Economically, do environmentally regulated firms perform worse? Evidence from the German manufacturing sector

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1 Introduction

The European Union (EU) has continuously been at the forefront of international climate policy, and the Paris Agreement has only consolidated the significance of its role. While the EU addresses climate change with many different approaches and mandates, the 2005 European Union Emissions Trading Scheme (EU ETS) stands as its single most important instrument in its climate policy. A priori, theory cannot discern how firms respond to the EU ETS. This is especially concerning if pollution abatement, which is the primary goal of this regulation, diminishes firms' economic performance. The relation between the EU ETS and the economic performance of firms becomes apparent through various possibilities of complying with the regulation. Namely, a regulated firm may surrender allowances to legitimate its emissions or sell the surplus on the market, in any case there are opportunity costs to emissions. A firm can also abate emissions through the change in input choice (e.g., switching fuels) or the adjustment of its production process (e.g., investment in energy efficiency or a reduction of fuel usage). Alternatively, a firm may choose to develop less emission intensive products or reduce its output. Further, compliance options are heterogeneous among firms and temporally different; some are viable in the short run, and some only in the long run.[1] Although all the abatement options will either demand an investment, reduce revenues, or increase costs, the empirical evidence on the EU ETS' impact on regulated firms is scarce. Therefore, researchers have argued that " a better understanding of the relationship between firms' behavior and the EU ETS is needed, not just for improving this specific climate policy, but also other emerging cap-and-trade programs" (Martin et al. (2015)).[2] This study is one response to this need. I use cost efficiency as a measure of economic performance and analyze its interplay with the EU ETS. The confidential data come from an administrative firm-level German production census (AFiD) over the period from 2003 to 2014 (T=12). Official governmental statistics and reports on the activities of the manufacturing sector also use these data. For narrowly defined industries in the German manufacturing sector, I first estimate cost frontiers using a stochastic cost frontier (SCF) analysis and determine time-varying firm-specific cost efficiencies.[3] Second, the SCF analysis allows me to explore the various potential drivers of firm-specific cost efficiencies: the regulation by the EU ETS, trading activity in emissions allowances, investments into research and development,

[1] Christiansen et al. (2005), Kanen (2006), Bertrand (2014), and Calligaris et al. (2018) recognize switching fuels as the dominant type of short-term abatement of firms participating in the EU ETS, due to relatively low related costs and small potential effects.

[2] As of 2017, governments had implemented 46 carbon pricing initiatives, or had scheduled implementation, around the globe. Half of them rely on ETS-type initiatives, and the other half on carbon taxes. Together these carbon pricing initiatives cover 8 gigatons of carbon dioxide equivalent ($GtCO_{2e}$) or 15 percent of global greenhouse gas (GHG) emissions. ETSs account for roughly two-thirds of the covered GHG emissions Klein and Lam (2017)).

[3] Throughout this paper, industries in the German manufacturing sector are classified according to the International Standard Industrial Classification of All Economic Activities (ISIC Rev 4.) of the United Nations. My narrow definition refers to 2-digit industry codes ranging from 10-33.

and exporting activity. Third, I use a stochastic meta frontier (SMF) analysis in order to compare yearly cost efficiencies between different industries in the German manufacturing sector and within each industry itself, as most of these industries comprise regulated and unregulated firms that potentially operate under heterogeneous frontiers in the long run. This analysis estimates meta cost efficiencies, the drivers of meta cost efficiencies, and the cost gap ratios. Fourth, after comparing cost efficiencies within and between industries, I identify and quantify the average treatment effect of the EU ETS on the cost efficiencies of regulated firms for a subset of 2-digit industries in a difference-in-differences (DD) framework. Fifth, for a subset of 2-digit industries, I perform a decomposition of the cost efficiencies into two sources, the technical and allocative efficiencies, by using a primal system approach (PSA). In my analysis I expose and address potential endogeneity issues in the selected cost frontier model and in the violations of the stable unit treatment value assumption (SUTVA). My empirical strategy is rooted in two hypotheses. My first hypothesis states that the EU ETS is not a significant driver of firm-level cost efficiency. The principal change that regulated firms experience when participating in the EU ETS is a relative increase in their input price because the regulation places a cost on their GHG emissions that unregulated firms do not experience. Unlike in the existing EU ETS impact evaluation literature, I account for the direct regulation of firms by the EU ETS in the frontier itself. I adjust the energy input price of regulated firms by adding the carbon price to their energy price. This way, the regulated firms' cost containment capabilities, are not by construction worse than their non-regulated counterparts'. My second hypothesis recognizes that for the EU ETS to be dynamically efficient, it must provide incentives for not only the emissions abatement but also for the innovation in clean technologies. The development of low-carbon technologies will ensure a cheaper reduction in carbon emissions in the future (Martin et al. (2015)). With the fixed technology, therefore, some abatement options, such as switching fuels, are limited. Furthermore, the EU ETS continuously decreases the cap on emissions to encourage stringent abatement behavior. To keep reducing emissions, at least a subset of regulated firms will have to innovate, which is in line with Hicks (1932), Porter (1991), and the widely popular Porter Hypothesis (Porter and Van der Linde (1995)).[4] Hence, for regulated firms in certain industries, their production isoquants may change in response to higher relative input prices as they experience the technical change through the induced innovation.[5] This dynamic can be described as divergence. This study divides the firms of the industries in the German manufacturing sector into two groups of firms: the group of "innovators" that comprises regulated firms, and the group of "non-innovators" that comprises unregulated firms. The SMF analysis enables the direct comparison of cost efficiencies between groups of firms operating under different technologies. The use of different technologies is embedded in my empirical setup in two different ways. First, in the absence of any innovation, firms operate in various industrial groups of the German manufacturing sector that use different technologies to produce different types of products. This difference requires the estimation of separate SCFs for each industry. Second, in the presence of innovation, regulated firms within a specific industry potentially innovate due to stringent environmental regulation, and therefore start operating under different technology compared to their unregulated counterparts. But the EU ETS also potentially has an indirect effect on unregulated firms. Both regulated and unregulated firms operate in the same market, provided they sell the same types of products. Due to increased prices for regulated firms, market shares are likely to shift towards the unregulated firms that represents indirect regulation by the EU ETS through competition. Both regulated and unregulated firms buy energy inputs, but regulated firms can pass through the higher energy input costs, which in turn again indirectly affects

[4] The Porter Hypothesis (PH) argues that a stringent environmental regulation does not necessarily harm firms' competitiveness, but actually even enhances it through enticing the restructuring of firms' operations. As Stadler and Di Maria (2018) point out, the PH inherently contrasts the traditional neoclassical view of firms' optimal production behavior, and instead argues that "there are ample opportunities for firms to make efficiency gains under the push of stringent environmental regulations." For an introduction to the PH, and an overview of the related literature, see Ambec et al. (2013)

[5] This change can also be described as a "jump" to a new cost frontier, which is in line with Breustedt et al. (2011).

unregulated firms (see Hintermann (2016)). An additional concern is knowledge spillovers that occur when regulated firms innovate. Nothing prevents unregulated firms from adopting this new innovation. In an empirical framework, the potential indirect regulation of the control group is known as the violation of the SUTVA. I develop robustness checks that address these concerns in various ways.

The literature that evaluates the impact of the EU ETS identifies emissions, economic performance, competitiveness, and innovation as the main outcomes of interest.[6] This literature only briefly addresses the firms' performance in terms of productivity. Recent work by Calligaris et al. (2018) combines the structural estimation of the firms' production function and techniques for policy evaluation to estimate the effect of the EU ETS on Italian manufacturing firms. Their findings show a significantly positive effect of the policy on total factor productivity that ranges from 12 to 18 percentage points with heterogeneous effects across industries. The manufacturing of basic metals and fabricated metal products is the main driver of this effect. Stadler and Di Maria (2018) focus on UK manufacturing and investigate the interplay between the UK Climate Change Levy and firms' technical efficiency. They estimate stochastic production frontiers in four large manufacturing industries. Their results confirm that the levy had a significantly positive impact on firms' technical efficiency. Particularly relevant to my work are the few studies that use the same confidential microdata for the German manufacturing sector to investigate different measures of productivity. Lutz et al. (2016) estimate industry-specific stochastic energy demand functions. For the period from 2003 to 2012, they identify determinants of the energy demand function and analyze potential drivers of energy efficiency. They find that energy use has increased over time across all industries, with a range of 2.7 to 6.2 percent per year. The estimated own-price elasticities of energy demand are estimated to range from -0.39 to -0.80. Their results show that exporting firms are for the most part more energy efficient than non-exporting firms. Lutz et al. (2016) also shows that firms that eventually fall under the EU ETS are less energy efficient in most industries than their unregulated counterparts. Investment into environmental protection and into research and development shows a positive association with energy efficiency. Löschel et al. (2016) combine the use of a SCF analysis and a DD approach with parametric conditioning strategies to investigate the relation between the EU ETS and firm-level technical efficiency in the period from 2003 to 2012. They find no significant effect of the EU ETS on the technical efficiency of regulated firms. When they analyze the treatment effects at the 2-digit industry level for four different industries, their results range from 1.34 to -1.67 percent. Further, they only find statistically significant and positive results for the paper industry. Lutz (2016) estimates the effects on firm-level total factor productivity using a structural production function approach for the period from 1999 to 2012. His results indicate a significantly positive impact of the EU ETS on the productivity during its first phase that ranges from 0.5 to 0.7 percent.

This study departs from the aforementioned literature along several dimensions. Existing studies on productivity analysis only use the production frontier approach. Kumbhakar et al. (2015) indicate that although helpful, this approach cannot address some of the key economic questions and concepts that are still not discussed in this literature, as it focuses solely on the technological input-output relation. Unlike prior efforts, I use a different measure of economic performance, the cost efficiency. The cost efficiency,also known as economic efficiency, reflects the embedded economic behavior of the cost frontier (firms' cost minimization). This measure is estimated with a SCF (Farell (1957)). In a cost minimizing framework, input allocation is optimal if producers allocate inputs such that the input price ratio equals the ratio of their marginal products. In that case, the actual cost differs from the optimal cost by the technical efficiency. If, however, the input allocation is suboptimal, the cost is higher due to both technical and allocative inefficiencies. My dataset contains

[6] For comprehensive overviews of these studies, please see Martin et al. (2015), Ellerman et al. (2016), and Joltreau and Sommerfeld (2016).

information not just on the production technology but also on the relative price ratios of inputs that allows me to examine the impact of both sources of inefficiency on costs through the decomposition of the cost efficiency by using the PSA. To my knowledge, no prior studies have empirically applied the PSA. This application means that in addition to examining whether and by how much a regulated firm can reduce its costs, I am able to identify how much of this cost reduction a firm can achieve through improvements in the production technology and how much through an optimal mix of inputs. A reasonable assumption is that improving allocative efficiency requires a lower amount of effort by a firm and is potentially cheaper than improving technical efficiency. As the industry tends to exaggerate how costly the EU ETS is, a deeper understanding of the sources of extra costs can provide important policy implications. My contribution encompasses not only the identification of the potential to increase cost efficiency at the industry level and its decomposition, but also the analysis of previously unaddressed potential drivers of cost efficiency. The most important driver that I analyze is the participation in the EU ETS. I find out whether the regulated firms can contain costs better, and I analyze their cost-efficiency levels in relation to different phases of the EU ETS, investment in R&D, and the export status. I also make use of the firm-specific transactions data from the European Union Transactions Log (EUTL) to elucidate which regulated firms have strategically accumulated excess allowances and how this active trading relates to their cost efficiency. My approach is unique because I investigate the firms' reactions to the EU ETS in both the short and long run, thereby accounting for the fact that input factors are variable only to a certain extent and that continuous emissions reductions must be supported with eventual innovation. Therefore, my empirical strategy enables the testing of the PH in a SCF analysis, which to my knowledge was previously done only by Stadler and Di Maria (2018). However, I argue that the testing of the PH inevitably requires the use of the SMF analysis, as innovation likely leads to a divergence into two different groups of firms operating under different frontiers. Previous papers using the SCF analysis have largely ignored potential endogeneity issues, which I address by a robustness check fitting an endogenous SCF following the methodology provided by Karakaplan and Kutlu (2017). Finally, in the SCF I account for the direct regulation of firms by the EU ETS. I adjust the energy input price of regulated firms by adding the carbon price to their energy price. This way, the treated firms are not by construction less cost efficient, as their total costs are higher due to emission costs related to the EU ETS. As I analyze the regulation by the EU ETS as a potential driver of cost efficiency, I am the first to measure an effect from the ETS that goes above and beyond pricing emissions to address the potential SUTVA violation. Furthermore, as a robustness check, I address the SUTVA by carrying out cost frontier estimations in less energy-intensive industries in which the problem of an increased price for the energy input for unregulated firms is less pronounced. My results indicate that the potential to increase cost efficiency still exists for most industries in the German manufacturing sector. The analysis of the cost efficiency drivers confirms that in most industries, exporting firms are more cost efficient than their counterparts. In contrast, innovating firms and firms that are regulated by the EU ETS are less cost efficient than unregulated firms. A subsample DD analysis confirms that the EU ETS decreases the cost efficiency of regulated firms in at least some 2-digit industries. Allocative inefficiency represents a much smaller source of higher costs than technical inefficiency in most of the industries. Due to the statistical disclosure issues of remotely accessed data and related time constraints, the current version of this study does not contain robustness checks that address the endogeneity and SUTVA violation issues. The remainder of the study is structured as follows: Section 2 provides some background to the policy. In Section 3, I describe the methods used and outline my empirical strategy. In Section 4, I describe the German production census and additional data used. Section 5 presents the results of my analysis. In Section 6, I conclude with a discussion.

