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Abstract

The use of price instruments is often advocated by economists, based on their ability to bring about marginal abatement cost equalisation, and hence to achieve targets at least cost. We use the EU ETS as a case study and test this theoretical prediction. We parametrically estimate separate enhanced hyperbolic distance functions for various industries of the German manufacturing sector and are therefore able to compute the shadow value of CO_2 emissions. We are the first to provide firm-level estimates of the marginal cost of CO_2 emissions using confidential administrative data for German manufacturing firms between 2005 and 2014. This allows for an unprecedented insight into the cost of the EU flagship climate policy for manufacturing firms. We are able to describe the evolution of the abatement costs over time and across industries, tracking the impact of changes in the policy design and its stringency on the behaviour of the firms in our panel. Our findings provide valuable information for policy makers in the European Union and beyond on the actual level of the costs imposed by climate change policy, and its distributional impacts across firms and industries.

JEL Classification: C23, D24, L60, Q52.

Keywords: Hyperbolic Distance Function, Stochastic Frontier Analysis, Cost-effectiveness, Emissions Trading.

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1 Introduction

The diffusion of market-based instruments as the tool of choice for environmental regulation over the past forty years is one of the great success stories in the sometimes turbulent relationship between economists and policy makers.[1] Economists favour market-based instruments because – so the theory suggests – if properly designed and implemented, they allow polluting emissions to be reduced at least cost to society. This result is achieved by providing the right incentives to the firms with the lowest cost of abatement to take on most of the clean-up activities (Stavins, 2003, for example). Indeed, when firms are faced with a price on pollution, they adjust their emissions to reach the point where, at the margin, the opportunity cost of emitting the next unit of pollution equals the abatement cost. Thus – it is claimed – market-based instruments are cost effective in that they bring about the equalization of the marginal cost of abatement across polluters.

The potential advantages of market-based instruments over alternative types of regulations are expected to emerge most clearly, therefore, in situations where the slope of the abatement cost curves differ substantially across firms (Newell and Stavins, 2003). Thus, the heterogeneity of the marginal abatement costs (MAC, henceforth) across sources underpins the claim that market-based instruments dominate other types of regulation in the short run – the so-called static efficiency. Whether MACs converge or diverge over time, moreover, determines the cost-dominance of price instruments in a dynamic sense, as well as giving insights into the effectiveness of trading in reducing compliance costs over time.

While these considerations motivate much of the economists' insistence on market-based instruments, surprisingly little research has been devoted to date to gauging their empirical validity, at least in part due to lack of adequate data. Most of the available empirical evidence to date has focussed on the U.S. experience with SO_2 emissions trading during Phase I of the market established under Title IV of the 1990 Clean Air Act Amendments (e.g. Coggins and Swinton, 1996; Swinton, 1998; Carlson et al., 2000; Swinton, 2002, 2004). As a consequence, the current evidence base is limited to the behaviour of U.S. coal-fired power plants between 1995 and 2000. The results from this literature broadly indicate that while there exists substantial heterogeneity in marginal abatement costs, suggesting the existence of large potential gains from trade, 'much of the cost savings available is being left on the table' (Swinton, 2002, p.402).[2]

This paper contributes to the literature on the effectiveness of emissions trading schemes by presenting evidence on both the level and the time path of the MAC for manufacturing firms under the

[1] According to the World Bank's Carbon Pricing Dashboard (https://carbonpricingdashboard.worldbank.org), as of 2020, 64 carbon related emissions trading initiatives were either implemented or scheduled for implementation, representing 12 $GtCO_2e$ GHG emissions, or 22.3% of global emissions.

[2] Carlson et al. (2000) similarly note that 'a comparison of potential cost savings in 1995 and 1996 with modeled costs of actual emissions suggests that most trading gains were unrealized in the first two years of the program'.

EU ETS. We use firm-level data on German manufacturing establishments over the period 2005-2014 – the first ten years of operation of the European Union Emissions Trading Scheme (EU ETS) – to estimate MACs at the firm level, across a range of industries. To the best of our knowledge we are the first to provide such estimates for firms in the EU ETS, allowing an unprecedented insight into the cost of the EU flagship climate policy. Armed with these estimates, we are able to describe the evolution of the MACs over time and across several manufacturing sectors; we are also able to directly address the claim that market-based instruments deliver cost-effective environmental regulation, a claim that underpins much of the policy debate on this type of instruments. Besides the academic interest of our results, our work is likely to provide invaluable information to policy makers in the European Union and beyond on the actual level of the costs implied by climate change policy, and its distributional impacts across firms and industries.

In what follows, we build on recent advances in the environmental performance analysis literature to estimate the shadow value of carbon dioxide (CO_2) emissions (Cuesta et al., 2009; Mamardashvili et al., 2016). The shadow values we compute measure the opportunity costs of reductions in CO_2 emissions in terms of foregone output, and thus provide a theoretically appropriate measure of the marginal cost of CO_2 abatement. Using the rich, firm-level administrative data made available by the German Statistical Office within the Amtlichen Firmendaten für Deutschland, or AFiD panel, we are able to estimate MACs for over 16,000 German firms, including about 500 firms participating in the EU ETS between 2005 and 2014. These firms provide a significant cross-section of the manufacturing sector in Germany, as they are drawn from such diverse industries as food, paper, chemicals and non-metallic products. Having recovered this information, we are then able to map the evolution of the cost of abatement across the German manufacturing sector over the first ten years of operation of the EU ETS.

Besides fitting within the literature referred to above, our work is related to the growing literature that aims to estimate the cost of market-based environmental policy. A significant portion of this recent literature has applied methods from productivity analysis to Chinese data, with a focus on the impact of the recent emissions trading schemes pilots. Due to a lack of micro-data of adequate quality, however, most of these studies use aggregate, sectoral-level data for different regions or provinces. Lee and Zhang (2012), for example, use Shephard input distance functions to estimate the MAC of CO_2 emissions in a cross-section of 30 Chinese manufacturing industries in 2009. Zhou et al. (2015) study a panel of manufacturing sectors in Shanghai for the period 2009-2011, covering the Shanghai's pilot ETS. Wang et al. (2017) use quadratic directional distance functions to estimate firm-level abatement costs in the steel and iron industry for a cross-section of 49 enterprises in 2014. Finally, Wu and Ma (2019) study the convergence over time of carbon shadow prices using a panel data-set of 286 cites between 2002 and 2013 and find no evidence of convergence across MACs in the medium run. Relative to our work here, the major drawback of these studies is that their models either fail to capture differences in production technology across industries, or are unable to provide a consistent picture of abatement costs over time.

The rest of the paper proceeds as follows, in Section 2 we provide a brief overview of the EU ETS and its design features. Section 3 introduces a simple conceptual framework to guide our analysis. There, we identify the key testable implications that follow from framing the firms' decisions as a compliance cost minimization decision in the presence of allowance trading among heterogeneous firms. In Section 4, we discuss the key methodological issues and our empirical implementation. From there, we move on to describe the data (Section 5). We present our empirical in Section 6 and conclude with a discussion of the main insights and the policy implications in Section 7.

2 The European Union Emissions Trading Scheme

The EU ETS is the central instrument of the European Union's (EU) climate policy and is one of the world's largest multi-national cap-and-trade schemes. It started operations in 2005 in accordance with Directive 2003/87/EC[3] and it currently regulates over 11,000 energy-intensive installations and airlines in 32 countries[4], representing about 40% of these countries' greenhouse gas (GHG) emissions.[5]

In the EU ETS, a cap is set on the total amount of greenhouse gases that can be emitted by the regulated entities. The cap is reduced over time, so that the total allowed emissions fall. Within this cap, firms receive emission allowances, known as EU Allowance Units (EUA), that are fully tradable across participating firms. Each EUA confers to the owner the right to emit one metric tonne of CO_2 equivalent. Regulated companies may also buy limited amounts of international credits from certified emission-saving projects around the world. As the total number of EUAs available is limited by the cap, they represent valuable assets, which creates an opportunity cost for each ton of CO_2 emitted by regulated installations. Participating installations are subject to a rigorous monitoring, reporting and verification process for their permits allocation and trading.

Participation in the EU ETS is mandatory for all combustion installations with a rated thermal input in excess of 20 MW. Industrial installations specializing in certain energy-intensive industrial activities exceeding specific capacity thresholds are also regulated.[6] We note that the inclusion criteria for the EU ETS apply at the installation level, whereas our unit of analysis is the firm. This is potentially problematic as there may be firms that do not own any regulated installation, and still

[3] European Parliament and Council (2003).

