The impact of the European Emission Trading Scheme on labor productivity

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Abstract

Examining the impact of the EU Emissions Trading System (ETS) on firm performance is crucial for understanding the real consequences of one of the most important European environmental policies. This study investigates the effects of the EU-ETS on various indicators of Italian manufacturing firms' performance, such as labor productivity, revenues, employment and value added on sales ratio. Utilizing company data from 2006 to 2020, we employ a novel Difference-in-Differences (DID) approach with multiple periods and multiple groups, drawing on the methodology proposed by Callaway and Sant'Anna (2021). The objective is to assess the causal impact of the EU ETS across three treatment groups corresponding to the three entry points into the regulatory system: first phase (2006), second phase (2008), and third phase (2013). The comparison is made against firms in the same sectors that were never subject to the regulation, serving as the control group. Our results reveal that the EU ETS fosters growth in labor productivity, albeit with heterogeneous effects depending on firms' entry timing. There's a dynamic effect observed, with longer exposure correlating to greater productivity gains. However, this positive effect seems to be driven more by workforce reduction than output augmentation, potentially due to outsourcing. Negative effects on the value-added-to-sales ratio suggest a shift towards a more fragmented production structure.

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1. Introduction

In 2005, the European Commission adopted the European Union Emissions Trading Scheme (EU ETS) as the EU's primary tool for combating climate change. In practice, European companies belonging to CO_2-emission-intensive sectors (both power generation and manufacturing industries) listed in the Directive 2003/87/CE ("establishing a scheme for greenhouse gas emission allowance trading within the Community") and exceeding a certain sector-specific threshold of installed capacity have been subject to regulation under the ETS. This scheme requires companies that want to emit greenhouse gases (GHGs) to either purchase allowances for pollution permits or face the cost of an investment to cut emissions. In either case, the environmental regulation is expected to add costs to firms and divert resources away from productive activities, thereby reducing productivity and, more generally, reducing the economic performance of these firms (Coase, 1981; Baumol and Oates, 1988; Palmer *et al.,* 1995).

An alternative hypothesis is that environmental policies such as the EU ETS may induce regulated firms to implement environmentally friendly innovations, which could, in turn, offset the negative effect of compliance costs on competitiveness, productivity, and other economic performance (Porter, 1991; Porter and Van der Linde, 1995). In other words, the expectation of higher emission costs relative to other production costs may incentivize firms to invest in new emission-reducing technologies, possibly positively impacting their performance.

Empirical testing of these alternative hypotheses can take on sociopolitical significance since lower performances translate into a loss of international competitiveness (*vis-à-vis* non-European firms), an incentive for such firms to outsource production to unregulated countries (carbon leakage; see Levinson and Taylor, 2008; Martin *et al.,* 2014), and ultimately a loss of jobs in the sectors in question. On the contrary, evidence of higher performance would encourage the policymaker in the implementation of the regulation scheme. In this type of impact analysis, the time elapsed since the shock (i.e., the firm's entry into the regulation system) may be a crucial element. Indeed, it takes time for the positive effects on productivity to materialize. We might expect an initial negative impact or, at most, no effect.

The EU-ETS scheme followed four phases. The first one ran from 2005 (2006 in the case of Italy) to 2007 and was a pilot phase: no banking or borrowing of permits with the subsequent phases was allowed, and allowances were allocated for free (grandfathering). The second phase ran from 2008 to 2012. The main differences in comparison to the first phase were a higher penalty for non-compliance (from 40 euros per ton of CO_2 in the first phase to 100 euros per ton), including N_2O emissions, and the possibility of banking permits across phases. Grandfathering remained the default allocation method. The third phase started in 2013 with a substantial reduction in the proportion of allowances allocated for free. For the manufacturing sector, the initial free allocation of 80% of total allowances was gradually decreased towards the declared target of 30%. Auctioning became the default method of allocating allowances, reinforcing the principle that those who want to pollute must pay to do so. Additionally, a Market Stability Reserve was introduced in January 2019, aimed at draining excess allowances from the market.

The ongoing fourth phase of the European Emission Trading System, spanning from 2021 to 2030, has introduced several new features, such as a more ambitious emissions reduction target and the incorporation of new sectors like maritime transport.

Previous studies on the economic impact of the EU-ETS solely investigated the first two phases, obtaining very mixed results (Martin *et al.,* 2016; Convery, 2009). More evidence is needed on the effects of the third phase, which is the most important one for understanding the fate of the enterprises in question. An exception is the study by D'Arcangelo *et al.* (2022) on the economic effect of the ETS on Italian firms, which covers the period 2005-2015.

In this paper, we contribute to filling this knowledge gap by analyzing the effects of the EU-ETS on labor productivity, revenues, and employment of the firms to which the regulated facilities belong. The focus is on Italian firms, which weigh about 9% of Europe's total number of regulated firms. For this purpose, we selected a panel of treated, i.e. regulated by the ETS, and never-treated, i.e. not regulated, firms, on which we collected information for the period from 2002 to 2020 by combining data from the EU ETS Transaction Log with the AIDA database (Bureau van Dijk). The case of Italy is of great interest since it ranks as the third-largest contributor to the overall environmental impact within the European Union, with approximately 10% of EU emissions originating from facilities located within its borders. Consequently, assessing the economic impact of the regulation system on Italian firms (specially manufacturing firms) is extremely important, particularly in light of the potential negative consequences on productivity, which is already characterized by a chronic trend of low (almost zero) growth (Calligaris, 2015; D'Arcangelo *et al.*, 2022).

Another relevant novelty of our analysis is the consideration of different treatment timings for various groups of firms. As mentioned above, only installations belonging to a selected list of sectors and having a certain production capacity threshold are covered by EU ETS regulations. Firms operating these installations are considered treated firms in our analysis. Never-treated firms are those in the same sectors but operating installations below this threshold. These firms can be regarded as very similar to regulated entities; they only differ from treated firms due to the lack of regulation. This provides an opportunity to apply the sort of quasi-experimental techniques most suited to assessing the causal impacts of environmental policies (Greenstone and Gayer, 2009; List *et al*., 2003). We compare ETS and non-ETS entities both before and after the treatment, applying a Difference-in-Differences (DID) study design that enables us to control for confounding factors that affect both regulated and unregulated entities (demand conditions, input prices, sector-specific policies, etc.), as well as firm-level heterogeneity (Abadie and Imbens, 2008; Abadie, 2005; Heckman *et al.,* 1997; Heckman *et al*., 1998; Smith and Todd, 2005). However, the entry of the installations (and thus of firms) within the regulation system in our sample occurred at different moments. A large share of firms entered the ETS in the first year (2006 in Italy); the others entered afterward in a very irregular timing path, with the beginning of the third phase (2013) as a crucial second mass entry.

All previous studies focused on those installations that entered the ETS in 2006 and removed the plants entered in subsequent years from their analysis or considered all firms as first treated in 2006 independently of their actual entry date. This choice can generate a loss of information, but it is an obliged choice if standard

DID methods based on the estimation of two-way fixed effects (TWFE) models are applied. By adopting a new DID approach with multiple periods and multiple groups (Callaway and Sant'Anna, 2021), this study aims to evaluate the causal effect of the ETS in Italy for three treatment groups entered into the regulation system in the first (2006), second (2008), and third phase (2013). The other firms in the same sectors as the treated firms comprise the never-treated group. The analysis focuses on firms in the manufacturing sector since they are more exposed to international competition than firms in the power sector. The last have higher possibilities to pass through the additional cost imposed by the EU ETS to their customers.

The rest of the paper is structured as follows. Section 2 reviews the literature on the policy evaluation of the EU ETS. Section 3 provides information on the data used in our empirical analysis. Section 4 discusses the empirical strategy we adopted. Results are discussed in section 5 and section 6 concludes.

