lee et al., 2010). One advantage of this method in my analysis is that it can deal well with multicollinearity. I tested using this method for calculating the propensity scores, in addition to the more traditional logistic regression method. However, Figure A1 shows that the scores for the control plants were almost all zero all very close to zero. The classification was thus too accurate for the scores to be used in this analysis, as the propensity scores for treatment and control groups should have more common support.

Figure A1: *Distributions of propensity scores*



The predictor variables that were used in the estimation were the same as with the logistic regression, i.e. mean pre-treatment gross production and plant expenditures, in addition to the categorical variables for the industries. Random forests have been criticized for being a "black box" type of tool, i.e. it is not possible to tell the exact process inside it. However, the algorithm still gives out the importance of each input feature (independent variable) used in the classification, so that it is possible to analyze which features have affected the results the most. In this case, the most important feature was the pre-treatment mean production, which was expected given that the subsidy is given based on past output. The estimated coefficients from the logistic regression gave similar results as the random forests feature importances.

C Robustness checks

In this section, I conduct some checks for the robustness of the results. I first change the subsidy dummy to create a placebo subsidy and a subsidy delayed by one year. I also modify the data so that only observations with no missing electricity variables are included, and then adjust the dependent variable. Finally, I check if using Poisson pseudo-maximum likelihood estimator instead of OLS changes the results. The purpose of these tests is to check if the way the compensation subsidy variable, missing variables or the empirical estimation method are defined would impact the results. In the case of the placebo subsidy, the purpose is also to make sure that there have been no previous differences in the treatment and control groups, even if the event study graphs indicated the parallel trend assumption to hold. My results are robust to all of these checks.

C.1 Placebo subsidy

First, to further confirm that there were no other diverging events between the subsidy recipients and non-recipients before the treatment period, I implement a placebo subsidy in the pre-treatment period. For this exercise, some earlier years before 2013 need to be included. I use the years 2009–2015 to have the same number of years as in the main analysis. The placebo subsidy is now given during 2013–2015. The propensity scores are still the same as in the baseline analysis, so that the data is balanced in the same way.

Table A2: *Placebo subsidy*

	Ln gross production	Ln employees	Ln wage	Ln electricity purchases	Ln gross production	Ln employees	Ln wage	Ln electricity purchases
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Placebo compensation subsidy	-0.060 (0.060)	-0.026 (0.052)	-0.018 (0.037)	0.008 (0.126)	-0.066 (0.063)	-0.022 (0.057)	-0.017 (0.039)	0.085 (0.140)
Permit costs	-0.004 (0.005)	0.023 (0.012)	0.000 (0.003)	0.001 (0.011)	-0.003 (0.005)	0.024 (0.013)	0.001 (0.003)	0.002 (0.012)
Plant fixed effect	X	X	X	X	X	X	X	X
Year fixed effect	X	X	X	X				
Industry-year fixed effect					X	X	X	X
Observations	1,533	1,546	1,537	956	1,533	1,546	1,537	956

Robust standard errors in parentheses, clustered at plant level. All regressions are weighted with the inverse propensity scores. The regressions include fixed effects for the year and plant. $* \; p < 0.05$, $** \; p < 0.01$, $*** \; p < 0.001$

Table A2 shows the results of this check. None of the estimated coefficients are statistically significant, not even in the case of the electricity purchases. These results therefore provide evidence of no previous divergences between the different groups of plants before the subsidy period.

C.2 Delayed subsidy

The subsidy for the year t is paid in the next year, t+1. As such, it could be possible that there is a slight delay in the effects of the subsidy. The expectation in the main analysis is that the plants already anticipate that they will get the subsidy and take it into account in their decisions, but I also test if the effects could be delayed. Table A3 shows the results of estimating the impact of a subsidy that was shifted one year into the future from the original subsidy. As can be seen, the results are similar as before, and do not show any significant impacts for the performance-related variables. The one noticeable difference is that the effect on electricity purchases is much larger than in the baseline.