[4] At the time of writing these include all 27 EU member states, as well as Iceland, Lichtenstein, Norway, Switzerland and the United Kingdom.

[5] This corresponds to about 4% of global GHG emissions.

[6] Details of the inclusion criteria can be found in European Parliament and Council (2003).

have higher emissions than some firms treated under the EU ETS, as 'treatment' status is assigned according to ownership of at least one included installation. Table 1 shows the total number of regulated firms in our data-set of German manufacturing firms across two-digit industries classified using ISIC Rev.4. codes (see Appendix 7).

The EU ETS has so far gone through three compliance periods, or 'Phases'. Phase I (2005-2007) served as the pilot phase, Phase II (2008-2012) coincided with the compliance period of the Kyoto Protocol, and the third Phase III is currently on-going and will continue until 2020. Having access to data for the period 2003-2014, our analysis focuses on the first two compliance periods and the beginning of the third phase. As noted by Ellerman et al. (2014), in its relatively short history the EU ETS underwent many important developments, both in terms of its scope, as well as its allocation mechanisms. In the first two phases, the allocation of permits was decentralized, relying on National Allocation Plans (NAP) and grandfathering. Firms are allowed to bank and borrow their allowances across years within any given compliance period, but allowances could not be transferred between Phases I and II, while they could be carried forward from Phase II onward. For this reason, Phase I can be perceived as completely decoupled from the following phases. Since the beginning of Phase III, moreover, additional sectors and gases were included, and the default mode of allocation changed to auctioning, while harmonized rules for free-allocation in specific sectors are implemented through a centralized allocation system. A single EU-wide cap is set, which decreases each year by a linear reduction factor of 1.74% of the average total quantity of allowances issued annually in Phase II (2008-2012). In line with the EU ETS 2030 target- i.e. 43% emissions reduction target relative to 2005 – in Phase IV (2021-2030) the cap on emissions will decline at an annual rate of 2.2%.

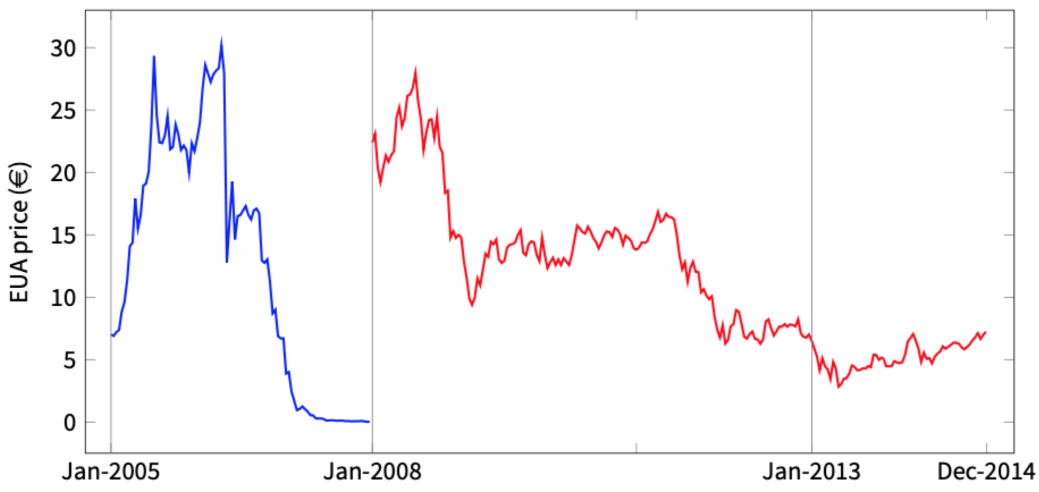


Figure 1: Daily EUA prices evolution in Phase I (2005-2007) and II-III (2008-2014); Source: Thomson Reuters Eikon.

The multiple design changes undergone by the EU ETS may be seen reflected in the EUA spot price development shown in Figure 1. In 2005, EUA prices were above 25 €on average. Due to the vast over-allocation of free allowances in Phase I, the EUA price approached zero in 2007. After the start of Phase II, the price recovered to between 20 €and 30 €, but the massive over-supply of allowances and the decline in economic activity due to the global financial crisis once again resulted in a price collapse during the second half of 2008. At the time, prices were also affected by the heavy use of certified emission reduction credits (CER). As banking was allowed from Phase II, EUA prices did not converge to zero, remaining around 15 €until another price plunge to below 10 €in the second half of 2011.

From its inception, the EU ETS has been the subject of considerable academic research tying up the various theoretical and empirical strands. Ellerman et al. (2016) provide a summary of the history and structure of the EU ETS, and review its performance over its first ten years in terms of emissions, allowance prices, and the use of offsets. The authors recognize three prominent features in the evolution of the scheme: a tendency towards greater centralization of functions, a move from free-allocation of allowances to auctioning, and a reduced role for offsets. Hintermann et al. (2015) discuss the literature on EUA price formation in the second compliance period of the EU ETS. They find that allowance prices were mainly affected by fuel prices, but that the cost of relevant abatement technologies also played an important role. Martin et al. (2015) review the ex-post EU ETS impact evaluation literature studying the behavior of regulated firms with respect to abatement, competitiveness, and innovation. Overall, the available evidence on EU ETS impacts suggests that the introduction of the scheme led to modest emission reductions, and to a small increases in innovation activity, while economic performance has been largely unaffected, with a few exception in specific sectors in a limited number of countries.

3 Marginal abatement costs and emissions trading – some theory.

Since the seminal contributions of Dales (168) and Montgomery (1972), one of the main tenets held by proponents of cap-and-trade schemes has been that they are able to deliver the required emissions reductions at least cost. The economic rationale underpinning this view relies on the incentives faced by emitting entities in the presence of a price on pollution. Once polluting emissions are subject to a charge, rational economic agents compare the cost they need to incur to abate each subsequent unit of pollution to the cost of releasing the pollutant in the environment. In other words, they compare their marginal cost of abating emissions to the current price of emitting the pollutant.

Focusing on the 'uniformly mixing' pollutant case – the relevant one in the case of CO_2 emissions – and limiting ourselves to a situation with just two emitters, the textbook case in favour of cap-and-trade is easily explained using a graph (see Figure 2).

Figure 2 plots the marginal abatement cost curves for two firms, firm *A* on the left, and firm *B* on the right. While they initially emit the same amount of pollution, $\bar{e}$, firm *A* faces relatively lower marginal costs of abatement. Assuming that a decision has been made to reduce emissions by half, we start from a situation where both sources are mandated to halve their own emissions. This situation is captured by points *A* and *B* in the figure where both firms emit 50% of their unregulated pollution. Firm *A*'s marginal cost of abatement is denoted by MAC_A, whereas firm *B*'s is indicated by MAC_B. The gray shaded areas $Ae_A\bar{e}$ and $Be_B\bar{e}$ measure the total cost of abatement facing each of the two firms.

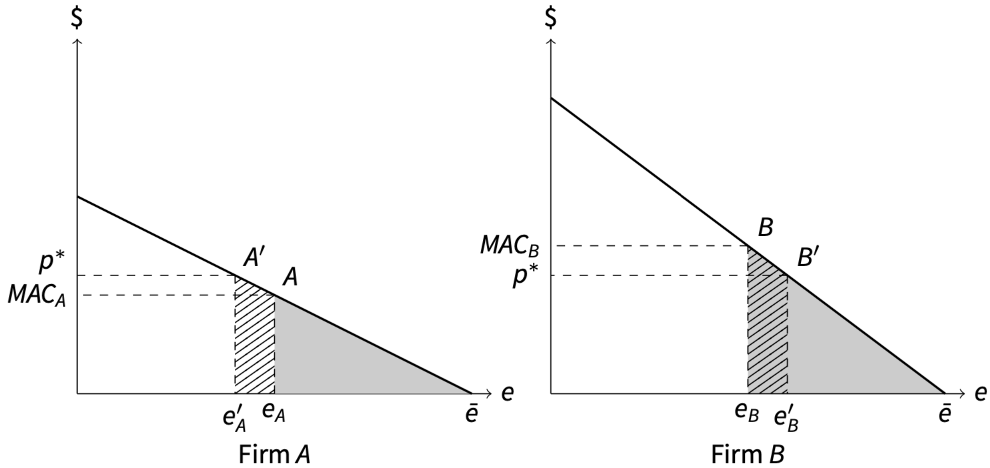


Figure 2: Emissions trading and the equi-marginal principle

Given that in the situation we just described the marginal abatement costs are not equalized across the two sources, it is clear that the overall cost of abatement is not minimized and there exist outstanding gains from trade.[7]