2. Literature review

Established in 2005, the EU ETS has spurred significant interest in research exploring its influence on firms' performance. The traditional theory (Coase, 1981; Baumol and Oates, 1988; Gray, 1987; Jaffe et al., 1995; Palmer et al., 1995) suggests that, by imposing additional costs on firms, environmental policies lead them to redirect resources from traditional uses towards emissions abatement or permit purchases. Such reallocation of resources may hinder productivity growth and diminish these firms' competitive edge in international markets. This would eventually lead to carbon leakage, i.e., firms may be induced to relocate production to other regions where emission constraints are less stringent, according to the pollution heaven hypothesis (Copeland and Taylor, 1994). An alternative view, the Porter hypothesis (Porter, 1991; Porter and Van der Linde, 1995), argues that these policies act as incentives for firms to innovate, leading to the discovery and adoption of new technologies. This, in turn, stimulates productivity growth and enhances the overall performance of regulated companies.

Many empirical studies have been conducted to test which of these two perspectives has prevailed in the case of the EU ETS. Verde (2020) and Martin et al. (2016) reviewed the existing literature on the ex-post evaluation of the EU ETS, assessing its effects on CO2 emissions, firms' economic performance, and competitiveness. In general, the effects of the instrument are evaluated based on performance indicators, including the number of employees (Commins et al., 2011; Marin et al., 2018; Colmer et al., 2018; Abrell et al., 2011; Dechezleprêtre et al., 2023), revenues (Marin et al., 2018; D'Arcangelo et al., 2022; Dechezleprêtre et al., 2023), value added (Klemetsen et al., 2016; Colmer et al., 2018; Marin et al., 2018; D'Arcangelo et al., 2022), and labor productivity (Marin et al., 2018; Klemetsen et al., 2016). The DID research design is the most commonly used in these studies, with or without various matching procedures. However, considerable heterogeneity exists among the results, which is often not statistically significant. Dechezleprêtre et al. (2023) found positive impacts on revenues, while Marin et al. (2018) found these positive effects only during the second phase. No significant results were detected for employees across all studies, except for a negative impact identified solely during Phase 1 by Marin et al. (2018). Labor productivity, on the other hand, was found to be positively influenced by the ETS in two studies: Klemesten et al. (2016), which examined Norwegian-regulated manufacturing plants, and Marin et al. (2018), which analyzed firm-level data from a large panel of European firms.

Total Factor Productivity (TFP) has also been considered in many studies with different results. Commins et al. (2011) found minor and adverse effects on TFP, but they defined participation in the EU ETS at the sector rather than at the firm level. The same result was found by Lundgren et al. (2015), while Marin et al. (2018) found no significant effect on TFP during the first and second phases of ETS. Koch and Themann (2022) estimated a stylized version of the neo-Schumpeterian productivity model. They found that the effect on TFP depends on the distance from the technological frontier within the industry. The EU ETS increases productivity among firms close to the frontier but negatively affects less advanced firms. No significant effect was found for most firms in the middle of the productivity distribution.

However, all the cited studies focus solely on the first EU ETS phase (2005-2007), essentially a pivotal period, or the second phase (2008-2012), when the market experienced a surplus of allowances. This surplus, coupled with the impact of the Great Recession, resulted in meager prices, altering the market mechanism and posing a threat to the system's overall effectiveness.

We contribute to the existing literature by extending the analysis to the third phase. It is crucial as it represents a period marked by significant changes that have enhanced the system's efficacy. This phase witnessed a substantial shift from grandfathering to auctioning as the primary method for allowances allocation. Notably, companies operating in the energy production sector no longer received free allocations of allowances during this phase. This approach aimed to increase cost-effectiveness, promote fair competition, and provide incentives for emission reduction efforts. Furthermore, the introduction of the Market Stability Reserve (MSR) enhanced market stability and addressed the surplus of allowances observed in the first and second phases.

In a more recent study, D'Arcangelo et al. (2022) analyzed the causal impact of the first ten years of the EU ETS on the TFP of Italian manufacturing firms, spanning from 2005 to 2015, thereby considering only three years of the initial phases. This study does not consider labor productivity as an outcome. In contrast, in the present study, we prefer to focus on this variable due to critical aspects related to the computation of the TFP. Moreover, by extending the analysis so that it encompasses a more extensive timeframe, including the entire third phase, we can better observe and understand the unfolding effects of the policy.

Another aspect that should be considered in the literature is the timing of the treatment. All the cited studies have only examined two periods: pre-ETS (before 2005) and post-ETS (after 2005). However, the EU ETS is a dynamic program where firms enter at different moments due to factors such as expanding the EU ETS coverage to new sectors or activities over time, or increasing production capacity beyond the established threshold. Consequently, not all EU ETS installations, and thus the companies that own them, have been part of the system from the beginning (2005) to the end of the observed period (2020). The dynamic nature of the

EU ETS, a critical aspect that needs to be addressed in the current literature, is essential for comprehensive consideration in any system impact analysis.

Only Marin et al. (2018) tried to consider this aspect, performing two separate estimations for the two phases of the scheme (2005-2007 and 2008-2012). However, using different estimations for distinct periods may overlook the treatment's interdependence and cumulative effects across the entire duration of the EU ETS. The dynamic nature of the EU ETS, with firms entering at different times, is a crucial aspect that has not been adequately addressed in the existing literature.

For this reason, we conduct an empirical analysis capable of effectively handling variations in treatment timing, enabling a more accurate assessment of the impact of the EU ETS on firms' outcomes. More specifically, we utilize an estimator proposed by Callaway and Sant'Anna (2021), which allows for the examination of dynamic treatment effects, and which captures how the impact of the policy may change as the system matures. By explicitly considering the timing of treatment and accounting for heterogeneity, this estimator helps mitigate potential biases that arise in analyzing treatments with dynamic and varying characteristics.

3. Data and outcomes

Our analysis relies on a tailored panel dataset of Italian firms constructed using two data sources. We started by collecting data on Italian installations covered by the ETS directly from the European Union Transaction Log (EUTL), the centralized registry. It provides essential information on regulated installations, including their emissions, location, and compliance. We then identified firms operating these installations using the company registration number, if available, or the Account Holder Name. These two pieces of information matched EUTL data with firm-level financial data from the ORBIS Bureau Van Dijk database. From the latter, we collected balance-sheet information (e.g., revenues, employment, fixed assets) for each regulated company, along with their activity code based on the NACE rev. 2 classification. Finally, we included non-ETS firms in our dataset by retrieving data for all companies operating within the same sectors for 2002-2020.

In Italy, the implementation of the ETS faced a one-year delay due to the late adoption of the National Allocation Plan[d]. Consequently, the first year of treatment was established in 2006. Therefore, as the pre-treatment period, we considered the four years from 2002 to 2005.

To ensure data consistency, we excluded all firms without observations be-fore 2006 and those lacking observations after 2006. We also excluded firms belonging to Sector 32 (“Other manufacturing goods”) of the NACE classification because of the lack of treated firms within this industry. As pointed out above, we focused on manufacturing firms, thus excluding firms belonging to Sector 35 (“Electricity, gas, steam, and air conditioning supply”). This cleaning procedure resulted in the loss of 47 treated firms, concentrated in the “2006” group since energy producers generally have a $C0_2$ capacity above the regulatory threshold (see Table

[d] Because of these delays, Italy has been subjected to infringement proceedings by the European Commission.

1 for the sectoral distribution of firms). Finally, for each outcome variable, we identified the outliers. The exclusion of the outliers had a limited impact on the number of treated firms included in the sample. After completing these steps, our dataset consisted of 60,819 firms, with a total number of observations equal to 933,972. In this sample, the treated firms have been grouped into three cohorts: those entered for the first time in the first phase (the group name is "2006"), in the second phase (the group name is "2008"), and in the third phase (the group name is "2013"). The average number of firms in each cohort is 277 in group "2006", 49 in group "2008", and 103 in group "2013".