Table A3: *Delayed subsidy*

	Ln gross production	**Ln employees**	**Ln wage**	**Ln electricity purchases**	**Ln gross production**	**Ln employees**	**Ln wage**	**Ln electricity purchases**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Compensation subsidy t+1	0.074 (0.059)	0.027 (0.052)	0.064 (0.048)	1.017** (0.351)	0.085 (0.063)	0.030 (0.053)	0.069 (0.047)	1.118** (0.382)
Permit costs	0.000 (0.001)	-0.001 (0.001)	0.000 (0.001)	-0.018 (0.017)	0.000 (0.002)	0.000 (0.001)	0.002 (0.001)	-0.016 (0.016)
Plant fixed effect	X	X	X	X	X	X	X	X
Year fixed effect	X	X	X	X				
Industry-year fixed effect					X	X	X	X
Observations	1,618	1,638	1,621	1,482	1,618	1,638	1,621	1,482

*Robust standard errors in parentheses, clustered at plant level. All regressions are weighted with the inverse propensity scores. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

C.3 Subsample without missing electricity variables

In the main results, the electricity purchases variable showed strong positive effects, whereas the other variables were not statistically significant. One thing to note is, however, that the electricity purchases have more missing values and thus fewer observations available. In this subsection, I check if using only the subsample where the electricity purchases variable is not missing has an impact on the other results. Table A4 shows the results of this estimation.

As can be seen, using the slightly adjusted data did not have a significant impact on the other variables. The conclusions that can be drawn from the results, i.e. no effects on the competitiveness related variables, thus remain the same as with the baseline estimations.

Table A4: *Subsample of data*

	Ln gross production	Ln employees	Ln wage	Ln electricity purchases	Ln gross production	Ln employees	Ln wage	Ln electricity purchases
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Compensation subsidy	0.022 (0.058)	-0.016 (0.050)	0.032 (0.039)	1.077** (0.380)	0.035 (0.060)	-0.011 (0.052)	0.038 (0.038)	1.188** (0.399)
Permit costs	-0.001 (0.001)	-0.002 (0.001)	0.000 (0.001)	-0.017 (0.018)	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	-0.016 (0.016)
Plant fixed effect	X	X	X	X	X	X	X	X
Year fixed effect	X	X	X	X				
Industry-year fixed effect					X	X	X	X
Observations	1,471	1,481	1,470	1,482	1,471	1,481	1,470	1,482

*Robust standard errors in parentheses, clustered at plant level. All regressions are weighted with the inverse propensity scores. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

C.4 Poisson pseudo-maximum likelihood estimator

The Poisson pseudo-maximum likelihood (PPML) estimator has recently gained popularity with e.g. trade flow analysis, as it can take into account heteroscedasticity of the data better than OLS, and in addition include zeros. Heteroscedasticity means that the variance of the error term of the dependent variable is not the same across the independent variable's values. My data only has positive values, so zeros are not a concern. However, according to different tests and a visual examination of the regression residuals, heteroskedasticity does appear to be present in my data. Clustering the standard errors at the plant level should handle this problem in my analysis, but I still also check if using PPML would impact the results. Table A5 shows these results that have been estimated by using the PPML estimator.

Table A5: *PPML estimator results*

	Ln gross production	Ln employees	Ln wage	Ln electricity purchases	Ln gross production	Ln employees	Ln wage	Ln electricity purchases
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Compensation subsidy	0.001 (0.064)	0.003 (0.052)	0.062 (0.051)	0.588 (0.310)	-0.005 (0.059)	-0.011 (0.056)	0.043 (0.044)	0.706* (0.336)
Permit costs	-0.001 (0.001)	-0.001* (0.000)	0.000 (0.000)	0.005 (0.004)	0.000 (0.001)	0.000 (0.000)	0.001** (0.000)	0.000 (0.004)
Plant fixed effect	X	X	X	X	X	X	X	X
Year fixed effect	X	X	X	X				
Industry-year fixed effect					X	X	X	X
Observations	1,618	1,638	1,621	1,482	1,618	1,638	1,621	1,482

*Robust standard errors in parentheses, clustered at plant level. All regressions are weighted with the inverse propensity scores. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

The PPML equation format here is $y_{it} = exp[\beta_0 + \beta_1 Subs_{it} + \beta_2 Permit_{it} + \nu_i + \nu_t + \epsilon_{ijt}]$, and the results should again be interpreted as $(e\beta - 1) * 100\%$. As can be seen in Table A5, the results still do now show significant impacts for the compensation subsidy. The signs of the estimated coefficients are now negative for gross production and number of employees, but as the error terms are large, these values are not statistically very different from zero. For the number of employees, the estimated coefficient is positive but also not statistically significant. These results further back up the conclusion that it cannot be said that the effect on the competitiveness variables has been positive. The electricity purchases variable still shows quite large positive effects, even if they are somewhat smaller than in the baseline estimation. Therefore, the results with PPML appear to be aligned with the baseline estimations.