2 Institutional Background

The EU ETS is the cornerstone of the EU's climate policy. The instrument was enacted by Directive 2003/87/EC in 2003 and implemented in 2005 to reduce GHG emmissions. The regulation's current target is a reduction of 40 percent to be achieved through a 27 percent share or more from consumption of renewable energy and through a 27 percent energy savings over the business-as-usual scenario. Both must be realized by 2030 and are relative to 1990 levels (European Council (2014b)). It operates on the cap-and-trade principle and nowadays includes 31 countries: the 28 EU member states as well as Iceland, Liechtenstein, and Norway. Regulated firms receive emission permits (EU Allowance Units (EUA)) that are fully tradable across firms in all participating countries. One EUA represents one metric tonne of CO_2 equivalent. At the end of each year, regulated firms must surrender their EUAs according to their verified emissions. The program currently covers 45 percent of EU's GHG emissions and encompasses more than 11,000 heavy energy-using installations. The EU has implemented the EU ETS in three consecutive compliance periods: Phase 1 (2005-2007) as the pilot phase, Phase 2 (2008-2012) that corresponds to the commitment period of the Kyoto Protocol, and Phase 3 (2013-2020) that implements the emission targets outlined in the 2020 Climate and Energy Package. Phase 4 is set to start in 2021 and continue until 2030 (European Parliament and Council (2009)). My analysis covers two pre-EU ETS years (2003 and 2004), the first two phases (2005-2012), and the first two years of the third phase (2013 and 2014). The cap of the EU ETS is currently annually lowered by 1.74 percent, which corresponds to a reduction in emissions by 21 percent relative to 2005 in 2020. With the onset of Phase 4, the cap will decrease by 2.2 percent annually (European Council (2014a)). The following figure describes the evolution of the EUA prices since the inception of the EU ETS. In the manufacturing sector, the EU

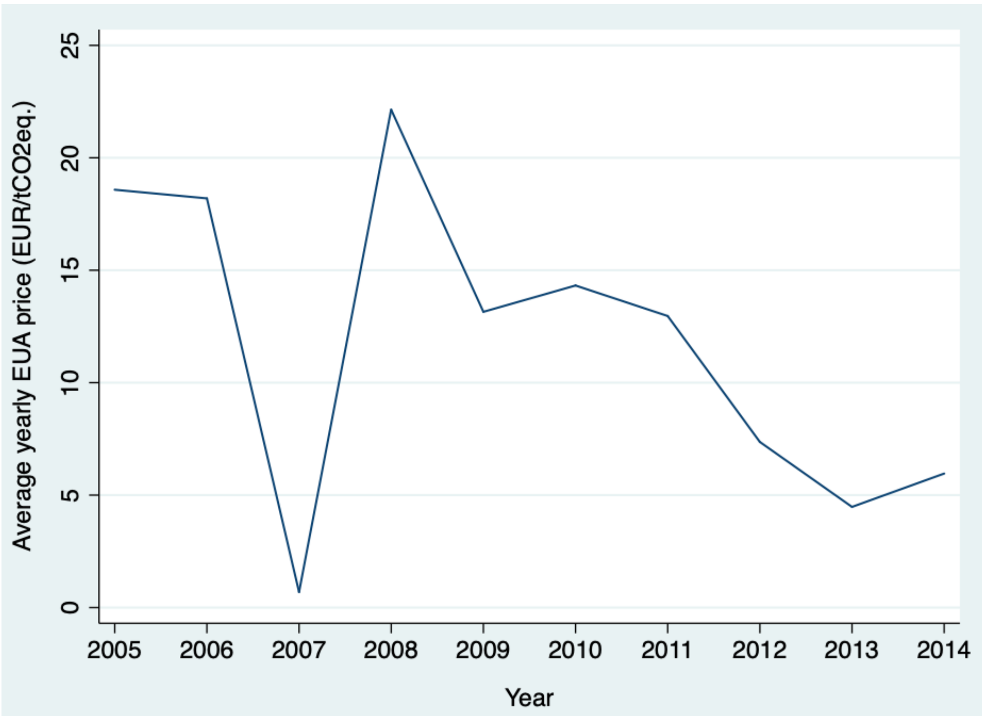


Figure 1: The evolution of the daily EUA closing prices in the sample period as yearly averages. Source: EEX, own depiction

regulates all combustion installations for the generation of electric power and heat with a total thermal rated input above 20 megawatts (MW) as well as energy intensive production processes. This production includes oil refining; the processing of ferrous metals; the manufacture of cement; the manufacture of lime; the manufacture of ceramics including bricks and glass; and the production and processes of pulp and paper.The EU ETS only regulates large installations with capacities in excess of process-specific thresholds, which are determined by regulation. The inclusion criteria creates variation in the treatment status, which is why both regulated and unregulated firms exist within the same industry.[7] I report on the number of regulated and unregulated firms in my dataset across the sample years in Table 1.

Table 1: The number of participating firms in the EU ETS across years

		2005			2010			2014		
ISIC Rev.4	Industry	Total	Unregulated	Regulated	Total	Unregulated	Regulated	Total	Unregulated	Regulated
10	Food products	4877	4836	41	4878	4832	46	4988	4940	48
11	Beverages	619	610	9	519	507	12	492	478	14
12	Tobacco products	25	-	-	21	-	-	22	-	-
13	Textiles	845	838	7	697	691	6	678	672	6
14	Wearing apparel	514	514	-	313	313	-	270	270	-
15	Leather and related products	188	188	-	137	137	-	122	122	-
16	Wood and products of wood and cork	1395	1380	15	1161	1139	22	1151	1127	24
17	Paper and paper products	858	772	86	825	723	102	794	687	107
18	Printing and reproduction of recorded media	1682	-	-	1490	1487	3	1316	1311	5
19	Coke and refined petroleum products	51	36	15	45	29	16	50	33	17
20	Chemicals and chemical products	1204	1134	70	1218	1138	80	1286	1201	85
21	Pharmaceutical products	285	278	7	255	249	6	275	268	7
22	Rubber and plastic products	2799	2788	11	2749	2734	15	2871	2857	14
23	Other nonmetallic mineral products	1909	1743	166	1646	1469	177	1668	1490	178
24	Basic metals	941	882	59	924	857	67	938	865	73
25	Fabricated metal products	6358	6354	4	6750	6744	6	7287	7284	3
26	Computer, electronic and optical products	1772	1767	5	1632	1628	4	1764	1761	3
27	Electrical equipment	2063	2056	7	1906	1899	7	2011	2004	7
28	Machinery and equipment n.e.c.	6177	6167	10	5298	5283	15	5530	5516	14
29	Motor vehicles, trailers, and semitrailers	1190	1180	10	1093	1085	8	1063	1054	9
30	Other transport equipment	350	341	9	256	249	7	281	273	8
31	Furniture	1095	1095	-	981	981	-	1000	1000	-
32	Other manufacturing	1624	1620	4	1458	-	-	1521	-	-
33	Repair and installation of mach. and equip.	308	308	-	1494	1488	6	1647	1641	6
	Total	39129	36887	535	37746	35662	605	39025	36854	628

Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations. Due to statistical disclosure and reidentification concerns, some information is missing.

3 Methodology

In large part, one can estimate the efficiency scores at the firm level by using two well-known frontier techniques, the stochastic frontier analysis (SFA) or the data envelopment analysis (DEA). The DEA is a non-parametric approach that was introduced by Charnes et al. (1978). Contrary to the SFA, this approach suffers from the inability to separate variations in efficiency from random noise. The latter is not directly attributable to the producer or the underlying technology. These shocks may be attributable to weather changes, economic adversities, or plain luck (Newhouse et al. (1994)). Wadud and White (2000) find that in most empirical studies the selection of the method used to measure efficiency is arbitrary and mainly based on the objective of the study, the data, and the personal preference of the researcher.

3.1 Stochastic Cost Frontier Analysis

The SCF analysis originates from the seminal work by Aigner et al. (1977) and Meeusen and van Den Broeck (1977) who introduced an econometric approach to frontier analysis with a composed error structure. One of the error components represents the noise that one can predominantly consider as a two-sided normally distributed variable, and the other represents cost (in)efficiency (CE). Thus, departures from the best-practice frontier, as estimated by the SCF analysis, may be either stochastic (random shocks) or deterministic (inefficiency). Unlike the production frontier, which is used

[7] For more details on the inclusion criteria of the EU ETS, please see European Parliament and Council (2003).

to estimate technical efficiency, the SCF identifies the minimum costs at a given output level, input prices, and existing production technology. The deterministic part of the distance to the SCF can be further decomposed into the allocative efficiency (AE) and technical efficiency (TE). Thus, technically efficient firms are not necessarily cost efficient. I use the SCF analysis to estimate a frontier for German manufacturing firms at the 2-digit industry level. To estimate the SCF consistently, I apply the pooled cross-section model to panel data, which is in line with Battese and Coelli (1993) and Battese and Coelli (1995).[8] Many other economic studies have used this model on efficiency with the SCF analysis and MFA methods.[9] In my econometric model, I assume that the functional form of the SCF is Cobb-Douglas.[10] Expressed in logs, the SCF can be written as:

$$lnTC_{it} = \alpha + \beta_1 lnY_{it} + \beta_2 lnP_{L_{it}} + \beta_3 lnP_{K_{it}} + \beta_4 lnP_{E_{it}} + \tau T + v_{it} + u_{it} \tag{1}$$

where TC_{it} denotes total costs; Y_{it} denotes the gross value of production; and $P_{L_{it}}$, $P_{K_{it}}$, and $P_{E_{it}}$ are input factor prices for labor, capital, and energy, respectively. T represents the time-trend variable that captures the technological change. α, β, and τ are technology parameters to be estimated. v_{it} is a normally distributed two-sided random-noise component with variance σ_v^2, and u_{it} is a non-negative inefficiency component of the idiosyncratic composed error term $\epsilon_{it} = v_{it} + u_{it}$. I assume the u_{it} to have a non-negative truncated normal distribution $u_{it} \sim N^+(\mu_{it}, \sigma_{u_i}^2)$.[11] Including my variables for cost-efficiency drivers, I can specify the model for the stochastic cost inefficiency effects u_{it} as:

$$u_{it} = z_{it}\delta + w_{it}, u_{it} \sim N^+(z_{it}\delta, \sigma_u^2) \tag{2}$$

where $z_{it} = (1, z_{it}^1, ..., z_{it}^L)$ represents a vector of factors that directly impact inefficiency. I use the participation in the EU ETS (ETS) and the interaction between the participation in the EU ETS and active trading ($ACTTRADE$) in the above model. I also include different EU ETS compliance periods ($PHASE1, PHASE2$) the export status (EXP), and the R&D ($RANDD$) activity. δ denotes a vector of parameters to be estimated, and w are unobservable iid random variables that are obtained by truncation of the normal distribution with a mean of zero and an unknown variance, $\sigma_{u_i}^2$. The parameters of the SCF (1) and the model for the cost efficiency effects (2) are estimated by applying the maximum likelihood estimation method (MLE). The appropriate likelihood functions and their partial derivatives with respect to the parameters of the model are outlined in the appendix of Battese and Coelli (1993).[12] The following equation represents the cost efficiency of a firm, as the deterministic part of its distance relative to the SCF:

$$CE_{it} = \frac{e^{X_{it}\beta + V_{it}}}{TC_{it}} = e^{-u_{it}} \tag{3}$$

It is estimated using the Battese and Coelli (1988) estimator.

[8] A future version of this paper will also contain results from a "true random- effects" model (TRE) that was introduced in Greene (2005a) and Greene (2005b). This specification disentangles the time-varying inefficiency from the firm-specific, time-invariant unobserved heterogeneity.

[9] See e.g. Fries and Taci (2005), Chapple et al. (2005), Estache and Rossi (2002), Zhang et al. (2003), Chen et al. (2014).

[10] Alternatively, a translog functional form could be assumed. Although a translog cost function is more flexible, it makes the later decomposition of cost efficiency very difficult due to the so-called "Greene-problem" (Kumbhakar et al. (2015)). Furthermore, the translog specification includes second-order terms and is potentially prone to multicollinearity (Farsi and Filippini (2008)).

[11] To correspond to a well-behaved production structure, the cost function must satisfy the following regularity conditions: continuity, symmetry, linear homogeneity in prices, monotonicity in prices and outputs, and concavity in prices. I satisfy the linear homogeneity restriction ($\sum_n \beta_n = 1.$) by dividing total costs and all input prices with $P_{K_{it}}$. Prior to estimating the cost function with the SCF, various tests were carried out on the skewness of the OLS residuals, monotonicity and concavity checks as well as the likelihood ratio test for presence of cost inefficiency.

[12] To estimate equations 1 and 2 with a single-stage approach, I use the Stata commands provided in Belotti et al. (2012).

3.2 Meta Frontier Analysis

There is often a considerable interest in measuring the performance of firms across different production groups.[13] While the efficiency of a firm‘s performance can be estimated by means of frontier estimation methods (e.g. SCF), efficiency levels from one firm to another are not directly comparable if firms‘ operations are based on different technologies (Lin (2011)). The MFA enables efficiency comparisons across groups of firms without assuming similar technologies. The concept behind MFAs was introduced in the seminal work by Hayami (1969), Hayami and Ruttan (1970), and Hayami and Ruttan (1971). It relies on the critical assumption that producers that operate in various production groups all have potential access to an array of production technologies. For a multitude of reasons, firms in some groups cannot choose the best technology from this array, instead they choose a sub-technology. The reasons may include specific circumstances, such as the regulation, the production environment, production resources, relative input prices; for each production group, a gap can be estimated that is the difference between the best technology and the chosen sub-technology. The best technology is represented by the meta frontier that is common to all production groups and envelops group-specific frontiers that represent the chosen sub-technologies. Efficiencies in the MFA framework are estimated relative to the frontier. These are known as meta efficiencies. We can decompose the meta-efficiency for each production group into a distance from the input-output point to the group-specific frontier (group-specific efficiency) and the distance between the group-specific frontier and the meta frontier (gap). By construction, meta efficiency is a product of the group-specific efficiency and the gap.

