The Impact of the European Carbon Market on Firm Productivity: Evidence from Italian Manufacturing Firms.*

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Abstract

The key policy adopted by the European Union to reduce greenhouse gas emissions is the Emission Trading System: a market for rights to emit. The introduction of this policy has raised concerns about possible detrimental effects on firms' production through an increase in polluting costs, unless firms change inputs or increase their productivity. In this paper, we provide evidence of the causal impact of this European policy on firms input choices and total factor productivity. We combine structural estimation of firms' production function and techniques for policy evaluation to estimate the effect of the EU ETS on Italian manufacturing firms. Our results show a positive effect of the policy on productivity with heterogeneous effects across sectors. Results also suggest that firms reacted to the policy not reducing their input or upgrading their capital but adjusting their production process.

Keywords: Emission trading; Environmental Policy; Manufacturing; Productivity.

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The opinion expressed and arguments employed herein are those of the authors and do not necessarily reflect the official views of the OECD or the governments of its members countries.

1 Introduction

The reduction of greenhouse gas (GHG) emissions from industrial production without hampering economic activity is a key policy goal for most developed economies. Economics literature advocates market-based instruments which incentivize firms with the lowest abatement costs to reduce emissions first, minimizing the loss of producers' surplus. Accordingly, in 2003 the EU established an emission allowances trading scheme, the European Union Emission Trading System (EU ETS). Today, this is the largest cap-and-trade scheme in the world and it covers approximately 11,000 energy intensive installations in the power generation and manufacturing industry sectors, amounting to 45% of the EU's GHG emissions.

The introduction of the EU ETS was accompanied by a fierce debate on the effects of environmental regulations on firms' performances. Economic theory does not provide clear predictions on the effect of environmental regulations on firms' performances (Gray, 1987; Porter, 1991; Porter and Van der Linde, 1995). Therefore, providing empirical evidence of the effect of the EU ETS on firms' productivity has first order policy implications. In particular, total factor productivity, which is the overall efficiency with which inputs are combined in the production process, plays a major role. On the one hand, firms are concerned about negative effects of policies on productivity. On the other hand, it is the main driver of GDP growth in advanced economies (Klenow and Rodriguez-Clare, 1997).

In this paper we identify the causal effect of the EU ETS on production choices and on total factor productivity (henceforth, TFP). We provide a conceptual framework to test whether such policy is merely increasing costs, or it is pushing firms towards a more efficient production. When compared to firms not affected by the policy, we observe a differential increase in materials expenditures for firms subject to EU ETS; but no change in other inputs nor reduction of output. We interpret these results as evidence of a change in input mix or of an increase in their efficiency. While we show an overall positive impact of the policy on TFP, this effect is heterogeneous across industries. Our results suggest that not all sectors face incentives to undergo substantial changes in their production processes, while others adjust only marginally, mainly through fuel switches.

Italy provides an excellent setting for studying the effect of EU ETS on TFP since it is the second largest manufacturing country in Europe. Given the important role of the manufacturing industry in the Italian economy, the Italian government has been concerned about the potential negative effects on firms of the policy.[1] In 2017, Italy indeed voted against the EU ETS review proposal, which introduces a new limit on GHG emissions.[2] For our analysis, we exploit a comprehensive Italian manufacturing corporation firms balance-sheet dataset, complementing it with EU ETS registry data.

In order to identify the causal effect of EU ETS on input expenditures and gross output, we develop an empirical framework which takes into account non random treatment assignment. 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. Our identification strategy is based on difference-in-differences matching estimators, as suggested in Fowlie et al. (2012) and in line with what is done in the literature on the economic effects of the ETS (Calel and Dechezlepretre, 2016; Wagner et al., 2014). The Italian manufacturing sector is characterized by firms of widely different sizes. This is important for our identification strategy: thanks to this heterogeneity, we observe unregulated firms that are comparable in size to the regulated ones.

Then, in order to investigate which channels explain the reduced form evidence, we turn to 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] In doing so, we slightly depart from standard assumptions allowing output elasticities with respect to inputs and TFP to vary as a function of the policy introduction.

Furthermore, to isolate the causal effect of the policy on TFP, we address treatment confoundedness, following two alternative strategies. First, we control for selection directly in the production function. 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). We augment it by controlling for firm size related variables in the law of motion of productivity. Second, we treat

[1] 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).

[2] "Proposal for a Directive of the European Parliament and of the Council amending Directive 2003/87/EC to enhance cost-effective emission reductions and low-carbon investments" on February 28th, 2017

[3] Using a control function approach we are taking into account the fact that inputs are endogenous functions of TFP and we are able to structurally model the effect of the policy. 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 when thinking to capital and material inputs.

the productivity estimates retrieved from the control function approach as the outcome variable in a matching difference-in-difference strategy.

Our paper finds support for the so called Porter (1991) hypothesis. Porter's intuition is that environmental policy can provide incentives to invest in technologies that not only reduce the environmental footprint, but also increase productivity. Our paper provides a different test on the Porter's hypothesis with respect to those in the existing literature. 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 have focused on the causal effect of the EU ETS, but without reaching any conclusive evidence on the impact of this policy on firm production choices (Martin et al., 2015; Jaraite et al., 2016; Klemetsen et al., 2016).[6] Although some of these studies investigate the effects of the scheme on firm outcomes using firm or plant-level data, none of them identifies the channels through which firms modified their production choices. Lutz (2016) and Löschel et al. (2018) attempt to investigate this question, but their analysis does not disentangle the different effects on performance and does not provide an explanation on the channels that determine a change in the production function. This paper fills this gap, identifying firms' reactions to the introduction of the policy, as well as the effect on TFP across different sectors.

The remainder of the paper is structured as follows. Section 2 describes some institutional features of EU ETS and we present the dataset we constructed. Section 3 provides a conceptual framework. Section 4 describes the empirical strategy. Section 5 Section 6 presents results and Section 7 concludes.

2 Background and data

In this section we provide information on the Emission Trading System and highlight some of the institutional features which we exploit to identify the effect of this environmental policy on total factor productivity. We also introduce a novel dataset we compiled combining balance sheet data of Italian manufacturing firms with the emission trading

[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 (Wagner et al., 2014; Petrick and Wagner, 2014; Calel and Dechezlepretre, 2016).

registry.

2.1 Emission Trading System

The EU ETS is a cap-and-trade scheme for CO2 emissions: each regulated plant has to offset emissions with a permit. The total number of permits, called EU Allowance Units (EUA), is set at European level. Each plant receive allowances that can be traded across regulated emitters in all countries participating to the scheme. At the end of each year (by April of next year), firms must own a number of allowances equivalent to the verified emissions.