If the emissions reductions were pursued via an emissions trading scheme, each firms would need to submit a sufficient number of permits to cover their emissions. If permits were initially grandfathered based on historical emissions, each firms would receive the same amount of permits, $e_A = e_B$. Since $e_A + e_B = \bar{e}$, the overall cap of this system is consistent with a 50% reduction relative to the unregulated situation. Given that pollution permits are now freely tradable, Firm *A* is willing to sell permits to Firm *B* as long as the price exceeds the cost of abating the following unit of pollution. As Firm *A* takes on more abatement its marginal cost increases, whereas Firm *B* accrues more permits, needs to abate less and moves down along the marginal abatement cost

[7] The gains from trade are a direct consequence of the convexity of abatement costs (i.e., increasing MACs), which is a natural assumption given that firms will carry out the cheapest abatement options first. Suppose that we start at the social optimum, in which the MACs are equalized across firms. Moving away from this point, while holding the cap constant, implies that some firms will have to abate more, whereas others abate less. If the abatement curves are convex, the cost increase for the former is necessarily greater than the cost savings for the latter.

curve. Figure 3 shows that at a price equal to p^*, i.e. at points A' and B', the cost of abatement for firm A has increased by the dashed area in left-hand panel, and decreased for the other firm by the shaded larger area in the left-hand panel. Given that in this situation the marginal cost of abatement is the same across the two sources, the total cost of abatement consistent with the cap has been achieved, and all possible gains from trade have been exhausted.

This discussion illustrates the basic mechanism underlying the working of an emissions trading scheme and suggests that following the introduction of a binding scheme, the permit price would find an equilibrium at a positive level, somewhere in between the MACs of the low-cost and high-cost sources. Based on this insight, one would thus expect to see the median MAC increase as the regulation forces low-cost firms to move up their marginal abatement cost curves to allow the less flexible sources to purchase their permits. This testable implication can be taken to the data.

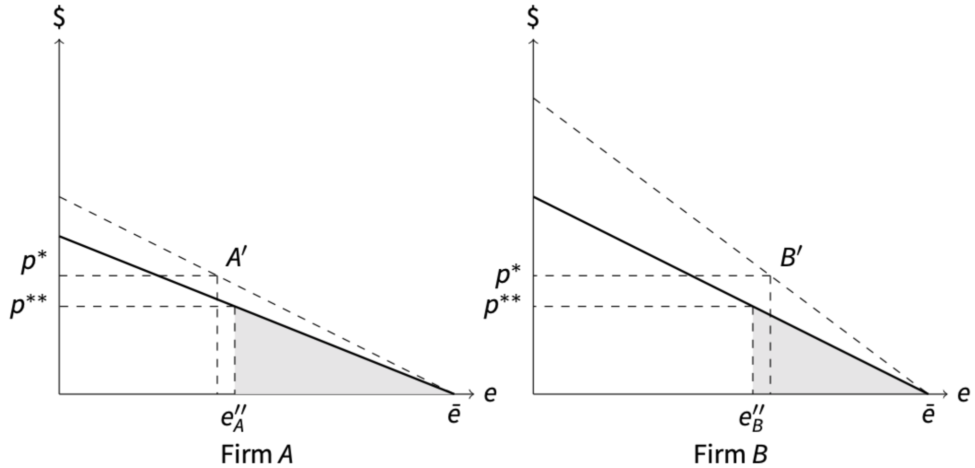


Figure 3: Emissions trading and technical change

A second aspect of the theoretical debate on emission trading that has received a lot of attention in the literature is the dynamic efficiency, namely its ability to induce technological change that would make the achievement of the target cheaper over time (Milliman and Prince, 1989; Goulder and Schneider, 1999; Requate and Unold, 2003; Gans, 2012). If one is willing once again to accept the textbook version of the events, it is easy to discuss the evolution of the MAC over time.[8] Figure 3 illustrates the standard case, where technical change leads to a downward pivot of the MAC curve. In the specific case described in the figure, Firm B manages to reduce its cost of abatement relatively more than Firm A, and is therefore willing to take on relatively more abatement than before. This is not necessarily the case, and the opposite might well happen. When the low-cost firm finds it easier to reduce its costs than the other, it will take on even more of the abatement and sell a larger amount of permits to the high-cost firm. Irrespective of the way in which the overall burden

[8] A rich literature argues that the changes induced to the MAC curve under endogenous technical change are much more complex and interesting than the simple pivot downwards over time described here. See, for example, the discussions in Amir et al. (2008), Bauman et al. (2008), Perino and Requate (2012), and Di Maria and Smulders (2017).

of abatement is shared, however, as long as the supply of permits is fixed, technical change leads to a reduction in the average cost of abatement, and hence in the equilibrium price. As a consequence of technology improving over time, one would therefore expect the average cost of abatement to decrease over time, *coeteris paribus*. This is a second testable implication in this context.

Of course, reality is much more complex than suggested by this stylized discussion, and the behaviour of firms correspondingly richer. For example, one might want to keep in mind is the role of grandfathering. When permits are allocated to firms by the regulator, rather than auctioned, it is difficult and politically unpalatable to set very stringent quotas, at least in the early phases of trading. If firms are given a generous allocation, the system might not felt stringent enough for them to change their behaviour. Thus, an excessive allocation of permits might mean that the shadow prices do not change, at least initially.

Even abstracting from the possibility of over-allocation, the model presented above assumes that MAC curves be smooth objects. In reality, such objects are likely to be step-wise functions at the level of the individual firm, with discontinuities occurring whenever further reductions in emissions require changes in processes or technologies. As a result, from the point of view of the individual firm, abatement might happen at constant, or slowly increasing, marginal cost until a point of discontinuity is reached, at which point purchasing permits might be a cheaper option to continuing abating. Therefore, empirically one might not observe the gradual, smooth changes dictated by the theory.

Furthermore, given that decisions and trades occur over time, it is clear that in a real market the permit price is a moving target and therefore the actual MACs for individual firms would arrange themselves in a spread around any reference price rather than precisely converging to any specific 'equilibrium level'.

Finally, any adjustment in the end depends on the firms learning how best to engage with the market. As learning takes time, especially in the early days of a trading scheme, it is likely that the MAC for different firms would converge rather sluggishly towards any reference level. Additionally, trading markets do not operate in a void and it is likely that they will be buffeted by aggregate shocks. These would lead to changes in the perceived stringency of the regulation, to different expectations and to different market positions across firms and over time.

Overall, while stylized theoretical discussions like the one above lead to clear predictions as to what one might expect to find in the data in the presence of functioning ETS, upon reflection it is difficult to expect that the theoretical predictions be realized as sharply in the empirical data. We will need to keep these aspects in mind when interpreting the patterns that emerge from our results below.

4 Enhanced hyperbolic distance functions and the marginal cost of abatement

Polluting emissions are usually modelled in economics as undesirable by-products of the production of desirable outputs. Pollution reductions are thus seen as the result of the conscious efforts made by firms to reduce such by-products, the MAC may therefore usefully be defined as the opportunity cost – in terms of lost output – of preventing the next unit of pollution being released.

A number of different approaches have been suggested in the literature to estimate the marginal costs of abatement, each with its own advantages and limitations. Bottom-up approaches use engineering estimates of the emissions reduction potential and the corresponding cost of different technical options to compose a curve by ranking these options from the least to the most expensive.[9] While informative as to the available technological portfolios, these analysis are clearly unsatisfactory as they miss most of the interactions and feedback that are relevant to economists, and they do not capture important transactions costs that keep firms from implementing some abatement steps.

Model-derived MAC curve can be constructed using multiple runs of either partial or general equilibrium models.[10] These estimates provide an aggregate picture of the economy-wide cost of abatement, but miss out on much of the nuances and details necessary to grasp the heterogeneous impacts of environmental regulation across firms and industries.

A more econometric approach is sometimes adopted, and the researcher specifies and estimates either the total cost function – to subsequently obtain the marginal costs by first order derivations – or directly the marginal cost functions.[11] The biggest issues with this type of approaches are that cost information data are rarely available, the multiple outputs produced by a firm are difficult to aggregate, and undesirable byproducts are rarely marketed and priced anyway.