3.2.1 Stochastic Meta Cost Frontier Analysis

The MFA was originally introduced using a production function approach. Sub-technologies are represented by production frontiers and enveloped by a meta production frontier. A gap between these frontiers is known as a production technology gap. In the many empirical applications since, the meta frontier concept was applied within the cost framework that is based on the Shephard Duality Theorem (Shephard (2012)).[14] In this case, we refer to the gap between the group frontiers and the meta frontier as a cost gap ratio (CGR) and in addition to the latter, estimate group-specific CE as well as the meta cost efficiencies (MCE). Usually, the MFA approach proceeds in two steps. In the first step, group-specific frontiers are estimated and then using these results, in the second stage the meta frontier is calculated. Prior methods, by Battese et al. (2004) and O'Donnell et al. (2008), use a deterministic meta-frontier programming method, which can be perceived as a mixed approach. The first step involves a conventional stochastic frontier analysis, and in the second step the use of linear (or quadratic) programming algebraic calculation to solve that the meta frontier envelops these group-specific stochastic frontiers. Amsler et al. (2017) have recently shown that such deterministic measurement methods of the meta-frontier distances are not appropriate. Their findings show that the use of deterministic approaches in which the stochastic nature of frontiers is neglected may result in smaller expected differences between the meta frontier and the group-specific frontiers.[15] In this study, I use the SMFA for two purposes. First, as depicted in Figure 2, I use it in order to compare cost efficiencies between different 2-digit industries of the manufacturing sector to learn which industry is most cost efficient. Second, I use it to test my hypothesis that the EU ETS in the long-run results in the innovative and non-innovative firms operating under heterogeneous cost frontiers within a 2-digit industry. As depicted in the right-hand side of the Figure 3,

[13] Nkamleu et al. (2006) compare agricultural productivity in different regions in Africa. Breustedt et al. (2011) apply the MFA concept to compare efficiencies of organic and conventional dairy farmers under the EU Milk Quota System. Bhandari and Ray (2012) apply the MFA to the Indian textiles industry and estimate different group frontiers based on ownership type, state, and organization.

[14] This was previously done by Chen et al. (2014) and Huang and Fu (2013), Huang et al. (2010), and Huang et al. (2010).

[15] In addition to advocating for the SMFA for measuring various meta components (e.g. CGR, MCE), Amsler et al. (2017) also show how to make predictions for these components and how to construct confidence intervals accordingly. In a future version of this paper, the confidence intervals of meta components will be constructed.

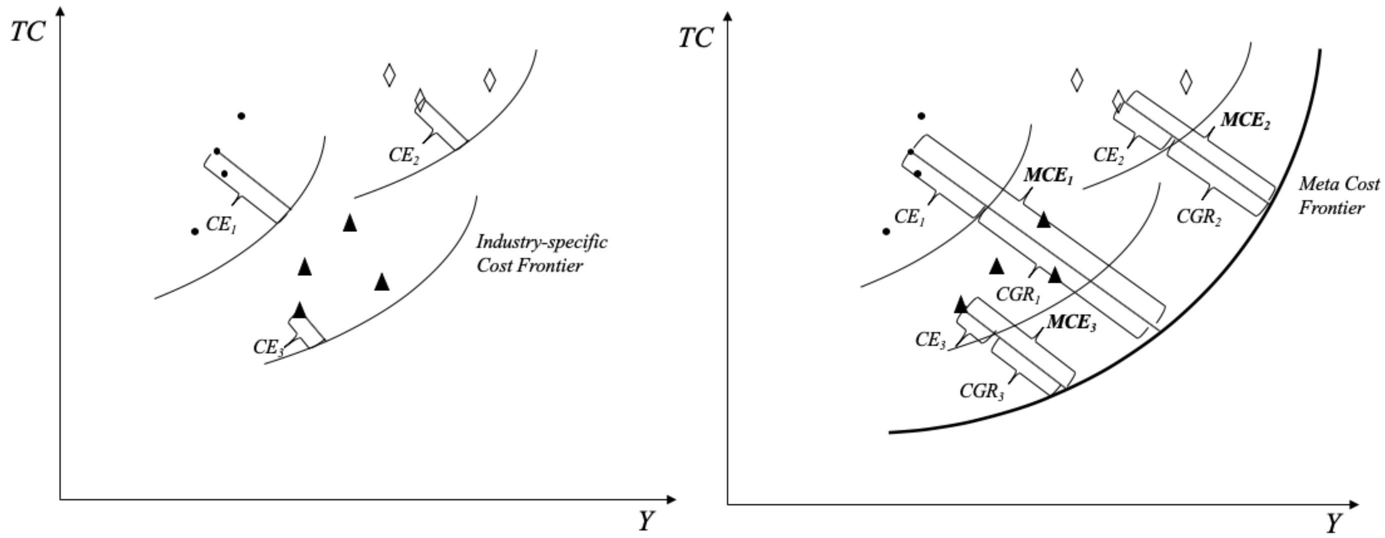


Figure 2: Use of meta-frontier analysis for inter-industry comparisons, Source: Own depiction

I estimate the CGR, CE, and MCE by using the method that was introduced by Huang et al. (2014), henceforth referred to as the HHL model.[16] Contrary to prior efforts, the HHL model uses a conventional maximum likelihood method to

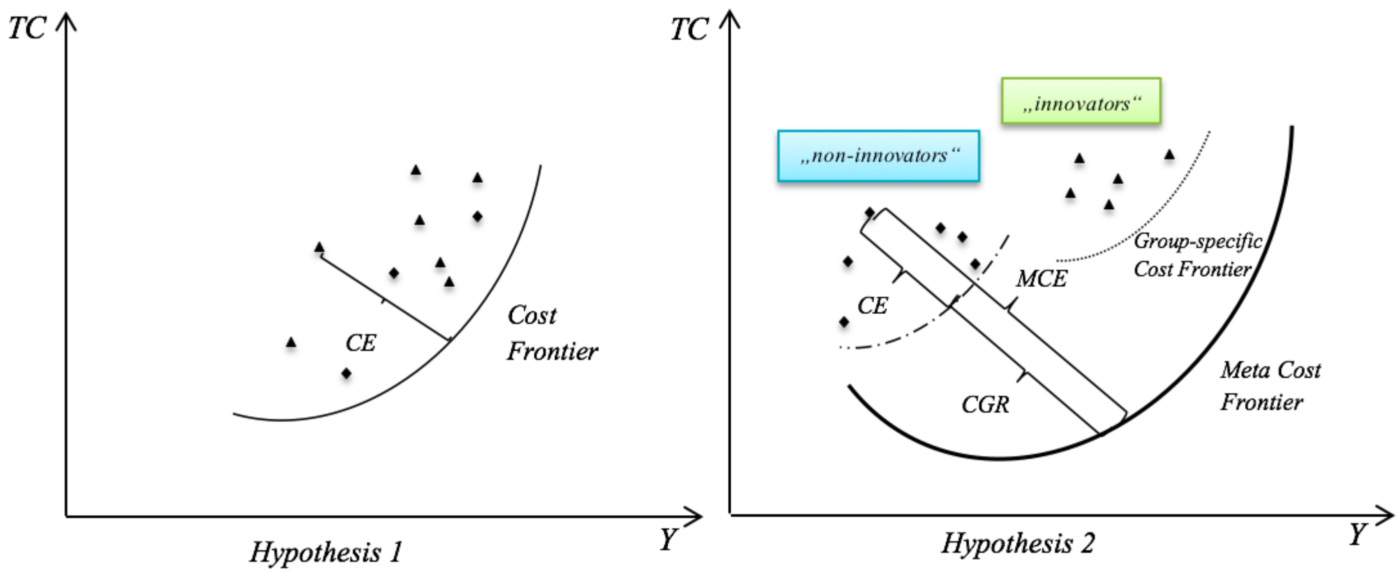


Figure 3: Use of meta-frontier analysis for intra-industry comparisons, Source: Own depiction

estimate the parameters of the stochastic frontier regression in both stages. Hence, the SMFA ensures that in the second-step statistical inferences can also be performed (in prior methods this would not be possible without bootstrapping and simulations). Furthermore, the CGRs can be directly estimated as conventional one-sided error terms, which enables the isolation of idiosyncratic shocks (using prior methods, the gaps would be contaminated). Finally, the HHL model further can specify the one-sided error term as a function of environmental variables beyond the control of the firm, which is in line with Battese and Coelli (1995). Using the HHL model in this study hence makes sense from a pragmatic perspective, as I can use the results obtained from the method in the previous section, as my first-stage results, and subsequently estimate the meta frontier.

[16] The empirical application of this model was previously, for example, carried out by Chen et al. (2014). In their study, they analyze and compare the cost efficiencies of Taiwan biotech and pharmaceutical firms.

First-step: Stochastic Cost Group Frontier Estimation

In the first stage, the cost frontier for each group, the regulated and unregulated firms, is specified as in (1) and (2). After the maximum likelihood estimation of (1), the group-specific cost efficiency relative to the SCF is estimated as outlined in equation (3). Finally, for each group, the linear residuals are predicted.

Second-step : Stochastic Cost Meta Frontier Estimation

I assume that for each narrowly defined industry in the manufacturing sector, the two group-specific SCFs are enveloped by the meta frontier. The meta frontier is estimated using the following equation (4) :

$$ln\hat{TC}_{it} = \alpha + \beta_1 lnY_{it} + \beta_2 lnP_{L_{it}} + \beta_3 lnP_{K_{it}} + \beta_4 lnP_{E_{it}} + \tau T + v_{it}^M + u_{it}^M \quad (4)$$

where $T\hat{C}_{it}$ denotes the adjusted total costs; Y_{it} denotes the gross value of production; and $P_{L_{it}}$, $P_{K_{it}}$ and $P_{E_{it}}$ are input factor prices for labor, capital, and energy, respectively. T represents the time-trend variable, which captures the technological change. α, β, and τ are technology parameters to be estimated. v_{it}^M is a normally distributed two-sided random-noise component with variance σ_v^2, and u_{it}^M is a non-negative meta inefficiency component of the idiosyncratic composed error term $\epsilon_{it}^M = v_{it}^M + u_{it}^M$. I assume the u_{it} to have a non-negative truncated normal distribution $u_{it}^M \sim N^+(\mu_{it}, \sigma_{u_i}^2)$. I use the following environmental variables to model group-specific cost inefficiency effects:

$$u_{it} = a_0 + a_1 RANDD_{it} + a_2 EXP_{it} + \epsilon_{it} \quad (5)$$

The MCE can be estimated in the following way:

$$MCE_{it}^* = \frac{e^{X_{it}\beta^* + V_{it}}}{\hat{TC}_{it}} = \frac{e^{X_{it}\beta^*}}{e^{X_{it}\beta}} \times \frac{e^{X_{it}\beta + V_{it}}}{\hat{TC}_{it}} \quad (6)$$

I use the following environmental variables to model the meta cost inefficiency effects:

$$u_{it}^M = a_0 + a_1 RANDD_{it} + a_2 EXP_{it} + a_3 PATENTS_{it} + \epsilon_{it}^M \quad (7)$$

The CGR represents the ratio between the expected total cost relative to the meta cost frontier and the expected total cost relative to the group-specific cost frontier. That is,

$$CGR_{it} = \frac{e^{X_{it}\beta^*}}{e^{X_{it}\beta}} \quad (8)$$

Therefore,

$$MCE_{it}^* = CE_{it} \times CGR_{it} \quad (9)$$

3.3 Differences-in-differences Approach

3.3.1 Parametric DD approach with conditioning strategies

In this step of my empirical analysis I identify and quantify the impact of the EU ETS by comparing changes in cost efficiency across German manufacturing firms that are affected differently by the EU ETS. Due to the inclusion criteria of the EU ETS, within narrowly defined industries, both regulated and unregulated firms exist that enables a quasi-experimental framework.[17] The specification of the difference-in-differences model that I estimate for the full sample in period 2003-2014 is formulated in the following equation 10,

$$\begin{aligned} ln(CE)_{it} = \beta_0 + \tau_1 ETS_i \times Phase1_t + \tau_2 ETS_i \times Phase2_t + \tau_3 ETS_i \times Phase3_t \\ + z_{it}\Psi + \alpha_i + \phi_t + \gamma_s + \eta_{st} + \epsilon_{it} \end{aligned} \tag{10}$$

where ETS_i indicates if a firm is regulated by the EU ETS. The parameter τ_1 on the interaction terms between ETS_i and the indicator ($Phase1_t$) for the period between 2005 and 2007 give the estimated effect of the EU ETS in the first phase. The parameter τ_2 on the interaction terms between ETS_i and the indicator ($Phase2_t$) for the period between 2008 and 2012 give the estimated effect of the EU ETS in the second phase. The parameter τ_3 on the interaction terms between ETS_i and the indicator ($Phase3_t$) for the period after 2013 give the estimated effect of the EU ETS in the third phase. I add control variables Ψ, namely capital stock, emissions, energy use and output per employee. To account for the observed and unobserved heterogeneities across regulated and unregulated firms, I additionally control for firm fixed-effects, α_i. The year fixed effects ϕ_t control for superior trends in cost efficiency in German manufacturing. The inclusion of industry fixed effects γ_s adjusts for all constant unobserved determinants of cost efficiency across industries. η_{st} denotes the full interaction terms between the industry and year fixed effects and nonparametrically absorbs within industry-productivity trends. The error term ϵ_{it} is assumed to have a mean of zero. When estimating the causal impact of the EU ETS on cost efficiency for a subset of 2-digit industries, γ_s and η_{st} drop out from the equation (10). I also investigate the average treatment effect of the EU ETS on the meta cost efficiency for a subset of 2-digit industries. The specification is the same as in the equation (10), except for the outcome variable being meta cost efficiency in logs, and γ_s and η_{st} dropping out.

