September 2022

Fondazione Eni Enrico Mattei

Working Paper

024.2022

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Keywords: Emission trading; EU ETS; Environmental Policy; Manufacturing; Productivity;ProductionFunction

JEL Classification: Q58; L23; L26

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December 29, 2021

Abstract

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We thank for useful comments Daniel Ackerberg, Jan De Loecker, Thierry Magnac, Florin Maican, Mario Liebensteiner, Giovanni Marin, Céline Nauges, Andrea Pozzi, Mar Reguant, Mathias Reynaert, Gabriele Rovigatti, François Salanié, Fabiano Schivardi, Ulrich Wagner as well as participants in the seminar and reading groups at the Toulouse School of Economics, TSE Energy and Climate Center Workshop on Energy Economics, Mannheim Energy Conference (2018), Environmental Regulation and Industrial Performance Workshop, University of Verona, EMEE 2018 International Workshop (FEEM, Milan), CEPR IO (Leuven), Applied Industrial Organizations workshop at the Barcelona GSE Summer Forum, World Congress of Environmental and Resource Economists (Gothenburg), 5th FAERE (Aix en Provence), 45th EARIE (Athens). All errors are ours.

The views expressed and arguments employed herein are those of the authors and do not necessarily reflect the official views of Compass Lexecon or its clients, nor the OECD or the governments of its members countries. Filippo Maria D'Arcangelo and Giulia Pavan ackowledge the financial support of the Toulouse School of Economics.

1 Introduction

The reduction of greenhouse gas (GHG) emissions arising from industrial production without hampering the economic activity is a key policy goal for most developed economies. To minimize the abatement cost, the economic literature advocates for market-based instruments aimed at providing incentives to the firms with the lowest abatement costs to reduce emissions first. In 2003, the EU established the European Union Emission Trading System (EU ETS), an emission allowances trading scheme. Today, it is the largest emissions cap-and-trade scheme in the world, covering approximately 11,000 energy-intensive installations in the power generation and manufacturing sector, amounting to 40% of the EU's GHG emissions.

The introduction of the EU ETS was accompanied by a fierce debate on its potential impact on the performance and competitiveness of regulated firms. Economists traditionally think that environmental regulations add costs to firms and divert resources away from productive activities, thereby slowing down productivity. This view implicitly assumes that the opportunity cost of polluting distorts firms' optimal production choices(Gray, 1987). In contrast, according to the Porter hypothesis (Porter, 1991), once firms expect higher prices on emissions relative to other costs of production, they have an incentive to make operational changes and invest in new emissions-reducing technologies, with a possible positive impact on their performance (Porter, 1991; Porter and Van der Linde, 1995). Therefore, providing empirical evidence of the effect of the EU ETS on firms' performance, as well as understanding how firms change their production choices accordingly, has first order policy implications.

In this paper we identify the causal effect of the EU ETS on firms' production, identifying how it has affected total output produced and input usage. As a measure of performance, we focus on total factor productivity (TFP) a highly policy-relevant measure of firms' efficiency.[1] We provide a conceptual framework to test whether the EU ETS is merely increasing firms' costs, or if it is pushing them towards a more efficient production. When compared to firms not subject to the policy, we observe a differential increase in expenditures for intermediates in the firms subject to it; but almost no change in other inputs. We interpret these results as evidence of a change in input mix. In addition, we

[1] For example, it is has been shown to be the main driver of GDP growth in advanced economies (Klenow and Rodriguez-Clare, 1997).

show the policy has an overall small but negative impact on TFP; however, this effect is heterogeneous across industries. Our results suggest that the majority of industries do not face the right incentives to undergo substantial changes in their production processes, but prefer to adjust only marginally, predominantly through fuel switches.

Our first contribution is building a novel and comprehensive dataset of Italian manufacturing firms, which combines balance-sheet data with the EU ETS registry. Italy is the third largest manufacturing country in Europe. Therefore, it is of utmost importance to evaluate the impact of such a policy (targeted to the manufacturing sector); especially considering that the Italian government has expressed concerns about its potential negative effect.[2] To sum up, Italy seems a very relevant case to look at, and the sample in our hands, which is representative of the population of Italian manufacturing firms, the right tool to properly look at this issue.

To identify the causal effect of EU ETS on input expenditures and gross output, we develop an empirical framework taking into account the non-random selection into policy. Firms fall within the regulation scope if their thermal or output capacity are above certain thresholds. These capacities are known only to firms and regulators. To accommodate this selection mechanism, we follow the literature and base our identification strategy on a difference-in-differences approach, conditioned on predictors of enrollment into treatment (Calel and Dechezlepretre, 2016; Colmer et al., 2018). The Italian manufacturing sector is an especially suitable candidate for this study. It is characterized by substantial size heterogeneity of its firms, allowing us to construct a suitable control group for our treated firms.

Our second contribution is investigating which channels explain the reduced form evidence using a structural model of production. We estimate firms' production functions, building on the empirical literature on TFP estimation (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015).[3] Crucially, we depart from standard assumptions, allowing output elasticities with respect to inputs and TFP to vary as a function

[2] In the last decades, Italy's per capita GDP has decreased by around 1% every 10 years. This deterioration in growth prospects mainly results from a substantial zeroing of productivity growth in all productive sectors (Calligaris, 2015).

[3] By using a control function approach, we take into account that inputs are endogenous functions of TFP and we are able to structurally model the policy's effect. By contrast, Greenstone et al. (2012) measure productivity using index number measures. The underlying assumption is that firms face no adjustment costs of input, a rather implausible assumption especially considering capital and material inputs.

of the policy introduction. This allows us to study how factor-specific productivities have been affected the policy.

Our third contribution is raising and addressing a problem of inference validity common in this literature. It is common to perform conditional difference-in-differences on the TFP obtained from a control function estimate of the production function. To obtain valid inference, we argue that it is necessary to include the associated estimation error in providing confidence intervals for the treatment effect. When the conditional diff-in-diff uses non-parametric conditioning (e.g. matching), this correction is computationally too cumbersome. Our approach consists in controlling for selection directly in the production function estimation procedure and using standard bootstrapping techniques for inference. We refer to the literature that studies the effect of firms' endogenous productivity change resulting from investments in export (De Loecker, 2013) or knowledge (Doraszelski and Jaumandreu, 2013), augmenting their approach by controlling for possible confounders to treatment in the law of motion of productivity. We show that this approach provides effects that are similar in sign, but smaller in magnitude than using the productivity estimates as the outcome variable in a diff-in-diff.

Our fourth contribution consists in showing that the EU ETS had a small and negative effect on TFP, although with mixed results across industries. Therefore, our paper does not fully support the Porter (1991) hypothesis, at least in the period analyzed. It must be noticed that our paper provides a different test on the Porter's hypothesis with respect to those in the existing literature, as non of it fully discusses the ways through which firms adjust their production choices. Indeed, Greenstone et al. (2012) look at the Clean Air Act,[4] a command and control instrument, while Porter's argument refers to market based type of policies such as the European cap-and-trade system.[5] Recent studies focus on the causal effect of the EU ETS, but without discussing the impact of this policy on firm production choices (Martin et al., 2015; Jaraite et al., 2016; Klemetsen et al., 2020).[6]

Lutz (2016), Marin et al. (2018) and Löschel et al. (2019) investigate how total factor productivity was affected by the EU ETS, but do not disentangle the different effects on performance or provide an explanation on the channels that determine a change in

[4]They show in a simple model how regulatory mandates require inputs that are not directly useful for production, leading to a reduction in TFP.

[5]See Ambec et al. (2013) for a review of the literature on Porter's hypothesis.

[6]Studies investigating the impact of EU ETS showed that it reduces the CO2 emissions and triggers the development of new low-carbon technologies throughout Europe (Colmer et al., 2018; Calel and Dechezlepretre, 2016; Petrick and Wagner, 2014).

the production function. We go beyond their approach in two ways. First, we allow the production function to change with the policy. This is important for us: it allows to study how the policy has affected individual factor productivity on top of total factor productivity. Moreover, not allowing the production function to depend explicitly on a policy variable raises problems of identification of the TFP. Second, we innovate on the methodology: we complement the approach already used in Lutz (2016) and Marin et al. (2018) to estimate the effects on TFP with an alternative one which provides valid inference. In those papers, the estimates of TFP are used as a dependent variable in a matching procedure without adjusting for the fact that the variable is estimated with error and that standard bootstrapping procedures are not consistent. In contrast, we elaborate a fully coherent structural model to identify the firms' reactions to the introduction of the policy, as well as the effect on TFP across different industries, which also provides valid standard errors.

The remainder of the paper is structured as follows. Section 2 describes some institutional features of EU ETS and the data. Section 3 provides a conceptual framework. Section 4 presents the conditional difference-in-differences approach and in Section 5 we discuss the empirical strategy for estimating the production function. Section 6 presents results and Section 7 concludes.

2 The EU ETS

The EU ETS is a cap-and-trade scheme for CO_2 emissions: each regulated plant has to offset emissions with a permit. The total number of permits, called EU Allowance Units (EUA), is set at the European level. Each plant receives or purchases allowances that can be traded with other regulated emitters in all countries participating to the scheme. At the end of each period (April of the next year), firms must surrender a number of allowances equivalent to the verified emissions. Non-compliant firms pay a penalty of €100 per ton of CO_2 they fail to offset.[7]

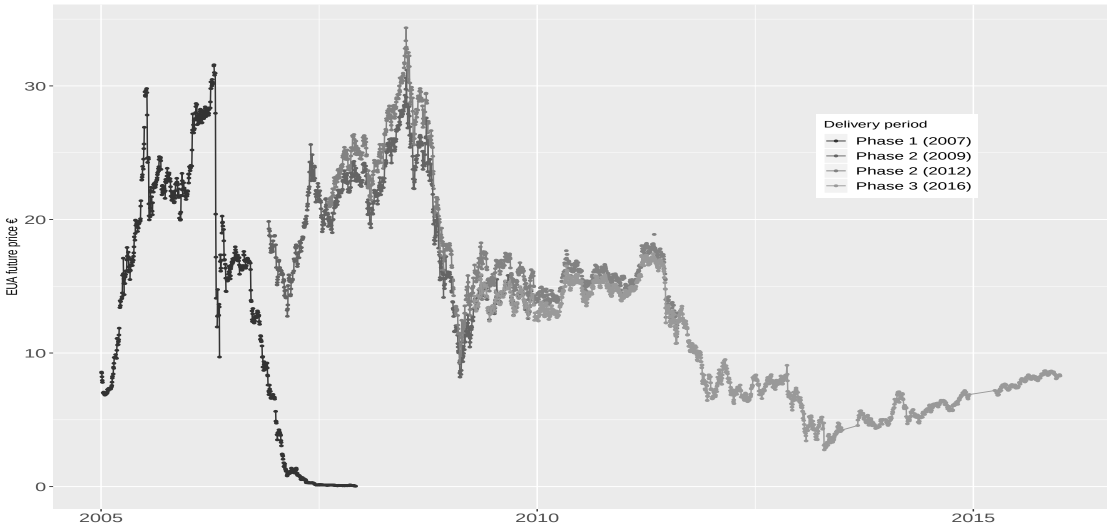
The policy was first announced in 2003 and came into effect in 2005. It was introduced in three phases that differed in the allowance allocation mechanism, sectoral scope and regulated polluters. During Phase 1 (2005-2007) all EUAs were allocated through grand-

[7] €40 in the fist phase.

fathering on the basis of industry-wide benchmarks and calculated for each firm according to their installed capacity and historical activity levels. Banking of allowances was not allowed. The cap was reduced by 6.5% in Phase 2 (2008-2013). Phase 3 (2014-2020) had an emission reduction target of 20%. Free allowance allocation was further reduced in the manufacturing sector from the initial 80% of total allowances, towards the declared target of 30%.[8]

The EU ETS regulation applies to combustion installations with a rated thermal input exceeding 20MW. Some productive processes are subject to stricter conditions based on output capacity. These "process regulated sectors" include paper products, manufacturing of coke and refined petroleum products, glass ceramics and cement, and basic metals.[9] Treatment status of different plants depend on their physical characteristics, which are hard to manipulate in the short run.

