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Cap-and-trade and produce at least cost? Investigating firm behaviour in the EU ETS

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Investigating firm behaviour in the EU ETS

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Abstract

A persistent concern in the literature on climate policy is that the emissions abatement, which is achieved via environmental regulation, has potentially adverse effects on firms’ economic performance. I investigate this issue in the context of the European Union Emissions Trading Scheme (EU ETS) and the German manufacturing sector. My investigation uses confidential data from an administrative firm-level production census. As a measure of the economic performance, I estimate cost efficiencies and their determinants for narrowly defined industries with a stochastic cost frontier (SCF) analysis. In order to directly compare cost efficiencies across treatment groups, I use a stochastic meta frontier (SMF) analysis. I provide additional evidence of the causal impact of the EU ETS on various types of firms’ costs with a difference-in-differences (DD) framework. My results indicate that the EU ETS regulation has resulted in a small but significant increase in costs across the German manufacturing sector. This increase is driven mostly by an increase in energy and capital costs. I demonstrate that the potential to increase cost efficiency exists for most industries in the German manufacturing sector. The analysis of the drivers of cost efficiency confirms that in most industries, exporting firms are more cost efficient than their counterparts. In contrast, the results show that innovating firms and firms that are regulated by the EU ETS are less cost efficient than unregulated firms.

Keywords: *Stochastic Frontier Analysis, Meta Frontier Analysis, EU ETS, Manufacturing Sector;*

JEL Codes: *D22, D24, N64, Q52*

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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 emerges most clearly through various compliance mechanisms. 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 by changing its input choice (e.g., switching fuels) or adjusting its production process (e.g., investment in energy efficiency or a reduction of fuel usage). Alternatively, a firm may 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. This analysis is based on a unique and confidential dataset, obtained by combining several micro-datasets and modules from AFiD over the period from 2003 to 2014 (T=12).³ For narrowly defined industries in the German manufacturing sector,

¹ Several authors have previously recognized fuel-switching as the dominant type of short-term abatement in the EU ETS, due to relatively low related costs (Christiansen et al., 2005; Kanen, 2006; Bertrand, 2014; Calligaris et al., 2019).

²As of 2019, governments had implemented 57 carbon pricing initiatives, or had scheduled implementation, around the globe. This comprises 28 emission trading systems (ETSs) in regional, national and subnational jurisdictions, and 29 carbon taxes, primarily applied on a national level. Together these carbon pricing initiatives cover 11 gigatons of carbon dioxide equivalent ($GtCO_2e$) or 20 percent of global greenhouse gas (GHG) emissions (World Bank Group, 2019)).

³AFiD stands for “Amtliche Firmendaten für Deutschland”, which translates to “Official Firm Data for Germany”. The AFiD data are provided by the German Federal Statistical Office and the Statistical Offices of the German Federal States. Official governmental statistics and reports on the activities of the manufacturing sector are based on these data.

I first examine to what extent the EU ETS affects firm's overall costs using a difference-in-differences (DiD) approach. Within this analysis I investigate whether additional regulatory costs are reflected in energy, capital or labour costs.⁴ Because a change in costs is not necessarily followed by a change in firm's cost-containment capabilities I then proceed by investigating the firm-level cost efficiency. First, I estimate industry-specific cost frontiers using a stochastic cost frontier (SCF) analysis and determine time-varying firm-specific cost efficiencies.⁵ The chosen empirical model allows me to explore the various potential drivers of cost efficiency: the regulation by the EU ETS, activity in trading of emissions allowances, investments into research and development, and exporting status. Most of the industries in the German manufacturing sector comprise regulated and unregulated firms that potentially operate under heterogeneous frontiers in the long run. This allows me to employ a stochastic meta frontier (SMF) analysis in order to compare cost efficiencies across treatment groups within each industry.⁶

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 lower 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

⁴In a future version of this paper the results of this analysis will be included in the paper.

⁵Throughout 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.

⁶In a future version of this paper my analysis of the interplay between the EU ETS and the cost efficiency will be extended in various ways. I will estimate a model which does not account for the EU ETS regulation in the frontier, and quantify the average treatment effect of the EU ETS on the cost efficiencies and metacost efficiencies of regulated firms for a subset of 2-digit industries in a Difference-in-Differences (DiD) framework. Furthermore, I will present different ways of adjusting for the EU ETS regulation in a stochastic frontier framework and show how the results differ based on the adjustment.

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)).⁷ 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.⁸ 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 industries of the German manufacturing sector that use different technologies to produce different types of products. This difference requires the estimation of separate frontiers for each industry.⁹ Second, in the presence of stringent environmental regulation, regulated firms operate in different cost environments than their unregulated counterparts. These additional costs could potentially force them into changing their production process (e.g., via innovation) and therefore to start operating under different technology compared to their unregulated counterparts. To what extent, if at all, this materializes in reality will depend on a multitude of factors. The most important factor stimulating innovation is the strength of the price signal in the EU ETS. Note, however that the effect of EU ETS is not constrained just to regulated 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

⁷The 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)

⁸This change can also be described as a "jump" to a new cost frontier, which is in line with Breustedt et al. (2011).