3.3.2 Non-parametric DD approach with nearest-neighbor matching

In the literature on cap-and-trade impact evaluation, the use of matching techniques is on the rise (Fowlie et al. (2012), Petrick and Wagner (2014), Calel and Dechezleprêtre (2016), Löschel et al. (2016)). Along with the parametric DD model with different conditioning strategies, I estimate a model based on non-parametric matching to the nearest neighbor, which is in line with Löschel et al. (2016). This way I do not have to pose any parametric assumptions on the relation between the cost efficiency and the explanatory variables z_{it}.[18] The adequate control group is identified using the Mahalanobis distance that determines similarity between firms by a weighted function of observable covariates for each firm. The weight is based on the inverse of the covariates' variance-covariance-matrix. This weighting enables me to form a control group using unregulated firms that resemble the firms in the treatment group and thus might be affected by unobservable confounding factors in the same way. I match the nearest neighbor with replacements, that is, unregulated firms can be used multiple times as a match. I match on the firms' output, emissions, capital stock, number of employees, and energy use in 2003. To form an adequate control group, when using the full sample, I match exactly on 2-digit industries, that is, within strata. The average treatment effect is estimated using the difference-in-differences matching estimator, which

[17] The identification strategy I use is established in the policy evaluation literature as the potential outcome framework. For a notable empirical application of this strategy in terms of climate policy evaluation, see Fowlie et al. (2012).

[18] Remaining needed assumptions are the assumption of conditional unconfoundedness and SUTVA. The common support assumption is critical to using matching. I assume that the conditional probability to be treated is larger than zero and smaller than one: $0 < \mathrm{P}[ETS_i = 1|\mathrm{X}] < 1$.

is in line with Heckman et al. (1997).

$$\hat{\tau} = \frac{1}{N}\sum_{j\in I_1}\left\{(CE_{jt'}(1) - CE_{jt^0}(0)) - \sum_{k\in I_0} w_{jk}(CE_{kt'}(1) - CE_{kt^0}(0))\right\} \tag{11}$$

where I_1 denotes the treated group of firms (in the EU ETS), and I_0 denotes the group of control firms (outside of the EU ETS). N represents the number of firms in the treatment group. The regulated firms are indexed by j, whereas the unregulated firms are indexed by k. w_{jk} denotes the weight placed on firm k when constructing the counterfactual estimated for the treated firms.

3.4 Primal System Approach

In this study, I assume that firms incur both technical inefficiency in the production of output and allocative inefficiency in the choice of the input mix. Both technical and allocative efficiencies have an impact on costs. The decomposition of cost efficiency into its sources (AE and TE) gives a better understanding of how much potential there is for cost reduction at the firm level in addition to how much of this cost reduction could come from improving the production technology and how much from allocating inputs more efficiently. This type of estimation in the cost frontier framework is not trivial, especially if flexible functional forms are selected to represent the underlying production technology. Estimating the translog functional form in this setting raises specification and estimation issues that are known as the Greene problem (Greene (1980)). As there is no easy solution to the cost efficiency decomposition if a flexible functional form is selected, I use the Cobb-Douglas functional form.[19] Existing literature predominantly addresses cost-efficiency decomposition with the cost system approach. A problem with estimating such a system econometrically is in deriving the likelihood function, because the elements of the input allocative inefficiency term appear in the cost function and in the cost share equations in a very nonlinear fashion.[20] The PSA is an alternative modelling strategy that allows the estimation of both technical and allocative efficiencies in cost frontier models by using system models with cross-sectional data. This system comprises a production function and the first order conditions of cost minimization. It is algebraically equivalent to the cost system for self-dual production functions, the only difference is in the starting point being a parametric production function instead of a cost function (Schmidt and Lovell (1979)). I estimate the primal half-normal model with no systematic error. This model estimates the cost minimization by using production function systems based on duality. The system's production frontier has the following form:

$$lnY = \alpha_0 + \sum_j \alpha_j lnx_j + v - u \tag{12}$$

where Y denotes the gross value added of production in logs, and x_j represents a vector of inputs, that is, labor use (L), energy use (E), and capital stock (K) in logs. v is a normally distributed two-sided random-noise component with variance σ_v^2, and u is the technical inefficiency component of the idiosyncratic composed error term with the distribution $u \sim N^+(0, \sigma_{u_i}^2)$ (henceforth, TIE). From the first order conditions for cost minimization, it follows that:

$$ln(\frac{\alpha_j}{\alpha_1}) - ln(\frac{w_j}{w_1}) - lnx_j + lnx_1 = \xi_j, j = 2, ...J. \tag{13}$$

[19] This function makes sense also for pragmatic reasons, as I have selected it both in the application of the SCF analysis and SMF analysis.
[20] See e.g. Mundlak and Hoch (1965), Schmidt and Lovell (1979), Schmidt and Lovell (1980).

where w is the vector of input prices, ξ_j is the non-negative allocative inefficiency (henceforth, AIE) for the input pair (j,1). I assume that $\xi \sim MVN(0, \Sigma)$.[21] Allocative inefficiency can be obtained from the residuals of equation (13). The model is estimated using MLE. After the estimation of this model, I compute the cost impact from the combined and separate effects of technical and allocative inefficiency ($C_{ratioTIE}$, $C_{ratioAIE}$, $C_{ratioBOTH}$).

4 Data

I use official data from a firm-level German production census (AFiD). The data is collected by the German Federal Statistical Office and the Statistical Offices of the German Federal States. The participation in the census is mandatory by law, and it includes all manufacturing firms with more than 20 employees. This longitudinal data is confidential and only accessible for scientific purposes and official government statistics. The data comprise various thematic modules that I combine for my analysis. The core part of the data is the cost structure survey (CSS), as it contains comprehensive annual information on outputs and inputs used by manufacturing firms. The CSS includes all manufacturing firms with more than 500 employees and a random sample of firms with more than 20 and less than 500 employees that is stratified according to the ISIC Rev.4 industry classification and the number of employees.[22] I also use the database AFiD-Panel Industrial Units that contains annual data from the Monthly Report on Plant Operation, the Census on Production, and the Census on Investment, that is, a full sample of all plants in manufacturing that belong to firms with a minimum 20 employees. At the plant level, I combine this data with the AFiD-Module Use of Energy that contains information on the purchase, sale, and use of electricity and fuel. In order to combine all data, the information is aggregated at the firm level. Finally, the production census is matched with the European Union Transaction Log (EUTL) from 2005 to 2014 in order to identify regulated firms and obtain the information on transactions of allowances.[23] In order to exclude potentially treated firms from the control group, I also match the AFiD with the Orbis database. Overall, I have the access to annual data from 2003 to 2014.[24]

4.1 SCF and SMF variables

My measure of total costs (TC) comes from the CSS.[25] My measure of output (Y) is the gross value of production of the firm. It comes from the Census on Production and is deflated by using 2-digit ISIC Rev.4 price deflators.[26] Firm-specific price of labor (P_L) is calculated as the paid gross yearly wages from the CSS divided by the annual average of the number of employees reported monthly in the production census. The firm-specific price of capital (P_K) is calculated as the residual price of capital. The residual capital costs (total costs that are not related to labor or materials) are divided by the capital stock and are computed with the perpetual inventory method. The firm-specific price of energy (P_E) is calculated as the total energy expenditure from the CSS divided by its total energy use, and is retrieved from the AFiD-Module Use of Energy. Energy costs are inflated by the emissions costs for treated firms in the period from 2005 to 2014. This inflation leads to higher energy prices for regulated firms than for unregulated firms. Emissions costs are calculated by multiplying

[21] The appropriate likelihood function and its partial derivatives with respect to the parameters of the model can be found in Kumbhakar et al. (2015), as well as, detailed explanation of the PSA approach and Stata commands.

[22] Additional information on the industry classification can be found in the Appendix.

[23] I present additional information on this matching procedure in the appendix.

[24] I also have data for the period from 1995 to 2002. However, the statistical offices have changed the survey that gathered the information on energy use in 2003, which hinders the inclusion of data pre-2003.

[25] This measure does not include the material consumption nor the use of external energy and water.

[26] I use industry-specific price deflators to remove the price component from an overall value measure and thereby isolate the volume component. The data on price deflators was retrieved from EU KLEMS (2017). The year 2010 is the base value.

annual emissions in tCO2 with the respective EUA price. Annual emissions are calculated using energy use and related CO_2 emission factors. All monetary values are deflated to the 2010 base value.[27] Table 2 reports on descriptive statistics of variables across different industries in period 2003-2014. For the model of cost inefficiency effects, the cost efficiency

Table 2: Descriptive statistics of variables

ISIC Rev. 4	Total Costs (EUR 1000)	Output (EUR 1000)	Price of Capital (EUR 1000)	Price of Labour (EUR 1000)	Price of Energy (EUR/kWh)	Capital Stock (EUR 1000)	Number of Employees	Energy use (Mwh)	Emissions (tCO_2)	Number of Firms
10	20161 (63471)	20839 (79875)	1,43 (4,03)	20,09 (9,84)	0,14 (1,02)	6391 (23000)	99 (224)	11700 (81000)	4050 (22314)	8367
13	10262 (19241)	12405 (23556)	1,29 (2,83)	26,32 (9,62)	0,11 (1,04)	5249 (10700)	99 (131)	9611 (25900)	3808 (9388)	1289
16	12715 (24323)	1194 (29417)	1,44 (4,19)	26,39 (8,46)	0,19 (1,65)	5362 (17000)	67 (115)	16800 (102000)	2821 (15882)	2149
19	1036800 (2982053)	677902 (2198909)	2,53 (4,58)	49,96 (16,51)	0,45 (3,37)	150000 (309000)	388 (725)	1640000 (4300000)	468189 (1230527)	74
20	67312 (361984)	78205 (373298)	1,96 (23,28)	39,82 (12,96)	0,35 (14,25)	36500 (184000)	263 (1234)	218000 (2280000)	67042 (609983)	1968
21	109414 (384318)	104273 (357973)	1,62 (3,29)	40,69 (13,61)	0,18 (1,60)	57300 (258000)	452 (1295)	26400 (92000)	9325 (27786)	450
22	22926 (65626)	19327 (55109)	1,14 (6,28)	29,36 (9,29)	0,14 (1,69)	7809 (23200)	129 (319)	8548 (34500)	4456 (14938)	4218
24	50556 (191335)	86211 (365361)	1,11 (3,40)	36,15 (10,13)	0,16 (2,15)	24500 (112000)	268 (838)	265000 (2790000)	97588 (907727)	1388
25	15104 (31800)	12985 (31952)	1,49 (16,93)	30,40 (9,59)	0,14 (1,29)	4737 (12600)	91 (166)	4180 (25700)	1942 (12127)	10583
26	36711 (149353)	31159 (135456)	1,68 (3,52)	37,48 (13,69)	0,47 (19,40)	12200 (90800)	166 497	4650 (35400)	2558 (18439)	3029
27	45680 (534098)	35504 (339797)	1,60 (3,28)	33,20 (11,55)	0,17 (1,35)	10700 (120000)	234 2604	5560 (49400)	2759 (23655)	3248
28	31269 (151348)	29633 (120373)	1,71 (12,79)	37,39 (12,20)	0,20 (6,20)	7912 (54100)	165 (792)	4322 (34600)	1934 (14188)	9521
29	164582 (1256032)	221849 (2304456)	1,79 (7,89)	33,10 (12,02)	0,50 (11,96)	60600 (584000)	729 (5904)	31900 (282000)	15432 (133666)	1807
30	71503 (305896)	88776 (388130)	1,56 (3,31)	35,37 (12,77)	0,19 (3,29)	24100 (142000)	440 (1623)	17800 (189000)	7410 (84517)	2171

Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations. Standard deviations in the parentheses.

drivers are obtained in the following way: Based on the commercial register number and the VAT number, I first match the European Emissions Transactions Log to the German official Business Register. In the next step, I can directly match the AFiD to the EUTL in the period from 2005 to 2014. This matching allows me to generate the dummy variable for the participation in the EU ETS (ETS). I also create a dummy variable for actively trading firms ($ACTTRADE$) by using information from EUTL. I identify the firm as an active trader if its number of trades in a given year exceeds the median of trades by all firms in that same year. I create dummy variables for the first ($PHASE1$) and the second phase ($PHASE2$) to implicitly control for varying EUA prices. The dummy variable for R&D activity ($RANDD$) is created by identifying firms whose R&D expenditure are positive. For the model of meta cost inefficiency effects, I create a dummy ($PATENTS$), that identifies a patent investing firm if investments into patents in a given year are positive. Table 3 reports on descriptive statistics of cost efficiency drivers across different industries in period 2003-2014.

4.2 PSA variables

In addition to the input price variables (P_L, P_K, P_E) and the output (Y) explained in the previous section, , I also need information on the capital stock (K), labor (L) and energy use (E) to apply the PSA. From the AFiD Panel Industrial Units, I use the investment information and compute the capital stock by applying the perpetual inventory

[27]Consumer Price Indices for Germany are retrieved from the World Bank Group. The base year is 2010.