In practice, direct cost functions estimation is increasingly replaced by an approach often referred to as environmental performance analysis. This approach relies on the primal representation of the technology for the determination of the technological opportunity cost of reducing undesirable outputs. In the present study, we build on this approach, which has its roots in production theory.

[9] A well-known example for this approach is the "McKinsey curve"; see `https://www.mckinsey.com/business-functions/sustainability/our-insights/greenhouse-gas-abatement-cost-curves`.

[10] Intuitively, price-emission pairs may be calculated in two alternative ways. One may run the models assuming different emission caps and derive the corresponding CO_2 prices, or run the model assuming a range of CO_2 prices and calculating the corresponding CO_2 emission levels.

[11] For empirical examples of total cost function estimations, see Hartman et al. (1997), Carlson et al. (2000) and Dasgupta et al. (2001). For direct marginal cost function estimations, see Wei and Rose (2009), De Cara and Jayet (2011) and Zhou et al. (2013).

Our framework starts from the explicit recognition that undesirable outputs (e.g. emissions) arise in most production processes as by-products of the production of the desirable ones. Keeping in mind both technical and economic constraints, a production possibility set can be defined and estimated, which highlights all the relevant trade-offs. Importantly, production units may have to sacrifice some of their desirable outputs by reallocating their productive resources to emissions abatement. Modelling polluting emissions as the undesirable output associated with the production of the desirable one, we are immediately able to interpret the slope of the transformation frontier as the opportunity cost of the undesirable output in terms of desirable output. Backing out from this ratio the shadow price for the undesirable output, i.e. the shadow price of CO_2 emissions, and recalling the definition of the MAC given above, we directly obtain an estimate of the marginal abatement costs of CO_2 emissions.

One of the advantages of our approach is that it relies on the distance function framework, which solely requires data on inputs and outputs (Shephard, 1953). The classical approaches to derive shadow prices within a distance function framework are based on Shephard radial and directional distance functions in either a parametric or a non-parametric framework (Shephard, 1970). The key difference between the two classical approaches is in their relative flexibility. The radial distance function expands good and bad outputs proportionally, whereas the directional distance function specifies a particular direction along which each output may be expanded or contracted.[12] Recent contributions have pointed out, however, that the classical approaches are inappropriate for environmental analysis, as they lack the necessary flexibility to allow for multiple abatement options (e.g. Zofío and Prieto, 2001; Cuesta et al., 2009).

In this paper, we follow the recent literature and base our analysis on the hyperbolic distance function framework, originally introduced by Färe et al. (1985) and Färe et al. (1989), and expanded upon by Cuesta et al. (2009). This framework is named after the hyperbolic path along which the technical efficiency is measured from the firm's current position inside the production possibility set, to the production possibility frontier, as shown in Figure 4.

Firm A is located inside the production possibility set and is thus technically inefficient. It is possible to project the position of the firm to the frontier and derive a measure of its efficiency in any number of ways. For example, one may choose to project it onto A by increasing its level of output while keeping the level of the input unchanged at X_A. This corresponds to the *output* distance function approach. Alternatively, the firm might be assumed to be able to contract its input use to the frontier while maintaining the original level of production y_A. One more possibility, which is the one we focus on in what follows, is that the firm might be allowed to simultaneously expand output and contract input use. If the expansion/contraction happens that the same rate, the

[12] For more details, see Shephard (1970), Chung et al. (1997) and Du et al. (2015).

projection to the frontier generates a hyperbolic path, and one gets a projection similar to $A - A''$ in the Figure. This latter approach is therefore called the hyperbolic distance function approach. Technical efficiency is measured in this latter case by the ratio $Y_A/Y_{A''}$.[13]

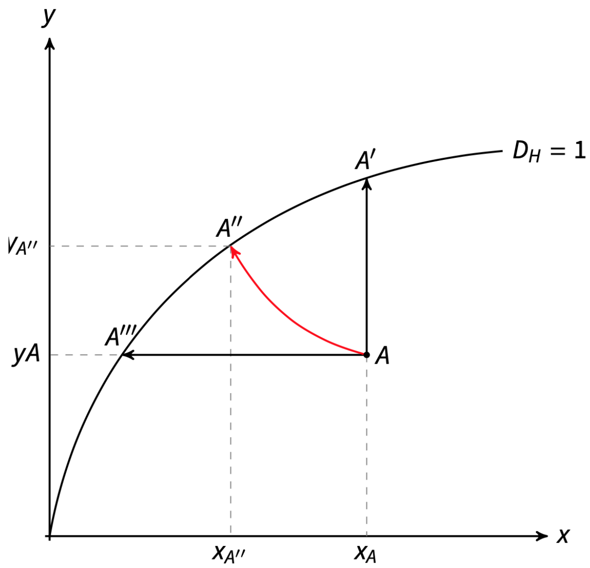


Figure 4: Output distance vs. hyperbolic distance function.
Source: Chaffai (2019)

In what follows, we use an enhanced hyperbolic distance function to measure the performance – known as the enhanced hyperbolic efficiency, $\theta \in (0,1]$ – of each firm.[14] In this context, we measure efficiency in terms of the firm's technical ability to equi-proportionately and simultaneously expand the desirable output vector ($\mathbf{y}$), while contracting the undesirable output vector ($\mathbf{b}$) and the input vector ($\mathbf{x}$), i.e.:

$$D_{EH}\left(\mathbf{x}, \mathbf{y}, \mathbf{b}\right) = \min_{\theta} \left\{\theta \in \left(0, 1\right] : \left(\mathbf{x}\theta, \frac{\mathbf{y}}{\theta}, \mathbf{b}\theta\right) \in T\right\}, \tag{1}$$

where T is the production possibility set,

$$T = \{\mathbf{x} \text{ can produce } \mathbf{y} \cap \mathbf{b}\}.$$

This is the case represented in Figure 4 by the curved arrow. Similar to conventional distance func-

[13] It is worth noting that when adopting an hyperbolic distance function approach, any improvement in technical inefficiency by firm A results in an increase in profits due to *both* an expansion of its revenues and a decline in costs. Conversely, within an output distance function framework firm A would only improve its revenue, holding inputs, and therefore costs, constant, whereas profits improvement only arise from decreases in costs, when using an input distance function approach. This reflects the fact that the hyperbolic distance function is dual to the profit function, whereas the output (input) distance function is the dual of the revenue (cost, respectively) function, see Cuesta and Zofío (2005) for a discussion.

[14] The distance function and the efficiency measurement are *enhanced* as they allow both the inputs and the undesirable outputs to be reduced at the same time as the output is expanded. This contrast with the hyperbolic distance function framework where only inputs and desirable outputs are considered (Cuesta and Zofío, 2005).

tions, hyperbolic distance functions can be estimated in either a parametric or a non-parametric efficiency framework. Non-parametric estimation relies on deterministic linear programming techniques such as the Data Envelopment Analysis (DEA) method introduced by Charnes et al. (1978).[15] This approach may be attractive in some applications as it does not require the imposition of any specific functional form, but do not allow for statistical noise in the data, nor do they allow to model and estimate the efficiency score alongside the frontier estimation.

Here, we apply a parametric approach and postulate, along with most of the literature, that the frontier has a translog specification, which provides a second order approximation to an arbitrary distance function. The translog specification is useful as it allows for the calculation of firm-specific elasticities of substitution between each combination of individual inputs and outputs (Christensen and Greene, 1971).[16] We rely on the Stochastic Frontier Analysis (SFA) model introduced by Aigner et al. (1977) and Meeusen and van Den Broeck (1977). The biggest advantage of this model compared to the deterministic approach discussed above lies in the possibility to explicitly control for the stochastic processes that may affect the efficiency frontier. This framework also allows for the estimation of standard errors and confidence intervals and therefore enables hypothesis testing. In what follows, we borrow extensively from Cuesta et al. (2009) and Mamardashvili et al. (2016) as we use SFA to parametrically estimate our enhanced hyperbolic distance functions.