Figure 1: Allowances price trend.



Notes: The figure reports prices of future contracts with EUAs as underlying assets for four different delivery years (EEX CFI ICE). Source: Thomson Reuters.

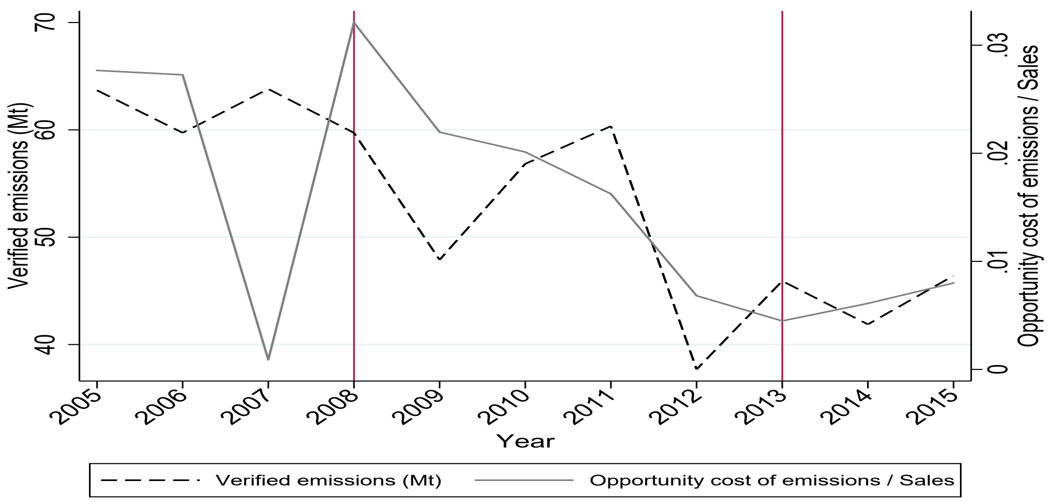
The EUA prices are determined in the market and have followed the evolution showed in Figure 1. Prices have dropped on several occasions, reaching historical lows in 2014 as a result of an unanticipated low demand for allowances. These drops have raised concerns about the efficacy of this policy, considered far below most estimates of the social cost of carbon.[10] Despite periods of low spot prices at the end of the first phase caused by firms'

[8]For a comprehensive review see Ellerman et al. (2016).
[9]For further details on sectors and thresholds see Appendix B.
[10]For instance, an estimation by Nordhaus (2017) place the social cost of carbon at 31 2010US$.

inability to bank allowances, prices have rarely fallen below €5. Even at prices far from the social cost of carbon, the financial impact of the EU ETS on firms is relevant because of emissions offsetting.

The case of the Italian manufacturing sector is particularly interesting in this context because many firms exhibited a positive net demand of allowances. Figure 2 shows that the total expenditures for emissions of Italian manufacturing firms was sizable: 2% of their sales on average. The figure also shows that these expenditures have decreased over time, not only following the reduction in prices but also as a consequence of lower demand.

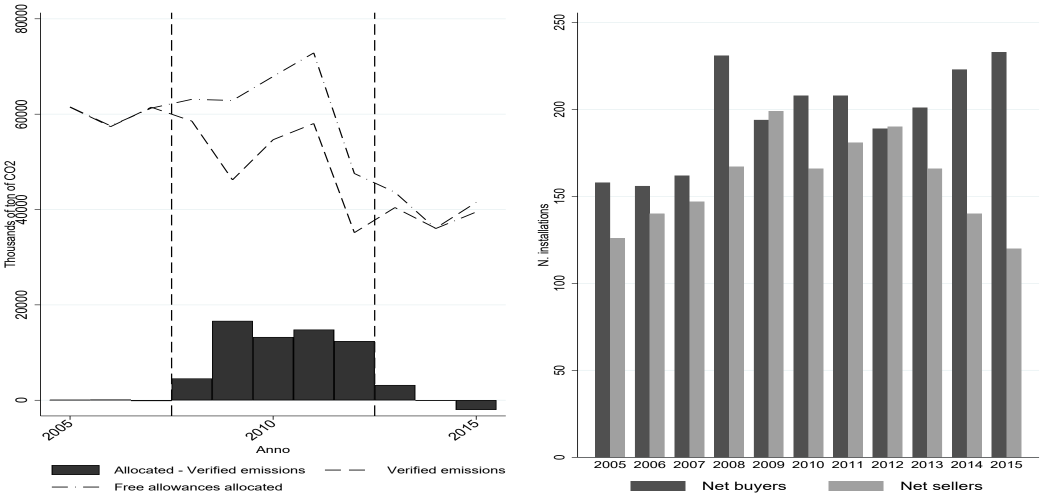
Figure 2: Emissions and emission intensity. Italian manufacturing firms.



Notes: The figure reports data from Italian manufacturing firms regulated by the EU ETS. The dashed line refers to the total emissions of CO2 and the solid line to the average emission intensity (opportunity cost of the verified emissions / real gross output).

Because of the generous free allocation of allowances at the beginning of each year, in many countries the majority of firms subject to the EU ETS were net suppliers of allowances to the market. This is not the case for Italian firms, whose initial free allocation was often insufficient to cover their total demand. Figure 3 (left panel) shows that, until 2014, the total allowances allocated to the manufacturing sector in Italy surpassed the verified emissions. The marginal cost of emitting is the same whether firms are in allowances surplus or deficit. This is because the marginal cost of purchasing one allowance or not selling one allowance is the same. However, the total cost of the policy is heterogeneous and depends on the initial allocation of allowances and the emission decision. A firm in allowance surplus experienced a benefit from the policy. The right panel in Figure 3 shows that there were roughly as many net buyers as net sellers of allowances. Contrary to many other countries which had only firms at a surplus, roughly half of the Italian regulated firms have suffered an increase in costs from the policy.

Figure 3: Short and long positions by year.
Italian manufacturing firms.



Notes: The figure reports data from Italian manufacturing firms regulated by the ETS. The left panel shows the total net position (number of allowances-number of verified emissions) of Italian manufacturing plants. The red dashed line refers to the total emissions of CO2 and the dash-dotted line to the total allowances allocated. The right panel shows separately total long positions (allowances $\geq$ emissions) and total short positions (allowances $\leq$ emissions).

In summary, given the characteristics of the monitoring mechanisms, firms can pursue three alternative strategies to reduce their emissions. They can either switch to less polluting fuels, change their production processes, or reduce output.[11] We formalize this argument in Section 4.

3 Data

We put together a unique and comprehensive database of Italian manufacturing firms, built from several sources.

First, the European Union Transaction Log (EUTL) database contains address, verified emissions and free allowances received by each installation.[12] It is maintained by

[11]Given the characteristics of CO_2 and the existing technology, no economically viable end-of-pipe abatement technology has been used.

[12]An installation is a stationary technical unit where one or more specific polluting activities is carried out. In our sample, 97%of installations coincide with a plant. We observe ten plants with multiple installations.

the European Commission and publicly available on its website. This allow us to identify firms with production plants in Italy subject to EU ETS between 2005 and 2015.

Second, the CERVED database contains balance sheet information for all Italian limited liability companies. The data are recorded by the Italian Registry of Companies and include financial statements filed at the Italian Chambers of Commerce. In particular, the information includes credit reports, company profiles and summary financial statements (balance sheet, profit and loss accounts and ratios). Data are available for each year between 1995 and 2015. We grouped the manufacturing firms into 2-digit industries according to the ATECO 2002 classification of economic activities.[13] We take from balance sheet data measures of output, labor, intermediates and capital inputs. We measure labor input using the cost of labor and the capital stock using the book value of fixed capital net of depreciation.[14] Intermediates are measured as purchases net of changes in inventories during the period. These variables are deflated through industry-specific deflators coming from the OECD STAN database (base year 2010).[15] We clean the database from outliers by dropping all observations with negative values for real value added, cost of labor or capital stock.

To match the two databases, we aggregated the EUTL data on installations at the firm-level and matched them to CERVED based on names and addresses. We matched 98% of firms in the CERVED database with the EUTL. We restricted the sample to active firms and excluded power generators. The final sample of regulated firms includes 497 firms. Table 1 reports details on the number of installations and firms under regulation for each of the three phases.

In addition, we complement the firm-level data with plant-level information obtained from the ISTAT dataset Asia, to check how many plants of a firm are under regulation. Among the regulated firms, 44% are mono-plants and 25% have two plants. Moreover, 50% of firms have all their plants regulated under ETS. Only 25% of the firms have less

[13] This is the Italian classification of economic activities elaborated by the National Institute of Statistics (ISTAT) according to the Nace Rev 1.1 (Reg. Commission n.29/2002).

[14] We compute the capital stock using the book value of fixed capital net of depreciation as the investment variable is not available in the data in hand: computing the capital stock through the Perpetual Inventory Method (PIM) is thus unfeasible. Note, however, that both approaches are characterized by sources of measurement errors. See, for instance, Collard-Wexler and De Loecker (2016).

[15] Specifically, we use: production (gross output) deflator for gross output; value added deflator for labor input; gross fixed capital formation deflator for capital input; intermediate inputs deflator for intermediates.

than half of their plants regulated under ETS.[16] This is reassuring because it means that most of the firms cannot relocate their production in non-regulated plants.