The policy was implemented in three Phases, which differ in the mechanism for allocating the allowances, sectors and polluters regulated. During the first phase (2005-2007) all EUAs were allocated through grandfathering, proportional by historical emissions. Permits allocated in this phase could not be carried forward in the following phases (banking). In the second phase (2008-2013) there was a reduction in the cap by 6.5%. The current phase started in 2014 and will last until 2020 with a reduction target of 20%. At the beginning of the third trading period, manufacturing industry received 80% of its allowances for free. This proportion will decrease gradually each year reaching 30% in 2020.[7] Since we are focusing on the effect of the policy until 2015, we are disregarding the role of emission allocation systems, although it could be of increasing relevance.

The EU ETS regulation applies to combustion installations with a rated thermal input exceeding 20MW. Moreover, some productive processes are subject to stricter conditions based on output capacity. These "process regulated sectors" include paper products, manufacture of coke and refined petroleum products, manufacture of glass ceramic and cement and manufacture of basic metals.[8] Therefore, treatment status of different plants depend on their physical characteristics of the plants, hard to manipulate in the short run.

The EUA prices[9] are determined in the market. Figure 1 show EUA prices evolution. These have been dropping several times over years because total verified emissions have been often below the cap. EUA prices are indeed one of the main concerns about the

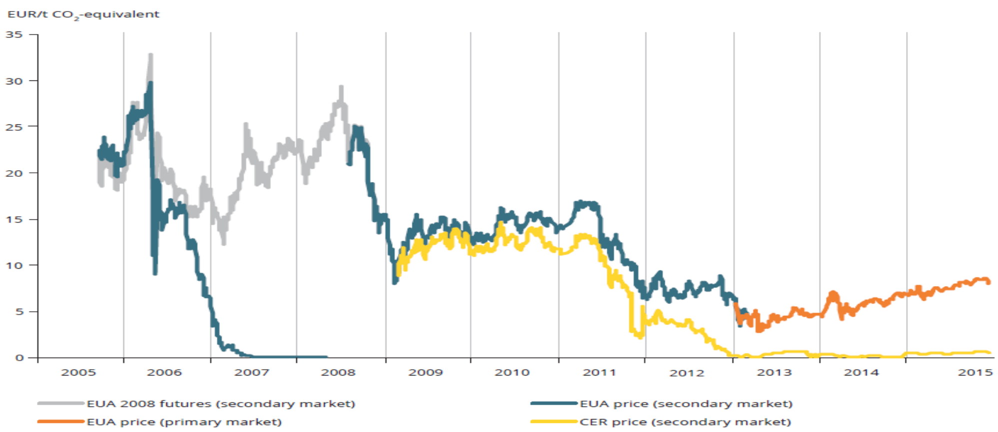
[7] For a comprehensive review see Ellerman et al. (2016).

[8] For further details on sectors and thresholds see Appendix A.

[9] Initially, all trading was over-the-counter (OTC) as it has been for all other cap-and-trade programs. However, in 2005 organized exchanges started offering intermediary and hedging services and their share has grown steadily to account now for as much as 80% of the trades.

efficacy of this policy: they are considered high enough to induce technological changes. Even if prices have been volatile, the volume of EUAs traded exceeded 50 million tons

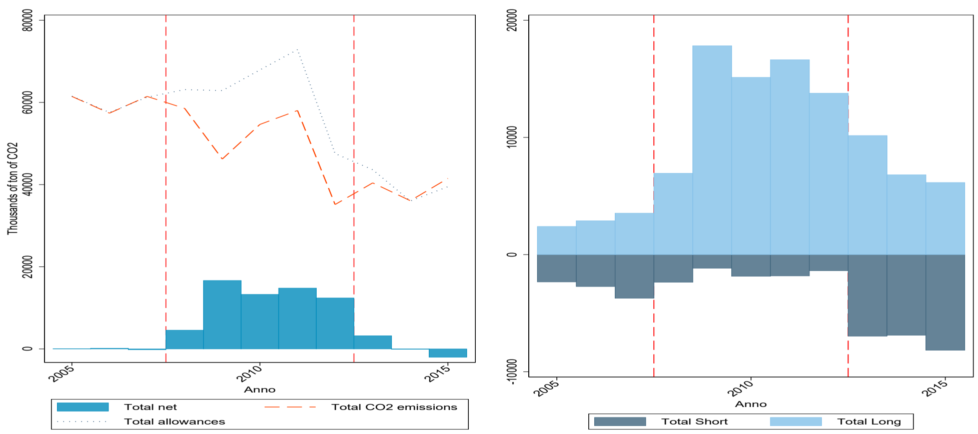
Figure 1: Allowances price trend.



Notes: The figure reports EUA prices both in the primary and secondary market as well as certified emission reduction (CER prices).
Source: EEX (EUA price), 2015; ICE ECX (CER price), 2015. Graph produced by European Environment Agency

per month in 2006, increasing tenfold over the course of the following 6 years. This suggests that, over the period, firms have increasingly internalized the opportunity cost of pollution.

Figure 2: Short and long positions by year.
Italian manufacturing firms.



Notes: The figure reports data from Italian manufacturing firms regulated by the ETS. 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 dot line to the total allowances allocated. Right panel shows separately total long positions (allowances $\geq$ emissions) and total short ones (allowances $\leq$ emissions)

Given this context, the case of the Italian manufacturing sector is particularly interesting. In fact, as Figure 2 shows, Phase I was characterized by balances total short and long positions, differently from other countries. Moreover, including data on the third Phase will help to identify the effect of the policy after the peak of the economic crisis.

For the monitoring[10] of the emissions due to combustion[11] or to the production process, firms can choose two approaches: calculation-based or measurement-based.

The calculation-based approach is the most commonly used for fossil fuel combustion. In this case, emissions are computed according to the following rule:
Emissions *(tCO_2)* = fuel quantity *(t)* x net calorific value *(GJ/t)* x emission factor *(tCO_2/GJ)* x oxidation factor *(%)*.
The calculation factors can be default one (based on the literature or used by member states for emission reports) or based on analyses (carried out according to EN standards or provided by fuel sellers). In the first case, the calculation factors are fixed, so the firm can only reduce the quantity of the fuel used to reduce its contribution to emissions, in the second case it could change the quality of the fuel used or adopt some technology to increase the fuel efficiency of the fuel.

Measurement-based approaches measure GHG emissions directly in the stack. In particular, the concentration of the GHG and the volumetric flow of the gas stream are measured. This approach is difficult to adopt in installations with many emission points or indeed impossible where there are open furnaces.