The first outcome variable we focused on was labor productivity, measured as the log of the ratio between revenues and the number of employees. Nominal revenues have been deflated using the annual price deflator specific to the corresponding two-digit industry level. We also considered the log of revenues and the log of employees separately to assess which of them mainly drives the effect on productivity. In order to thoroughly understand the dynamics related to productivity effects, we considered the value-added on sales ratio (an indicator of vertical integration) as an outcome variable.

Table 1. Distribution of ETS and non-ETS firms by sector.

Sector	Non-ETS Firms		ETS Firms		Total
10	4,371	98.20%	80	1.80%	4,451
11	807	98.41%	13	1.59%	820
12	9	90.00%	1	10.00%	10
13	2,848	99.16%	24	0.84%	2,872
14	3,019	99.93%	2	0.07%	3,021
15	2,160	99.95%	1	0.05%	2,161
16	1,850	99.62%	7	0.38%	1,857
17	1,217	92.83%	94	7.17%	1,311
18	2,300	99.87%	3	0.13%	2,303
19	164	94.80%	9	5.20%	173
20	1,926	98.12%	37	1.88%	1,963
21	299	96.76%	10	3.24%	309
22	3,358	99.56%	15	0.44%	3,373
23	3,714	96.79%	123	3.21%	3,837
24	1,267	96.94%	40	3.06%	1,307
25	11,889	99.87%	16	0.13%	11,905
26	2,213	99.91%	2	0.09%	2,215
27	2,549	99.84%	4	0.16%	2,553
28	7,899	99.89%	9	0.11%	7,908
29	885	99.66%	3	0.34%	888
30	655	99.39%	4	0.61%	659
31	2,913	99.97%	1	0.03%	2,914
33	2,008	99.95%	1	0.05%	2,009
Total	60,320		499		60,819

Sources: authors' calculations.

Table 2. Distribution of ETS and non-ETS firms by year

	Year	Non-ETS Firms		ETS Firms		Total
Pre-treatment	2002	52,554	99.15%	448	0.85%	53,002
	2003	49,969	99.13%	441	0.87%	50,410
	2004	56,951	99.18%	468	0.82%	57,419
	2005	57,892	99.18%	479	0.82%	58,371
Phase 1	2006	58,046	99.18%	481	0.82%	58,527
	2007	57,929	99.17%	486	0.83%	58,415
Phase 2	2008	55,674	99.15%	475	0.85%	56,149
	2009	46,273	99.01%	463	0.99%	46,736
	2010	39,077	98.88%	444	1.12%	39,521
	2011	54,006	99.14%	467	0.86%	54,473
	2012	51,524	99.11%	465	0.89%	51,989
Phase 3	2013	49,554	99.08%	458	0.92%	50,012
	2014	47,423	99.07%	446	0.93%	47,869
	2015	45,771	99.04%	443	0.96%	46,214
	2016	44,253	99.02%	436	0.98%	44,689
	2017	42,785	99.01%	429	0.99%	43,214
	2018	41,349	98.98%	424	1.02%	41,773
	2019	37,875	99.27%	278	0.73%	38,153
	2020	36,764	99.27%	272	0.73%	37,036
Total		925,669		8,303		933,972

Sources: authors' calculations.

4. Methodology

To evaluate the impact of the ETS on firms' productivity, we use a Difference-in-Differences (DID) approach. In the canonical DID setup, there are two time periods (say $t-1$ and t) and two groups: no one is treated in $t-1$, while in period t some units are treated, and some units are not (the control group). If, in the absence of treatment, the average outcomes for treated and control groups follow parallel paths over time (parallel trends assumption), one can estimate the average treatment effect for the treated subpopulation (ATT) by comparing the average change in outcomes experienced by the treated group with the average change in outcomes experienced by the control group. In this standard approach, the ATT can be estimated by using a two-way fixed effects (TWFE) estimator (Imbens and Wooldridge, 2009):

$$Y_{it} = \alpha_i + \alpha_t + \beta D_{it} + \epsilon_{it} \quad (1)$$

where α_i and α_t are individual and time-fixed effects, ϵ_{it} is an error term, D_{it} is a treatment dummy variable equal to one if unit i is treated in period t and zero otherwise, and β is the treatment parameter, i.e. in our case the ATT effect of the ETS on labor productivity.

The static model (1) is often extended to the "dynamic" TWFE linear regression specification:

$$Y_{it} = \alpha_i + \alpha_t + \sum_{e=-K}^{-2} \delta_e \, D_{it}^e + \sum_{e=0}^{L} \beta_e \, D_{it}^e + \vartheta_{it} \quad (2)$$

where ϑ_{it} is an error term, D_{it}^e is an indicator for unit i being e periods ($e \geq 0$) away from initial treatment at time t, and K and L are positive constants. Here, the parameters of interest, β_e, measure the effect of participating in the treatment at different lengths of exposure to the treatment. At the same time, δ_e are the pre-event coefficients which can also be used as a diagnostic tool to assess the parallel trend assumption. Dynamic or event study TWFE regression model (2) allows us to determine if the treatment effect increases or decreases with elapsed treatment time.

Our analysis considers different groups of treated units corresponding to the three groups of firms that entered the regulation system during the first, second, and third phases, respectively. With multiple groups, β (or β_e) is a weighted average of individual two-group/two-period DID estimators with the weights proportional to the group size. However, when different groups are treated in different periods, as in our case, some of the 2×2 estimates enter the average with negative weights. The reason is that already-treated units (i.e., firms that already entered the ETS) act as controls, and changes in a portion of their treatment effect over time are subtracted from the DID estimates. In these cases, the TWFE can generate biased estimates of the ATT.
A natural way to solve this problem is to compute the group-time average treatment effect, i.e., the impact of ETS for each of the three groups for each year after the shock. Following Callaway and Sant'Anna (2021), we define G as the period of the first treatment of each firm (2006, 2008, and 2013 in our case), which also identifies the group to which it belongs. Therefore, the average effect of participating in the treatment for firms in group g at time t is given by:

$$ATT(g,t) = E\left[Y_t(g) - Y_t(0) | G_g = 1\right] \quad (3)$$

where G_g is a binary variable equal to 1 if a firm is first treated (i.e., enters the ETS) in period g, $Y_t(g)$ denotes the potential outcome of firms at time t if they entered the ETS in period g, and $Y_t(0)$ denotes untreated firms' potential outcome at time t. Callaway and Sant'Anna (2021) propose a methodology to identify, estimate, and make inferences about $ATT(g,t)$ when the parallel trends assumption holds potentially only after conditioning on observed pre-treatment covariates (X). Specifically, the group-time ATT for group g in period t is nonparametrically identified and given by

$$ATT(g,t) = E\left[\left(\frac{G_g}{E(G_g)} - \frac{\frac{p_g(X)C}{1-p_g(X)}}{E\left(\frac{p_g(X)C}{1-p_g(X)}\right)}\right)\left(Y_t - Y_{g-1} - m_{g,t}(t)\right)\right] \quad (4)$$

where $p_g(X)$ is the generalized propensity score (GPS), with $C = 1$ for never treated firms, Y_t is the potential outcome at time t, Y_{g-1} is the potential outcome in the period $g - 1$, and $m_{g,t}(t) = E[Y_t - Y_{g-1}|X, C = 1]$ is the population outcome regression for the "never-treated" group. This is a weighted average of the "long difference" of the outcome variable, with the weights depending on the propensity score. Therefore, the algorithm uses observations from the control group and group g, omitting other groups, and assigns more weight to observations from the control group with characteristics similar to those frequently found in group g.

The estimate of $ATT(g,t)$ is obtained using a two-step strategy. In the first step, one estimates the nuisance functions for each group g and time t, $p_g(X)$ and $m_{g,t}(t)$. In the second step, one plugs the fitted values of these estimated functions into the sample analog of $ATT(g,t)$ in (2) to obtain estimates of the group-time average treatment effect. Callaway and Sant'Anna (2021) also propose using a computationally convenient multiplier-type bootstrap procedure to obtain simultaneous confidence bands for the group-time average treatment effects to conduct asymptotically valid inference.