Table 1: EUTL summary statistics

	Phase I	Phase II	Phase III	Total
Installations under regulation	1041	1163	1236	1516
Firms under regulation	563	670	740	837
- *Manufacturing*	446	475	425	497

Note: The table reports details on the number of Italian installations and firms under regulation as reported in the European Union Transaction Log (EUTL).

Table 2: Descriprive Statistics

	Mean	**St. Dev.**	**5th pctile**	**25th pctile**	**50th pctile**	**75th pctile**	**95th pctile**
A. Manufacturing firms (N. obs: 92,124)							
Real Value Added	1.91	30.38	0.038	0.16	0.42	1.10	5.54
Real Gross Output	8.52	121.0	0.15	0.58	1.51	4.28	23.6
Real Cost of Capital	1.67	16.46	0.008	0.05	0.20	0.83	5.28
Real Cost of Labor	1.16	7.519	0.021	0.11	0.29	0.75	3.58
Real Cost of Intermediates	4.71	89.35	0.009	0.15	0.56	1.92	12.4
B. Manufacturing firms, under EU ETS (N. obs: 492)							
Real Value Added	59.6	393.9	0.97	3.78	12.2	37.0	227.6
Real Gross Output	267.1	1267.0	4.26	14.6	51.8	166.7	836.8
Real Cost of Capital	63.0	187.9	1.40	5.94	17.2	48.7	231.8
Real Cost of Labor	25.8	68.16	0.57	2.04	6.70	21.2	119.5
Real Cost of Intermediates	158.6	862.9	1.38	5.89	23.5	90.1	441.1

Notes: All variables are in million of euro deflated using 2010 prices.
An observation is a firm. All the statistics refer to the year 2003. We report the distribution of real value added, real gross output, real cost of capital, labor and intermediaries for all the manufacturing firms and for the ones under regulation.

Our empirical strategy to estimate the impact of the policy hinges on the comparison between firms under the EU ETS and firms with similar characteristics that are not. Table 2 shows descriptive statistics for the production variables we investigate. In particular, we stress two elements which guide our comparison: firms subject to the policy are on average bigger than the others, but there are same-sized firms in the two groups.

Finally, we relied on qualitative data to complement and reinforce our quantitative analysis. We reviewed technical reports from trade associations discussing the possible strategies adopted in recent years to reduce GHG emissions. Further, some informa-

[16] ASIA database does not distinguish between productive plants and administrative branches. If a firm has the offices at a different address it would result in a non-regulated plant.

tion related to technology adoption at industry level is contained in the "Best Available Technique" reference document.[17]

4 Conceptual framework

We discuss in this section how firms react to the introduction of emission prices, providing a conceptual framework to interpret the empirical results.

We consider a firm i at time t with a (industry-specific) Cobb-Douglas production function, generating gross output (y_{it}) from labor (l_{it}), capital (k_{it}) and intermediates (m_{it}).

The Cobb-Douglas production function expressed in logs is:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it}, \tag{1}$$

where ω_{it} is a persistent term reflecting the (log) total factor productivity. As standard in the literature, we assume that capital is a dynamic input and predetermined at time t, meaning that it can only be adjusted with delay, to accommodate time-to-build. In contrast, intermediates are a static input that can be adjusted flexibly by the firm throughout t. Intermediates are of particular interest for us, as they include expenditures for each fuel and polluting intermediate good, albeit in an unknown proportion. Finally, we assume labor to be a static input, in the sense that current levels of labor do not affect future profits[18]. However, firms adjust labor to the realization of productivity ω_{it}. We interpret a positive price of emissions as an indirect increase in the cost of intermediates. Therefore we expect firms to react in one of the following ways.

First, an increase in price determines a decrease in the demand for intermediates, m_{it}. With decreasing marginal returns, l_{it} should decrease immediately, while k_{it} decreases with an adjustment. From a reduction in inputs, it follows a reduction in output y_{it}. This intuitive result takes place if no other element in equation (1) changes with the introduction of the policy.

Second, the firm can vary the mix of intermediates, on top of the total expenditure for

[17] "Best Available Technique" reference document is carried out in the Framework of Article 13(1) of the Industrial Emissions Directive (IED, 2010/75/EU).

[18] Alternatively, we could have considered dynamic labor. We follow most of the recent literature on production function estimation (De Loecker, 2011; Collard-Wexler and De Loecker, 2014), but our approach is flexible and our results are robust to this alternative.

this input. Imagine a paper mill that can choose between two sources to produce energy needed for production: coal or biomass. Coal is cheaper, but biomass are exempted from the EU ETS emission inventory. For sufficiently high prices of emissions, the firm will therefore switch from the former energy source to the latter. Switching costs are often negligible, as some fuels are completely substitutable in production. As a result, a positive price of emissions could be associated with the apparently paradoxical effect of an increase in intermediates expenditures. A flexible form of (1), in which β_m is allowed to vary with the introduction of the policy, can help rationalize this effect. While the "true" production function of the firm remains unchanged, i.e. the marginal productivity of each fuel does not change, a varying β_m can capture whether the fuel mix itself has changed.[19]

Finally, firms might undergo more structural changes in production to reduce the negative effect of emission pricing. In response to a positive price of emissions, firms might intervene by fine-tuning or completely changing their production processes. As suggested in Porter (1991), the incentive to reorganize and improve the firm's environmental performance may help spur actions that positively spillover to production. These changes can take place through investments in new equipment and new technologies but also through a more efficient use of the extant ones made possible by investments in R&D and organizational or optimization efforts. We expect these changes to have an effect on productivity, ω_{it}, and possibly on the input elasticities, $\{\beta_r\}_{r=l,k,m}$. If the firms realized considerable tangible investments, we could even expect an increase in k_{it}.

5 Empirical Model

5.1 Treatment assignment and conditional difference-in-differences

First, we are interested in estimating the causal impact of the EU ETS on firm-level production choices. Changes in output or inputs can be interpreted under the lens of the conceptual framework of the previous section to investigate firms' reaction to the policy. Selection into treatment is not random and this needs to be taken into account

[19]We avoid adopting a value added production function not to rule out this effect. With a value added production function intermediates are a perfect complement to production and their demand is perfectly determined. We decide thus to adopt this more general approach, allowing some substitutability of intermediates with other inputs, even if it might pose challenges to identification.

to isolate a causal effect of the EU ETS. If we could observe thermal input and process-based targets around the threshold, we would be able to exploit a regression-discontinuity design. Since these selection variables are not observed for neither treated and untreated installations, it is impossible to use this approach nor to form a suitable control group at the installation level. We thus follow the prevalent literature (Petrick and Wagner, 2014; Calel and Dechezlepretre, 2016; Colmer et al., 2020) and form a control group at the firm level, exploiting the fact that variation in treatment at the installation level causes sufficient variation in treatment. We define a treated firm as having at least one installation under EU ETS, helping to take into account potential within-firm spillovers (Colmer et al., 2020), although the prevalence of mono-plant firms limits the relevance of this channel.

Because larger, treated installations tend to belong to larger firms, we control for potential unobservable confounders, conditioning our estimates to a set of firms' characteristics. This approach exploits the fact that treatment variation can be observed within comparable groups of firms. We estimate four conditional difference-in-differences: three parametric and one semi-parametric based on matching. The difference-in-differences approach has been successfully used in the evaluation of cap-and-trade schemes (Fowlie et al., 2012). It is attractive for our purposes because it exploits both time and cross-sectional variations in the policy assignment to take into account potential unobserved confounders. This approach works under an assumption of "parallel trends": in the absence of treatment, the evolution in firms' outcomes would have been the same in the treatment and control group, conditional on observable firms' characteristics. We test this assumption exploiting the time dimension of our panel (see Appendix C).

We denote with Y_{it} our outcomes of interest: the deflated gross output and the deflated values of labor, capital, and intermediates. Let the policy dummy τ_t take value of 1 at the introduction of the policy (e.g. 2005) and be 0 otherwise. The treated firms are those with plants under the EU ETS for a whole phase and the untreated firms are those never subject to the policy in any phase. The treatment dummy D_i takes value 1 if the firm is treated and 0 otherwise. Finally, T_{it} collects the interactions of the time and treatment dummy.

The three parametric models are described by the following specification:

$$Y_{it} = \alpha_0 + \alpha_1 D_i + \alpha_2 \tau_t + \alpha_3 T_{it} + f(X_i) + \nu_{it}, \tag{2}$$

where α_0 is the intercept, α_1, α_2, and α_3 are the estimand parameters, X_i is a $k \times 1$ vector of controls (listed below), and ν_{it} is an i.i.d. error term. The three models differ in the way X_i enters into the specification. Here, $\widehat{ATT} = \hat{\alpha}_3$ is the parameter of interest for each model and outcome of interest.

We complement our parametric specifications with a semi-parametric one, using a matching procedure based on the propensity score. This "matched difference-in-differences" has the advantage of not imposing any of the parametric assumptions on X_i and limits the analysis to the treated firms that have a comparable counterpart in the control group. Based on estimates of the propensity score, $\hat{\pi}_i$, each treated firm gets matched with one or more firms, whose set we denote with $\mathcal{J}(\hat{\pi}_i)$.

$$\widehat{ATT}^{match} = \frac{1}{N_1^T} \sum_{t=2005}^{2015} \sum_{i \in \mathcal{D}_t} \left(Y_{it} - \frac{1}{M_{it}} \sum_{j \in \mathcal{J}(\hat{\pi}_i)} Y_{jt} \right) - \frac{1}{N_0^T} \sum_{t=1995}^{2004} \sum_{i \in \mathcal{D}_t} \left(Y_{it} - \frac{1}{M_{it}} \sum_{j \in \mathcal{J}(\hat{\pi}_i)} Y_{jt} \right),$$

where N_1^T and N_0^T are the observations for treated firms after and before treatment, respectively; $\mathcal{D}_t$ is the set of treated firms at time t; and M_{it} is the number of matches to firm i at time t.