2.2 Data

We collected a unique and comprehensive database of Italian manufacturing plants. This database is built from several sources:

The Community Independent Transaction Log (CITL) database contains all installations[12] under regulation in the first Phase while the European Union Transaction Log (EUTL) contains data on the subsequent phases. It is run by the European Commission and publicly available on its website. This allow us to identify firms with production plants in Italy subject to ETS between 2005 and 2015.

The CERVED database contains balance sheet information for Italian limited liability

[10]Commission Regulation (EU) No 601/2012 of 21 June 2012 on the monitoring and reporting of GHG emissions pursuant to Directive 2003/87/EC of the European Parliament and of the Council.
[11]Notice that emissions from biomass are monitored but not accounted as emissions.
[12]As defined by the Directive "installation' means a stationary technical unit where one or more activities listed in Annex I are carried out and any other directly associated activities which have a technical connection with the activities carried out on that site and which could have an effect on emissions and pollution."

companies. The data are recorded by the Italian Registry of Companies and from financial statements filed at the Italian Chambers of Commerce. The information provided 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 matched the 893 account holders in the CITL registers with the firms in the CERVED database, 875 firms were recorded in both databases (98%). In particular, we restricted our attention to the 497 firms which are listed as manufacturing in CERVED and received at least once emission allowances. In Table 1 details on the number of installations and firms under regulation in the three phases are reported. In order match the datasets, we aggregate data at firm level. We also combine these databases with information at plant level (ISTAT dataset Asia), in order to check how many plants of a firm are under regulation. Among the regulated firms, 44% of them are mono-plants and 25% have 2 plants. Moreover, 50% of the firms have all their plants regulated under ETS. Only 25% of the firms have less than half of their plants regulated under ETS.[13] Therefore, most of the firms cannot relocate their production in non regulated plants.

Table 1: CITL 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).

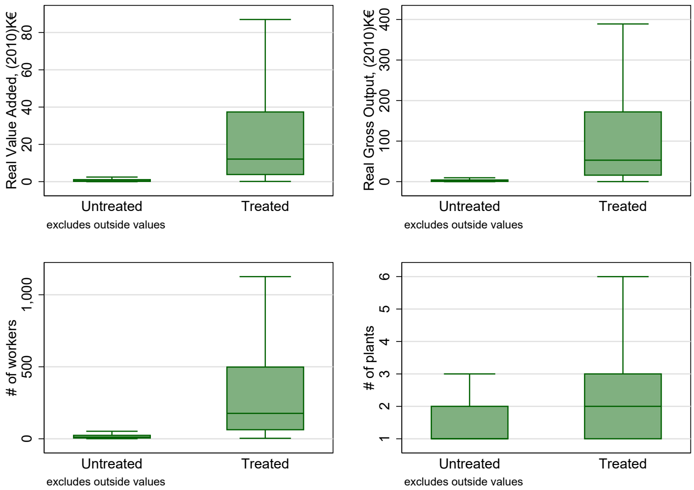
On average firms subject to the policy are bigger than the others. How Figure 3 shows there are some untreated firms similar to the treated ones. Given that firm-level productivity dynamics may vary significantly across the treatment and comparison groups, we adopt two different approaches to overcome the non-random assignment into treatment rule.

Further, information related to technology adoption at industry level is contained in the "Best Available Technique" reference document.[14] We also collected technical report from Federation of industry company which discuss the possible strategies adopted in

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

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

Figure 3: Firms characteristics (2002)



In the diagrams we report the distribution of real value added, gross output, number of workers and number of plants for firms treated and not treated in the "process regulated sectors": paper products, manufacture of coke and refined petroleum product, manufacture of glass ceramic and cement and manufacture of basic metals.

the recent years to reduce GHG emissions. We interviewed as well managers of the Italian registry of emissions who provided industry level information about fuel usage for regulated firms.

3 Conceptual framework

To help the interpretation of our measures of interest in the empirical section, we discuss here how firms react to the introduction of emission prices. We draw economic intuitions under the particular assumptions we will employ in the next section to obtain identification. There, we will restate more explicitly the assumptions.

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

The Cobb-Douglas production function expressed in logs:

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

where ω_{it} is a persistent term reflecting the total factor productivity and ε_{it} is a standard i.i.d. error term capturing unanticipated shocks to production and measurement errors. While capital has dynamic implications and can only be adjusted with delay, materials and labor are static inputs chosen by the firm flexibly. The three inputs are observed as aggregated expenditures in our data, but in reality each one pools together heterogeneous factors. Materials are of particular interest for us, as they include expenditures for each fuel and polluting intermediate good, albeit in an unknown proportion.

We interpret a positive price of emissions as an indirect increase in the cost of materials. We therefore expect firms to possibly react in one of the following ways. First, an increase in its price determines a decrease in m_{it}. Because of the decreasing marginal returns, l_{it} also decreases 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 not only the total expenditures in materials, but also their mix. Imagine a paper mill that can choose between two sources to produce energy needed for production: coal and biomasses. Coal is cheaper, but biomasses 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. In many cases this change is done at no additional cost or delay, as some fuels are completely substitutable in production. Being able to observe only expenditures, a positive price of emissions could be associated with the apparently paradoxical effect of an increase in materials. 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.[15]

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 fine-tuning or changing completely their production processes. Moreover, as suggested in Porter (1991), the incentive to reorganize and improve the firm's environmental performance may help spur actions that positively spillover onto 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, through investments in R&D and organizational or optimization efforts. We expect these changes to have an effect on

[15] This effect being of particular interest for us, we avoid adopting a value added production function. In that context, materials are a perfect complement to production and their relation with productivity is therefore ruled out. We decide thus to adopt this more general approach, at the cost of assuming frictions in the price of materials.

productivity ω_{it}, and possibly on the input elasticities β. If the firms realize considerable tangible investments, we can also expect to observe a change in k_{it}.

4 Empirical strategy

In this section, we first develop an empirical strategy to estimate the policy effect, taking into account the selection on observables issue and time-varying confounders. We then illustrate how we identify production function parameters. Finally, we discuss two strategies to causally relate the policy to changes in total factor productivity.