Table 3: Descriptive statistics of cost efficiency drivers

ISIC Rev. 4	ETS	EXP	RANDD	ACTTRADE	PHASE1	PHASE2	PATENTS
10	0.074	0.055	0.127	0.086	0.077	0.071	0.105
13	0.011	0.025	0.016	0.003	0.013	0.011	0.018
16	0.033	0.027	0.033	0.021	0.030	0.034	0.066
19	0.026	0.001	0.001	0.058	0.024	0.023	0.002
20	0.126	0.042	0.030	0.142	0.129	0.123	0.036
21	0.011	0.009	0.006	0.010	0.013	0.010	0.012
22	0.021	0.079	0.069	0.016	0.020	0.021	0.055
24	0.107	0.028	0.016	0.094	0.109	0.103	0.019
25	0.009	0.152	0.176	0.002	0.009	0.010	0.128
26	0.007	0.061	0.052	0.001	0.010	0.006	0.053
27	0.011	0.059	0.052	0.007	0.011	0.012	0.052
28	0.022	0.185	0.153	0.008	0.021	0.022	0.134
29	0.015	0.033	0.025	0.020	0.018	0.014	0.031
30	0.045	0.048	0.038	0.040	0.017	0.072	0.039

Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations. Standard deviations in the parentheses.

method explained in detail in Lutz (2016). The number of employees in the firm indicates the use of labor. I compute the aggregated energy use based on detailed information on electricity and fuel use in the AFiD Module Use of Energy.

5 Results

In this section I present the estimated stochastic cost frontier as well as the simultaneously estimated relations of different drivers and energy efficiency for 14 2-digit industries. I also present results of the stochastic meta cost frontier analysis for in terms of inter- and intra-industry comparisons. I conclude with preliminary results of the DD analysis and the PSA.

5.1 Stochastic Frontier Analysis

Parameter estimates of the stochastic cost frontier model in Table 4 vary across industries, reflecting heterogeneity. Estimates have plausible signs from an economic point of view. The positive sign of output and normalized input prices can be interpreted as follows: given the technology, a respective increase in these variables would increase total costs. Price of energy accounts for a relatively small share of total costs, whereas the contrary can be observed for the price of labor. The negative and highly statistically significant time trend hints at the fact that the total costs decreased over time in all industries except for industries (19), (25), (28), and (30). This decrease suggests that a change in the technology of production occurred during the observation period, although the time-trend variable captures also other time-trend effects. The results range from -0,005 in industry (16) to -0,031 in industry (27), which reflects a decrease in total costs of 0.5 to 3% per year. Table 5 presents the relation between several determinants and cost efficiency. I find that participation in the EU ETS is a significant driver of cost inefficiency in most industries, which means that regulated firms in these industries are worse at containing costs than their non-regulated counterparts. EU ETS seems to regulate less cost efficient firms. Investment into research and development is associated with increased cost inefficiency in most industries, as well as, active trading with emission permits. I can show for the first time that there is a positive relationship between exporting and cost efficiency of manufacturing firms. There are two indicators for cost efficiency in my model. First, the estimates of λ denote the relative contribution of the variance in cost efficiency (σ_u) in proportion to the variance of the error (σ_v). The statistical significance of λ indicates the presence of cost efficiency. I can identify

Table 4: Estimation results for the stochastic cost frontier

ISIC Rev.4	$\ln Y$	$\ln P_E$	$\ln P_L$	T
10	0.647^{***}	0.162^{***}	0.708^{***}	-0.013^{***}
13	0.708^{***}	0.099^{***}	0.858^{***}	-0.013^{***}
16	0.726^{***}	0.047^{***}	0.885^{***}	-0.005^{**}
19	0.809^{***}	0.026	0.533^{***}	0.009
20	0.742^{***}	0.062^{***}	0.876^{***}	-0.021^{***}
21	0.845^{***}	0.142^{***}	0.833^{***}	-0.006^{**}
22	0.814^{***}	0.158^{***}	0.770^{***}	-0.020^{***}
24	0.708^{***}	0.052^{***}	0.971^{***}	-0.013^{***}
25	0.761^{***}	0.111^{***}	0.863^{***}	0.003^{***}
26	0.779^{***}	0.038^{***}	0.929^{***}	-0.013^{***}
27	0.807^{***}	0.087^{***}	0.854^{***}	-0.031^{***}
28	0.801^{***}	0.085^{***}	0.913^{***}	0.001
29	0.772^{***}	0.060^{***}	0.940^{***}	-0.011^{***}
30	0.671^{***}	0.013	1.000^{***}	-0.004

Notes: *p<0.10, **p<0.05,***p<0.01; Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

Table 5: Estimation results for the cost inefficiency drivers and variance parameters

ISIC Rev.4	ETS	$RANDD$	EXP	$ACTTRADE$	$PHASE1$	$PHASE2$	σ_u	$\lambda_u = \sigma_u/\sigma_v$
10	0.838^{***}	0.482^{***}	-0.392^{***}	0.192^{*}	-0.121	-0.080	0.455^{***}	0.882^{***}
13	0.764	0.238^{***}	-0.738^{***}	0.349	0.445	0.275	-0.592^{***}	1.622^{***}
16	0.496^{***}	0.327^{***}	-0.005	-0.217	0.125	0.156	0.573^{***}	1.809^{***}
19	1.444^{***}	-1.039^{***}	-2.144^{***}	0.847^{**}	0.455	0.116	1.353^{***}	5.050^{***}
20	0.935^{***}	0.308^{***}	-0.887^{***}	0.676^{***}	0.001	0.158	0.795^{***}	1.955^{***}
21	1.723^{***}	0.450^{***}	-1.408^{***}	0.361	-0.790	-0.701	0.946^{***}	2.700^{***}
22	0.337^{**}	0.338^{***}	-0.189^{***}	0.196	-0.051	0.124	0.405^{***}	1.254^{***}
24	0.301^{***}	0.428^{***}	-0.074	0.316^{***}	0.078	0.127	0.230^{***}	0.480^{***}
25	0.917^{***}	0.512^{***}	-0.330^{***}	0.240	-0.303	-0.219	0.502^{***}	1.542^{***}
26	2.319^{**}	0.204^{***}	-0.692^{***}	-0.082	-0.245	0.160	0.776^{***}	2.148^{***}
27	0.857^{**}	0.246^{***}	-0.447^{***}	0.622^{*}	-0.283	0.164	0.631^{***}	1.853^{***}
28	1.138^{***}	0.216^{***}	-1.165^{***}	0.060	-0.006	0.008	0.706^{***}	2.244^{***}
29	1.246^{***}	0.647^{***}	-1.265^{***}	0.194	0.196	0.104	0.699^{***}	1.764^{***}
30	1.527^{***}	0.790^{***}	-1.112^{***}	-0.066	0.218	0.104	1.044^{***}	3.322^{***}

Notes: *p<0.10, **p<0.05,***p<0.01; Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

cost inefficiencies for all of the industries presented. These inefficiencies suggest I can reject the null hypothesis of $\lambda = 0$, as there are differences in cost efficiency between firms within a specific narrowly defined industry. The second indicator is the cost efficiency score. These scores are presented in Table 6. The highest possible score is one that indicates there is no potential for cost efficiency improvements in a specific 2-digit industry. In the Appendix, Figures 4 and 5 show the the development of mean cost efficiency scores over time and between treatment groups for selected 2-digit industries.

5.2 Stochastic Meta Frontier Analysis

The results in Table 6 give some indication about cost saving potential of firms in a specific industry. In order to make meaningful comparisons of cost efficiency between different industries (inter-industry comparison), and different treatment groups within an industry (intra-industry comparison), SMF analysis is required.

5.2.1 Inter-industry Comparison

The results in Table 7 confirm that the estimation of separate stochastic cost frontiers for each industry in the period 2003-2014 is appropriate, as the cost efficiency, estimated using the pooled cost frontier (CE_{pooled}), consistently deviates from the cost efficiency estimated using industry-specific cost frontiers (CE_{group}). For industries (10), (13), (21), (22),

Table 6: Average yearly cost efficiency for 2-digit industries

ISIC Rev.4	Industry	CE	sd	p10	p50	p75	N
10	Food	0.734	0.095	0.615	0.748	0.802	20720
13	Textiles	0.752	0.110	0.610	0.776	0.830	4630
16	Wood and products of wood and cork	0.652	0.154	0.425	0.682	0.773	4622
19	Coke and refined petroleum products	0.547	0.273	0.128	0.638	0.784	488
20	Chemicals and chemical products	0.663	0.157	0.430	0.704	0.780	9396
21	Pharmaceutical products	0.675	0.157	0.452	0.711	0.777	2129
22	Rubber and plastic products	0.750	0.104	0.612	0.771	0.826	10247
24	Basic metals	0.792	0.111	0.641	0.843	0.868	7154
25	Fabricated metal products	0.724	0.121	0.570	0.747	0.810	21673
26	Computer, electronic and optical products	0.669	0.152	0.468	0.701	0.779	8351
27	Electrical equipment	0.691	0.136	0.516	0.716	0.789	10653
28	Machinery and equipment n.e.c.	0.748	0.122	0.591	0.776	0.832	26574
29	Motor vehicles, trailers, and semitrailers	0.730	0.126	0.575	0.760	0.817	7432
30	Other transport equipment	0.593	0.194	0.316	0.632	0.742	2622

Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

(24) and (29), estimation using the pooled cost frontier underestimates the actual cost efficiency, while the opposite is true for the remaining industries. If one were to directly compare CE_{group} scores between different industries, one could

Table 7: The comparison of mean cost efficiency scores using SCF and SMF analyses in years 2003, 2005 and 2010

Year	2003				2005				2010			
ISIC Rev.4	CE_{pooled}	CE_{group}	CGR	MCE	CE_{pooled}	CE_{group}	CGR	MCE	CE_{pooled}	CE_{group}	CGR	MCE
10	0,6291	0,7367	0,7328	0,5405	0,6323	0,7349	0,7387	0,5423	0,6223	0,7322	0,7305	0,5352
	(0,1701)	(0,0929)	(0,1593)	(0,1369)	(0,1648)	(0,0959)	(0,1574)	(0,1339)	(0,1683)	(0,0934)	(0,1606)	(0,1389)
13	0,6746	0,7509	0,7758	0,5828	0,6810	0,7527	0,7811	0,5884	0,6853	0,7535	0,7966	0,6008
	(0,1205)	(0,1033)	(0,0647)	(0,0926)	(0,1292)	(0,1136)	(0,0647)	(0,1005)	(0,1231)	(0,1065)	(0,0632)	(0,0974)
16	0,7041	0,6503	0,9228	0,5998	0,7068	0,6549	0,9222	0,6033	0,7010	0,6493	0,9190	0,5962
	(0,1273)	(0,1544)	(0,0250)	(0,1419)	(0,1233)	(0,1509)	(0,0254)	(0,1377)	(0,1271)	(0,1506)	(0,0281)	(0,1376)
19	0,6895	0,5834	0,9125	0,5598	0,6633	0,5540	0,9211	0,5309	0,6378	0,5349	0,9297	0,5126
	(0,2743)	(0,2751)	(0,1683)	(0,2835)	(0,2597)	(0,2588)	(0,1515)	(0,2665)	(0,2616)	(0,2767)	(0,1358)	(0,2774)
20	0,7004	0,6667	0,9363	0,6241	0,7103	0,6731	0,9423	0,6340	0,7139	0,6619	0,9522	0,6301
	(0,1486)	(0,1523)	(0,0145)	(0,1424)	(0,1455)	(0,1492)	(0,0141)	(0,1400)	(0,1500)	(0,1573)	(0,0117)	(0,1495)
21	0,6658	0,6675	0,8790	0,5870	0,6721	0,6790	0,8748	0,5941	0,6703	0,6859	0,8554	0,5879
	(0,1597)	(0,1703)	(0,0528)	(0,1568)	(0,1541)	(0,1571)	(0,0543)	(0,1447)	(0,1404)	(0,1403)	(0,0563)	(0,1307)
22	0,6904	0,7403	0,8454	0,6256	0,7037	0,7506	0,8519	0,6393	0,7126	0,7495	0,8678	0,6501
	(0,1180)	(0,1086)	(0,0412)	(0,0952)	(0,1136)	(0,1038)	(0,0382)	(0,0921)	(0,1124	(0,1069)	(0,0343)	(0,0940)
24	0,7101	0,8053	0,8682	0,6970	0,7297	0,7969	0,8846	0,7021	0,7352	0,7896	0,9015	0,7096
	(0,1256)	(0,0864)	(0,0505)	(0,0680)	(0,1219)	(0,1071)	(0,0451)	(0,0836)	(0,1234)	(0,1142)	(0,0378)	(0,0948)
25	0,7353	0,7257	0,9204	0,6675	0,7299	0,7257	0,9133	0,6625	0,7131	0,7232	0,8889	0,6427
	(0,1080)	(0,1227)	(0,0178)	(0,1116)	(0,1123)	(0,1240)	(0,0194)	(0,1127)	(0,1079)	(0,1153)	(0,0243)	(0,1029)
26	0,7164	0,6574	0,9485	0,6236	0,7283	0,6700	0,9497	0,6362	0,7413	0,6797	0,9540	0,6485
	(0,1322)	(0,1511)	(0,0110)	(0,1437)	(0,1296)	(0,1490)	(0,0124)	(0,1418)	(0,1282)	(0,1481)	(0,0084)	(0,1415)
27	0,6829	0,6734	0,9061	0,6106	0,7076	0,6915	0,9175	0,6348	0,7392	0,6998	0,9422	0,6593
	(0,1312)	(0,1384)	(0,0234)	(0,1286)	(0,1195)	(0,1293)	(0,0200)	(0,1208)	(0,1110)	(0,1273)	(0,0115)	(0,1200)
28	0,7422	0,7305	0,9409	0,6874	0,7547	0,7520	0,9371	0,7048	0,7367	0,7413	0,9285	0,6883
	(0,1066)	(0,1282)	(0,0114)	(0,1218)	(0,0998)	(0,1183)	(0,0121)	(0,1121)	(0,1047)	(0,1221)	(0,0149)	(0,1144)
29	0,6938	0,7225	0,8871	0,6414	0,7067	0,7334	0,8897	0,6527	0,7111	0,7324	0,8990	0,6587
	(0,1317)	(0,1250)	(0,0271)	(0,1143)	(0,1307)	(0,1245)	(0,0260)	(0,1135)	(0,1343)	(0,1290)	(0,0233)	(0,1180)
30	0,6863	0,5967	0,9327	0,5558	0,6837	0,6011	0,9310	0,5606	0,6986	0,5924	0,9451	0,5590
	(0,1654)	(0,1996)	(0,0384)	(0,1851)	(0,1721)	(0,2070)	(0,0543)	(0,1930)	(0,1400)	(0,1849)	(0,0304)	(0,1736)

Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations. Standard deviations in parentheses.

conclude that industry (24) is the most cost efficient industry of the German manufacturing sector, and that industry (19) is the least cost-efficient one in years 2003, 2005 and 2010. But such a direct comparison is not valid, as these cost efficiency scores were estimated using different stochastic cost frontiers. As Table 7 shows, the estimation using SMF paints a different picture. The only valid direct comparison is the one of meta cost efficiency scores (MCE), which ranks industry (24) as the most cost-efficient industry in year 2003 and 2010, whereas the first place is overtaken by industry (28) in 2005. The differences in ranking of firms over time, using SCF and SMF, are reported in Table 8. The development of mean meta cost-efficiency scores over time is depicted in Figure 6 in the Appendix.