5.1.1 Estimation

We choose the control variables X_i based on their correlation with the assignment variable, their data completeness and especially their possible confounding effect. We consider these variables at a specific year before the implementation of the policy to control for the pre-policy conditions. In particular, we include in X_i the following control variables: industry, geographical location, firm's age, number of workers, and number of plants. To capture non-linear effects of the variables we also include quadratic transformations of the continuous variables and a full set of interactions (with the exception of geographical location because of data limitations). For the industry controls we employ 62 dummies according to the Italian 2-digits ATECO classification, which help to take into account industry-specific unobservables. For geographical location, we consider four intercept shifters for each Italian macro-region: north-east, north-west, center, and south and islands. This variable is especially important for the Italian case due to its spatial heterogeneity and helps controlling for specific characteristics of the geographical market, including different exposure to shocks in the foreign output and inputs markets. Firm age is the number of years since the administrative foundation of the firm. Number of plants and (log) number of workers are extracted from the values reported for 2004 by the ASIA database, to capture firms size. Size can correlate with selection into treatment, as well as inputs prices and access to technology, and these two variables control for it.[20]

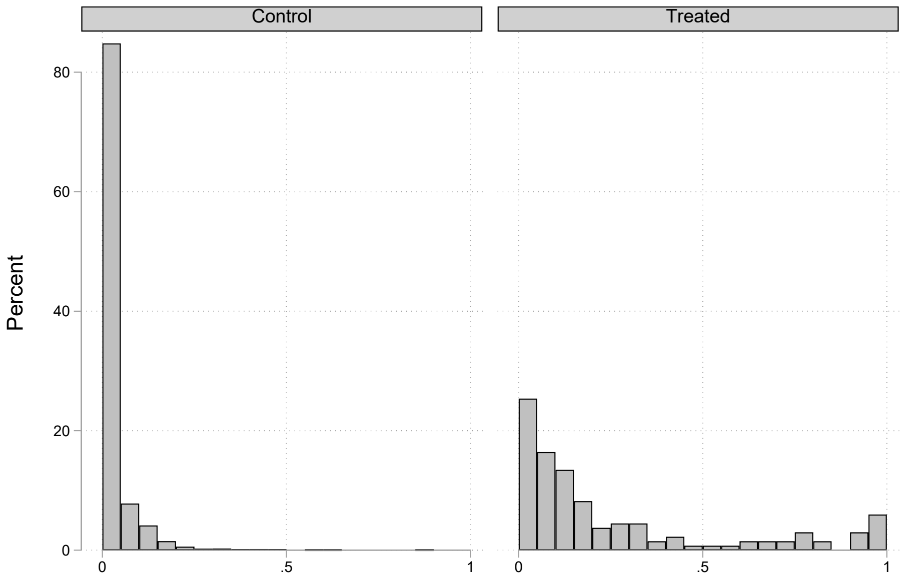
Our first specification of (2) includes all the controls linearly, so that $f(X_i) = \alpha_4 X_i$, where α_4 is a $1 \times k$ vector of parameters. In the second specification, we include the propensity score as a control, $f(X_i) = \alpha_5 \hat{\pi}(X_i)$, where α_5 is a single parameter. The propensity score is defined as the probability of being included in the treatment conditional on the observables and is estimated in a first stage using a logit specification. The work of Rosenbaum and Rubin (1983) suggests that, if the first stage is correctly specified, this method is equivalent to the previous one. Using the propensity score in a parametric specification is useful to assess the robustness of the matching procedure, leveraging the entirety of the dataset, rather than only matched firms. We estimate by OLS the first two models, while the third specification includes firm-level fixed effects. The fixed effects absorb all firm-specific time-invariant characteristics, including the pre-treatment observables of the firm. We use a standard within estimator and OLS to estimate this model.

The matching procedure is as follows. We want to provide narrow matching criteria, to be sure that the matched firms are similar to the treated firms. As in Calel and Dechezlepretre (2016) we impose matching within strata defined by the intersection of industry and geographical region. Exact industry matching controls for industry-wide exogenous changes in market conditions and accounts for industry-specific innovations in production. Exact geographical matching, performed on the region, is very important to control for local market conditions and institutional changes at the local level, which vary widely in the Italian case. The other controls enter linearly in the logit specifications.[21] A

[20]In all of our specifications, we also experiment with other controls, extracted from the firms' 2004 balance sheet accounts and the Italian statistical registry. These include export, inventory, physical capital depreciation and a different measure for the number of workers. None of these is significant or affects significantly the results and we therefore exclude them from the analysis.

[21]See Appendix A for further details.

Figure 4: Propensity Score by treatment.



Notes: We plot the propensity score for treated firms (firms that are under EU ETS in the three phases) and controls (firms that have never been under EU ETS). We restrict the sample away from 0 and 1 to graphically show the overlapping region. The matching procedure is furthermore refined by imposing within stratum matching.

visual exploration (Figure 4) suggests that not every treated firm has sufficiently similar untreated firms to compare to: a majority of firms in our dataset is in fact sensibly smaller than those under EU ETS. Due to this skeweness in some strata, no match can be established for firms in Coke and refined products and we do not find a match for 47% in Textile, concentrated in the South of Italy. Notwithstanding, a common support can be established for 72% of the firms.

To perform the matching, we opt for a nearest neighbors selection with replacement and caliper (a threshold in the maximum score distance). Details of our procedure are given in Appendix A. While the objective of the matching procedure is primarily to ensure pre-treatment parallel trends, it is reassuring that the outcome variables are not statistically different between matched treated and control firms in the pre-treatment period (Table A.1 in Appendix). Our preferred estimates are based on the comparison with up to five nearest neighbors.[22] In our main specification, we impose a caliper equal to 0.15, roughly equal to three standard deviations of the propensity score, as standard in the literature.

[22]We also explore the options with one and twenty nearest neighbors. Results do not change.

5.2 Production function approach

Analyzing input and output choices provides the first descriptive evidence of the policy's effect. To explain the reduced form evidence and understand more intimately how the EU ETS has affected production and productivity, we structurally estimate the firms' production function.

Our approach is characterized by two major features. First, it recognizes the importance of allowing input choices to correlate with a time varying TFP. Employing intermediates to proxy for productivity, we use Ackerberg et al. (2015)'s control function to address this well-known simultaneity problem. Second, we allow the parameters of the production function to explicitly depend on the policy variables. We allow the firm's EU ETS status to impact its productivity, as well as the other parameters of the production function. To this end, we use within our structural model the intuition built for the difference-in-differences to control for sample selection in the treatment.

Let the policy variable d_{it} collect the three dummies, τ_t, D_i and T_{it}, i.e. it denotes whether the firm is treated or untreated and whether it is observed in a pre-treatment or post-treatment year. We consider the following empirical counterpart of (1), allowing it to depend on the policy variable d_{it}:

$$y_{it} = y(l_{it}, k_{it}, m_{it}; \omega_{it}, \beta) = \beta_l(d_{it})l_{it} + \beta_k(d_{it})k_{it} + \beta_m(d_{it})m_{it} + \omega_{it} + \varepsilon_{it}, \tag{3}$$

where ε_{it} is an i.i.d. error term capturing unanticipated shocks to production and measurement errors. The estimand parameters are the industry-wide elasticities of output to labor, capital and intermediates, $\beta = \{\beta_r(d_{it})|r = l, k, m\}$, and the logarithm of total factor productivity, ω_{it}. By having β depend explicitly on d_{it}, we allow the production function to vary between treated and control firms, before and after the introduction of the policy. Because there are three inputs and four treatment statuses, β is composed of 12 parameters for each industry. Having such a flexible production function is crucial. First, it accommodates a more realistic behavior of firms, allowing them to adjust their productive process as a response to the policy. Capturing this adjustment is an innovative contribution of this paper. Second, this flexibility is meant to assure that the TFP, which is a functional of β_r and the data, is identified by actual variations in performances and not by changes in these elasticities.

We allow ω_{it} to be idiosyncratic and to vary over time. Since inputs are chosen by the firm with some knowledge of ω_{it}, a clear problem of endogeneity arises in the estimation of (3). In our setting, as in Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015), identification relies on a distributional assumption on productivity and an assumption on inputs demand.[23]

First, we take distributional assumptions on productivity. Let I_{it-1} be the set of information available in $t-1$. We assume that productivity follows a first-order Markov process, with transition probabilities $P(\omega_{it+1}|I_{it}) = P(\omega_{it+1}|\omega_{it}, \mathbf{z}_{it})$, where $\mathbf{z}_{it}$ are state variables affecting the Markov process. We moreover formulate the assumption, common in this literature, that the innovation to productivity, ξ_{it+1}, is mean independent of all information known at time t. In practice, we consider the following parametric law-of-motion for TFP:

$$\omega_{it+1} = \rho_1\omega_{it} + \rho_2\omega_{it}^2 + \rho_3\omega_{it}^3 + \gamma_1 D_i + \gamma_2\tau_t + \gamma_3 T_{it} + \gamma_4 X_i + \xi_{it+1}, \tag{4}$$

where $\rho = \{\rho_1, \rho_2, \rho_3\}$ and $\gamma = \{\gamma_1, \gamma_2, \gamma_3, \gamma_4\}$ are arrays of conformable parameters. We include two sets of variables in $\mathbf{z}_{it}$: all the policy variables, D_i, τ_t, and T_{it} as well as the controls X_i. As in De Loecker (2013) and Doraszelski and Jaumandreu (2013), a law of motion for TFP that includes the policy variables allows for systematic differences in treatment and control firms. It accommodates a more credible expectation formation process: if firms expect to update production as a reaction to the policy, they will anticipate the associated change in productivity. Since a higher productivity is associated with higher inputs, not taking this adjustment into account would bias the estimates of β. Including X_i in $\mathbf{z}_{it}$ allows ω_{it+1} to correlate with the firm's initial size and to control for the selection into treatment. Finally, note that we follow the literature (Franco and Marin, 2017; Van Leeuwen and Mohnen, 2017; Ley et al., 2016) and allow the policy variable T_it to affect productivity with a lag. This is important in our context, because we allow the firm to adjust all its inputs (including capital), before imputing any productivity change to the policy.

[23]Differently from them, we assume non linear pricing in intermediates. This assumption, as in Balat et al. (2016), allows identification of β_m. This assumption is credible in our setting because there are quantity discounts in intermediates introducing a friction in the demand for m_{it}, which is therefore not completely collinear with (l_{it}, ω_{it}). Yet, if average prices are different among firms, the question arises of whether the moment conditions correctly identifies the production function when the price schedule changes over time. Including controls associated with the size of the firm helps dealing with this problem.

The second assumption we take is on input demand: in particular we assume that intermediates demand is a strictly monotone function of ω_{it}, conditional on the state variables:[24]

$$m_{it} = f(\omega_{it}, k_{it}, l_{it}, \mathbf{z}_{it}), \tag{5}$$

so that f is invertible, given k_{it}, l_{it}, and $\mathbf{z}_{it}$. We can then proxy for the unobservable productivity with the observable demand of intermediates, m_{it}, given the other arguments of the function, i.e. $\omega_{it} = f^{-1}(m_{it}, k_{it}, l_{it}, \mathbf{z}_{it})$. We follow De Loecker (2013, 2007) in assuring monotonicity by letting this demand depend on all relevant state variables through $\mathbf{z}_{it}$. Since carbon trading is associated with an increase in the cost of intermediates, conditioning demand on the policy variables is crucial. Not doing so leads to an underestimation of ω_{it} for firms under the EU ETS, because lower material demand is wrongly associated with lower productivity rather than higher cost.