4.1 EU ETS effects

We identify the effect of the EU ETS introduction as an average effect of the treatment on the treated (ATT) for firms' inputs and outputs. We define the ATT as:

$$ATT = E[Y_{it'}(1) - Y_{it'}(0)|D_i = 1]$$

Let $D_i = 1$ if firm is subject to EU ETS. Potential outcomes $Y_{it}(1)$ and $Y_{it}(0)$ are inputs expenditures and output revenues of firm i at time t' (after the introduction of the policy) conditional on being regulated by the policy. Observing variables of interest before and after the introduction of the EU ETS, it is possible to estimate the unobservable counterfactual outcomes $E[Y_{it'}(0)|D_i = 1]$ with a difference-in-difference estimator. That is, we assume that input expenditure and output trends would be the same in the absence of the policy. This is particularly useful to take into account sectoral variations, such as price/quantity drops due to the economic crisis. However, the EU ETS assignment into treatment is not random: the running variable that determines whether firms are affected by the policy is their input or output capacity, as described in Section 2.1. Therefore, firms in the treatment group tend to be bigger than firms in the control group. Since firm size is likely correlated with firm productivity growth, simply comparing treated and untreated firms lead to a biased estimate. The idea is to tackle the potential bias using firms observables (i.e. firm age, number of workers, number of plants) that correlates with the probability of being treated. Comparing firms that are similar in size and other observable characteristics helps in satisfying the parallel trend assumption required by the diff-in-diff, in the spirit of Heckman et al. (1997). [16]

4.2 Production function

We define a revenue production function:

$$y_{it} = y(l_{it}, k_{it}, m_{it}, \omega_{it}; \beta(ETS_{it})) = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \tag{2}$$

where $\beta(ETS_{it}) = \{\beta_l, \beta_k, \beta_m\}$[17] and ω_{it} are allowed to vary with ETS_{it}. With a small abuse of notation, to isolate the effect of being regulated from differences in size and time effects, ETS_{it} includes three variables: t a dummy variable equal to one in the years of the treatment, T is a dummy variable equal to one for the treated firms and D_{it} is a dummy variable equal to one for the firms under treatment in the years of treatment.

In our setting, as in Olley and Pakes (1996) (OP), Levinsohn and Petrin (2003) (LP) and Ackerberg et al. (2015) (ACF), identification relies on distributional assumptions on productivity and on assumptions on input demand. We assume that productivity follows a Markov process, with transition probabilities $P(\omega_{it}|\omega_{it-1}, ETS_{it})$. Notice that, as in De Loecker (2013) and Doraszelski and Jaumandreu (2013), this specification of transition probabilities allows the low of motion of the ω_{it} to vary with the policy variables:

$$\omega_{it+1} = g(\omega_{it}, ETS_{it}) + \xi_{it+1} \tag{3}$$

where ξ_{it+1} is an additive innovation. We assume in particular that the effect of being regulated at time t affects productivity at $t + 1$. We assume that intermediate inputs demand is a strictly monotone function of ω_{it}. We follow De Loecker (2013, 2007) in assuring this monotonicity by including all relevant state variables. In particular, since carbon trading is associated with an increase in cost of materials, we condition demand on ETS_{it}.[18] We implicitly assume that firms are price takers in the input and output market.

[16] An alternative to the matching strategy would have been to leverage the discontinuity in treatment assignment and compare firms at the cutoff. In fact, albeit they vary by industry, the rules for inclusion into ETS are sharp and known. Unfortunately, data on individual installations' thermal input and (especially) output capacity are private information that we cannot observe.

[17] We are able to identify β_m using gross output because we assume non linear pricing in M_{it}. This assumption, as in Balat et al. (2016), is credible because it there are quantity discounts in M_{it}. This introduces a friction in the demand for M_{it}, which is therefore not completely collinear with (L_{it}, ω_{it}).

[18] The monotonicity assumption is indeed verified if the firm is choosing M_{it} to maximize its static profits and the production function is well specified (De Loecker, 2013; Doraszelski and Jaumandreu, 2013).

This assumption is supported by the fact that we are focusing on homogeneous goods and we estimate parameters at sector-level. If this assumption is violated, the estimate of ω might be upward biased. However, in our application the problem is less severe since we are focusing on the differences of *omega* for firms operating in the same market and similar in dimension. Lastly, we allow the parameters of the production function to be different between firms subject or not subject to ETS and to vary before and after the introduction of the policy, capturing possible changes in technology following the introduction of the policy. This insures that the gain in TFP we observe due to the policy is not capturing a change in output elasticity with respect to input.

4.3 EU ETS effect on TFP

We propose two alternative methods to take into account the correlation between the treatment status and productivity, while quantifying the effect of the EU ETS on TFP. The introduction of the ETS in the productivity process does not solve the bias due to the definition of regulated firms (only firms with big output capacity are regulated).

Firstly, we model the productivity process described in equation (3) taking into account the differences in observable characteristics. These characteristics enter linearly in the production function to avoid curse of dimensionality issues.

Secondly, we rely on matching on observables, following the current literature on the economic effects of the ETS and similarly to De Loecker (2007), to control for a potential selection effect. However, inference is problematic in this setting (Abadie and Imbens, 2006). We use this alternative procedure for two main reasons. First, to have comparable results with respect to other studies. Second, to take advantage of non parametric matching, which intuitively correct for confounding effects on treatment effects.

5 Estimation

5.1 Matching difference-in-differences

We estimate the average effect of the treatment on the treated (ATT) as:

$$\hat{ATT} = \frac{1}{N_{1t'}} \sum_{i \in \mathcal{I}} \left(\mathtt{Y}_{it'}(1) - \frac{1}{M_{it'}} \sum_{j \in \mathcal{J}_i(\hat{\pi})} \mathtt{Y}_{jt'}(0) \right) - \frac{1}{N_{1t}} \sum_{i \in \mathcal{I}} \left(\mathtt{Y}_{it}(0) - \frac{1}{M_{it}} \sum_{j \in \mathcal{J}_i(\hat{\pi})} \mathtt{Y}_{jt}(0) \right) \tag{4}$$

where t and t' denote pre- and post-ETS period; N_{1t} is the number of treated firms at time t; $\hat{\omega}_{1ti}$ is estimated TFP for firms under ETS after its introduction; M_{it} is the number of matches to firm i at time t'; $\mathcal{I}$ is the set of firms under the policy and $\mathcal{J}_i(\hat{\pi})$ is the set of non-treated firms matched to i, based on the propensity score estimates $(\hat{\pi})$.[19]

The set of firms' characteristics chosen to specify the propensity score is crucial. We want to provide narrow matching criteria, to be sure that the matched firms are in fact similar to the treated ones. As in Calel and Dechezlepretre (2016) we impose matching within strata defined by the intersection of industry and geographical region. Exact industry matching, performed at the 2-digit NACE level, controls for industry-wide exogenous changes in market conditions and accounts for industry-specific innovations in production. Geographical matching, performed on four Italian macro-areas[20], helps to control for local market conditions and changes in local institutions.

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.[21] Visual exploration of Figure 4 suggests that not every treated firm has a sufficiently similar one to compare to: a majority of firms in our dataset is in fact sensibly smaller than those under ETS. Notwithstanding, a common support can be established for most of the strata and a significant overlap is found for the majority of the firms, so that they could be matched to at least one in the control.