We start by defining the enhanced hyperbolic efficiency for firm i in year t as:

$$EHE_{it} = D_{EH}\left(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}\right). \tag{2}$$

If the technology satisfies the usual axioms, then the distance function satisfies a number of properties (See Färe et al., 1985; Cuesta and Zofío, 2005; Cuesta et al., 2009, for details). In particular, it is non-decreasing in the desirable outputs, and non-increasing in the undesirable output and in all the inputs as well as being almost homogeneous of degrees (-1, 1, -1, 1).[17]

The almost homogeneity property implies:

$$D_{EH}\left(\frac{\mathbf{x}_{it}}{\lambda}, \lambda\mathbf{y}_{it}, \frac{\mathbf{b}_{it}}{\lambda}\right) = \lambda\, D_{EH}\left(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}\right)\ \forall\ \lambda > 0. \tag{3}$$

[15] Färe et al. (1989) adapted non-parametric hyperbolic distance function for the purposes of environmental performance analysis. This led to the rise of directional distance functions, which are essentially a special case of a hyperbolic distance function. Examples of empirical applications of DEA in this context can be found in Boyd et al. (2002), Lee et al. (2002), Maradan et al. (2005) Kaneko et al. (2010), Choi et al. (2012).

[16] The translog specification is also common in Shephard radial functions applications, whereas quadratic functional forms are usually used for directional distance functions.

[17] Aczél (1979, Ch.7) defines a function Fx, y as almost homogenous of degrees (k_1,k_2,k_3) if $F\left(\mu^{k_1}x, \mu^{k_2}y\right) = \mu^{k_3}F\left(x, y\right), \forall\mu > 0$.

Since equation (3) holds for any $\lambda > 0$, we may set $\lambda = \frac{1}{y_{mit}}$, where y_{mit} stands for the m-th output, and obtain:

$$D_H\left(\mathbf{x}_{it}y_{mit}, \frac{\mathbf{y}_{it}}{y_{mit}}, \mathbf{b}_{it}y_{mit}\right) = \frac{1}{y_{mit}} D_H\left(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}\right). \tag{4}$$

Taking logarithms on both sides of (4) and rearranging, we get:

$$\ln D_{EH}\left(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}\right) = \ln D_{EH}\left(\mathbf{x}_{it}y_{mit}, \frac{\mathbf{y}_{it}}{y_{mit}}, \mathbf{b}_{it}y_{mit}\right) + \ln y_{mit} \tag{5}$$

To derive an estimable form of the hyperbolic distance function, we first append an error term v_{it} to equation (5), and then substitute that expression into equation (2). Rearranging, we get:

$$-\ln y_{mit} = \ln D_{EH}\left(\mathbf{x}_{it}y_{mit}, \frac{\mathbf{y}_{it}}{y_{mit}}, \mathbf{b}_{it}y_{mit}\right) - \ln EHE_{it} + v_{it} \tag{6}$$

where $\ln HE_{it}$ is the familiar (in-)efficiency term, and v_{it} represents statistical noise.

Färe et al. (2002) show that the hyperbolic distance function is the dual of the profit function.[18] This duality is underpinned by the relation between hyperbolic distance function and the Georgescu-Roegen's notion of the 'return to the dollar' measure, defined as the ratio of revenue to expenditure and costs. Since we are interested in the trade-offs that emerge when trying to reduce polluting emissions, we follow Cuesta et al. (2009) and define our profitability function

$$\pi\left(\mathbf{x}, \mathbf{p}, \mathbf{q}\right) = \max_{\mathbf{y},\mathbf{b}}\left\{\frac{\mathbf{py}}{\mathbf{qb}}, : D_{EH}\left(\mathbf{x}, \mathbf{y}, \mathbf{b}\right) \leq 1\right\}, \tag{7}$$

where $\mathbf{p}$ and $\mathbf{q}$ stand for the vectors of desirable and undesirable output (shadow) prices, respectively and $\mathbf{x}$ denotes inputs.

Following Färe et al. (1993), the shadow price for the j-th undesirable output b_j in terms of the m-th desirable one can be expressed as

$$q = p\frac{\partial D_{EH}\left(\mathbf{x}, \mathbf{y}, \mathbf{b}\right)/\partial b_j}{\partial D_{EH}\left(\mathbf{x}, \mathbf{y}, \mathbf{b}\right)/\partial y_m}. \tag{8}$$

The second term at the right-hand side corresponds to the slope of the distance function, i.e. $-dy_m/db_j$, and therefore measures the change in the amount of the good outcome, y_m in this case, necessary to reduce an additional unit of the bad output b_j. Since this is the definition of the MAC for b_j that we started out with, it is clear that (8) gives us the tool we need to compute the MAC.

[18] Similar duality can be proven for other distance functions: the output distance function is dual to the revenue function and the input distance function is dual to the cost function (Shephard, 1970; Färe et al., 1993; Hailu and Veeman, 2000). As the hyperbolic distance function measures the ability to expand desirable outputs (revenue) and contract inputs and undesirable outputs (costs) and is essentially a hybrid of output and input distance functions, its duality to profitability function is intuitive.

To implement the methodology discussed above, we need to specify a functional form for the enhanced hyperbolic distance function. In what follows, we assume a translog specification with one desirable output – the gross value of production – y_1, one undesirable output – CO_2 emissions – b, and four inputs – expenditures for labour, capital, materials, and energy –, which we identify by x_k with $k \in 1, 2, 3, 4$ in the order.

The corresponding translog enhanced hyperbolic distance function (D_{EH}) is therefore:

$$\begin{aligned} -\ln y_{1it} =& \alpha_0 + \sum_{k=1}^{4} \alpha_k \ln \left(x_{kit} y_{1it}\right) + \frac{1}{2} \sum_{k=1}^{4} \sum_{l=1}^{4} \alpha_{kl} \ln \left(x_{kit} y_{1it}\right) \ln \left(x_{lit} y_{1it}\right) \\ & + \beta_b \ln \left(b_{it} y_{1it}\right) + \frac{1}{2} \beta_{bb} \left(\ln \left(b_{it} y_{1it}\right)\right)^2 \\ & + \sum_{k=1}^{4} \gamma_{kb} \ln \left(x_{kit} y_{1it}\right) \ln \left(b_{it} y_{1it}\right) + \psi_t d_t + u_{it} + v_{it}, \end{aligned} \tag{9}$$

where k and l denote the different inputs, i is the firm indicator, t reflects the time dimension, given the panel structure of our data, and d_t indicates time dummies. The composed error terms in equation (9) is comprised of a non-negative inefficiency term, u_{it}, and a random symmetric error term, v_{it}.

We estimate separate enhanced hyperbolic functions by industry, using a Stochastic Frontier Analysis (SFA) approach.[19] To avoid convergence problems, we divide each output and all input variables by their geometric mean. The elasticities can therefore be evaluated at sample means. As we have only one desirable output (y_1), the almost homogeneity conditions are imposed using the gross value of production. We estimate a stochastic half-normal model, which assumes a half-normal distribution for u_{it} and a normal distribution for v_{it}. We follow Mamardashvili et al. (2016) and allow for heteroskedasticity in both u_{it} and v_{it}, i.e.

$$\begin{aligned} \sigma_{u,it}^2 &= e^{\mathbf{z}_i' \boldsymbol{\rho}} \\ \sigma_{v,it}^2 &= e^{\mathbf{w}_i' \boldsymbol{\tau}} \end{aligned} \tag{10}$$

where $\mathbf{z}_i$ and $\mathbf{w}_i$ are variables that affect the variance of each component of the error term and ρ and τ are vectors of parameters to be estimated.

As **z** variables we use dummies that control for the exporting and R&D status of our firms. Our **w** variables, instead, are regional dummies – north, east or west –, keeping the south of Germany as the reference region.

Finally, using the expression in (8) and the estimated technology parameters, we are able to cal-

[19]We estimate our distance functions using Maximum Likelihood Estimation methods. For our estimations we use the statistical software package Stata Version 15. We classify industries at the two-digit ISIC Rev. 4 code level, codes 10-33.

culate firm-specific shadow prices of undesirable output (CO_2 emissions) with respect to the desirable output (gross value of production).

5 Data

To estimate translog enhanced hyperbolic distance functions at the industry level, we use the administrative, confidential panel dataset for German manufacturing firms (AFiD) spanning the ten years between 2005 and 2014.[20] Our desirable output is the gross value of production in euros, (y_1), the undesirable output is CO_2 emissions in metric tons (b), and three inputs: material expenditure, (x_1), capital stock, (x_2) and labor expenditure, (x_3), all of which are once again measured in euros.