Finally, we do not observe firm-specific output prices and we must instead use revenues as a measure of output. This is a well-known and standard problem in the literature. As a consequence, if this assumption is violated, the estimate of ω_{it} might be upward biased, if lower input prices or higher output prices correlate with higher levels of ω_{it}. However, in our application the problem is less severe. First, most firms we consider produce homogeneous goods in internationally competitive markets. Second, we are controlling for the firms' dimension and geographical location, i.e. we compare similar firms in similar markets. Finally, since we look explicitly at differences in TFP for treated and control firms, any remaining bias should cancel out. However, we cannot completely disentangle the effects of the EU ETS on technological productivity and output prices.

5.2.1 Estimation

We perform the estimation of the production function separately for each 2-digit industry. We split each sample in four: treated and control firms, before and after the policy implementation. Remembering that each parameter $\beta_r(d_{it})$ depends on the policy variable d_{it}, from now on we suppress the argument for notational simplicity. For our estimation approach, we follow Ackerberg et al. (2015). By inverting (5), we substitute ω_{it} in (3)

[24]Notice that the monotonicity assumption is verified if the firm is choosing m_{it} to maximize its static profits and the production function takes certain functional forms, e.g. Cobb-Douglas (De Loecker, 2013; Doraszelski and Jaumandreu, 2013).

with $f^{-1}(m_{it}, k_{it}, l_{it}, \mathbf{z}_{it})$ to obtain our first stage regression:

$$y_{it} = \phi(l_{it}, k_{it}, m_{it}, \mathbf{z}_{it}) + \varepsilon_{it}, \tag{6}$$

where $\phi(l_{it}, k_{it}, m_{it}, \mathbf{z}_{it}) = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + f^{-1}(m_{it}, k_{it}, l_{it}, \mathbf{z}_{it})$. None of the parameters are identified at this point because of collinearity between the inputs and ω_{it}. We fit a polynomial of degree 3 in the arguments to approximate the unknown function, $\phi(\cdot)$ and obtain its estimate, $\hat{\phi}$. We then replace $\omega_{it} = \hat{\phi}_{it} - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it}$ and $\omega_{it+1} = \hat{\phi}_{it+1} - \beta_l l_{it+1} - \beta_k k_{it+1} - \beta_m m_{it+1}$ in (4), to obtain an expression for ξ_{it+1} as a function of all the unknown parameters: $\xi_{it+1}(\beta, \rho, \gamma)$.[25]

We obtain estimates for the output elasticities with respect to inputs, β, and the total factor log-productivity, ω_{it}, in a second stage. The identifying moment conditions are:

$$E\left\{(\xi_{it+1} + \varepsilon_{it+1})\begin{pmatrix} k_{it+1} \\ m_{it} \\ l_{it} \\ \mathbf{z}_{it} \end{pmatrix}\right\} = 0. \tag{7}$$

We form the sample analog of (7) for $\xi_{it+1}(\beta, \rho, \gamma)$ using starting values for the unknown parameters β, ρ and γ. In practice, we use OLS estimates for β as starting values and retrieve starting values for the other parameters from the implied values of ω_{it}. Through iteration we then obtain as estimates those value that minimize this criterion. Finally, we use these estimates to recover the implied (log) productivity: $\hat{\omega}_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_m m_{it}$.

5.3 The effect on TFP

Unlike the variables explored in Section 5.1 (output and inputs), TFP is not directly observed, but estimated. We propose two alternative methods to quantify the effect of

[25]That is:

$$\begin{aligned}\xi_{it+1}(\beta, \rho, \gamma) &= \hat{\phi}_{it+1} - \beta_l l_{it+1} - \beta_k k_{it+1} - \beta_m m_{it+1} \\ &- \rho_1\left(\hat{\phi}_{it} - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it}\right) - \rho_2\left(\hat{\phi}_{it} - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it}\right)^2 \\ &- \rho_3\left(\hat{\phi}_{it} - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it}\right)^3 - \gamma_1 D_i - \gamma_2 \tau_t - \gamma_3 T_{it} - \gamma_4 X_i.\end{aligned}$$

the EU ETS on TFP. In the spirit of the "conditional difference-in-differences" strategy of section 5.1, these approaches take into account the correlation of the treatment status, the firm's size, and productivity.

Our first and preferred method is fully consistent with the structural model. In our approach, equation (4) is instrumental to form moment conditions to estimate the production function. However, it also provides a model of how ω_{it} evolves conditional on the policy variables. Since we need an estimate of (4) to estimate the production function (3), the comparison between treated and control firms intervenes directly at this stage. Similar to the conditional diff-in-diff, we can interpret estimates of γ_3 as the short-run treatment on the treated effect of the EU ETS on productivity. This method has the advantage to provide valid inference, which is assured by the same (block-)bootstrapping procedure we use to provide standard errors to the estimates of β. The main drawback is that semi-parametric approaches, such as matching, are not implementable within the structural model. To address selection into treatment we rely instead on parametric assumptions on how X_i enter in the TFP's law of motion.

The second approach we implement uses the estimates of $\hat{\omega}_{it}$ as data and applies the same conditional difference-in-differences strategies used for the other variables and introduced in Section 5.1. This is, for example, the approach adopted by De Loecker (2007) in a different context and by Lutz (2016) and Marin et al. (2018) in studying the EU ETS. In practice, we estimate the three parametric models described by equation (2) as well as the semi-parametric model, using $\hat{\omega}_{it}$ as the outcome variable. Proceeding this way has two advantages. First, it produces results that are more easily comparable to those on the other outcomes of interest because it uses a similar estimation techniques. Second, it allows the use of a matching procedure to impose a tighter comparison between treated and control firms than the one granted by linear controls. The main drawback of this approach is that standard inference is invalid and using bootstrap is computationally unfeasible, or simply invalid.[26] We estimate the effects using this approach for comparison

[26]The problem emerges because $\hat{\omega}_{it}$ is generated data and comes with an estimation error, which must be accommodated in building confidence intervals for the ATT. Even the case of conditional difference-in-differences with linear controls is problematic in practice. A valid approach in this case consists in (block-)bootstrapping the first stage (the production function estimation) and not re-sampling in the second stage (the diff-in-diff), to obtain the estimated standard errors. We found this approach computationally unfeasible. Since we have two specifications with propensity scores, one parametric and one semi-parametric, we would need to accommodate this additional stage in the bootstrapping procedure (Abadie and Imbens, 2008). In this case, a valid bootstrapping procedure would build on Otsu and Rai (2017).

with the existing literature but, given its invalid inference, we caution against relying too much on these estimates.

6 Results

In this section, we present the estimated effect of the policy on intermediaries, capital and labor expenditures, and on gross outputs. Then, we report the production function estimates based on the estimation procedure. We use these results to explore how firms changed their production processes, through the lens of the conceptual framework of Section 4. Finally, we provide estimates of the effect of the EU ETS, following the two empirical strategies described in Section 5.3.

6.1 Effects on firms' inputs and output

As described in Section 5.1, we run different conditional difference-in-differences specifications to identify the effect of the introduction of the policy on input expenditures. Table 3 presents the results of the four conditional diff-in-diff strategies, reporting the average treatment on the treated (ATT) and the coefficients of the other policy variables, for five outcomes of interest: gross output, expenditures for intermediates, labor and capital, and the ratio of intermediates over gross output. The first three columns present results for the parametric specifications: column 1 includes all the controls, X_i, i.e. size and market controls and their transformations; column 2 includes instead the propensity score as a linear control; and column 3 includes firm-specific fixed effects. Finally, column 4 presents the semi-parametric matched diff-in-diff estimates.

The results are similar across them despite the substantial differences in the specifications. Notice in particular how the matching procedure restricts the number of firms analyzed with respect to the parametric specifications. Treated firms present characteristics that are very different from the untreated firms: only 1.95% of total firms are in the common support and an even smaller fraction is matched (583 total firms). This does not severely impact results, which are similar in sign and magnitude across the specifications.

We find that the EU ETS increased on average total output and intermediates expenditures. Gross output increased by 13 to 23% and intermediates expenditures by 16 to 27% overall in the nine post-treatment years we consider. The estimates are lower and

Table 3: CONDITIONAL DIFF-IN-DIFF RESULTS

	Linear controls	PS control	FE	Matching
Gross output (log)				
ATT ($\hat{\alpha}_3$)	0.2287***	0.2013**	0.1781***	0.1272*
	(0.0445)	(0.0620)	(0.0153)	(0.0523)
Treat. Group ($\hat{\alpha}_1$)	0.2175***	0.4603**		
	(0.0593)	(0.1763)		
Treat. Date ($\hat{\alpha}_2$)	0.1040***	0.0331***	0.0991***	
	(0.0039)	(0.0067)	(0.0012)	
Materials expenditures (log)				
ATT ($\hat{\alpha}_3$)	0.2697***	0.1905**	0.1822***	0.1622**
	(0.0520)	(0.0712)	(0.0207)	(0.0594)
Treat. Group ($\hat{\alpha}_1$)	0.2033*	0.4105*		
	(0.0823)	(0.1994)		
Treat. Date ($\hat{\alpha}_2$)	0.1030***	0.0268**	0.0826***	
	(0.0057)	(0.0083)	(0.0017)	
Labor expenditures (log)				
ATT ($\hat{\alpha}_3$)	0.0631	0.0629	0.0378*	0.0168
	(0.0419)	(0.0591)	(0.0175)	(0.0465)
Treat. Group ($\hat{\alpha}_1$)	0.0671	0.2910		
	(0.0363)	(0.1742)		
Treat. Date ($\hat{\alpha}_2$)	0.2698***	0.2106***	0.2858***	
	(0.0035)	(0.0064)	(0.0014)	
Capital expenditures (log)				
ATT ($\hat{\alpha}_3$)	0.1852**	0.1293	0.1151***	-0.0112
	(0.0609)	(0.0804)	(0.0247)	(0.0709)
Treat. Group ($\hat{\alpha}_1$)	0.5968***	0.8250***		
	(0.0747)	(0.1949)		
Treat. Date ($\hat{\alpha}_2$)	0.2939***	0.1917***	0.2667***	
	(0.0063)	(0.0096)	(0.0020)	
Materials / Gross output				
ATT ($\hat{\alpha}_3$)	0.0521*	0.0049	0.0165	0.0512*
	(0.0249)	(0.0265)	(0.0118)	(0.0259)
Treat. Group ($\hat{\alpha}_1$)	-0.0191	-0.0524		
	(0.0365)	(0.0450)		
Treat. Date ($\hat{\alpha}_2$)	-0.0072*	-0.0217***	-0.0243***	
	(0.0030)	(0.0034)	(0.0010)	
Observations	745,009	348,557	927,170	
Firms	73,331	21,246	109,710	583

Only coefficients of the policy variables are reported. Standard errors are clustered at the firm level for the first three specifications and block-bootstrapped for matching (500 repetitions).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

more reliable in the matching specification, because it does a better job at controlling for firm attrition, limiting the analysis on a sub-sample of firms that stay in the market for the whole period. In relative terms, we find some evidence that the material intensity, i.e. the expenditure for intermediates over revenue, has slightly increased. In contrast, expenditures for labor have not increased as a consequence of treatment. Evidence for capital is less unequivocal and only some specifications point in the direction of a positive effect. Across industries, the matching specification provides substantially different results for capital, when compared to the parametric ones (but not for the other outcomes of interest). We posit that the matching procedures drop the smaller firms from the control group and that these firms have systematically different investing patterns.