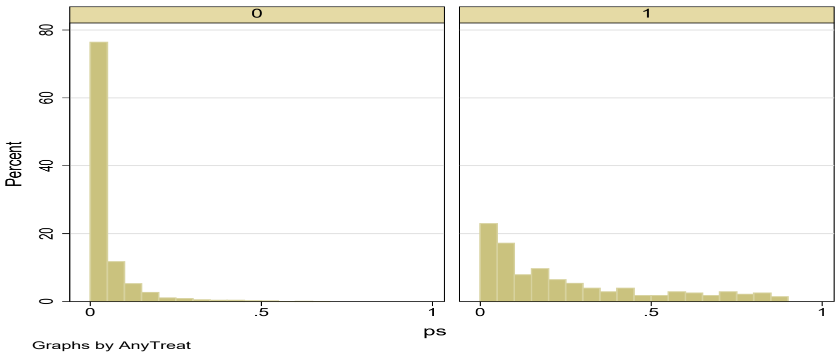
In order to perform the matching, we opt for a nearest neighbors selection with replacement and caliper (a threshold in the maximum score distance). Our preferred estimates

[19]Propensity score is as a synthetic measure to control for several covariates (Rosenbaum and Rubin, 1983).

[20]The four macro-regions are: Northwest, Northeast, Center, South and Islands.

[21]See AppendixB for further details.

Figure 4: Propensity Score by treatment.



Notes: We plot the propensity score for treated firms (firms that are under ETS in the three phases) and untreated ones (firms that have never been under 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.

are based on the comparison with up to five nearest neighbors. We explore as well with one and twenty nearest neighbors, although the results do not change much because of the limited number of matched firms. In our main specification, we impose a caliper equal to 0.1. That is roughly equal to two standard deviations of the propensity score, so that we can address the very large size of some treated firms.

Our preferred estimate is based on one-to-five nearest neighbor matching. Each firm is matched on average with 4.7 firms. The counterfactual for each firm regulated by the policy is constructed starting from the 835 unique firms matched, as the mean outcome calculated among the five untreated firms with the most similar propensity score.

In our main analysis, we define a firm as treated if it has all its plants under ETS regulation throughout all its phases, and non treated if none of its plants is under ETS. We do so for two reasons. First, we want to exclude the possibility for firms under our definition of treatment to reallocate production from plants under regulation to non-regulated plants, with confounding effects on treatment effects. Second, since our outcome variables are ultimately measured at the firm-level, we want to avoid defining a measure for partial treatment, when only a fraction of a firm's plant are under regulation.

5.2 Production function

We follow Ackerberg et al. (2015) estimation approach. In the first stage we estimate

$$y_{it} = \phi(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \tag{5}$$

where $\phi(l_{it}, k_{it}, m_{it}) = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + f_t^{-1}(m_{it}, k_{it}, l_{it}, ETS_{it})$.

Output elasticities with respect to input are estimated in the second stage. Since k_{it} is chosen at time $t-1$ and l_{it} is chosen at $t-b$ where $(0 < b < 1)$, in the second stage we identify β_l and β_k using two independent moment conditions of the productivity shock ξ_{it+1}. These are obtained by the assumptions on the productivity process in (3): the productivity follows a first-order Markov process, implying that ξ is mean independent of all information known at time t. Thus, we rely on the following moment conditions:

$$E\{\xi_{it} A(z_{it})\} \tag{6}$$

where $z_{it} = (m_{it-1}, l_{it-1}, k_{it})$. ξ_{it} is obtained exploiting the Markov chain assumption: $\omega_{it} = E(\omega_{it}|\omega_{it-1}) + \xi_{it} = g(\omega_{it-1}, ETS_{it-1}) + \xi_{it}$. We employ generalized method of moments to estimate labor and capital elasticities. Then, we use these estimates to recover the implied productivity.

5.3 EU ETS effect on TFP

The first approach relies on the assumption that bigger firms have a different productivity process. Therefore, we use firm observables in 2002 related to firm size to allow different evolutions of ω. These observables include firm age, number of workers, number of plants and macro-regional dummies in 2002. That is, we allow the low of motion of productivity, as described in equation (3) to depend on the lagged policy status and on firms observables:

$$\omega_{it+1} = g(\omega_{it}, ETS_{it}, obs_i) + \xi_{it+1} \tag{7}$$

Including obs_i in the data generating process, we allow ω to vary differently depending on the size of the firms, which is correlated with the probability of being treated. Doing so, we can interpret directly the coefficient of ETS_{it} as the marginal effect of being regulated on total factor productivity. In order to isolate the effect of being regulated from time effects and pre-existing differences, we defined ETS_{it} as it is standard in the Diff-in-diff literature. That is, it includes three variables: t a dummy variable equal to one in the years of the treatment, T is a dummy variable equal to one for the treated firms and D_{it} is a dummy variable equal to one for the firms under treatment in the years of treatment. Our variable of interest is D_{it}, which captures the average productivity gains of firms under ETS in the years in which the policy is in act in a given sector.

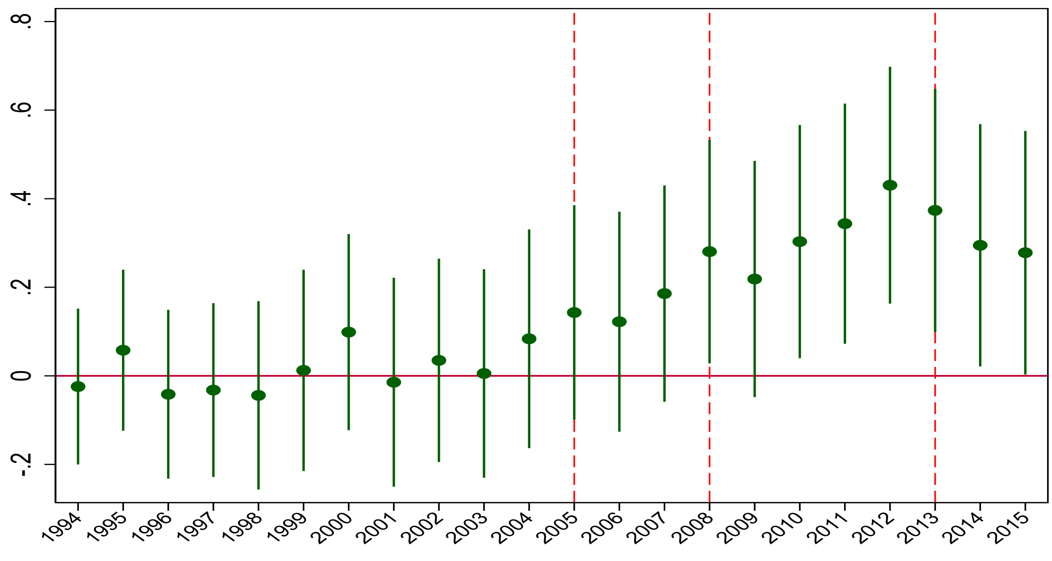
6 Results

In this section, we first present the estimated effect of the policy on material expenditures, gross outputs, capital and labor expenditures in order to verify which of the strategies described in the conceptual framework were undertaken by the firms. Then, we report the production function estimates based on the estimation procedure described in Section 4.2. Lastly, we provide estimates of the effect of the Emission trading scheme following the two strategies described in Section 4.3.