C.5 Per worker variables

The main analysis of this paper has focused on absolute values of metrics related to firm competitiveness, but another factor of interest could be the productiveness of the workers. This can be checked by dividing the gross production by the number of employees. In addition, dividing the wages by the employees can tell us if the workers have benefited from the subsidy. The interpretation of electricity purchases per worker is not as straightforward, but it is included to check for any size impacts in the results regarding this variable. Using the per worker values is the approach that Ferrara & Giua (2022) also use. Table A6 shows the results of this exercise for my analysis.

Table A6: *Dependent variable divided by number of employees*

	Ln gross production per worker (1)	Ln wage per worker (2)	Ln elec. purch. per worker (3)	Ln gross production per worker (4)	Ln wage per worker	Ln elec. purch. per worker
Compensation subsidy	0.028 (0.042)	0.051 (0.028)	1.094** (0.390)	0.034 (0.044)	0.051 (0.030)	1.200** (0.414)
Permit costs	0.001 (0.001)	0.001* (0.001)	-0.015 (0.018)	0.000 (0.001)	0.001* (0.001)	-0.015 (0.016)
Plant fixed effect	X	X	X	X	X	X
Year fixed effect	X	X	X			
Industry-year fixed effect				X	X	X
Observations	1,617	1,620	1,481	1,617	1,620	1,481

*Robust standard errors in parentheses, clustered at plant level. All regressions are weighted with the inverse propensity scores. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

Again, it cannot be shown that the compensation subsidy has had an impact on these competitiveness metrics. Therefore, the specification of the dependent variable should not impact my results.

C.6 Spillover effects

The compensation subsidy was granted on the plant level, but many of the plants belong to larger corporations that also have plants that did not receive the subsidy. It is possible that some of these plants have been used as control plants in the main analysis. However, the firm as a whole can have benefited from the subsidy, so in other words spillover effects to the non-treated plants of the same firm cannot be ruled out without further analysis.

In this robustness check, the compensation subsidy is defined as 1 for all plants of a firm that has received the subsidy for at least one plant. The propensity scores have been recalculated so that the treated plants use the new definition. There are now 93 (instead of 61) treated and 235 (instead of 174) control plants.

Table A7: *Adjusted compensation subsidy dummy*

	Ln gross production	Ln employees	Ln wage	Ln electricity purchases	Ln gross production	Ln employees	Ln wage	Ln electricity purchases
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Compensation subsidy	0.033 (0.056)	-0.005 (0.044)	0.032 (0.044)	0.428* (0.167)	0.027 (0.057)	-0.009 (0.043)	0.025 (0.043)	0.502** (0.189)
Permit costs	-0.002* (0.001)	-0.002 (0.001)	0.000 (0.001)	-0.002 (0.007)	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)	-0.002 (0.007)
Plant fixed effect	X	X	X	X	X	X	X	X
Year fixed effect	X	X	X	X				
Industry-year fixed effect					X	X	X	X
Observations	2,242	2,265	2,242	2,026	2,242	2,265	2,242	2,026

Robust standard errors in parentheses, clustered at plant level. All regressions are weighted with the inverse propensity scores. $* p < 0.05$, $** p < 0.01$, $*** p < 0.001$

Table A7 shows the results with the adjusted compensation subsidy dummy. As can be seen, the results are still not statistically significant for our main variables of interest. On the other hand, the electricity purchases variable now shows weaker effects. This could be due to some of the previous control and now treated plants having little changes in this variable. The results regarding electricity purchases thus appears to be sensitive to changes in the data, while the no effects found in the financial metrics are more robust.