Under the lens of the conceptual framework of Section 4, we interpret the results as follows. Firms reacted to the introduction of the policy changing their production processes, rather than simply adjusting inputs and output for the given technology. If not, the effect of the EU ETS would be negative on both the output and the inputs. Instead, we observe an overall increase of economic activity in the treated firms. These results are consistent with evidence that emissions trading did not lower employment nor gross output of manufacturing firms (Petrick and Wagner, 2014).

The across-the-board increase in material expenditures is consistent with fuel switching. Since less polluting fuels are more expensive, fuel switching should increase material expenditures compared to unregulated firms. Systematic fuel switching is also consistent with two phenomena reported to us during interviews with the Italian Emissions Registry managers: the increase in biomass use and the substitution of coke with natural gas in regulated installations. Biomass and natural gas are usually more expensive than coal, but they are associated with lower expenditures for EUAs (biomass is exempted and gas has a lower carbon content).

Third, these results suggest a more structural intervention on production processes than just fuel switching. A structural change in production is consistent with a slow adjustment and persistent policy effects on output, intermediaries and labor. This point is well illustrated in Figures C.1 to C.4 in Appendix A. Variations in the revenue share of input expenditures could be caused by firm re-optimizing inputs after a change in production and changes in performances could be consistent with changes in TFP. None of these results are fully conclusive. Hence, we proceed below with a structural estimation of the production function to assess these hypotheses.

As a robustness check, we investigated whether partially regulated firms, i.e. firms with only a fraction of controlled plants under EU ETS, responded differently than fully regulated firms. To do so, we tested whether these firms faced an incentive to reallocate inputs from the regulated plants to the unregulated ones they control. We regressed the plant-level annual change in the number of employees on a dummy variable for being regulated, taking into account only firms with at least one plant under the EU ETS and the years 2004-2012, and controlling for region and industry fixed effects. This strategy is equivalent to test the null hypothesis that the (conditional) mean number of employees in regulated and unregulated plants is the same. The results need to be interpreted with caution because of the limited trailing years of data in our possession. Nonetheless, we do not find any statistical difference between the two groups, reinforcing our general identification strategy.[27]

Table 4: Diff-in-diff results by industry

Materials (m_{it})		Labor (l_{it})		Capital (k_{it})		Output (y_{it})	
FE	Matching	FE	Matching	FE	Matching	FE	Matching
Food products and beverages (*N. firms: 24,253; 91*)							
0.1357**	-0.154	-0.0495	-0.2015*	0.1035	-0.1705	0.1498***	-0.1225
(0.0509)	(0.0988)	(0.0488)	(0.0823)	(0.0625)	(0.12)	(0.0405)	(0.0865)
Textiles (*N. firms: 13,295; 35*)							
-0.0866	0.1641	-0.2838***	0.1074	-0.3683***	0.0687	-0.1974***	0.0674
(0.078)	(0.1251)	(0.0591)	(0.0612)	(0.091)	(0.1156)	(0.0536)	(0.0654)
Pulp, paper and paper products (*N. firms: 3,843; 158*)							
0.2994***	0.3926***	0.0942**	0.1157*	0.1743***	0.0439	0.2960***	0.3121***
(0.0323)	(0.0712)	(0.0297)	(0.0463)	(0.0462)	(0.0804)	(0.0252)	(0.0586)
Basic chemicals (*N. firms: 6,977; 47*)							
-0.0676	-0.0941	-0.059	-0.0574	-0.0114	0.5452***	0.0714	-0.0458
(0.0636)	(0.1128)	(0.0572)	(0.088)	(0.0853)	(0.1267)	(0.0492)	(0.0922)
Other non-metallic mineral products (*N. firms: 13,210; 152*)							
0.1664***	0.0434	-0.0439	-0.0158	0.0941	-0.2140*	0.0569	-0.0016
(0.0418)	(0.1055)	(0.0348)	(0.0811)	(0.0485)	(0.0974)	(0.032)	(0.0864)
Basic metals (*N. firms: 3,208; 49*)							
0.4545***	0.4448***	0.1684**	0.1860*	0.1166	0.1898	0.4228***	0.4407***
(0.0688)	(0.1327)	(0.058)	(0.0903)	(0.0767)	(0.135)	(0.0523)	(0.0896)

Average Treatment on the Treated (ATT) of the EU ETS on (log) inputs and output, by industry. The numbers in parenthesis next to the industry name represent the number of firms (treated and controls) in the analysis for the fixed effects and matching specification respectively. Standard errors are clustered at the firm level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[27] We find that, on average, regulated plants decrease by 0.5 employees less than non-regulated ones. The standard error of this estimate is 3.1, hence we cannot reject the null hypothesis.

6.1.1 Industry results on inputs and output

We complement the aggregate results with an industry analysis, focusing on the "process regulated sectors"[28] and two industries characterized by a large number of regulated firms ("Food products" and "Textile"). Table 4 presents the estimates of the ATT for two specifications, fixed effects and matching, by industry and outcome of interest. We choose these two specifications as they differ the most in the estimates and are based on substantially different identifying strategies. The results show a heterogeneous effect of the EU ETS across industries. "Pulp and paper" and "Basic metals" were the most affected, across outcomes of interest. Firms under the EU ETS in these industries experienced an overall increase in activity, with a more than proportional increase in output and material expenditures. The fixed effects specification (but not matching) also picks significant increases in output and intermediates in "Food products" and a significant activity reduction in the "Textile industry". The only industry to significantly increase capital endowment as a consequence of the EU ETS is "Basic chemicals", although this result is not robust to both specifications.

6.2 Effects on the production function

Table 5 reports estimates of the production function parameters, i.e. the output elasticity to inputs, following Section 5.2. Since production processes vary across industries, we perform the analysis at the 2-digit industry level. We report the results for the five EU ETS process regulated sectors[29] (Pulp and paper, Coke and refined petroleum, Basic chemicals, Other non-metallic mineral products and Basic metals) and the other two industries with enough regulated firms to identify the elasticities of inputs with respect to outputs (Food and beverages and Textiles). For each input (material, labor and capital), we present the results as follows. The "no ETS" column shows the elasticity of pre-policy unregulated firms, the "ETS" column shows the additional effect of being a firm under the EU ETS policy, the "Post-Policy" column reports the difference in the elasticities after the introduction of EU ETS and the "Post-Policy ETS" columns report the estimate of the differential effect in the elasticity for firms under EU ETS after its introduction. The output elasticity for firms under EU ETS after the introduction of the policy is equal

[28] We however exclude here Coke and refined products, for which the number of regulated firms in our dataset is too small to provide meaningful results.

[29] See Appendix B

to the sum of all columns.[30] For brevity, we do not provide standard errors for these sums, but in most cases they are extremely small. This is due to the very large number of observations we have (standard errors are indeed larger for treated firms, which are sensibly less).

Results show that, independently from the policy, firms that are under the EU ETS have an inherently different production function than those that are not. For instance, regulated firms have an output elasticity of capital often larger than unregulated ones. Not controlling for this initial difference could have lead to an overestimate of the effect of the EU ETS on production function.

Focusing on capital and labor elasticities, we find that overall the output elasticity to capital and labor fell after 2005 both in regulated and unregulated firms. It fell even more among firms subject to the EU ETS. While statistically significant, this effect is however small in most industries. This reduction in labor- and capital-specific productivity was not accompanied by an adjustment in labor and capital endowments (see Table 4). These results are consistent with a story of reorganization of labor and capital that accommodates, rather than lead to, changes in the production process.

When looking at intermediates, we estimate as expected larger changes in β_m in regulated firms. As mentioned in the conceptual framework, changes in this parameter could be related to firms unobservable decisions such as changes in the quality of intermediates. With the exception of "Pulp and paper" and "Basic chemicals", β_m has increased in all industries by 7 to 14 percentage points. In contrast, unregulated firms increased their material-specific productivity much less or not at all, depending on the industry. With the results on intermediates in the previous section, these findings suggest that firms might have undertaken fuel switching as a response to the EU ETS.

6.3 Effects on total factor productivity

In this section we report the results of the two alternative methods adopted to quantify the effect of the EU ETS on TFP, as described in Section 5.3. We report the results by industry, focusing on those presented in the previous section.

[30]For example, take the point estimates of $\beta_m(d_{it})$ for "Food products and beverage": the pre-treatment coefficients are 0.6047 and 0.6747 ($0.6047 + 0.07$) in the control and treatment group respectively, and the post-treatment coefficients are 0.6146 ($0.6047 + 0.0099$) and 0.7542 ($0.6047 + 0.07 + 0.0099 + 0.0696$) respectively.