Table 8: The comparison of rankings using SCF and MCF analyses across years

	2003		2005		2010	
Ranking	SCF	MCF	SCF	MCF	SCF	MCF
1.	24	24	24	28	24	24
2.	13	28	13	24	13	28
3.	22	25	28	25	22	27
4.	10	29	22	29	28	29
5.	28	22	10	22	29	22
6.	25	20	29	26	10	26
7.	29	26	25	27	25	25
8.	27	27	27	20	27	20
9.	21	16	21	16	21	13
10.	20	21	20	21	26	16
11.	26	13	26	13	20	21
12.	16	19	16	30	16	30
13.	30	30	30	10	30	10
14.	19	10	19	19	19	19

Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

5.2.2 Intra-industry Comparison

The use of SMF analysis is also required if one wants to directly compare cost efficiency of firms operating in different groups, under heterogeneous stochastic cost frontiers, using different technologies. My second hypothesis stating that innovation, encouraged by the EU ETS regulation, in some industries potentially causes a divergence of regulated and non-regulated firms, has thus far been proven for industries (19) and (21). The Likelihood Ratio Test confirmed, that the

Table 9: The comparison of mean cost efficiency scores between differently treated groups across years

Year	CE	CGR	MCE	CE	CGR	MCE
ISIC Rev. 4 (19)		treatment group			control group	
2003	0,8262	0,6259	0,5309	0,7023	0,8415	0,5915
	(0,1816)	(0,1767)	(0,2168)	(0,2264)	(0,0515)	(0,1915)
2005	0,8015	0,6382	0,5292	0,6878	0,8268	0,5714
	(0,2162)	(0,1753)	(0,2365)	(0,2107)	(0,0670)	(0,1825)
2010	0,7732	0,6972	0,5573	0,6865	0,8011	0,5662
	(0,2416)	(0,1500)	(0,2444)	(0,2357)	(0,1069)	(0,2103)
ISIC Rev. 4 (21)		treatment group			control group	
2003	0,5709	0,5917	0,3378	0,6714	0,9773	0,6563
	(0,1265)	(0,1577)	(0,1124)	(0,1673)	(0,0024)	(0,1638)
2005	0,6228	0,6719	0,4190	0,6832	0,9776	0,6680
	(0,1544)	(0,1794)	(0,1536)	(0,1536)	(0,0024)	(0,1503)
2010	0,6431	0,6638	0,4259	0,6899	0,9786	0,6752
	(0,1429)	(0,2128)	(0,1553)	(0,1365)	(0,0018)	(0,1336)

Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations. Standard deviations in parentheses.

use of heterogeneous frontiers for the treated and non-treated group is superior to using a homogeneous/pooled stochastic cost frontier. Table 9 shows that in the case of industry (19), when directly comparing cost efficiencies (CE), estimated using separate stochastic cost frontiers for treated and control groups of firms, treated firms are more cost-efficient than control firms in years 2003, 2005 and 2010. The latter direct comparison is not valid, as it requires the SMF approach. When comparing the meta cost efficiency scores (MCE), the treatment group actually consistently demonstrates lower cost efficiency compared to the control group. Admittedly, the difference decreases over time. For industry (21), the application of SMF analysis exposes big differences between the cost efficiency of treatment and control group of firms. While the direct comparison of CE scores would indicate a difference of roughly 10%, the comparison of MCE scores indicates a difference of more than 30% in year 2003. This difference in MCE decreases over time. Figure 7 in the Appendix depicts intra-industry comparison of yearly mean meta cost efficiency scores across treatment groups for 2-digit industries (19) and (21).

5.3 Difference-in-differences Analysis

Table 10 reports the results of the parametric DD model described in Section 3.3.1 for the full sample (industries (10)-(33). The outcome variable is the cost efficiency, measured against a pooled stochastic cost frontier in logs. Table 10 shows the estimates of specification that includes control variables, fixed effects and full interaction terms on industry and year.

5.3.1 Cost efficiency measured against a stochastic cost frontier

Table 10: Parametric DD approach treatment effects of a full sample

Dependent Variable: Cost efficiency in logs	
Full sample	
Phase1	-0.153*
Phase2	-0.161*
Phase3	-0.157*
Year FE	yes
Firm FE	yes
Industry FE	yes
Industry × Year FE	yes
Additional Controls	yes
# Observations	175359

Standard errors are computed by employing the block bootstrap algorithm with 500 replications. *p<0.10, **p<0.05,***p<0.01; Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

As shown by Bertrand et al. (2004), conventional standard errors in DD applications with long time series and a high serial correlation in the outcome variable are inconsistent. Therefore, I apply the block bootstrap procedure with 500 replications in order to obtain adequate standard errors for the estimated treatment effects clustered at the firm-level. My results show a significant negative effect of the EU ETS on firm-level cost efficiency of 15.3 percent during the first compliance period. The estimated treatment effect for the second compliance period is 16.1 percent, and 15.7 percent for the third compliance period. Table 11 reports the treatment effects estimated using the non-parametric DD approach with nearest-neighbor matching, described in Section 3.3.2. When matching with the nearest neighbor, I obtain an average negative treatment effect of 14 percent, for the first compliance period. When adding the five closest neighbors to the control group, it increases the treatment effect to -15.4 percent. Adding the twenty closest neighbours, further increases the negative treatment effect to -15.7 percent. Also for the second and third compliance period, the nearest neighbor matching shows significantly negative estimates. As the industries within the manufacturing sector produce very different

Table 11: Non-parametric DD approach with matching: treatment effects for the full sample

Dependent Variable:	Cost efficiency in logs		
Full sample	one neighbor	five neighbors	twenty neighbors
Phase1	-0.140***	-0.154***	-0.157***
Phase2	-0.143***	-0.166***	-0.171***
Phase3	-0.140***	-0.167***	-0.169***
Year FE	yes	yes	yes
Firm FE	yes	yes	yes
Industry FE	yes	yes	yes
Industry × Year FE	yes	yes	yes
Additional Controls	yes	yes	yes
# Observations	7042	11529	19444

Standard errors are computed by employing the block bootstrap algorithm with 500 replications. *p<0.10, **p<0.05,***p<0.01; Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

goods, face different market conditions on input and output markets, the effect of the EU ETS on the regulated firms potentially varies across industries. The average treatment effect over all industries, shown in Tables 10 and 11 therefore does not provide the full picture of the impact of the EU ETS. For this reason, I analyze the effect of the EU ETS for selected subsample of 2-digit industries: coke and refined petroleum products (19), pharmaceutical products (21), rubber and plastic products (22) and basic metals industry(24). The results of the subsample analysis in Table 12 confirm the

Table 12: Parametric DD approach treatment effects for selected 2-digit industries

Dependent Variable:	Cost efficiency in logs			
ISIC Rev.4	19	21	22	24
Phase1	-0.086	-0.092 **	-0.109***	-0.272***
Phase2	-0.034	-0.126***	-0.201***	-0.311***
Phase3	-0.117	-0.320***	-0.171***	-0.277***
Year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Additional Controls	yes	yes	yes	yes
# Observations	487	2129	10242	7154

Standard errors are computed by employing the block bootstrap algorithm with 500 replications. *p<0.10, **p<0.05,***p<0.01; Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

heterogeneity of the treatment effect, however this empirical strategy also reduces the sample size. Consequently, the precision of the estimates decreases in comparison to the analysis using the full sample. The biggest negative average treatment effect is found for industry (24), ranging from -27.2 percent in the first compliance period, to -31.1 percent in the second compliance period and -27.7 percent in the third compliance period. For industry (19), the impact of the EU ETS is negative but insignificant. Table 13 shows the results of non-parametric DD approach for a subsample of

Table 13: Non-parametric DD approach with matching: treatment effects for selected 2-digit industries

Dependent Variable:	Cost efficiency in logs											
ISIC Rev.4	19			21			22			24		
# Neighbors	1	5	20	1	5	20	1	5	20	1	5	20
Phase1	-0.073	-0.071	-0.089*	-0.064	-0.067	-0.075	-0.110***	-0.119***	-0.113***	-0.271***	-0.274***	-0.271***
Phase2	-0.091	-0.050	-0.045	-0.190**	-0.178***	-0.103	-0.205***	-0.218***	-0.204***	-0.316***	-0.322***	-0.310***
Phase3	-0.175**	-0.118	-0.105	-0.334***	-0.322***	-0.256***	-0.205***	-0.178***	-0.182***	-0.284***	-0.289***	-0.277***
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Additional Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
# Observations	220	269	359	102	229	419	151	340	732	914	1496	2492

Standard errors are computed by employing the block bootstrap algorithm with 500 replications. *p<0.10, **p<0.05,***p<0.01; Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

industries. The biggest differences are observed in industries (19)and (21). For industry 19, the EU ETS now demonstrates a significant negative average treatment effect of -17.5 percent in the third compliance period using the nearest-neighbor, and a significant negative average treatment effect of -8.9 percent in the first compliance period using the next twenty neighbors. For industry (21), the average negative treatment effects are lower than in table 12. The difference in outcomes is expected as, applying the matching algorithm, I avoid the functional assumptions of the parametric DD model and I only compare the regulated firms with very similar unregulated firms. Furthermore, I am only able to compare firms that remain in the sample during the considered time.

5.3.2 Cost efficiency measured against a meta stochastic cost frontier

As the industries within the manufacturing sector also differ in terms of regulation, the average treatment effect for specific industries shown in Table 13, fails to account for potential operation under heterogeneous frontiers and overstates the impact of the EU ETS. For this reason, I also analyze the effect of the EU ETS on meta-cost efficiency of treated firms in logs for industris (19) and (21). As expected, Table 14 indicates drastically different results. The average treatment

Table 14: Parametric DD approach treatment effects for selected 2-digit industries

Dependent Variable: Meta cost efficiency in logs		
ISIC Rev.4	19	21
Phase1	0.018	-0.001
Phase2	0.051	-0.018
Phase3	0.002	-0.129*
Year FE	yes	yes
Firm FE	yes	yes
Additional Controls	yes	yes
# Observations	487	2129

Standard errors are computed by employing the block bootstrap algorithm with 500 replications. *p<0.10, **p<0.05,***p<0.01; Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

effect of the EU ETS on firms in industry (19) is now much smaller, positive, and statistically insignificant. The average treatment effect of the EU ETS on firms in industry (21) is also smaller, remains negative, and is slightly statistically significant only in third compliance period (-12.9 percent).