The AFiD data-set contains information on the firms' annual general characteristics and their cost structure, and is particularly detailed in terms of the use of fuels and electricity. We construct this unique dataset by combining several microdatasets and modules: the AFiD Panel *Industriebetriebe* (AFiD Panel on Manufacturing Plants), the AFiD Module *Energieverbrauch* (AFiD Module on Energy Use), the *Kostenstrukturerhebung* (Cost Structure Survey) and the *Unternehmensregister* (Company Register). These modules are provided by the German Federal Statistical Office and the Statistical Offices of the German Federal States and the information disclosure is mandatory for all surveyed firms and plants.[21] We additionally combine data from the European Union Transaction Log (EUTL) in order to identify German manufacturing firms regulated under the EU ETS. We also use other external data to calculate CO_2 emissions, and to estimate the capital stocks. The data-sets are finally merged at the firm-level, using plant- and firm-level identifiers. All monetary variables are deflated to 2010 euros. For additional information on the merger, see Appendix 7.[22]

The AFiD Panel Manufacturing Plants contains information on employment, foreign and domestic sales, salaries and investments for all German manufacturing plants with more than 20 employees. We obtain gross value of production from this panel and we deflate it using two-digit ISIC deflators.[23] We follow Lutz (2016) and use the perpetual inventory method and investment information to calculate capital stocks. This method also involves the use of external datasets. The procedure is described in detail in Appendix 7. Having information on foreign sales, we define the firm as an exporter if the sales are positive in at least two consecutive years. This plant-level panel

[20] Note that AFiD stands for *Amtliche Firmendaten für Deutschland*, in English: Official Firm Data for Germany.

[21] Detailed descriptions of the AFiD Panel Manufacturing Plants are provided by Koch and Migalk (2007) and Wagner (2010). The Cost Structure Survey is explained in depth by Fritsch et al. (2004) and Lutz (2016). Additional information on the Company Register can be found in Koch and Migalk (2007). Petrick et al. (2011) thoroughly inform on the AFiD Module on Energy Use.

[22] The AFiD data has been previously used in the context of the EU ETS by Petrick and Wagner (2014), Lutz (2016), Lutz et al. (2017), Richter and Schiersch (2017),Löschel et al. (2019).

[23] The deflators are retrieved from Destatis portal GENESIS at https://www-genesis.destatis.de/genesis/online. Specifically we use the Producer Price Index 61241-0004.

also includes information on the federal state in which the firm's headquarters are located. We use this information to allocate each firm into one of the regions- north, east, west and south.

The AFiD Module on Energy Use provides detailed information on the annual fuel and electricity use at the plant-level. The data is provided in units of energy content (kWh), which allows us to calculate firm-level energy use from 15 different fuels including electricity, district heat and primary fuels. We subsequently calculate direct CO2 emissions by transforming each of the fuel inputs (without electricity) to CO2 emissions using fuel-specific emissions factors.[24]

The Cost Structure Survey reports annual information on various types of costs and inputs at the firm-level. The participation in the survey is mandatory for all German manufacturing firms with more than 500 employees. Information on smaller and medium firms (20 - 500 employees) are collected from a large random sample, stratified at the two-digit industry level and size class level. This random sample is redrawn every four years, and some SMEs are surveyed every time if they operate in certain concentrated industries. We obtain information on R&D expenditures from this survey, and define the firm as an R&D intensive firm if its expenditures are positive in two consecutive years. We obtain our materials and labor expenditures from the CSS and deflate them using two-digit ISIC deflators.

Table 1: Summary Statistics

ISIC Rev.4	Capital Expenditure (1000 EUR)	Labour Expenditure (1000 EUR)	Materials Expenditure (1000 EUR)	Gross Value of Production (1000 EUR)	Direct Emissions (tCO2)	#Firms
10	113285	37706	296892	369905	91393	41
	128644	49351	430683	431809	167025	
17	74348	17215	94710	146263	91063	71
	116044	16434	111291	164412	110632	
20	291604	100087	375796	618008	632746	69
	615444	273923	793477	1360860	2235636	
23	43949	16545	34601	76716	95714	124
	54223	26420	46402	100472	186665	
Sector	266674	134104	630272	817216	309698	478
	963547	620604	2942850	3762113	1531106	

Mean values of the main variables in our model. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

Table 1 presents the summary statistics for the EU ETS firms in our dataset. In our analysis, we focus on four industries, namely Food Products (ISIC code 10), Paper and Paper Products (17), Chemical and Chemical Products (20), and Non-metallic Mineral Products (23), for which we have a sufficient number of ETS treated firms.[25]

[24] We use the CO2 emission factors officially published by the German Federal Office for the Environment, Umweltbundesamt (2018).

[25] FDZ (2017) dictates the confidentiality rules that apply to the export of results based on the AFiD panel. In our cases, we are constrained to a minimum sample size of around 20 EU ETS firms per year, resulting in the four sectors mentioned in the main text.

6 Results

Table 2 presents the results of our estimations of the distance function in (9). The first column refers to the estimation of the distance function at the level of the Manufacturing sector as a whole, the other four columns present estimates for each of the sectors individually. Overall, the the coefficients have broadly the expected sign and tend to be statistically significant.

Table 2: Frontier Estimates - (2003-2014)

	All manufacturing		10		17		20		23	
Variable	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value
β_b	0.001**	(0.009)	-0.006**	(0.002)	-0.000	(0.990)	0.002	(0.320)	0.001	(0.547)
β_{bb}	0.000	(0.971)	-0.003*	(0.026)	0.002	(0.074)	-0.004***	(0.000)	0.001	(0.326)
α_1	-0.224***	(0.000)	-0.205***	(0.000)	-0.175***	(0.000)	-0.189***	(0.000)	-0.242***	(0.000)
α_{11}	-0.049***	(0.000)	-0.070***	(0.000)	-0.048***	(0.000)	-0.028**	(0.001)	-0.118***	(0.000)
α_2	-0.090***	(0.000)	-0.091***	(0.000)	-0.093***	(0.000)	-0.103***	(0.000)	-0.076***	(0.000)
α_{22}	-0.0254***	(0.000)	-0.0510***	(0.000)	-0.060***	(0.000)	-0.068***	(0.000)	-0.049***	(0.000)
α_3	-0.186***	(0.000)	-0.198***	(0.000)	-0.209***	(0.000)	-0.215***	(0.000)	-0.192***	(0.000)
α_{33}	-0.068***	(0.000)	-0.073***	(0.000)	-0.097***	(0.000)	-0.073***	(0.000)	-0.077***	(0.000)
α_4	-0.021***	(0.000)	-0.022***	(0.000)	-0.025***	(0.000)	-0.019***	(0.000)	-0.006	(0.081)
α_{44}	-0.007***	(0.000)	-0.004	(0.091)	-0.031***	(0.000)	-0.022***	(0.000)	-0.025***	(0.000)
α_{12}	0.006***	(0.000)	0.022***	(0.000)	0.027**	(0.005)	0.021*	(0.014)	0.039***	(0.000)
α_{13}	0.040***	(0.000)	0.073***	(0.000)	0.023***	(0.000)	0.033***	(0.000)	0.059***	(0.000)
α_{14}	0.021***	(0.000)	-0.009*	(0.021)	0.005	(0.366)	-0.026***	(0.000)	0.022***	(0.000)
α_{23}	0.019***	(0.000)	-0.004	(0.061)	0.048***	(0.000)	0.032***	(0.000)	0.014***	(0.000)
α_{24}	-0.013***	(0.000)	0.028***	(0.000)	-0.012	(0.069)	0.024***	(0.000)	0.004	(0.394)
α_{34}	0.004***	(0.000)	-0.009***	(0.000)	0.029***	(0.000)	0.011***	(0.000)	0.002	(0.338)
γ_{1o}	-0.006***	(0.000)	-0.011***	(0.000)	-0.001	(0.657)	0.010***	(0.000)	0.003	(0.291)
γ_{2o}	0.007***	(0.000)	0.006*	(0.018)	0.002	(0.518)	-0.011***	(0.000)	-0.005*	(0.039)
γ_{3o}	0.001**	(0.002)	0.014***	(0.000)	-0.008***	(0.000)	0.002	(0.104)	0.002	(0.168)
γ_{4o}	-0.003***	(0.000)	-0.008***	(0.000)	0.005**	(0.009)	0.006***	(0.000)	-0.002	(0.184)
α_0	-0.466***	(0.000)	-0.433***	(0.000)	-0.364***	(0.000)	-0.461***	(0.000)	-0.431***	(0.000)
σ_u^2										
Exporter	0.001	(0.903)	-0.130***	(0.000)	-0.292**	(0.008)	-0.706***	(0.000)	-0.257***	(0.000)
R&D	-0.569***	(0.000)	-0.064*	(0.015)	0.083	(0.256)	0.204***	(0.001)	-0.057	(0.238)
Inv. mach.	0.023**	(0.003)	0.227***	(0.000)	0.281***	(0.000)	0.427***	(0.000)	0.162***	(0.000)
Patents	0.139***	(0.000)	-0.139***	(0.000)	-0.116*	(0.021)	0.185***	(0.000)	0.200***	(0.000)
Constant	-2.001***	(0.000)	-2.527***	(0.000)	-3.557***	(0.000)	-2.772***	(0.000)	-2.658***	(0.000)
σ_v^2										
South	-0.459***	(0.000)	-0.935***	(0.000)	0.071	(0.609)	0.565***	(0.000)	-0.410***	(0.000)
East	-0.547***	(0.000)	-0.861***	(0.000)	0.408**	(0.010)	0.341**	(0.002)	-0.581***	(0.000)
West	-0.544***	(0.000)	-1.164***	(0.000)	1.337***	(0.000)	0.517***	(0.000)	-0.383***	(0.000)
Constant	-4.197***	(0.000)	-3.853***	(0.000)	-5.881***	(0.000)	-4.696***	(0.000)	-4.557***	(0.000)
N.obs.	168,079		20,335		4,763		9,123		8,664	