Estimated $ATT(g,t)$ values can be directly used for learning about treatment effects heterogeneity (i.e., they allow us to consider how the effect of ETS varies by group and time) and to construct aggregate causal effect parameters. The simplest way of combining $ATT(g,t)$ across g and t is the weighted average of $ATT(g,t)$ putting more weight on $ATT(g,t)$ with larger group sizes:

$$\theta_W^O = \frac{1}{k}\sum_{g\in G}\sum_{t=2}^{T} \mathbf{1}\{g \le t\}\, ATT(g,t) P(G = g|G \le T) \qquad (5)$$

with $k = \sum_{g\in G}\sum_{t=2}^{T} 1\{g \le t\}\, P(G = g|G \le T)$. Unlike β in the TWFE regression specification (1), this simple combination of the $ATT(g,t)$ immediately rules out troubling issues due to negative weights.

Estimated $ATT(g,t)$ values can also be aggregated to highlight treatment effect heterogeneity with respect to the length of exposure to the treatment, avoiding the pitfalls associated with the dynamic TWFE specification in (2):

$$\theta_{es}(e) = \sum_{g\in G} \mathbf{1}\{g + e \le t\} P(G = g|G + e \le T) ATT(g, g + e) \qquad (6)$$

This is the average effect of participating in the treatment e time periods after the treatment is adopted across all groups that are ever observed to have participated in the treatment for exactly e time periods. We can also compute an overall treatment effect parameters by averaging $\theta_{es}(e)$ across all event times (i.e. all positive lengths of exposure):

$$\theta_{es}^O = \frac{1}{T-1}\sum_{e=0}^{T-2} \theta_{es}(e) \qquad (7)$$

Finally, another aggregate measure that may be of interest in our analysis is the average group-specific treatment effect:

$$\theta_{sel}(g) = \frac{1}{T-g+1}\sum_{t=g}^{T} \sum ATT(g,t) \qquad (8)$$

Note that $\theta_{sel}(g)$ is the average effect of being treated among firms in group g, across all their post-treatment periods. We can also consider an average across groups of $\theta_{sel}(g)$ as an overall measure of treatment effect in place of θ_W^O:

$$\theta_{sel}^{O} = \sum_{g \in G} \theta_{sel}(g)\, P(G = g | G \leq T) \qquad (9)$$

This alternative measure has the advantage of not putting more weight on groups that participate in the treatment for longer.

5. Results

5.1 Identification strategy

We apply the methodology discussed in Section 4 to analyze the effect of participating in the ETS on labor productivity and its components (revenues and employment) and on the value added on sales ratio. We expect that the impact of ETS on productivity is dynamic, i.e., it changes with exposure to the treatment and varies across firms according to the timing of treatment.

The vast majority of previous studies tried to understand the effect of ETS on productivity using 2005/6 as a first-entry year for all treated firms, thus neglecting the variation in the timing of ETS participation across firms. As discussed above, our identification strategy follows a different approach. In particular, we define groups by the time period when a firm first entered the ETS. Most firms (two-thirds) joined the ETS in the first phase, but one-third became treated groups in the second and third phases. Therefore, we classify treated firms into three groups: “2006”, “2008”, and “2013”. The rest of the sample comprises never-treated firms belonging to the same sectors as the treated.

We also adopt a generalized propensity score (GPS) approach to attribute weights to firms in the control group. In particular, we assume that only firms with the same characteristics would follow the same trend in outcome variables without treatment (“conditional parallel trends assumption”, on which the adopted DID methodology is based).

The variables used to compute the GPS through the estimation of a logit model are time-invariant firm characteristics (indicating whether the firm is of small or medium size in terms of employment), a set of sectoral dummies, firms’ average pre-treatment period (2002-2005), growth rates of labor productivity, revenues, investment intensity, and fixed assets. This set of X variables changed with the outcome and was selected to satisfy the parallel trend assumption. Summary statistics for these variables and outcome variables are presented in Table 3, along with the t-tests comparing mean values between each treated and the untreated groups. Treated firms exhibit, on average, a higher level of labor productivity, higher revenues, and a higher number of workers than untreated firms. Treated firms also have a higher value-added per unit of sales than untreated ones. The two groups also differ in terms of other characteristics. ETS firms are, on average, larger and have a higher growth rate in labor productivity, revenues, and fixed assets during the pre-treatment period than non-ETS firms.

Table 3. Summary statistics for treated and never-treated units and *t*-test results.

	Obs	Mean	Std. Dev.	dif	t value
Labor productivity	933,972	5.139	0.824		
Non-ETS	925,669	5.133	0.822		
ETS	8,303	5.764	0.720		
				-0.632	-69.75***
Revenues	938,066	7.593	1.494		
Non-ETS	931,162	7.573	1.476		
ETS	6,904	10.299	1.420		
				-2.726	-152.9***
Employees	943,871	2.574	1.115		
Non-ETS	937,573	2.562	1.105		
ETS	6,298	4.387	1.121		
				-1.826	-130.7***
Value added on sales ratio	892,056	0.315	0.16		
Non-ETS	883,845	0.316	0.160		
ETS	8,211	0.266	0.129		
				0.05	28.03***
SMES	926,744	0.994	0.076		
Non-ETS	920,812	0.995	0.070		
ETS	5,932	0.85	0.357		
				0.145	147.85***
LARGE	926,744	0.006	0.076		
Non-ETS	920,812	0.005	0.070		
ETS	5,932	0.15	0.357		
				-0.145	-148***
Growth_Lab_prod	901,854	0.053	0.224		
Non-ETS	896,100	0.053	0.224		
ETS	5,754	0.081	0.211		
				-0.028	-9.5***
Growth_Revenues	901,854	0.048	.204		
Non-ETS	896,100	0.048	0.204		
ETS	5,754	0.051	0.178		
				-0.003	-1.05
Growth_Investment_ Intensity	892,042	-0.017	0.193		
Non-ETS	887,452	-0.017	0.193		
ETS	4,590	-0.005	0.147		
				-0.013	-4.3***
Growth_Fixed Assets	901,083	0.045	0.253		
Non-ETS	895,278	0.045	0.253		
ETS	5,805	0.056	0.210		
				-0.011	-3.1***

**p<0.10; **p<0.05; *** p<0.01.*

Sources: authors' calculations

5.2 The Impact of ETS on Labor Productivity

The first set of results uses labor productivity as the outcome variable. Summary measures of ATT effects are reported in Table 4 column i, the event-study results are displayed in Figure 1, and the heterogeneous group-time average treatment effects results are reported in Figure 2. All inference procedures use clustered bootstrapped standard errors at the firm level and account for the autocorrelation of the data. The plots include simultaneous 99% confidence bands and contain pre-treatment estimates that can be used to test the parallel trends assumption and treatment effect estimates in post-treatment periods.

Aggregate statistics support the view that the ETS led to increased labor productivity. The simple average ATT effect (θ_W^O) in Table 4 (weighted only by group size) indicates that being covered by ETS regulation leads to an 11.4% increase in labor productivity in comparison with what the situation would have been without environmental regulation. This aggregate parameter is notable at the 1% level of significance.

ETS also has a dynamic effect. Figure 1 clearly shows that the impact of ETS changes depending on the span of time the policy has been in place. In particular, the impact of ETS on labor productivity appears to be positive and increasing in magnitude the longer firms are exposed to the regulation: during the first year that a firm enters the ETS, labor productivity is estimated to increase by 10%; after 12 years, it is estimated to increase by 19%. It is also worth noting that all pre-treatment ATT parameters in Figure 1 are insignificant (their confidence interval contains zero), thus supporting the parallel trend assumption.

However, the overall impact of ETS on productivity masks a strong heterogeneity across the three groups. Indeed, the group-specific average – $\theta_{sel}(g)$ – is significantly positive only for firms first treated in the first phase ("2006") and indicates an average increase in productivity of 11,2%. For firms first treated in the second ("2008") and the third phase ("2013"), there is no significant effect. Since firms in group "2006" were exposed for more time to treatment than the other firms, the weighted average of all group- time treatment effects (ATT), with weights proportional to group size (θ_{sel}^O) turns out to be slightly lower than the overall simple ATT (10.1% versus 11.4%).