6.1 EU ETS effects

We take advantage of the matching procedure to perform a meaningful comparison of input expenditures for regulated and non regulated firms. In figures 5 we plot the differences in material expenditures over years. The increase in material expenditure of treated firms with respect to untreated ones is consistent with fuel switch and increased TFP.

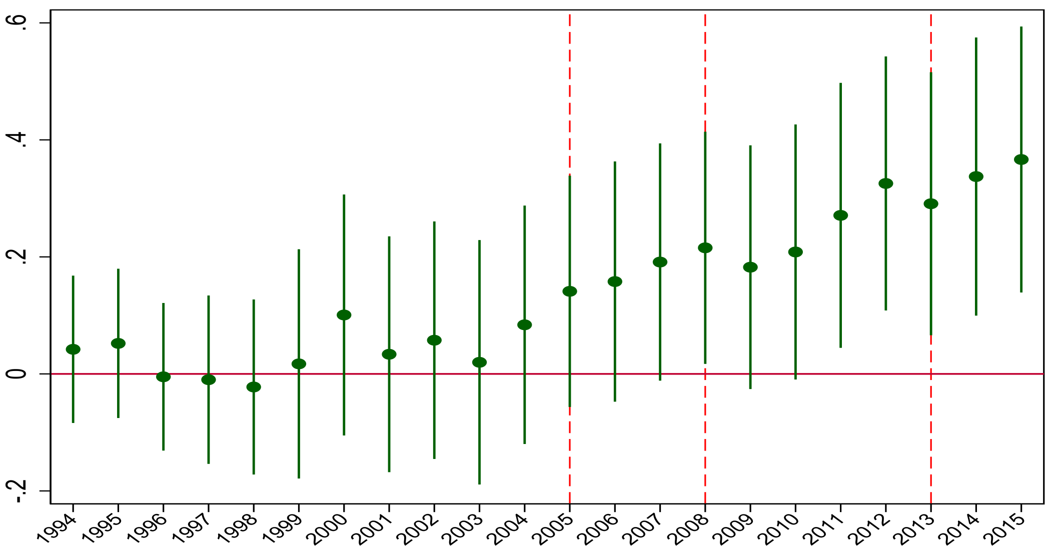
Figure 5: LOG(REAL MATERIAL EXPENDITURES)



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 6 shows that treated firms did not reduce their gross output compared to the untreated ones, instead they increased it. These results are in line with evidences that emissions trading did not lowered employment, gross output or exports of German manufacturing firms (Petrick and Wagner, 2014).

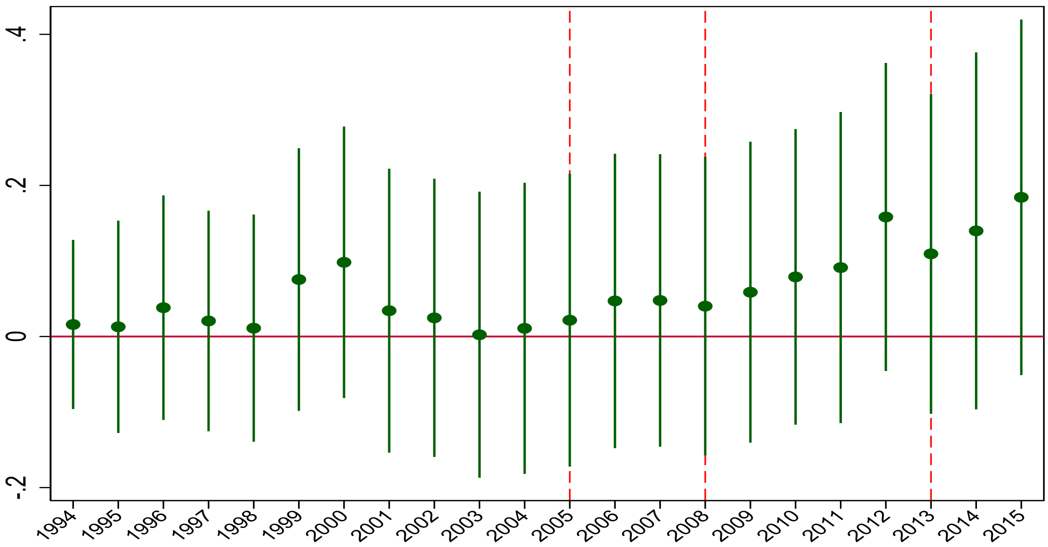
Figure 6: log(Real gross output)



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.

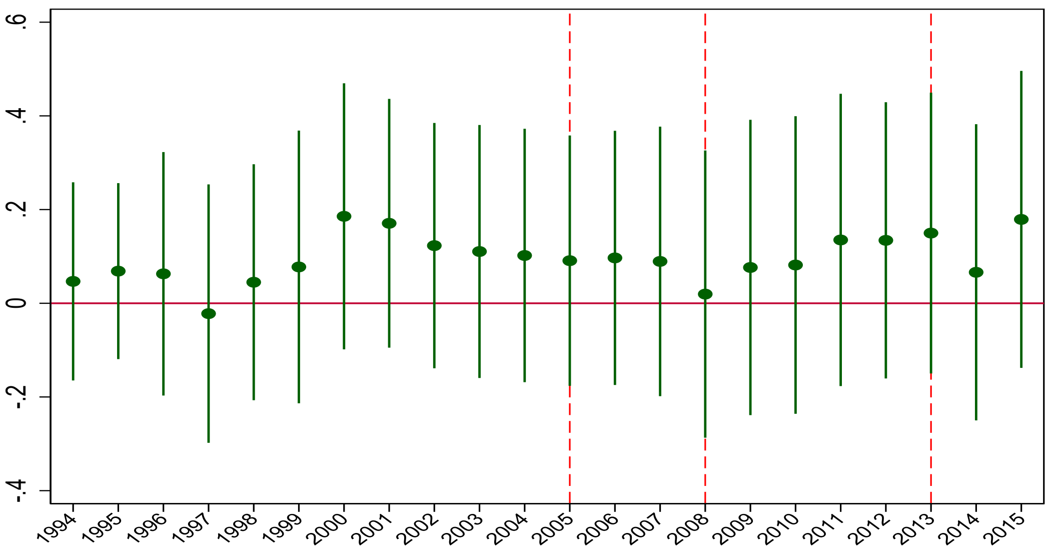
Figures 7 and 8 provide another interesting result: here we plot the coefficients of the regression of the difference of log capital and labor expenditures over years. These shows that the differential increase in gross output was not due to increase in capital and labor but to the increase in material expenditure and total factor productivity. Capital and labor expenditure do not vary differently over time between treated and untreated firms.