5.4 Primal System Approach

Table 15 reports PSA estimation results. The first two columns show the output technical efficiency (TE) and inefficiency (TIE). For industry (16) in 2003, for example, the firms produce around 31.92 to 43.36 percent less on average than their maximum potential output due to technical inefficiency. The third and fourth column show the input allocative inefficiency for energy (AIE_E) and capital (AIE_K) relative to labour. For all industries and years we observe negative mean values, this means that labor/energy and labor/capital ratios are on average lower than the cost minimizing ratios. This result additionally shows that capital is overused relative to both labour and energy (confirmation of the Averch-Johnson hypothesis). The fifth column ($Count$), reports the percentage of firms that overuse capital relative to both labour and fuel. For all firms, varying and increasing returns to scale (RTS) are found. I also computed the effect of technical and allocative inefficiencies on costs. As estimates of allocative inefficiency for each pair of inputs only tell us whether an input is relatively overused, I first needed to compute the impact of technical and allocative inefficiency on input demand, and then used these estimates subsequently to calculate their impact on cost. The eight column reports the cost of technical

Table 15: Estimation results of technical and allocative efficiency in cost frontier model across years for selected 2-digit industries (16), (20) and (25)

	No systematic error									With systematic error
$Year$	TE	TIE	AIE_E	AIE_K	$Count$ (%)	RTS	$C_{ratioTIE}$	$C_{ratioAIE}$	$C_{ratioBOTH}$	$Count$ (%)
ISIC Rev. 4 (16)										
2003	0,6808	0,4336	-0,0714	-0,0918	12,01	1,3032	0,4294	0,0690	0,5274	25,45
	(0,0837)	(0,1528)	(0,9635)	(0,6498)			(0,2180)	(0,1162)	(0,2807)	
2005	0,7256	0,3545	-0,0608	-0,0741	12,20	1,3091	0,3308	0,0757	0,4301	25,56
	(0,0661)	(0,1067)	(0,9955)	(0,6728)			(0,1200)	(0,1287)	(0,1989)	
2010	0,7868	0,3321	-0,1375	-0,1178	16,29	1,2953	0,0025	0,0862	0,0889	34,57
	(0,0221)	(0,1005)	(1,1043)	(0,6821)			(0,0001)	(0,1254)	(0,1257)	
ISIC Rev. 4 (20)										
2003	0,6193	0,5595	-0,0479	-0,0698	33,31	1,1827	0,6864	0,0744	0,8167	59,88
	(0,1168)	(0,2513)	(1,2425)	(0,5968)			(0,4877)	(0,1134)	(0,5937)	
2005	0,6885	0,4206	-0,0385	-0,0570	32,23	1,1647	0,4512	0,0780	0,5654	56,98
	(0,0806)	(0,1656)	(1,2568)	(0,5848)			(0,1976)	(0,1118)	(0,2800)	
2010	0,6691	0,4572	-0,0706	-0,0688	36,27	1,2035	0,4799	0,1157	0,6562	65,79
	(0,0855)	(0,1690)	(1,3943)	(0,6237)			(0,2294)	(0,3523)	(0,6112)	
ISIC Rev. 4 (25)										
2003	0,6940	0,4114	-0,0280	-0,0707	12,83	1,1950	0,4571	0,0471	0,5253	23,96
	(0,0958)	(0,1994)	(0,8331)	(0,5660)			(0,3922)	(0,0745)	(0,4226)	
2005	0,6879	0,4207	-0,0246	-0,0658	13,01	1,2230	0,4536	0,0481	0,5228	24,21
	(0,0882)	(0,1646)	(0,8274)	(0,5625)			(0,3462)	(0,0678)	(0,3748)	
2010	0,6893	0,04007	-0,0320	-0,0672	16,92	1,2184	0,0006	0,0475	0,0481	31,39
	(0,0923)	(0,1406)	(0,8039)	(0,5347)			(0,0004)	(0,0734)	(0,0730)	

Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations. Standard deviations in parentheses.

inefficiency ($C_{ratioTIE}$), computed by comparing costs with and without technical inefficiency. The ninth column reports the cost of allocative inefficiency ($C_{ratioAIE}$). The tenth column evaluates the cost impact when both types of inefficiencies are assumed to exist ($C_{ratioBOTH}$). My findings suggest that technical inefficiency is predominantly a higher source of extra cost than allocative inefficiency, except for industry (16) and (25) in year 2010. The last column refers to the Primal Half-Normal Model with Systematic Error in which systematic allocative inefficiency ($\xi \sim MVN(\rho, \Sigma)$) is allowed for. This approach is an extension of the one described in Section 3.4. Estimated inefficiencies, although not reported here, are found to be similar to those in Table 15. As systematic overutilization of capital relative to any other input is allowed for here, the percentage of firms that overused capital is much higher than in the fifth column.

6 Concluding discussion

This paper provides the first comprehensive analysis of the relationship between firm economic performance and the regulation by the EU ETS in the context of the German manufacturing sector, using official firm-level production census data for the period 2003-2014. German manufacturing sector is the biggest European CO_2 emitter, and the share of gross domestic product (GDP) accounted for by manufacturing is higher in Germany than in any other European country (52%), which renders it important to investigate in the context of environmental policy impacts. For fourteen 2-digit industries of the German manufacturing sector I estimate a SCF to recover firm-specific cost efficiencies as a measure of economic performance. My results indicate that the potential to increase cost efficiency exists in all industries and that the cost-efficiency estimates are heterogeneous. Little is known about the determinants of cost efficiency in the German manufacturing sector, the drivers were selected based on relevance for research and policies. The analysis of drivers confirms a positive relationship between exporting and the cost efficiency for most of the industries. On the contrary, the regulation by the EU ETS, investments into research and development, as well as active trading of emission permits are all associated with lower cost containment capabilities. The latter rejects my first hypothesis, as the regulation by the

EU ETS seems to be a significant driver of cost-inefficiency, even-though I have accounted for higher energy prices for regulated firms in my cost frontier model. These results do not allow me to draw a clear conclusion about the relationship between the EU ETS and the cost efficiency, but they might suggest that the EU ETS regulates less cost-efficient firms, or that the impact of the EU ETS materializes in more than just an energy price increase for regulated firms. For instance, higher R&D investments for regulated firms could increase regulated firms' total costs, which would make them appear less cost-efficient. One way to test this claim would be to model this R&D investment as an additional output in the cost frontier. Furthermore, if significant investments into R&D were actually made by most of the regulated firms, then the unexpectedly low carbon prices would make most of them very unprofitable in the short run. Using my adjustment for energy prices directly in the cost frontier, I could test whether significantly higher carbon prices would confirm my first hypothesis.

In order to make cost-efficiency comparisons between industries and between treatment groups within industries, I employed SMF analysis. Inter-industry comparison suggests that the most cost-efficient industry is the industry producing basic metals, whereas the least cost-efficient industry is the industry producing coke and refined petroleum products. My results also indicate considerable dynamics in the development of meta cost efficiencies over time. The results of the intra-industry comparison suggest a confirmation of my second hypothesis as regulated and non-regulated firms operate under heterogeneous frontiers in industries (19) and (21). In both industries, treated firms are confirmed to be less cost-efficient than the control firms. However the difference in cost-efficiency levels is found to be decreasing over time.

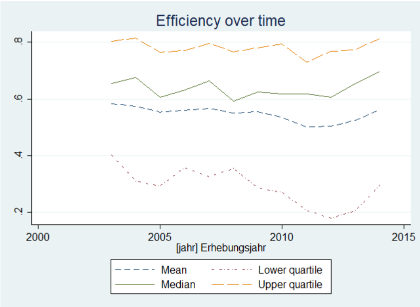
Combining the DD model with parametric conditioning strategies and non-parametric nearest-neighbor matching allows me to isolate the average treatment effect of the EU ETS on firm-specific cost efficiencies. Results suggest that the EU ETS does not homogeneously affect various industries of the German manufacturing sector, but that the effect was predominantly negative and mostly highly statistically significant in all three compliance periods. However, as the estimation of cost efficiency using homogeneous frontiers for regulated and non-regulated firms is potentially problematic in light of the EU ETS regulation, I also investigate the average treatment effect of the EU ETS on firm-specific meta cost efficiencies. As expected, the results are very different. The negative treatment effect is slightly significant for just one of the two industries, and only in the third compliance period. For the other industry, there is no significant effect of the EU ETS on treated firms. Although these results are preliminary, they do confirm that the use of SMF is critical when evaluating the impact of the EU ETS.

In my study, I also employ the PSA to provide a deeper understanding of sources of extra cost for firms in various industries of the German manufacturing sector. I find that the allocative inefficiency is a much smaller source of extra cost than the technical inefficiency, which suggests that investment in the existing more efficient technology or innovation would reduce the total costs of firms in the long run. From a policy perspective, the creation of the Innovation Fund in the fourth phase of the EU ETS is, therefore, a step in the right direction. My PSA results also suggest a systematic overuse of capital in relation to energy and labour, which confirms the Averch-Johnson hypothesis.

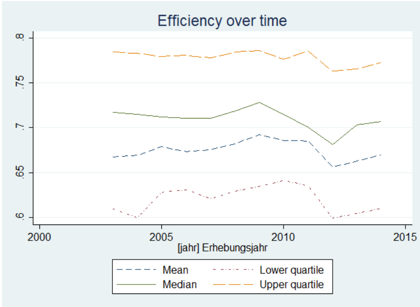
The fact that I find a significant negative effect of the EU ETS on firm-level cost-efficiency is surprising. Previous literature, although not directly related to cost-efficiency, found very small and mostly insignificant impacts of the EU ETS in terms of firms productivity. At this stage of my research, I cannot fully clarify the mechanisms at work for a number of reasons. First, when interpreting my results I assumed that EU ETS only influences treated firms. Due to spillover and equilibrium intra-industry effects, the SUTVA is likely violated, which is one of the obvious limitations to my study. In a future version of this paper, the importance of SUTVA violation will be addressed in various robustness checks. Second, German manufacturing firms are not subject solely to the EU ETS regulation. In my study I neglect to consider other regulatory instruments, such as energy taxes and electricity price surcharges, that might interact with the effect of the EU ETS. Third, in its current form, my stochastic cost frontier model suffers from potential endogeneity concerns. My measure of output is potentially endogenous, as it is a choice variable for most firms. Energy input prices are potentially endogenous because of negotiations between firms and energy suppliers, e.g. fixed-term contracts between electricity generators and firms or long-term gas contracts. My measure of labour costs, affecting the input price for labour, could also be endogenous because of unobserved input quality. In the existing stochastic frontier analysis literature, the use of solutions such as the control function for the unobservables, introduced by Olley and Pakes (1992) and Levinsohn and Petrin (2003), is not straightforward, due to non-linearities. For this reason, the issue of endogeneity in stochastic cost frontier models has so far been somewhat ignored. Health economics and health services research, has previously addressed these concerns using a two-stage residual inclusion approach.[28] Recently, Karakaplan and Kutlu (2017) developed their own stochastic frontier estimator, which has been proven to outperform standard stochastic frontier estimators, as it can treat the endogeneity of both frontier and inefficiency variables. Their estimator is easy to implement in Stata using their module. In a future version of the paper I will present the results of using the latter approach, to address the endogeneity in my emprical application. Finally, it is also possible that the observed negative effect is actually reflecting a short run shock, as treated firms made considerable investments into research and development. Low EUA prices have not made it possible to contain their costs better during my observed period, but it would be interesting to check whether these strong effects are still present in recent years, as the EUA prices have risen. Future work could tackle some of these issues.

[28]For more information, see Garrido et al. (2012).

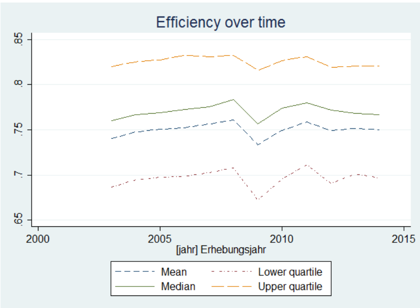
7 Appendix



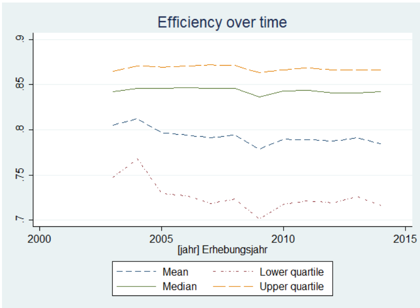
(a) Coke and refined petroleum products



(b) Pharmaceutical products

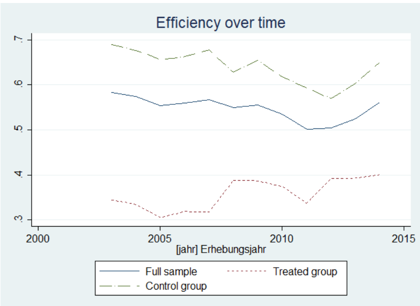


(c) Rubber and plastic products

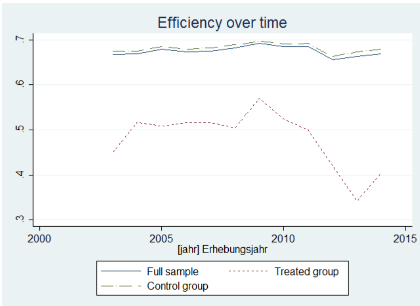


(d) Basic metals

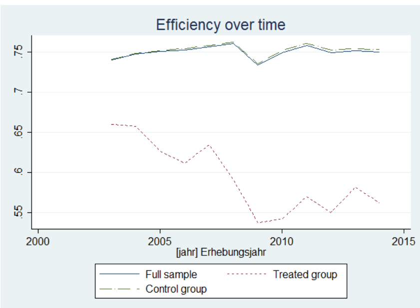
Figure 4: Mean cost efficiency scores across the years for selected 2-digit industries (19), (21), (22), (24). Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.