Finally, Figure 2 shows the average treatment effects for each group in each year. It is worth noting that, for each group, all pre-treatment effects estimates, provided with 99% simultaneous confidence intervals, are not statistically significant (confidence bands encompass the 0). This means that the assumption of parallel trends also holds for each treatment group.

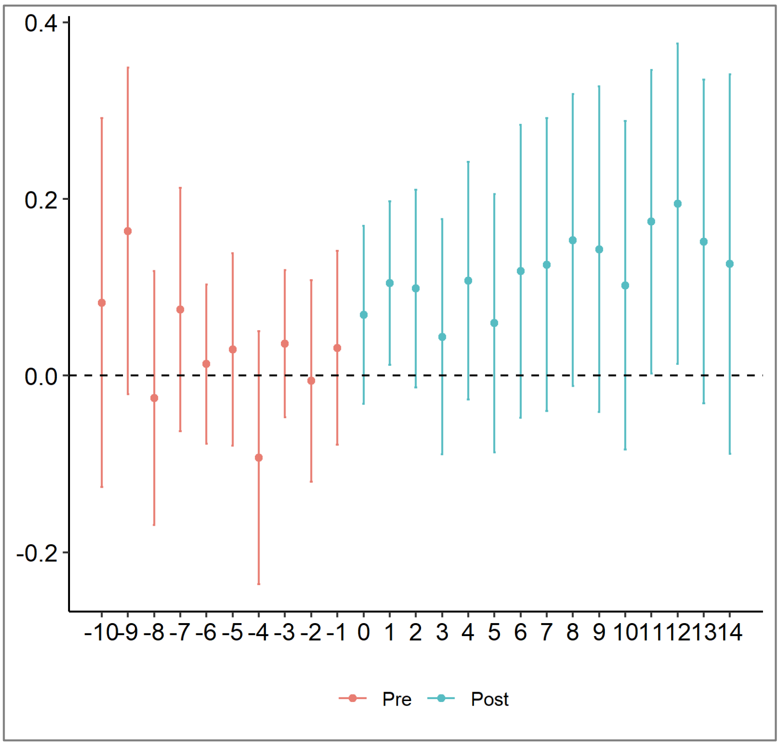
Table 4. Estimations results

	Log of labor productivity *(i)*	Log of revenues *(ii)*	Log of employees *(iii)*	Value added on sales ratio *(iv)*
Simple average	0.114*	-0.039	-0.167*	-0.024*
	(0.031)	(0.043)	(0.043)	(0.006)
Dynamic average	0.118*	-0.043	-0.177*	-0.025*
	(0.037)	(0.040)	(0.044)	(0.006)
Group average	0.101*	-0.052	-0.167*	-0.023*
	(0.030)	(0.041)	(0.039)	(0.006)
-- 2006	0.112*	-0.047	-0.204*	-0.032*
	(0.037)	(0.047)	(0.050)	(0.007)
-- 2008	0.288	0.174	0.095	0.014
	(0.112)	(0.109)	(0.133)	(0.017)
-- 2013	-0.029	-0.181	-0.212*	-0.017
	(0.057)	(0.095)	(0.057)	(0.009)
N of observations	933,972	938,066	943,871	892,056

Note: In this table, there are aggregated treatment effect parameters and bootstrapped standard error clustered at the firm level in parentheses.

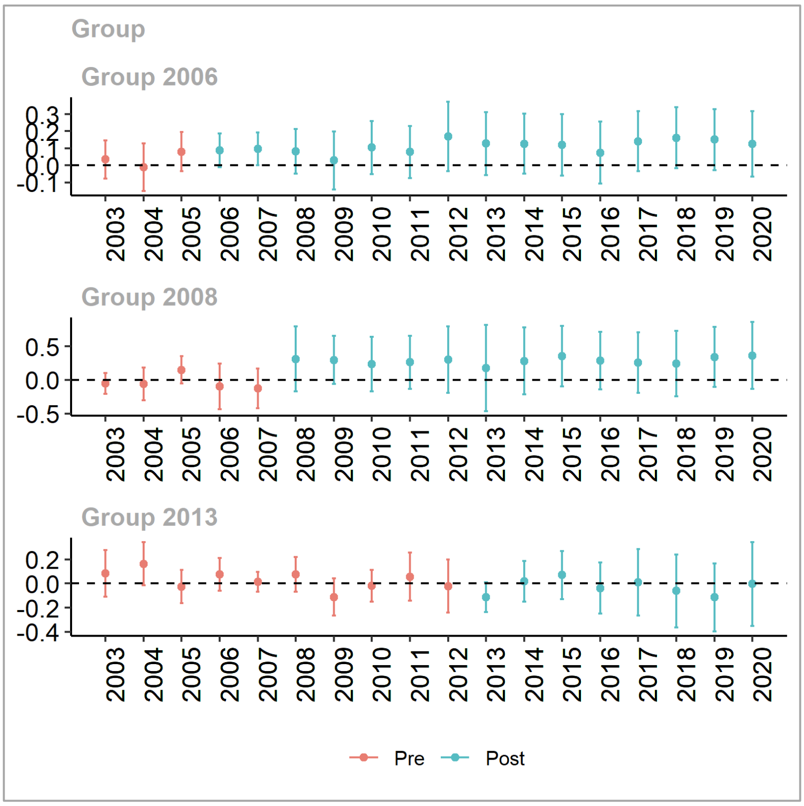
**: the star indicates that the 99% confidence band does not cover zero. The first row reports the weighted average (by group size) of all available group–time average treatment effects, as in equation 3. The second row reports the dynamic average effect (the overall summary of ATT based on event-study / dynamic aggregation, see equation 5). The third row reports the weighted average of the three group-specific average treatment effects, as in equation 7, reported in rows "2006", "2008", and "2013". Unbalanced panel data.*

Figure 1. Dynamic Average Effect by length of exposure. Outcome: Log of labor productivity.



Note: The effects of ETS are estimated under the conditional parallel trends assumption. Red lines give point estimates and uniform 99% confidence bands for pre-treatment periods (g>t) allowing for clustering at the firm level. Under the null hypothesis of the conditional parallel trends assumption holding in all periods, these should be equal to zero. Green lines provide point estimates and uniform 99% confidence bands for the treatment effect of ETS (for the post-treatment periods g ≤ t) allowing for clustering at the firm level.

Figure 2. Group average effect for each group, 2002-2020. Outcome: Log of labor productivity.



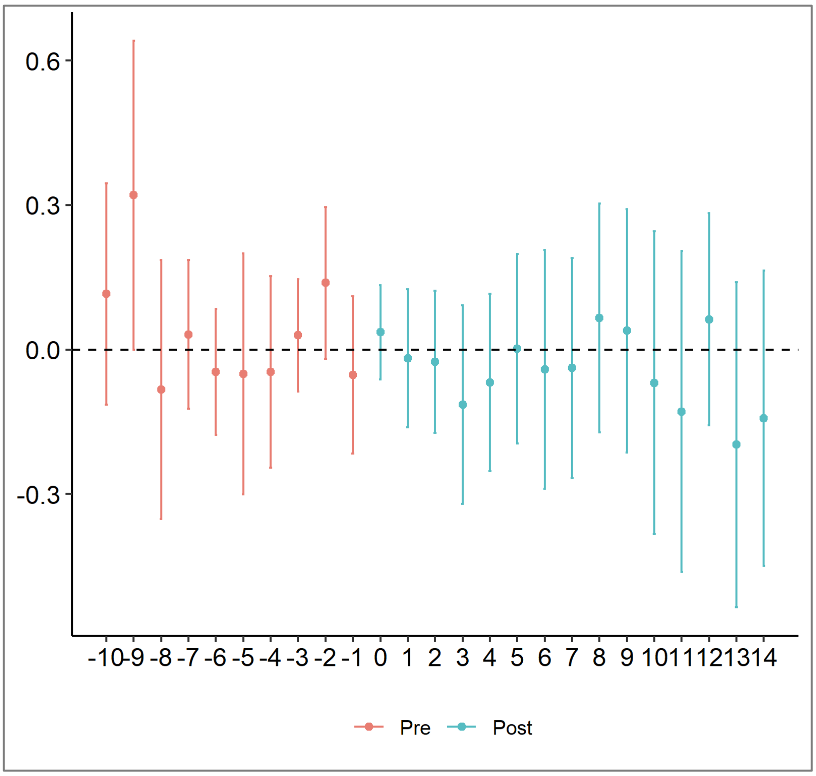
Note: See Notes in Figure 1.