Table 5: Production function estimates of output elasticity to inputs

	Intermediaries				Labor				Capital			
	Pre-Policy		Post-Policy		Pre-Policy		Post-Policy		Pre-Policy		Post-Policy	
Industry	no ETS	ETS	no ETS	ETS	no ETS	ETS	no ETS	ETS	no ETS	ETS	no ETS	ETS
Food products and beverages	0.6047	+0.0700	+0.0099	+0.0696	0.2189	-0.0464	+0.0237	-0.0722	0.0440	+0.0331	-0.0329	-0.0051
	(0.0000)	(0.0015)	(0.0001)	(0.0000)	(0.0166)	(0.0133)	(0.0187)	(0.0018)	(0.0083)	(0.0243)	(0.0203)	(0.0054)
Textile	0.4344	+0.0172	-0.0135	+0.1042	0.3608	-0.0167	+0.0280	-0.0235	0.0296	+0.0417	-0.0213	-0.0792
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0041)	(0.0005)	(0.0062)	(0.0015)	(0.0043)	(0.0011)	(0.0029)	(0.0016)
Pulp, paper and paper products	0.5192	+0.0415	+0.0140	-0.0816	0.2704	-0.0444	-0.0067	+0.0148	0.0326	+0.0427	-0.0158	+0.0789
	(0.0000)	(0.0003)	(0.0009)	(0.0004)	(0.0422)	(0.0107)	(0.0429)	(0.0176)	(0.0068)	(0.0128)	(0.0121)	(0.0081)
Coke, refined petroleum products	0.5438	+0.0789	+0.0565	+0.1182	0.2313	-0.0485	-0.1482	-0.1056	0.0020	-0.0636	+0.0589	-0.0342
and nuclear fuel	(0.0000)	(0.0060)	(0.0042)	(0.0037)	(0.0924)	(0.0926)	(0.0780)	(0.0893)	(0.0723)	(0.0613)	(0.0397)	(0.0732)
Basic chemicals	0.5542	-0.0185	-0.0261	-0.0309	0.2972	+0.0935	+0.0814	+0.0589	0.0369	+0.0314	-0.0510	-0.0173
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0136)	(0.0021)	(0.0116)	(0.0016)	(0.0053)	(0.0032)	(0.0061)	(0.0021)
Other non-metallic mineral products	0.5004	-0.1159	+0.0470	+0.0683	0.3465	+0.0165	-0.0090	-0.0056	0.0512	+0.0729	-0.0506	-0.0562
	(0.0000)	(0.0015)	(0.0001)	(0.0001)	(0.0072)	(0.0051)	(0.0102)	(0.0058)	(0.0099)	(0.0043)	(0.0068)	(0.0040)
Basic metals	0.5282	-0.0599	+0.0691	+0.1374	0.2882	+0.0505	-0.0461	-0.2588	0.0425	-0.0396	-0.0476	+0.0934
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0090)	(0.0047)	(0.0115)	(0.0017)	(0.0077)	(0.0103)	(0.0083)	(0.0015)

Standard errors in parenthesis are computed employing a clustered bootstrapping procedure with 100 repetitions.

We report the results obtained from our production function estimation procedure. Table 6 shows the estimates for γ_3 in equation (4). Since ω_{it} is the logarithm of TFP, we interpret γ_3 as a percentage change. This parameter captures a structural change on the motion of the TFP, specific to treated firms in the treatment period, and can thus be interpreted as the causal impact of the EU ETS on productivity under the unconfoundedness assumption. The results show rather mixed effects of the policy on Total Factor Productivity among industry, all generally small. Two industries, Food products and beverages and Basic chemicals, show an increase in TFP due to the EU ETS by 0.92% and 1.61% respectively. However, the EU ETS had an overall negative and significant impact on the other industries, although of relatively small magnitude.

Table 6: Effect of the EU ETS on TFP. Structural estimation

Industry	%
Food products and beverages	0.92***
	(0.01)
Textile	-1.02***
	(0.68)
Pulp, paper and paper products	-0.28***
	(0.03)
Coke, refined petroleum products and nuclear fuel	-1.02
	(1.36)
Basic chemicals	1.61***
	(0.01)
Other non-metallic mineral products	-0.93***
	(0.13)
Basic metals	-0.25***
	(0.02)
Fabricated metal products, except machinery and equipment	-1.20***
	(0.01)

The table reports the estimate of the effect of the EU ETS on TFP, expressed as percentage changes of $\exp(\omega_{it})$ and estimated with our structural model. Standard errors in parenthesis are computed by employing cluster bootstrap with 100 repetitions.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Together with those in the previous sections, these results suggest that most industries have not undertook substantial technological changes as a consequence of the EU ETS. While some industries experienced a general increase of activity (Pulp and paper and Basic metals), this has not necessarily followed from an increase in total factor productivity.

This is not true for all: regulated chemical firms increased their capital investment suggesting new investments (see Table 4). Indeed, after the introduction of the EU ETS some firms in the chemical industry converted or adopted new technologies with the explicit goal of reducing emissions.[31]

Since we do not observe idiosyncratic prices, it should be kept in mind that the results we report refer to revenue TFP, which is a mixture of technical TFP and price variations. It is however reassuring that market shares stayed roughly constant in the period in most industries. A change in market shares, and thus market power, in the treated firms could be associated with an increase in output prices and mistakenly attributed to a change in technological TFP. In two industries we observe a statistically significant increase in the average market shares for the treated firms with respect to the control: Basic metals (+23%) and Pulp and paper (+8%). While this fact helps explaining the increase in output and intermediates reported above, it might bias towards zero our TFP estimates for these two industries. TFP is endogenous to market shares and thus disentangling the two effects is arduous. Nonetheless, in an attempt to control for the market structure, we include the market shares as a control in our estimates and the results are not statistically different from the one reported above.

Finally, table 7 reports results for the alternative method based on the conditional difference-in-differences strategies described in Section 5.1. The ATTs are obtained using $\hat{\omega}_{it}$ as the outcome of interest. All specifications show a decrease in TFP, with especially large negative effects for Basic metals and Other non-metallic mineral products (cement, clinker etc.). The matching specification show the largest results, with decreases comprised between -5% and -20% over the 10 years analyzed. Although we report estimates for the clustered standard error, these estimates are severely biased towards zero, as they disregard the errors deriving both from the matching procedure and the estimation of total factor productivity. We therefore do not report significance levels.

It is reassuring that results from the structural and diff-in-diff approaches go in the same direction, although the point estimates of the latter tend to be much larger. Part of this difference is due to the imprecise estimates that the diff-in-diff provides. This is more evident in the first and the second column: using linear covariates or the propensity score

[31] The two main innovations were the conversion from mercury cell processes to membrane technology in chlorine and caustic soda production and the reduction in emissions from carbon black production (Taurino et al., 2016).

Table 7: Effect of the EU ETS on TFP in percentage. Diff-in-diff

	Linear controls	PS control	FE	Matching
Food products and beverages (*N. firms: 24,253; 91*)				
	-0.29%	-3.16%	-0.56%	-8.19%
	(2.56)	(3.53)	(1.41)	(2.34)
Textile (*N. firms: 13,295; 35*)				
	-5.33%	-6.46%	-6.50%	-9.30%
	(3.51)	(3.72)	(2.23)	(2.90)
Pulp, paper and paper products (*N. firms: 3,843; 158*)				
	-2.02%	0.91%	-2.44%	-4.97%
	(2.16)	(2.62)	(0.81)	(1.30)
Basic chemicals (*N. firms: 6,977; 47*)				
	2.93%	-4.83%	-4.31%	-8.48%
	(3.40)	(3.59)	(1.69)	(3.08)
Other non-metallic mineral products (*N. firms: 13,210; 152*)				
	-13.67%	-12.46%	-14.24%	-19.57%
	(1.40)	(1.58)	(1.07)	(1.58)
Basic metals (*N. firms: 3,208; 49*)				
	-5.66%	-10.68%	-5.96%	-11.70%
	(2.37)	(3.75)	(1.59)	(2.51)

The table reports the estimate of the effect of the EU ETS on TFP, expressed as percentage changes of $\exp(\omega_{it})$ and estimated in four conditional diff-in-diff specifications. The standard errors we report in parenthesis should be understood as a lower bound of the actual estimates.

as controls should not substantially affect results, but the two estimates tend to diverge. It is however possible that the diff-in-diff strategy does a better job at controlling for the idiosyncratic firms' characteristics, which correlate with treatment and productivity. The matching procedure drops from the common support some of the largest treated firms which experienced an increase in productivity, exacerbating the difference.

Overall, our results suggest that the policy had a negative effect on firms' productivity. While the effect is overall small and heterogeneous across industries. Although an effect of the EU ETS on economic outcomes through productivity cannot be excluded, it seems not to have a major impact. On the contrary, in most industries treated firms sustained their economic performance with the help of fuel switching and despite the reduction in TFP.

7 Conclusions

One of the main concerns related to the introduction of carbon prices is the potential negative effect on economic performance. Debates on this topic have animated political discussion when the proposals for the new phases of the EU ETS were drafted. European states are currently designing the Post-2020 EU ETS compliance Phase and the Italian government has shown major concerns on the economic effect of more stringent regulation.

This paper contributes to this debate by investigating the causal effect of the first three phases of the EU ETS on firms' outcomes, production function and TFP of Italian manufacturing firms regulated by this directive. We perform a battery of conditional diff-in-diffs on directly observable variables, such as inputs and output, controlling parametrically and non-parametrically for size observables. To investigate individual and total factor productivities, we estimate structurally the production function. In doing so, we take into account the estimation bias of endogenous input choices and we allow the policy to affect both them and the technology. To estimate the effect of the EU ETS on firm level TFP, we provide a new fully coherent structural approach to address selection into treatment. The strength of this approach is that, contrary to other papers, provides valid inference. We complement these findings following the literature and estimating a matching diff-in-diff, with TFP as outcome variable.

Our results are consistent with the theoretical predictions that firms would react to an increase in price of emissions by switching intermediates. However, we did not find evidence of decreased outcomes or capital and labor. Across our two models for TFP we find a small and negative effect of the policy, but our point estimates differ in magnitude. A formal comparison of the results is made impossible by the absence of valid confidence intervals for the matching diff-in-diff, but a computationally feasible variation of the method by Otsu and Rai (2017), taking into account the additional production function estimation first step could provide that.

Appendix

A Matching procedure

We stratify our data in 65 strata, i.e. distinct combination of industry (ATECO 2-digits) and geographical area (5 Italian macro-regions). To provide a comparison measure for firms within the same stratum, we parametrically specify the propensity score as a function of pre-treatment age, (log) number of workers and number of plants. We proceed to estimate it by logit.

In this stage we could have used other input and output observables, such as measures for capital, labor or material expenditures, or an output observable. Since these measures proxy well for size, which is correlated with the actual selection variables, they would have helped in defining the propensity score. However, we explicitly restrain to do so, since we use all these measures in our estimation of TFP. Chabé-Ferret (2017) shows that selecting on pre-treatment outcome increases the bias of diff-in-diff when there are auto-correlated temporary shocks in the outcome variable. Since our main outcome variable, TFP, is generated starting from these observables, we want to avoid that autocorrelated shocks in them carry over into our ATT estimates, producing biased estimates. We use 2002 data to avoid the risk of firms' strategic sorting outside of treatment: the EU ETS had just been announced and the selection rules were not well defined yet, therefore it is impossible that firms have influenced the treatment assignment.[32]

We have at least one firm on 65 strata, but we are able to estimate nontrivial propensity scores only for 34.[33] We further restrict our analysis to a balanced panel of firms: we want to avoid that results be driven by the exit of firms or by unexpected correlations of productivity with gaps in our data. As a result, we initially restrict our scope from 98,839 firms to 41,622 (out of which 255 are treated according to our definition). We consider this a conservative choice, that helps address the very large size of some treated firms: the number of matched treated firms drops to 228 (27 are dropped).

We experiment with the number of neighbors (1, 5, and 20) we consistent results. We also explore with different calipers (between 1 and 5 standard deviations), but results are not affected. Yet, we find the choice of the caliper to be somewhat important in

[32] For the number of plants we use the closest year available to us, which is the 2004.