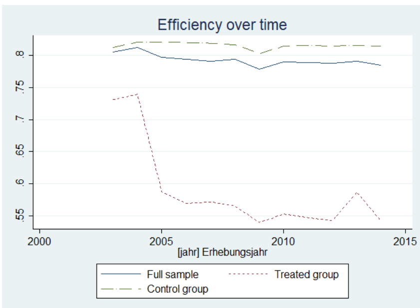
(a) Coke and refined petroleum products



(b) Pharmaceutical products



(c) Rubber and plastic products



(d) Basic metals

Figure 5: Regulated firms and unregulated firms mean cost efficiency scores across the years for selected 2-digit industries (19), (21), (22), (24). Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

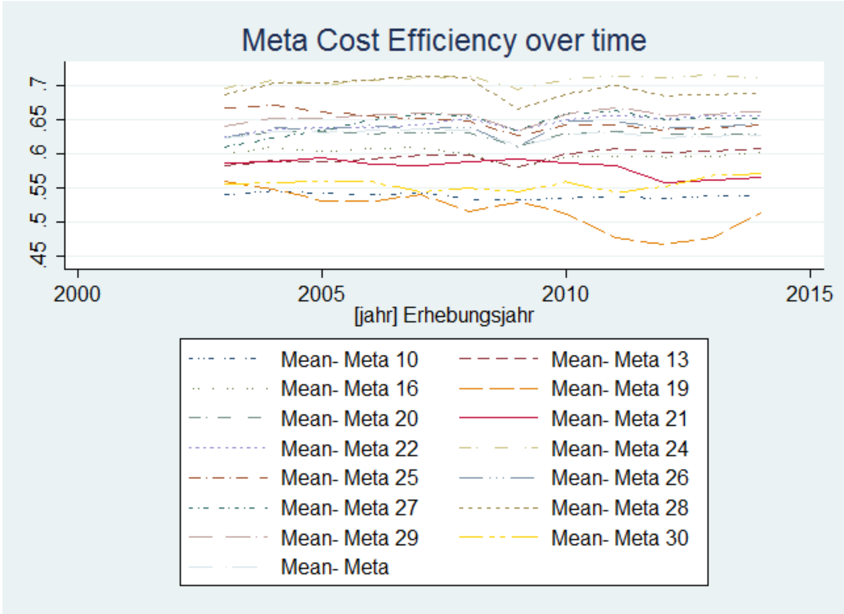
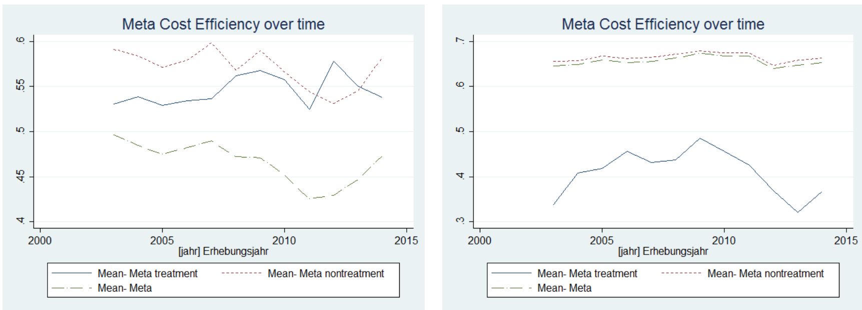


Figure 6: Inter-industry comparison of yearly mean meta-cost efficiency scores. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.



(a) Coke and refined petroleum products

(b) Pharmaceutical products

Figure 7: Intra-industry comparison of yearly mean meta cost efficiency scores across treatment groups for selected 2-digit industries (19), (21). Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

A Further data description

2-digit industry level classification:

In the period 2003-2008, the industry classification in my 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. I reclassified the years before 2008 using official reclassification guide of the statistical offices at the four-digit industry code level, to be able to use the ISIC Rev.4 classification throughout. In the interest of having enough observations, I carry out the final analysis on the two-digit industry level.

Merging of AFiD, EUTL and Orbis:

I combine different modules of AFiD data set via plant and firm-level identifiers. Matching AFiD data with EUTL and Orbis, however, requires a three-step procedure. Firstly, EUTL and Orbis information are combined in a single dataset. Then, this external dataset of firms is combined with the German Business Register using information on commercial register number, VAT number, address and emissions in order to obtain a unique company identification number. Using the latter, external dataset can be combined with the AFiD dataset. I am able to match 83 percent (1117 firms) of the firms in the EUTL with the commercial register number. My matching is 6 percent better than in previous attempts by authors using the same data. The firms that are not matched mainly belong to non-manufacturing sectors.

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References

Aigner, D., C. K. Lovell, and P. Schmidt (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics 6*(1), 21–37.

Ambec, S., M. Cohen, S. Elgie, and P. Lanoie (2013). The porter hypothesis at 20:can environmental regulation enhance innovation and competitiveness? *Environmental Economics and Policy*.

Amsler, C., C. J. O?donnell, and P. Schmidt (2017). Stochastic metafrontiers. *Econometric Reviews 36*(6-9), 1007–1020.

Battese, G. E. and T. J. Coelli (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of econometrics 38*(3), 387–399.

Battese, G. E. and T. J. Coelli (1993). *A stochastic frontier production function incorporating a model for technical inefficiency effects*, Volume 69. Department of Econometrics, University of New England Armidale.

Battese, G. E. and T. J. Coelli (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics 20*(2), 325–332.

Battese, G. E., D. P. Rao, and C. J. O'donnell (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis 21*(1), 91–103.

Belotti, F., S. Daidone, G. Ilardi, and V. Atella (2012). Stochastic frontier analysis using stata.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How much should we trust differences-in-differences estimates? *The Quarterly journal of economics 119*(1), 249–275.

Bertrand, V. (2014). Carbon and energy prices under uncertainty: A theoretical analysis of fuel switching with heterogenous power plants. *Resource and Energy Economics 38*, 198–220.

Bhandari, A. K. and S. C. Ray (2012). Technical efficiency in the indian textiles industry: A non-parametric analysis of firm-level data. *Bulletin of Economic Research 64*(1), 109–124.

Breustedt, G., U. Latacz-Lohmann, and T. Tiedemann (2011). Organic or conventional? optimal dairy farming technology under the eu milk quota system and organic subsidies. *Food Policy 36*(2), 223–229.

Calel, R. and A. Dechezleprêtre (2016). Environmental policy and directed technological change: evidence from the european carbon market. *Review of economics and statistics 98*(1), 173–191.

Calligaris, S., F. M. D'Arcangelo, and G. Pavan (2018). The impact of the european carbon market on firm productivity: Evidence from italian manufacturing firms. *Working Paper*.

Chapple, W., A. Lockett, D. Siegel, and M. Wright (2005). Assessing the relative performance of uk university technology transfer offices: parametric and non-parametric evidence. *Research Policy 34*(3), 369–384.

Charnes, A., W. W. Cooper, and E. Rhodes (1978). Measuring the efficiency of decision making units. *European journal of operational research 2*(6), 429–444.

Chen, C.-M., T.-C. Sheng, and Y.-L. Yang (2014). Cost efficiency analysis of taiwan biotech and pharmaceutical industry: The application of stochastic meta frontier model. *International Journal of Economics and Finance 6*(11), 131.

Christiansen, A. C., A. Arvanitakis, K. Tangen, and H. Hasselknippe (2005). Price determinants in the eu emissions trading scheme. *Climate Policy 5*(1), 15–30.

Ellerman, A. D., C. Marcantonini, and A. Zaklan (2016). The european union emissions trading system: ten years and counting. *Review of Environmental Economics and Policy 10*(1), 89–107.

Estache, A. and M. A. Rossi (2002). How different is the efficiency of public and private water companies in asia? *The World Bank Economic Review 16*(1), 139–148.

EU KLEMS (2017). Growth and productivity accounts: Statistical module, esa 2010 and isic rev. 4 industry classification. Technical report, September 2017 release.

European Council (2014a). Conclusion euco 189/14 of the european council of 23 and 24 october 2004. Technical report, Official Journal of the European union,CO EUR 13.

European Council (2014b). *A policy framework for climate and energy in the period from 2020 to 2030.* Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committe and the Committe of the Regions, COM(2014) 15 final.

European Parliament and Council (2003). Directive 2003/87/ec of the european parliament and of the council of 13 october 2003 establishing a scheme for greenhouse gas emission allowance trading within the community and amending council directive 96/61/ec. Technical report, Official Journal of the European union, L 275, 32-46.

European Parliament and Council (2009). Directive 2009/29/ec of the european parliament and of the council of 23 april 2009 amending directive 2003/87/ec so as to improve and extend the greenhouse gas emission allowance trading scheme of the community. Technical report, Official Journal of the European union, L 140, 63-87.

Farell, P. (1957). Dea in production center: An input-output mode. *Journal of Econometrics 3*, 23–49.

Farsi, M. and M. Filippini (2008). Effects of ownership, subsidization and teaching activities on hospital costs in switzerland. *Health economics 17*(3), 335–350.

Fowlie, M., S. P. Holland, and E. T. Mansur (2012). What do emissions markets deliver and to whom? evidence from southern california's nox trading program. *American Economic Review 102*(2), 965–93.

Fries, S. and A. Taci (2005). Cost efficiency of banks in transition: Evidence from 289 banks in 15 post-communist countries. *Journal of Banking & Finance 29*(1), 55–81.

Garrido, M. M., P. Deb, J. F. Burgess Jr, and J. D. Penrod (2012). Choosing models for health care cost analyses: issues of nonlinearity and endogeneity. *Health services research 47*(6), 2377–2397.

Greene, W. (2005a). Fixed and random effects in stochastic frontier models. *Journal of productivity analysis 23*(1), 7–32.

Greene, W. (2005b). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of econometrics 126*(2), 269–303.

Greene, W. H. (1980). On the estimation of a flexible frontier production model. *Journal of Econometrics 13*(1), 101–115.

Hayami, Y. (1969). Sources of agricultural productivity gap among selected countries. *American Journal of Agricultural Economics 51*(3), 564–575.

Hayami, Y. and V. W. Ruttan (1970). Agricultural productivity differences among countries. *The American economic review 60*(5), 895–911.

Hayami, Y. and V. W. Ruttan (1971). Induced innovation in agricultural development.

Heckman, J. J., H. Ichimura, and P. E. Todd (1997, 10). Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *The Review of Economic Studies 64*(4), 605–654.

Hicks, J. R. (1932). Marginal productivity and the principle of variation. *Economica* (35), 79–88.

Hintermann, B. (2016). Pass-through of co2 emission costs to hourly electricity prices in germany. *Journal of the Association of Environmental and Resource Economists 3*(4), 857–891.

Huang, C. J., T.-H. Huang, and N.-H. Liu (2014). A new approach to estimating the metafrontier production function based on a stochastic frontier framework. *Journal of productivity Analysis 42*(3), 241–254.

Huang, M.-Y. and T.-T. Fu (2013). An examination of the cost efficiency of banks in taiwan and china using the metafrontier cost function. *Journal of Productivity Analysis 40*(3), 387–406.

Huang, T.-H., L.-C. Chiang, K.-C. Chen, and P. H. Chiu (2010). An application of the meta-frontier cost function to the study of bank efficiencies and technology gaps in 16 european countries. *Management Review 29*(3), 25–43.

Huang, Y.-J., K.-H. Chen, and C.-H. Yang (2010). Cost efficiency and optimal scale of electricity distribution firms in taiwan: An application of metafrontier analysis. *Energy Economics 32*(1), 15–23.

Joltreau, E. and K. Sommerfeld (2016). Why does emissions trading under the eu ets not affect firms' competitiveness? empirical findings from the literature.

Kanen, J. L. (2006). *Carbon trading and pricing.* Environmental Finance Publications.

Karakaplan, M. U. and L. Kutlu (2017). Endogeneity in panel stochastic frontier models: an application to the japanese cotton spinning industry. *Applied Economics 49*(59), 5935–5939.

Klein, N. and L. Lam (2017). Carbon pricing watch 2017.

Kumbhakar, S., H. Wang, and A. Horncastle (2015). *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata.* Cambridge University Press.

Levinsohn, J. and A. Petrin (2003). Estimating production functions using inputs to control for unobservables. *The review of economic studies 70*(2), 317–341.

Lin, Y.-H. (2011). Estimating cost efficiency and the technology gap ratio using the metafrontier approach for taiwanese international tourist hotels. *Cornell Hospitality Quarterly 52*(3), 341–353.

Löschel, A., B. J. Lutz, and S. Managi (2016). The impacts of the eu ets on efficiency- an empirical analyses for german manufacturing firms. *Discussion Paper No.16-089*, 33.

Lutz, B. J. (2016). Emissions trading and productivity: Firm-level evidence from german manufacturing. pp. 36.

Lutz, B. J., P. Massier, K. Sommerfeld, and A. Löschel (2016). Drivers of energy efficiency in german manufacturing: A firm-level stochastic frontier analysis.

Martin, R., M. Muûls, and U. J. Wagner (2015). The impact of the european union emissions trading scheme on regulated firms: What is the evidence after ten years? *Review of environmental economics and policy 10*(1), 129–148.

Meeusen, W. and J. van Den Broeck (1977). Efficiency estimation from cobb-douglas production functions with composed error. *International economic review*, 435–444.

Mundlak, Y. and I. Hoch (1965). Consequences of alternative specifications in estimation of cobb-douglas production functions. *Econometrica: Journal of the Econometric Society*, 814–828.

Newhouse, J. P. et al. (1994). Frontier estimation: How useful a tool for health economics? *Journal of health economics 13*(3), 317–322.

Nkamleu, G. B., J. Nyemeck, and D. Sanogo (2006). Metafrontier analysis of technology gap and productivity difference in african agriculture.

O'Donnell, C. J., D. P. Rao, and G. E. Battese (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics 34*(2), 231–255.

Olley, G. S. and A. Pakes (1992). The dynamics of productivity in the telecommunications equipment industry. Technical report, National Bureau of Economic Research.

Petrick, S. and U. J. Wagner (2014). The impact of carbon trading on industry: Evidence from german manufacturing firms.

Porter, M. E. (1991). Towards a dynamic theory of strategy. *Strategic Management Journal 12*(S2), 95–117.

Porter, M. E. and C. Van der Linde (1995). Toward a new conception of the environment-competitiveness relationship. *The Journal of Economic Perspectives 9*(4), 97–118.

Schmidt, P. and C. K. Lovell (1979). Estimating technical and allocative inefficiency relative to stochastic production and cost frontiers. *Journal of econometrics 9*(3), 343–366.

Schmidt, P. and C. K. Lovell (1980). Estimating stochastic production and cost frontiers when technical and allocative inefficiency are correlated. *Journal of Econometrics 13*(1), 83–100.

Shephard, R. W. (2012). *Cost and production functions*, Volume 194. Springer Science & Business Media.

Stadler, B. and C. Di Maria (2018). Climate policy and the efficiency of firms: new evidence from uk manufacturing.

Wadud, A. and B. White (2000). Farm household efficiency in bangladesh: a comparison of stochastic frontier and dea methods. *Applied Economics 32*(13), 1665–1673.

Zhang, A., Y. Zhang, and R. Zhao (2003). A study of the r&d efficiency and productivity of chinese firms. *Journal of Comparative Economics 31*(3), 444–464.