5.3 The impact of ETS on revenues and employment

To understand the driving factors behind the positive effect on labor productivity, we separately considered the impact of the ETS on revenues and employees. The estimation results of the ETS effect on the log of revenues are reported in Table 4, column *ii*, while Figures 3 and 4 show, respectively, the event study results and the heterogeneous group-time average treatment effects results.

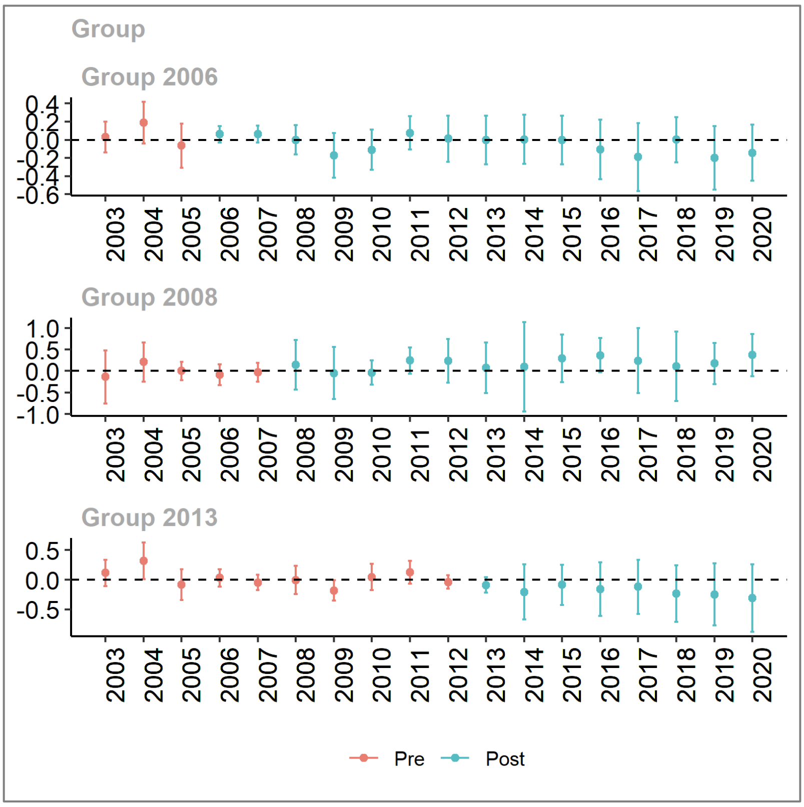
The simple average ATT effect on revenues is negative, indicating that being regulated by the ETS results in a roughly 4% decrease in turnover compared to what would have occurred without regulation. However, this result is not statistically significant. Also, the dynamic average effect, $\theta_{es}(e)$, is negative (-4,3%), but not significant. When disaggregating these aggregate results by group-specific average effect – $\theta_{sel}(g)$ – a positive effect emerges for the 2008 group; however, it remains non-significant. Meanwhile, for the 2006 and 2013 groups, the negative and non-significant impact on revenues persists. In conclusion, our results do not confirm the hypothesis posited by Dechezleprêtre *et al.* (2023) that firms regulated by ETS can pass through the costs of environmental policies and enhance product quality and sales prices, thereby increasing revenues.

Figure 3. Dynamic Average Effect by length of exposure. Outcome: Log of revenues.



Note: See Notes in Figure 1.

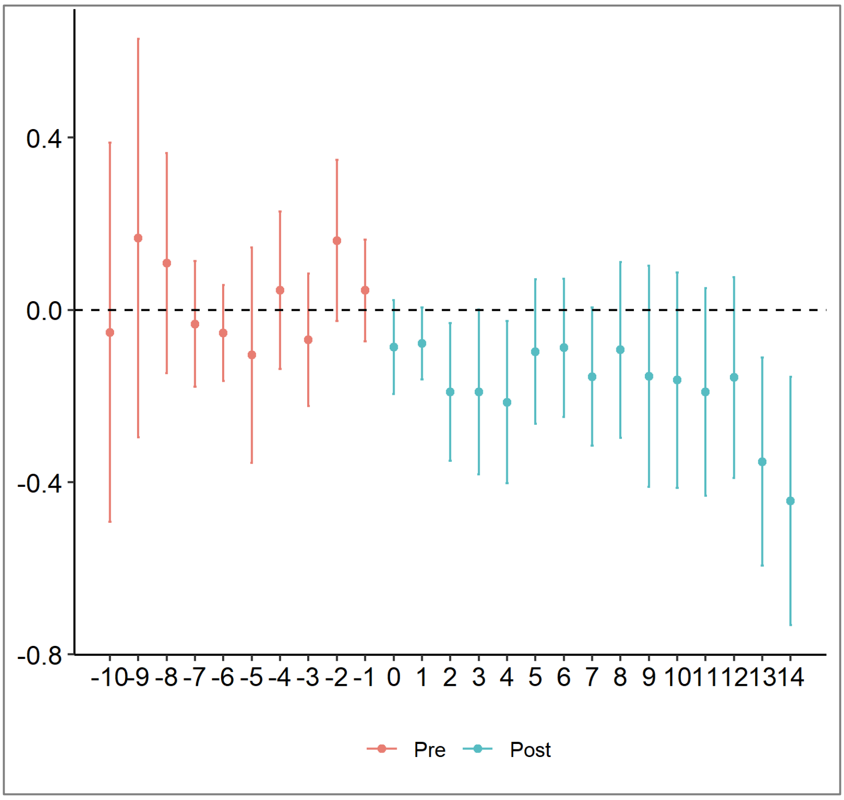
Figure 4. Group average effect for each group, 2002-2020. Outcome: Log of revenues.



Note: See Notes in Figure 1.