Figure 8: 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.

Figure 7: 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.

To conclude, we provide evidences that the introduction of the EU ETS induced an increase in material expenditures. We do not observe fuel expenditures or quantity. However, interviewing the Italian emission registry managers, we can conclude that this evidences are consistent with the trend of treated installations to increase the usage of biomasses and substitute coke with natural gas. Moreover, we show that the indirect effects of the change in price of the emissions predicted by the economic theory are not verified. That is, treated firms do not lower their gross output or inputs with respect to not treated firms. Therefore, firms must have adopted unobservable strategies that can affect estimated production function parameters.

6.2 Production function

Table 2 reports production function parameters' estimates. The first column of each input is the estimate for the reference group (no ETS before the introduction of the policy), the "ETS" columns refer to the additional effect of being a firm under the ETS policy, the "Post Policy" columns report the coefficients of the difference in productivity after the introduction of ETS and, finally, the "ETS Post Policy" columns report the estimate of the differential effect in the elasticity for firms under ETS after the introduction of ETS. That is, the output elasticity for firms under ETS after the introduction of the policy is equal to the sum of all the previous estimates.

Production functions vary significantly across industries, we report here the coefficients of the four ETS process regulated sectors (Pulp and paper, coke and refined petroleum, other non-metallic mineral products and basic metals) and the other four sectors in which there are enough regulated firms to identify the elasticity of inputs with respect to outputs (Food and beverages, textiles, basic chemicals and fabricated metal products).

Results show that letting output elasticity of capital vary between regulated and non regulated firms, this changes quite substantially in some sectors. For instance, in pulp and paper sector regulated firms have an output elasticity more than double than the unregulated ones. However, looking at the differential effect after the introduction of the policy, the change is either small or not significant. Looking at labor productivity, there are some statistically significant differences among the coefficients of the groups, however the magnitude is very small. We can conclude that within industries output elasticity with respect to labor and capital is constant.

As mentioned in the conceptual framework, we are interested in changes in β_m since they could be correlated to firms unobservable decisions such as changes in the quality of materials. The magnitude of the differences between regulated and unregulated firms is small in most of the sectors (5-10% of variation w.r.t. the baseline), suggesting that

Table 2: PRODUCTION FUNCTION ESTIMATES.

Industry	Capital				Labour				Materials			
	Pre Policy	ETS	Post Policy	ETS Post Policy	Pre Policy	ETS	Post Policy	ETS Post Policy	Pre Policy	ETS	Post Policy	ETS Post Policy
Food products and beverages	0.04852 (0.0127)	0.0442083 (0.0331)	-0.03486 (0.02270)	-0.0308245 (0.0075)	0.2437 (0.0078)	-0.0962 (0.0024)	0.0191 (0.0076)	-0.0090 (0.0021)	0.6151 (0.0000)	0.0917 (0.0022)	0.0139 (0.0001)	0.0422 (0.0000)
Textiles	0.0248 (0.0043)	0.0054 (0.0055)	-0.0198 (0.0050)	-0.0476 (0.0022)	0.4136 (0.0077)	-0.0821 (0.0024)	0.0189 (0.0076)	-0.0133 (0.0021)	0.4541 (0.0000)	0.1011 (0.0000)	-0.0064 (0.0001)	0.0648 (0.0000)
Pulp, paper and paper products	0.0335 (0.0111)	0.0567 (0.0165)	-0.0213 (0.0140)	0.0588 (0.0057)	0.3350 (0.0428)	-0.0736 (0.0111)	-0.0561 (0.0295)	0.0354 (0.0118)	0.4989 (0.0000)	0.0267 (0.0001)	0.0590 (0.0004)	-0.0787 (0.0002)
Coke, refined petroleum products and nuclear fuel	0.0744 (0.06516)	-0.0499 (0.0470)	-0.0022 (0.0373)	0.0533 (0.0460)	0.2354 (0.0997)	-0.0833 (0.0659)	-0.1538 (0.0730)	-0.0536 (0.0536)	0.5250 (0.000)	0.0876 (0.0049)	0.1139 (0.0040)	-0.0020 (0.0028)
Basic chemicals	0.04163 (0.0060)	0.0297 (0.0028)	-0.0395 (0.0054)	-0.0022 (0.0019)	0.3339 (0.0082)	0.0460 (0.0016)	0.0418 (0.0129)	0.0549 (0.0012)	0.5277 (0.0002)	-0.0565 (0.0000)	-0.0032 (0.0002)	-0.0108 (0.0000)
Other non-metallic mineral products	0.0559 (0.0070)	0.0894 (0.0093)	-0.0495 (0.0051)	-0.0551 (0.0072)	0.3747 (0.0135)	0.0351 (0.0036)	-0.0260 (0.0104)	0.0148 (0.0044)	0.4932 (0.0000)	-0.1166 (0.0002)	0.0606 (0.0001)	0.0499 (0.0001)
Basic metals	0.0532 (0.0007)	-0.0802 (0.0126)	-0.0348 (0.0080)	0.1007 (0.0018)	0.3045 (0.0094)	0.0523 (0.0068)	-0.0645 (0.0138)	-0.2591 (0.0027)	0.4932 (0.0000)	-0.1166 (0.0000)	0.0606 (0.0000)	0.0499 (0.0000)
Fabricated metal products, except machinery and equipment	0.0554 (0.0061)	-0.0082 (0.0006)	-0.0307 (0.0028)	-0.0616 (0.0019)	0.4277 (0.0041)	-0.2124 (0.0001)	-0.0054 (0.0040)	-0.0154 (0.0018)	0.3746 (0.0000)	0.2299 (0.0000)	0.0274 (0.0000)	0.0782 (0.0000)

Standard errors in parenthesis are computed by employing cluster bootstrap with 100 repetitions.

change in ouput elasticity is not the main channel through which firms readjusted their production functions.