[33] This means that those strata that are particularly sparse are dropped because they contain no or very few firms in treatment or in control.

this context: while a too small caliper restricts the number of matches, leaving too few observations for reliable inference, a caliper that is too big results in loose matches. We report the results for a caliper of 3 standard deviations, which strikes a good balance.

Table A.1: PRE-TREATMENT DIFFERENCE BETWEEN MATCHED TREATED AND CONTROL GROUP FIRMS

	Treatment	Control	Difference
Gross output (log)	10.441	10.012	0.429
	(1.414)	(1.331)	(0.877)
Labor expenditures (log)	8.316	8.088	0.228
	(1.410)	(1.309)	(0.788)
Capital expenditures (log)	9.223	8.438	0.785
	(1.523)	(1.254)	(1.202)
Materials expenditures (log)	9.592	9.237	0.355
	(1.611)	(1.422)	(1.085)
Materials / Gross output	-0.849	-0.776	-0.073
	(0.464)	(0.291)	(0.449)
TFP (log)	2.313	2.396	-0.083
	(0.518)	(0.267)	(0.497)

B EU ETS regulated sectors and thresholds

The sectors and the threshold are specified in the Annex I of the Directive 2003/87/EC integrated by the Directive 2009/29/EC. "The thresholds values given below generally refer to production capacities or outputs. Where several activities falling under the same category are carried out in the same installation, the capacities of such activities are added together."

Activities: Power stations and other combustion plants ≥20MW

Oil refineries

Coke ovens

Production and processing of ferrous metals: metal ore (including sulphide ore) roasting or sintering installations; installations for the production of pig iron or steel (primary or secondary fusion) including continuous casting, with a capacity exceeding 2.5 tonnes per hour.

Cement clinker: installations for the production of cement clinker in rotary kilns with a production capacity exceeding 500 tons per day or lime in rotary kilns with a production capacity exceeding 50 tons per day or in other furnaces with a production capacity exceeding 50 tons per day.

Glass: Installations for the manufacture of glass including glass fiber with a melting capacity exceeding 20 tons per day.

Lime, bricks, ceramics: Installations for the manufacture of ceramic products by firing, in particular roofing tiles, bricks, refractory bricks, tiles, stoneware or porcelain, with a production capacity exceeding 75 tons per day, and/or with a kiln capacity exceeding 4 m3 and with a setting density per kiln exceeding 300 kg/m3

Pulp: from timber or other fibrous materials

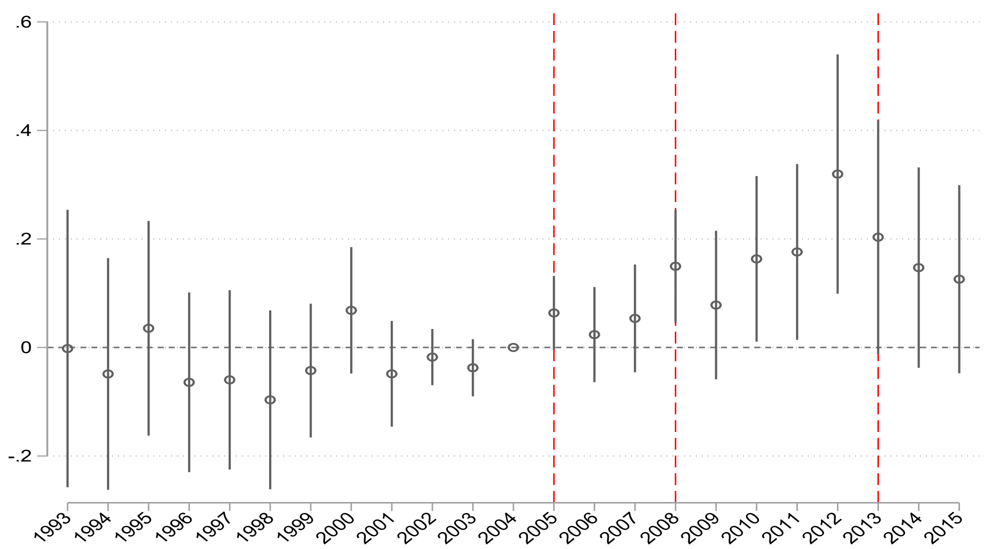
Paper and board: with a production capacity exceeding 20 tons per day.

Aluminium (from phase 3) Petrochemicals (from phase 3) Aviation (from 1.1.2014)

Aviation was included in 2013 and until 2016 the EU ETS applies only to flights between airports located in the European Economic Area (EEA).

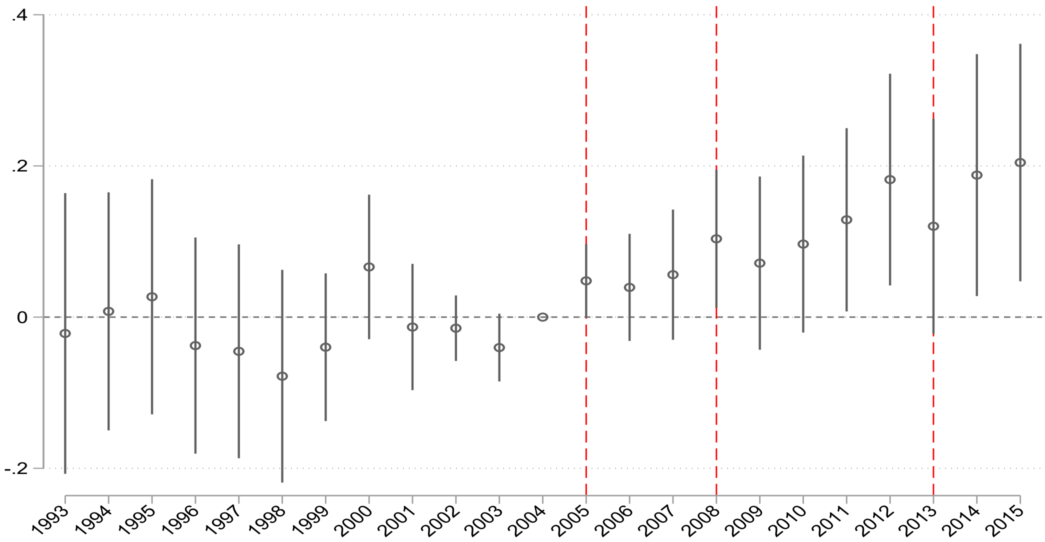
C Figures

Figure C.1: LOG(REAL MATERIAL EXPENDITURES)



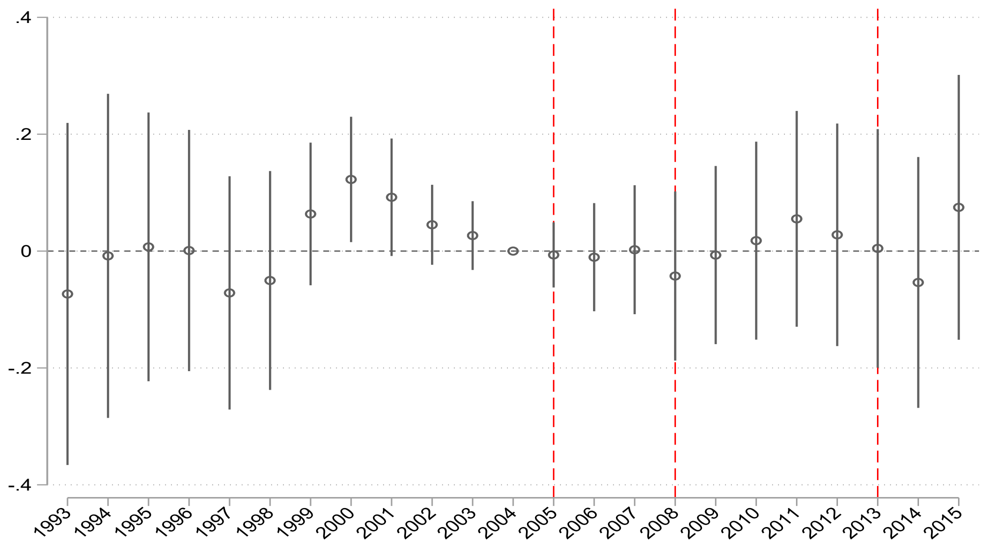
Notes: We plot the coefficients of the regression of the difference of log of material expenditures between matched ETS and non-ETS firms on the years before and during the policy.

Figure C.2: LOG(REAL GROSS OUTPUT)



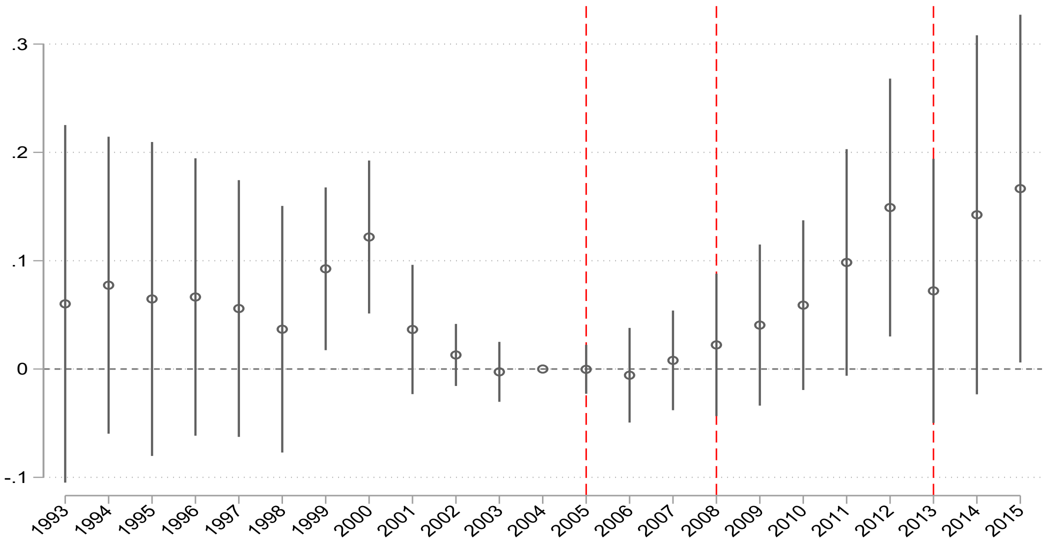
Notes: We plot the coefficients of the regression of the difference of log of gross output between matched ETS and non-ETS firms on the years before and during the policy.

Figure C.3: LOG(REAL CAPITAL EXPENDITURES)



Notes: We plot the coefficients of the regression of the difference of log of capital expenditure between matched ETS and non-ETS firms on the years before and during the policy.

Figure C.4: log(Real labor expenditures)



Notes: We plot the coefficients of the regression of the difference of log of labor expenditure between matched ETS and non-ETS firms on the years before and during the policy.

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