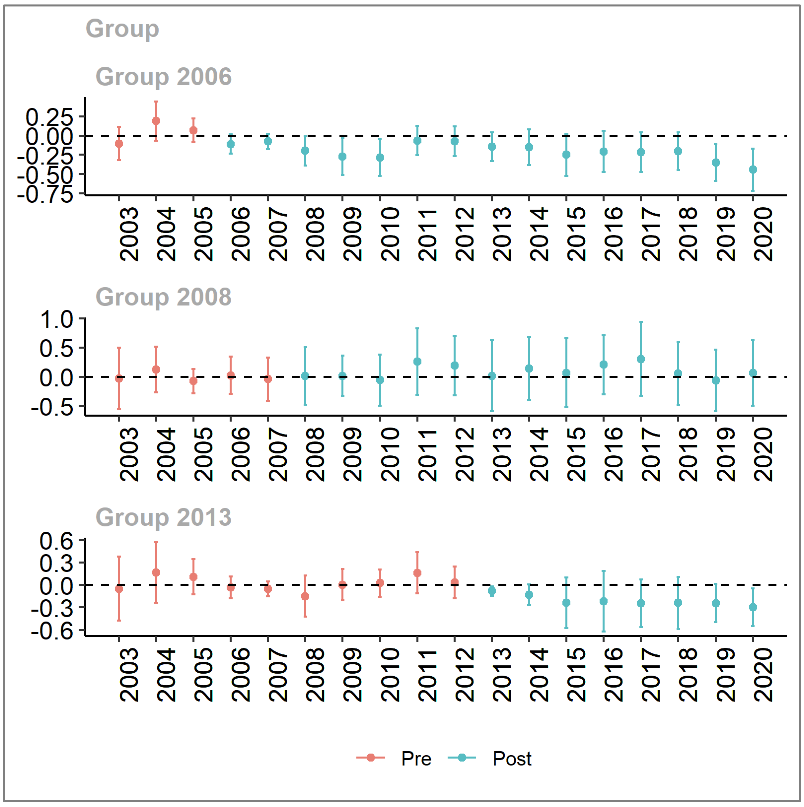
The effect of the ETS on the log of employees is reported in Table 4 column *iii*. The findings support the view that environmental regulations have negative impacts on employment. The simple average ATT effect (θ_W^O) indicates that the number of employees in regulated firms is, on average, 16% lower during the ETS period compared to what it would have been had they not been regulated. This result is significant at the 1% level of significance. The dynamic effect is also negative and strongly significant. As shown in Figure 5, as the duration of participation in the ETS increases, the impact on the number of workers intensifies. Therefore, by the 14th year of treatment, the negative effect is much more pronounced. Also, in this case, evidence supports the parallel trend assumption, as all the pre-treatment ATT parameters are not statistically significant. Finally, considering the group-specific average effect, some differences emerge across the three groups. As shown in Figure 6, the average impact is negative and strongly significant for group “2006”, i.e., firms first treated in the first phase, and group “2013”, i.e., firms first entering the system in 2013. There is a positive effect on employees for firms that were first treated in 2008, though not statistically significant. These findings align with those of Marin *et al.* (2018), who identified a significant and negative impact on employment, but specifically for the first phase of the ETS.

Figure 5. Dynamic Average Effect by length of exposure. Outcome: Log of employees.



Note: See Notes in Figure 1.

Figure 6. Group average effect for each group, 2002-2020. Outcome: Log of employees.



Note: See Notes in Figure 1.

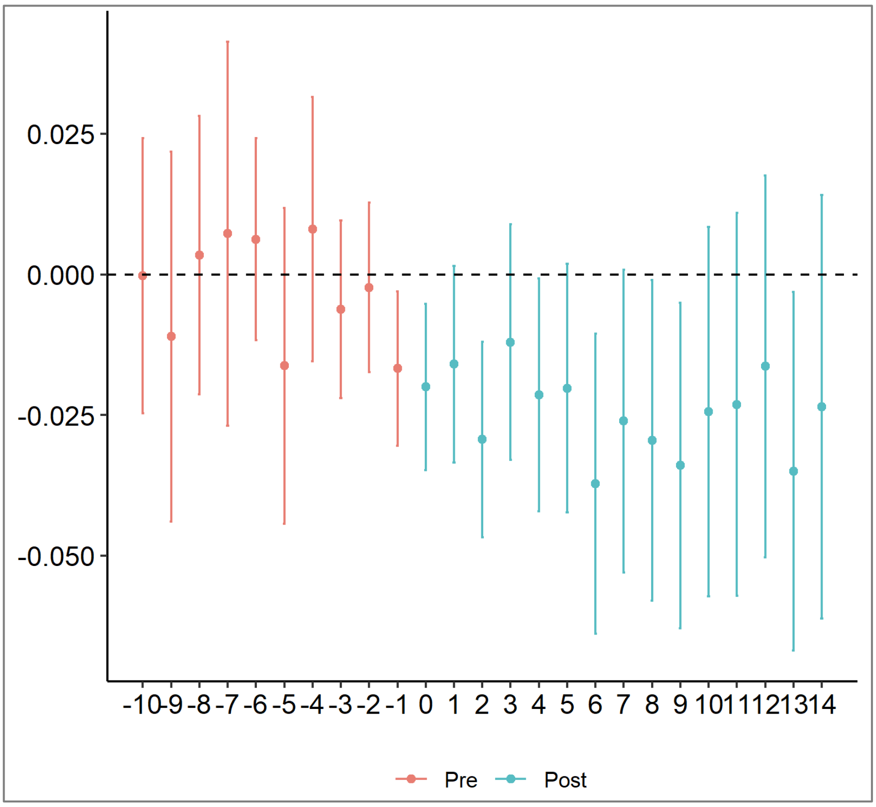
5.4 The impact of ETS on the value-added on sales ratio

The results discussed in the previous section show that ETS positively impacts labor productivity for Italian manufacturing firms subject to environmental regulation. However, this seemingly positive effect appears to be driven by a negative impact of regulation on employment rather than a positive one on output (revenues). One possible explanation for this result could stem from the fact that, due to the additional costs of carbon regulation, companies operating in more energy-intensive industries have partly disintegrated the production process and relocated some of their activities to countries where environmental regulations are not enforced or are less restrictive, to protect their competitiveness. This is especially likely for the metal and cement industries (Santamaria *et al.*, 2014, Sato *et al.*, 2015).

To verify this hypothesis, we estimate the impact of ETS on the ratio between value-added and turnover, a proxy of vertical disintegration (Gianelle and Tattara, 2008). A decrease in this ratio suggests that intermediate inputs are traded among firms rather than produced internally, leading to more prolonged or intricate supply chains. Summary measures of ATT effects are reported in Table 4 column *iv*, the event-study results are displayed in Figure 7, and the heterogeneous group-time average treatment effects results are reported in Figure 8.

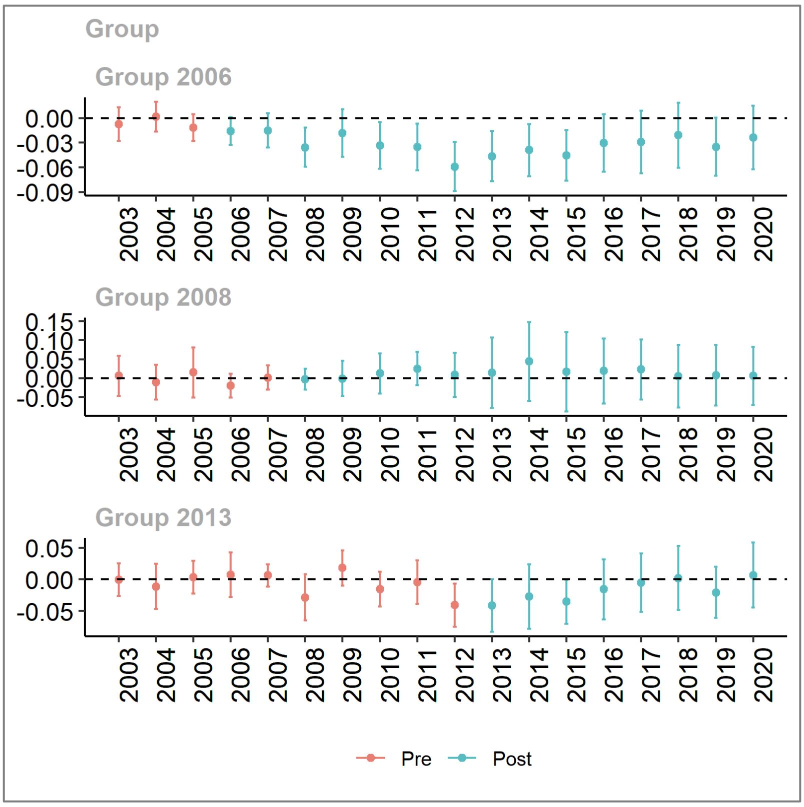
The estimation of the simple average ATT parameter indicates that being covered by ETS regulation reduces the value created per unit of sales by 2.4% compared to what would have been without environmental regulation. This aggregate parameter is significant at the 1% level of significance. This result supports the hypothesis that part of the production process has been outsourced, with firms choosing to buy intermediate goods rather than produce them internally. The dynamic average ATT effect is also negative and highly significant, implying that the longer the treatment duration (participation in the system), the greater the impact intensity. The time profile of the dynamic effect on the ratio of value-added to revenue appears to mirror that on labor productivity. Consistently with the results obtained from examining the effects on labor productivity, there is also heterogeneity in the effects when analyzing the value-added on revenues across the three groups of treated firms. Indeed, the group-specific average is confirmed significantly negative only for firms first treated in the first phase ("2006") and indicates an average reduction in value-added per unit of revenues by 3.2%. For firms of the second ("2008") and the third ("2013") groups treated, there is no significant effect.