Notes: This table reports sector and industry-specific enhanced hyperbolic distance frontier estimates. Year fixed effects are included in all estimations.
*, **, *** indicate 10%, 5% and 1% statistical significance, respectively.

Given our specification of the inefficiency component of the error term, $\sigma^2_{u,it}$, in (10), a larger value for the variance implies a lower level of efficiency for the firm. Consequently, when interpreting the coefficients a negative one suggests that the variable it refers to contributes positively to the firm's efficiency. For example, in line with the literature on exporting and productivity, we find that for all the sectors we investigate, firms that are flagged as 'exporters' tend to have a higher level of efficiency (Bernard et al., 1995; Bernard and Bradford Jensen, 1999; Aw et al., 2011; Atkin et al., 2017). Interestingly, we also find that a higher level of investment in machinery is associated with a lower level of efficiency.

The estimates in Table 2 are used to compute the shadow price of carbon emissions in terms of output, i.e. the marginal abatement cost, for each of the firms in our sample. Table 3 shows the shadow price, for each year in our sample, in terms of the mean, median, 10th and 90th percentile. Tables A.1-A.4 in the Appendix contain the corresponding results for 2-digit industries.

Table 3: Shadow prices for EU ETS firms - All Manufacturing (2003-2014)

Year	N.obs.	Mean	10th perc.	Median	90th perc.
2003	315	51.60	1.40	10.52	138.99
2004	323	46.12	1.26	9.49	111.49
2005	311	42.23	1.39	10.21	85.67
2006	307	138.30	1.40	12.03	134.79
2007	330	293.89	1.27	10.16	155.06
2008	362	209.85	1.40	9.31	97.11
2009	396	244.41	1.28	9.94	101.48
2010	396	92.72	1.26	10.61	103.54
2011	385	221.58	1.34	10.10	111.20
2012	397	319.32	0.86	9.22	92.86
2013	397	286.75	1.06	9.39	95.39
2014	400	197.15	1.23	8.60	115.28

Notes: This table reports shadow prices computed based on the estimates for each industry's frontier for ETS firms.

The first aspect that emerges from these results is that there is significant heterogeneity both across and within industries. From the first point of view, both the Paper and Paper Products (ISIC 17) and the Non-metallic Mineral Products (ISIC 23) industries have significantly lower shadow prices than either the Food and Food Products (ISIC 10) and Chemical and Chemical Products (ISIC 20) ones. While the median price ranges over time between 25 and 15 €/ton in the former industries, a level broadly in line with current and historical market prices, in the two other industries the median values hover between 80-100 in most years.

The range of variation within each of the industries is also significant. The 10-90 percentile spread is significant even for low-cost industries – among Paper and Paper Products firms, the spread is over 250 €/ton in 2005 – and positively staggering in high-cost ones – in Food and Food Products, the spread exceeds 600 €/ton in multiple years.

These estimates imply that compliance with the EU ETS might be very onerous indeed for some firms in the absence of emissions trading. They also point to a very skewed distribution of MACs among firms and industries, suggesting that there exists significant scope for cost savings from permit trading among German manufacturing firms.

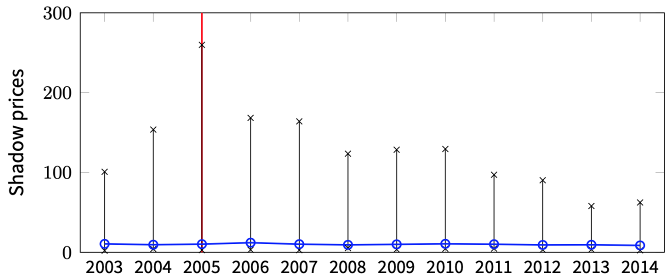
Having estimated the enhanced hyperbolic distance function and derived the shadow prices for CO_2 emissions for each of the firms in the four industries we discuss here, we are now in a position to turn to the main objective for this paper, i.e. to assess the claim that emission trading leads to the equalization of the marginal cost of abatement across sources over time - see Section 3.

In Section 3, we put forward the suggestion that, following the introduction of emissions trading, one would expect at least some firms to move up their MAC curve, both to comply with the new restrictions and to take advantage of the possibility of selling surplus permits on the market. As a consequence, the first piece of evidence that emissions trading changes the behaviour of firms in ways consistent with the theory would be to find an increase in the MAC, especially at the lower end of the MAC distribution.

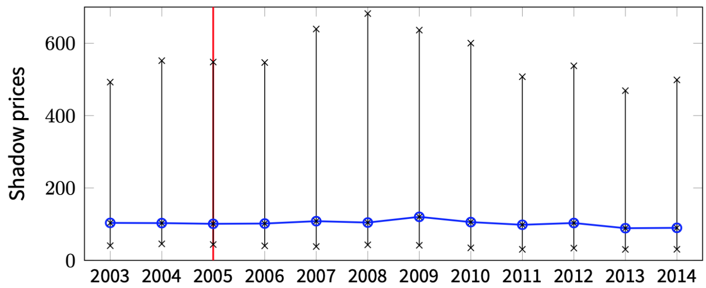
To address this question, we graph our industry-specific results in Figure 5. The graphs plot the 10-90 percentile spread of the MACs for EU ETS firms in the whole sector and in each industry, together with the median (the continuous line in the graphs). For most of the industries and manufacturing as a whole, the median increases over the first phase of the EU ETS, suggesting that in line with the theory, and despite the generous allocation and the low permit prices, some degree of abatement did take place in the EU ETS during phase I (Ellerman and Buchner, 2008; Anderson and Di Maria, 2008).

The second testable implication discussed above focussed on the role of technological change, both in terms of innovation proper and adoption of best practices. Our discussion led us to conclude that over time, as new processes and technical solutions are developed and adopted, firms should become more adept at abating their emissions, and the marginal costs should decrease, *coeteris paribus*. Our graphs provide suggestive evidence that this is indeed happening. For all our industries, and very markedly for manufacturing as a whole, the 10-90 percentile spread narrows remarkably and the lower bound decreases over time.

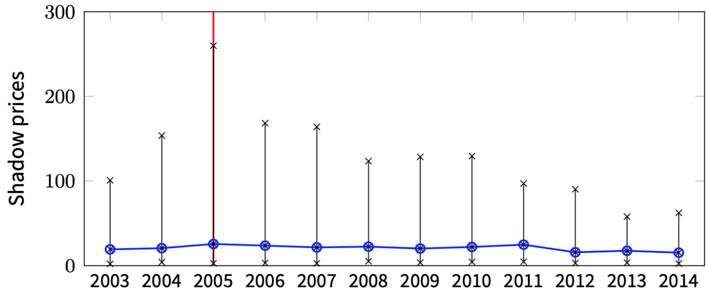
This is work in progress. In a future update of this paper, we will econometrically test for convergence. Furthermore, we will test whether firms with low abatement costs (as measured before the start of the EU ETS) have lower emissions per unit of production than otherwise similar firms that have a higher abatement cost. Such a shift of abatement from low-cost to high-cost firms is the source of the efficiency gain of an ETS relative to a command-and-control regime that would require equal (proportional) abatement across all firms.