6.3 Effect of ETS on firm productivity

Structural estimation

In Table 3 we report the coefficients of the Markov process, as described in equation (7). The results show a significant but not stable effect of the policy on Total Factor Productivity. Sectors such as textiles, basic chemicals and non metallic products (glass, ceramic, etc.) decrease productivity in the first phase 2-8%, while in the following phases the positive effect ranges between 9 and 20%. In other sectors, such as paper production, coke production, basic metals and machinery production, after an initial positive effect on TFP, they experience a negative effect in the second phase, to recover only in the third phase.

Table 3: Estimated productivity gain due to ETS.

Industry	PhaseI	PhaseII	PhaseIII
Food products and beverages	0.040	-0.091	-0.005
	(0.0000)	(0.0000)	(0.0000)
Textiles	-0.066	0.207	0.097
	(0.0000)	(0.0000)	(0.0000)
Pulp, paper and paper products	0.094	-0.025	0.068
	(0.0000)	(0.0000)	(0.0000)
Coke, refined petroleum products	0.094	-0.025	0.068
and nuclear fuel	(0.0000)	(0.0000)	(0.0000)
Basic chemicals	-0.0793	0.1611	0.068
	(0.0000)	(0.0000)	(0.0000)
Other non-metallic mineral products	-0.0246	0.142	0.089
	(0.0000)	(0.0000)	(0.0000)
Basic metals	0.033	-0.042	0.125
	(0.0000)	(0.0000)	(0.0000)
Fabricated metal products,	0.003	-0.036	0.050
except machinery and equipment	(0.0000)	(0.0000)	(0.0000)

Standard errors in parenthesis are computed by employing cluster bootstrap with 100 repetitions.

Matching diff-in-diff

Table 4 reports the estimated treatment effect based on the difference-in-difference matching estimator described in Section ??. In column 1 we report the nearest neighbor matching with caliper, without adding any other covariate. In column 2 we split the effect of the policy in the three phases.[22] In column 3 and 4 we report the result of the previous two columns adding the industry fixed effect and the interactions. That is, sectoral coefficients should be interpreted as deviation from the mean.

The results show a significant positive effect of the EU ETS on firm-level productivity ranging between 12 and 18% percent points under all specifications. Looking at sectoral level, the positive effect is mainly driven by the manufacture of basic metals and fabricated metal products. The only sector where we estimate a negative effect of the policy is the "Other not metallic product", which include many different sub-sectors (glass, ceramic, bricks and cement).

7 Conclusions

One of the main concerns related to introducing carbon prices is related to the potential negative effect on economic performances. Debates on this topic have animated political discussion when new-phases proposal 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 a more stringent regulation. This paper contributes to this debate investigating the causal effect of the first three phases of the EU ETS on total factor productivity of Italian manufacturing firms regulated by this directive.

The industry production function is structurally estimated, taking into account estimation biased due to the endogeneity and incorporating the possibility that the policy could affect both the input choices and the productivity process. In order to estimate the effect of ETS on firm level TFP, we implemented two different strategies in order to overcome the issues related to EU ETS design: only larger and more polluting firms are regulated by ETS. That is, we recovered the ETS effect from the structural estimation of production function after controlling for observables and we followed a matching diff-in-diff strategy where we matched regulated firms with similar unregulated ones.

[22] Phase I, 2005-2007; Phase II 2008 - 2013; PhaseIII 2014-2015.

Table 4: Matching Diff-in-Diff

	(1)	(2)	(3)	(4)
Policy	0.181		0.135	
	(0.122)		(.023)	
PhaseI		0.173		0.135
		(0.058)		(0.031)
PhaseII		0.156		0.127
		(0.058)		(0.028)
Phase III		0.233		0.147
		(0.063)		(0.032)
		Textiles		
*Policy			-0.006	
			(0.071)	
*PhaseI				-0.053
				(0.089)
* PhaseII				0.013
				(0.100)
*PhaseIII				-0.009
				(0.080)
		Pulp, paper and paper products		
*Policy			-0.082	
			(0.042)	
*PhaseI				-0.102
				(0.044)
*PhaseII				-0.077
				(0.043)
*PhaseIII				-0.069
				(0.060)
		Basic chemicals		
*Policy			0.612	
			(0.166)	
*PhaseI				0.056
				(0.0682)
PhaseII				0.493
				(0.194)
*PhaseIII				0.905
				(0.068)
		Other non-metallic mineral products		
*Policy			-0.232	
			(0.069)	
*PhaseI				-0.204
				(0.075)
*PhaseII				-0.274
				(0.086)
*PhaseIII				-0.190
				(0.088)
		Basic metals		
*Policy			1.492	
			(0.068)	
*PhaseI				1.561
				(0.071)
*PhaseII				1.498
				(0.069)
*PhaseIII				1.429
				(0.103)
Fabricated metal products, except machinery and equipment				
*Policy			0.564	
			(0.086)	
*PhaseI				0.737
				(0.089)
PhaseII				0.547
				(0.053)
*PhaseIII				0.475
				(0.097)
Industry FE	NO	YES	NO	YES
Observations	1,938	1,938	1,938	1,938

The table reports the result of the regression of the difference of log(TFP) over a dummy variable "Policy" equal 1 if a firm is regulated from 2005 to 2015. The dummy variables "PhaseI" "PhaseII" "PhaseIII" refer to the three phases of the policy, namely 2005-2007, 2008-2012, 2013-2015.

We find evidences that support the theoretical predictions that firms would react to an increase in price of emissions switching materials. However, we did not find evidences of decreased outcomes or capital and labor. The main results are related to an increase in total factor productivity in some sectors and, in general, no negative impact of the policy on TFP. This means that firms adjusted their production processes with unobserved strategies that affected TFP.

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Appendix - Not for publication

A 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 $\geq$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).

B Matching procedure

Propensity score definition:

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.

We could have used in this stage 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 in turns 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 used 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 auto-correlated 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 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. [23]

We have at least one firm on 65 strata, i.e. distinct combination of industry and geographical area, but we are able to estimate nontrivial propensity scores only for 34 of these.[24] We further restrict our analysis to a balanced panel of firms: we want to avoid that results are 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).

Caliper definition:

We consider this a conservative choice, that helps addressing the very large size of some treated firms: the number of matched treated firms drops to 228 (27 are dropped). We explore different calipers, generally with consistent results. Yet, we find the choice of the caliper to be very important in 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.

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

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

Figure B.1: Propensity Score by stratum.

Notes: We plot the propensity score for each stratum with enough common support. We restrict the sample away from 0 and 1 to graphically show the overlapping region.