Figure 7. Dynamic Average Effect by length of exposure. Outcome: Value-added on sales ratio.



Note: See Notes in Figure 1.

Figure 8 Group average effect for each group, 2002-2020. Outcome: value-added on sales ratio.



Note: See Notes in Figure 1.

6. Conclusions

In this study, we investigated the impact of the EU-ETS on labor productivity, revenues, and employment of Italian firms in the regulated sectors to understand how this environmental policy affects firm performance. To do so, we rely on company data related to the period from the launch of the EU Emissions Trading System (ETS) in 2006 in Italy to the end of Phase 3 in 2020.

Our results reveal that the EU ETS stimulates labor productivity growth, but heterogeneous effects depend on the timing of the firms' entry into the regulation system. In particular, the effect is significantly positive only for firms first treated in the first phase ("2006"), while there is no significant effect for firms first treated in the second ("2008") and the third phase ("2013"). This result is consistent with the evidence of an aggregate dynamic effect of ETS: the positive impact of ETS increases the longer firms are exposed to the regulation. However, this increase in labor productivity seems to occur through a reduction in the number of employees rather than an output (revenues) increase. At the same time, this reduction in employment is not accompanied by a corresponding decrease in turnover. One possible explanation for this result lies in the decision to outsource certain phases of the production process. Therefore, to verify if this is the case, we studied the ETS's impact on the value-added/revenues ratio, a traditional measure of vertical integration. Notably, a negative effect was observed, supporting our initial hypothesis. Firms may have resorted to outsourcing specific production stages, leading to a more fragmented production structure. Further research could investigate the dynamics linking the EU-ETS to workforce management strategies and the adoption of efficiency-enhancing technologies. It is also essential to consider the varied effects of the EU-ETS on another performance indicator, that is the Total Factor Productivity.

References

Abadie, A., 2005. Semiparametric difference-in-difference estimators. Rev. Econom. Stud. 72, 1–19.

Abadie, A., & Imbens, G. W. (2008). On the failure of the bootstrap for matching estimators. *Econometrica*, 76(6), 1537-1557.

Abrell, J., Ndoye Faye, A., & Zachmann, G. (2011). *Assessing the impact of the EU ETS using firm level data* (No. 2011/08). Bruegel working paper.

Baumol, W. J., & Oates, W. E. (1988). *The theory of environmental policy*. Cambridge University Press.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of econometrics*, *225*(2), 200-230.

Calligaris, S. (2015). Misallocation and total factor productivity in Italy: Evidence from firm-level data. Labour 29 (4), 367{393.

Coase, R. H. (1981). The Coase theorem and the empty core: a comment. *The Journal of Law and Economics*, *24*(1), 183-187.

Colmer, J., Martin, R., Muûls, M., & Wagner, U. J. (2018, July). Emissions trading, firm behavior, and the environment: evidence from French manufacturing firms. In *IZA Workshop: Labor Market Effects of Environmental Policies, Bonn, Germany*.

Convery, F.J. (2009) Reflections—the emerging literature on emissions trading in Europe. *Review of Environmental Economics and Policy* 3(1):121–137

Commins, N., Lyons, S., Schiffbauer, M., & Tol, R. S. (2011). Climate policy & corporate behavior. *The Energy Journal*, *32*(4), 51-68.

Copeland, B.R., Taylor, M.S. (1994), North-South trade and the environment. *The Quarterly Journal of Economics*, 109, 755-787.

D'Arcangelo, Filippo Maria, Pavan, Giulia, Calligaris, Sara, 2022. The Impact of the European Carbon Market on Firm Productivity: Evidence from Italian Manufacturing Firms. FEEM Work. Pap., 24

Dechezleprêtre, A., Nachtigall, D., & Venmans, F.2023. The joint impact of the European Union emissions trading system on carbon emissions and economic performance.

Heckman, J.J., Ichimura, H., Todd, P., 1997. Matching as an econometric evaluation estimator: Evidence from evaluating a job training program. Rev. Econom. Stud. 64 (4), 605–654.

Heckman, J.J., Ichimura, H., Smith, J., Todd, P., 1998. Characterizing selection bias using experimental data. Econometrica 66 (5), 1017–1098.

Gianelle, C., & Tattara, G. (2008). The value of international outsourcing: an empirical study of Veneto clothing industry. DSpaceUnipr. https://hdl.handle.net/1889/887

Gray, W. B. (1987). The cost of regulation: OSHA, EPA and the productivity slowdown. *The American Economic Review*, *77*(5), 998-1006.

Greenstone, M., & Gayer, T. (2009). Quasi-experimental and experimental approaches to environmental economics. *Journal of Environmental Economics and Management*, 57(1), 21-44.

Jaffe, A. B., Peterson, S. R., Portney, P. R., & Stavins, R. N. (1995). Environmental regulation and the competitiveness of US manufacturing: what does the evidence tell us?. *Journal of Economic literature*, *33*(1), 132-163.

Klemetsen, M.E., Rosendahl, K.E. and Jacobsen, A.L. (2016) The impacts of the EU ETS on Norwegian plants' environmental and economic performance. NMBU Working Paper 3/2016, Norwegian University of Life Sciences School of Economics and Business.

Koch, N., & Themann, M. (2022). Catching up and falling behind: Cross-country evidence on the impact of the EU ETS on firm productivity. *Resource and Energy Economics*, *69*, 101315.

Levinson, A., Taylor, M.S., 2008. Unmasking the pollution haven effect. *International Economic Review*. 49 (1), 223–254.

List, J. A., Millimet, D. L., Fredriksson, P. G., & McHone, W. W. (2003). Effects of environmental regulations on manufacturing plant births: evidence from a propensity score matching estimator. *Review of Economics and Statistics*, 85(4), 944-952.

Marin, G., Marino, M., & Pellegrin, C. (2018). The impact of the European Emission Trading Scheme on multiple measures of economic performance. *Environmental and Resource Economics*, *71*, 551-582.

Martin R, MuûlsM, De Preux LB, Wagner UJ (2014) Industry compensation under relocation risk: a firm-level analysis of the EU Emissions Trading Scheme. American Economic Review 104(8):2482–2508.

Martin, R., Muûls, M., & Wagner, U. J. (2016). The impact of the European Union Emissions Trading Scheme on regulated firms: what is the evidence after ten years?. *Review of environmental economics and policy*.

Palmer, K., Oates, W. E., & Portney, P. R. (1995). Tightening environmental standards: the benefit-cost or the no-cost paradigm?. *Journal of economic perspectives*, *9*(4), 119-132.

Porter, M., 1991, "American Green Strategy," Scientific American, 264, 168.

Porter, M. E., & Linde, C. V. D. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of economic perspectives*, *9*(4), 97-118.

Santamaria et al 2014 Santamaría, A., Linares, P., & Pintos, P. (2014). The effects of carbon prices and anti-leakage policies on selected industrial sectors in Spain–Cement, steel and oil refining. Energy Policy, 65, 708-717.

Sato, M., Neuhoff, K., Graichen, V., Schumacher, K., & Matthes, F. (2015). Sectors under scrutiny: evaluation of indicators to assess the risk of carbon leakage in the UK and Germany. Environmental and Resource Economics, 60, 99-124.

Smith, J. A., & Todd, P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators?. Journal of econometrics, 125(1-2), 305-353.

Verde, S. F. (2020). The impact of the EU emissions trading system on competitiveness and carbon leakage: the econometric evidence. *Journal of Economic Surveys*, *34*(2), 320-343.