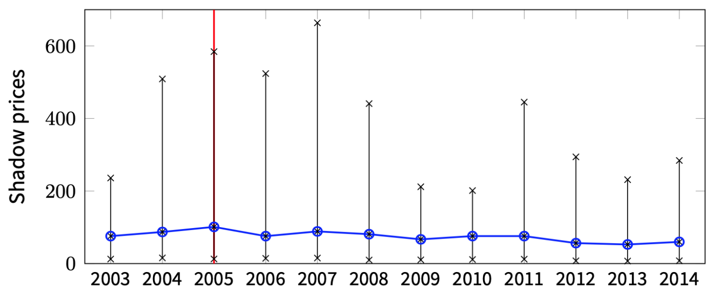
(a) All Manufacturing (ISIC 10-33)



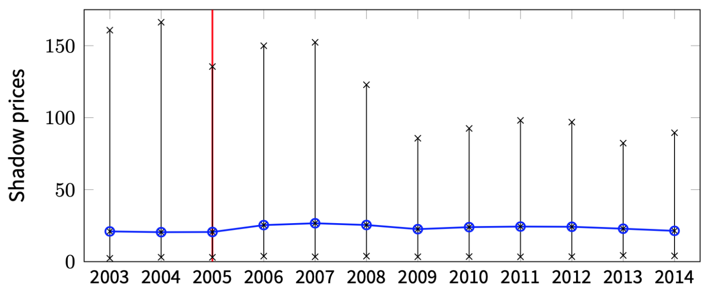
(b) Food and Food Products (ISIC 10)



(c) Paper and Paper Products (ISIC 17)



(d) Chemical and Chemical Products (ISIC 20)



(e) Non-metallic Mineral Products (ISIC 23)

Figure 5: Evolution of the shadow price over time, for the manufacturing sector overall (top) and for individual industries.

7 Discussion and conclusions

In this paper we aimed to shed some empirical light on the theoretical prediction that emissions trading allows the achievement of pollution reduction targets at least cost. We focussed on the EU ETS as our case study and used a panel of confidential data on over 16,000 German manufacturing firms between 2005 and 2014. Within an enhanced hyperbolic distance function approach, we are able to construct estimates of the shadow price of CO_2 emissions for each firms in each period. Since these shadow prices represent the opportunity cost, in terms of foregone marketable output, of reducing emissions by one tonne, they provide a direct estimate of the marginal cost of CO_2 abatement.

The median marginal costs of abatement we estimate range from as low as 10 €to over 150 €for the manufacturing sector as a whole, suggesting that there exist ample scope for trading among manufacturing firms and much cost saving to be had.

Using the shadow prices, we compare their evolution of time to the theoretical priors derived from a model of compliance cost minimization in the presence of emissions trading. The theory suggests that the MAC should increase, following the introduction of the emission trading scheme, as low cost firms move up their marginal abatement cost curves to comply with the regulation and to benefit from the returns provided by trading their excess allowances. The second prediction that we derive from our discussion of the theory is that, *coeteris paribus*, as new technologies are brought to bear on the process of abatement over time, the marginal cost of abatement should decline.

Despite the many confounding factors present in the data, our empirical estimates speak clearly of (median) shadow prices that increase over the first few periods of the EU ETS, reflecting the increased drive to reducing emissions; they also provide evidence of a narrowing in the spread of shadow prices over time and a decline in both the lower bound of the distribution we focus on and in the median. Both these patterns are consistent with the theoretical predictions and we take them as suggestive evidence that emissions trading operates in practice like the theory suggests.

These findings ought to provide valuable information for policy makers in the European Union and beyond on the actual level of the costs imposed by climate change policy, and its distributional impacts across firms and industries within a crucial and politically sensitive sector like manufacturing.

Note: Parts of this is work are still in progress and as such subject to change. We kindly ask the reader to refer to the most recent updates of our work by using the external **link** provided at the beginning of the document.

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Appendix

Further Data Description

2-digit industry level classification:

In the period 2005-2008, the industry classification in our dataset ("Wirtschaftszweig") is based on NACE Revision 1.1. After 2008, the classification has changed in accordance with the European implementation NACE Revision 2 (Statistical Classification of Economic Activities in the European Community) of the UN classification ISIC Revision 4. We reclassify the years before 2008 using official reclassification guide of the German Statistical Offices at the four-digit industry code level, to be able to use the ISIC Rev.4 classification throughout.[26] In the interest of having enough observations, we carry out the final analysis on the two-digit industry level and estimate separate hyperbolic and enhanced hyperbolic distance functions for each two-digit industry.

Merging of AFiD and EUTL:

We combine different modules of AFiD data set via plant and firm-level identifiers. Matching AFiD data with EUTL requires a multi-step procedure. First it is combined with the German Company Register using information on commercial register number, VAT number and the address in order to obtain a unique company identification number. Using the latter, the external dataset can be combined with the AFiD dataset. We were able to assign 83 percent (1117 firms) of the firms in the EUTL a commercial register number and merge it with AFiD. The firms that are not matched mainly belong to non-manufacturing sectors. We proceed by dropping all non-EU ETS firms from the final dataset.

[26] For more details on reclassification codes, see Statistisches Bundesamt (2008).

Additional Tables and figures

Table A.1: Shadow prices - Food products (2003-2014)

Year	N.obs.	Mean	10th perc.	Median	90th perc.
2003	33	197.11	40.63	103.61	492.72
2004	33	218.13	45.72	103.05	551.97
2005	34	205.37	43.85	101.06	548.19
2006	34	199.85	40.22	101.82	546.88
2007	36	249.66	38.28	108.38	639.36
2008	41	320.92	42.98	104.55	682.06
2009	41	356.59	41.71	120.31	636.35
2010	43	299.32	34.57	105.80	600.41
2011	43	279.51	30.49	98.38	507.57
2012	45	209.00	33.90	103.30	537.77
2013	46	186.44	30.32	88.96	469.11
2014	45	182.49	30.65	89.90	498.81

Notes: This table reports shadow prices computed based on the estimates for each industry's frontier for ETS firms.

Table A.2: Shadow prices - Paper and paper products (2003-2014)

Year	N.obs.	Mean	10th perc.	Median	90th perc.
2003	47	49.64	2.02	19.22	100.82
2004	44	56.96	4.13	20.64	153.68
2005	45	147.42	2.75	25.60	259.86
2006	47	70.16	3.16	23.62	168.33
2007	48	61.14	2.72	21.57	163.98
2008	53	45.95	5.24	22.43	123.49
2009	52	44.05	3.56	20.20	128.45
2010	56	57.09	4.44	22.07	129.38
2011	57	47.18	4.65	24.77	97.09
2012	59	42.95	3.13	15.78	90.25
2013	56	35.73	3.47	17.58	57.97
2014	63	34.75	2.47	15.30	62.41

Notes: This table reports shadow prices computed based on the estimates for the industry's frontier for ETS firms.

Table A.3: Shadow prices - Chemicals and chemical products (2003-2014)

Year	N.obs.	Mean	10th perc.	Median	90th perc.
2003	54	128.91	12.40	75.74	235.90
2004	56	154.15	15.65	87.15	509.00
2005	58	165.14	12.70	101.11	584.34
2006	59	211.28	14.38	75.64	523.84
2007	59	199.88	15.25	88.66	663.65
2008	68	421.40	9.77	81.03	440.98
2009	67	109.82	10.23	66.79	211.75
2010	71	129.71	11.18	75.82	201.29
2011	71	180.17	12.10	75.74	445.08
2012	77	252.91	7.64	56.39	294.12
2013	75	135.15	6.98	52.68	231.31
2014	76	140.29	7.78	59.74	284.24

Notes: This table reports shadow prices computed based on the estimates for the industry's frontier for ETS firms.

Table A.4: Shadow prices - Other Non-metallic products

Year	N.obs.	Mean	10th perc.	Median	90th perc.
2003	84	70.39	2.32	20.99	160.76
2004	90	49.57	3.05	20.47	166.27
2005	90	47.80	3.02	20.58	135.50
2006	93	50.94	3.83	25.37	149.95
2007	96	60.95	3.36	26.66	152.33
2008	113	45.95	3.82	25.44	122.86
2009	113	35.82	3.39	22.57	85.66
2010	115	39.27	3.52	23.96	92.55
2011	117	42.85	3.35	24.36	98.13
2012	121	40.56	3.47	24.21	96.94
2013	120	40.66	4.33	22.87	82.28
2014	121	39.45	4.03	21.38	89.51

Notes: This table reports shadow prices computed based on the estimates for the industry's frontier for ETS firms.