⁹In theory, the meta-frontier approach allows me to compare cost efficiencies across different industries by enveloping all industry-specific frontiers with a common sectoral meta-frontier. In the existing context, these results do not warrant any important policy implications. Nevertheless, I present these results in the Appendix.

turn again indirectly affects 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. For all of the aforementioned reasons, the actual innovation effect of the EU ETS and resulting heterogeneity in production technologies across treatment groups may be limited. In an empirical framework, the potential indirect treatment of the control group is known as the violation of the Stable Unit Treatment Value Assumption. In this paper I provide a robustness check that addresses at least some of these concerns. The literature that evaluates the impact of the EU ETS identifies emissions, economic performance, competitiveness, and innovation as the main outcomes of interest.¹⁰ This literature only briefly addresses the firms' performance in terms of productivity. Recent work by Calligaris et al. (2019) 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. (2017) 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. (2017) 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

¹⁰For comprehensive overviews of these studies, please see Martin et al. (2015), Ellerman et al. (2016), and Joltreau and Sommerfeld (2019). Recent interesting papers analyzing these issues are Dechezleprêtre and Sato (2017) and Dechezleprêtre et al. (2018).

a positive association with energy efficiency. Löschel et al. (2019) 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. In the model applied in this study, I will assume that any cost inefficiencies arise only due to technical inefficiency and that firms are allocatively fully efficient.¹¹ My contribution encompasses not only the identification of the potential to increase cost efficiency at the firm and industry level, 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

¹¹Using the so-called Primal System Approach one could empirically examine the sources of inefficiency by decomposing cost efficiency into allocative and technical inefficiency. This could help identify how much of cost reduction a firm can achieve through improvements in the production technology and how much through an optimal mix of inputs. I leave this for future work. For more information, see Kumbhakar et al. (2015).

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.

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 potential violation by carrying out cost frontier estimations in less electricity-intensive industries in which the problem of an increased price for the energy input for unregulated firms is less pronounced.¹²

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. 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 AFiD data and additional data sources used. Section 5 presents the results of

¹²In a future version of this paper, I provide the results of this robustness check.

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 emissions. 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 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

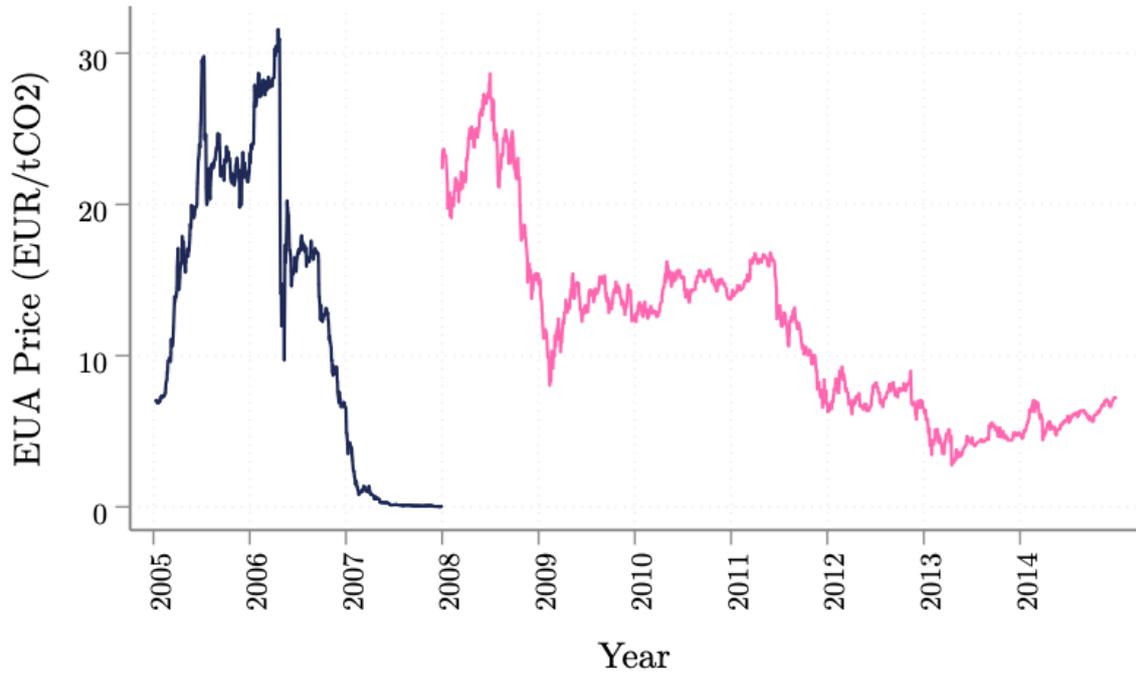


Figure 1: The evolution of the daily EUA prices for the period 2005-2014. Source: Thomson and Reuters, own depiction

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.¹³ I report on the number of regulated and unregulated firms in my dataset across the sample years in Table 1.

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.

¹³For more details on the inclusion criteria of the EU ETS, please see European Parliament and Council (2003).

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

ISIC Rev.4	Industry	2005			2010			2014		
		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.

3.1 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 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 as depicted in Figure 2. 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).¹⁴ Many other economic studies have used this model on efficiency with the SCF analysis and MFA methods.¹⁵ In my econometric model, I assume that the functional form of the SCF is Cobb-Douglas.¹⁶ Expressed in logs, the SCF can be written as:

$$\ln TC_{it} = \alpha + \beta_1 \ln Y_{it} + \beta_2 \ln P_{L_{it}} + \beta_3 \ln P_{K_{it}} + \beta_4 \ln P_{E_{it}} + \tau T + v_{it} + u_{it} \quad (1)$$

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 $u_{it} \sim N^+(\mu_{it}, \sigma_{u_i}^2)$.¹⁷ Including my variables for cost-efficiency drivers, I can specify the model for the stochastic cost inefficiency effects u_{it} as:

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

where $z_{it} = (1, z_{it}^1, \dots, z_{it}^L)$ 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

¹⁴A 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.

¹⁵See e.g. Fries and Taci (2005), Chapple et al. (2005), Estache and Rossi (2002), Zhang et al. (2003), Chen et al. (2014).

¹⁶Alternatively, 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)).

¹⁷To 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.

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).¹⁸ The following equation represents the cost efficiency of a firm, as the deterministic part of its distance relative to the SCF:

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

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

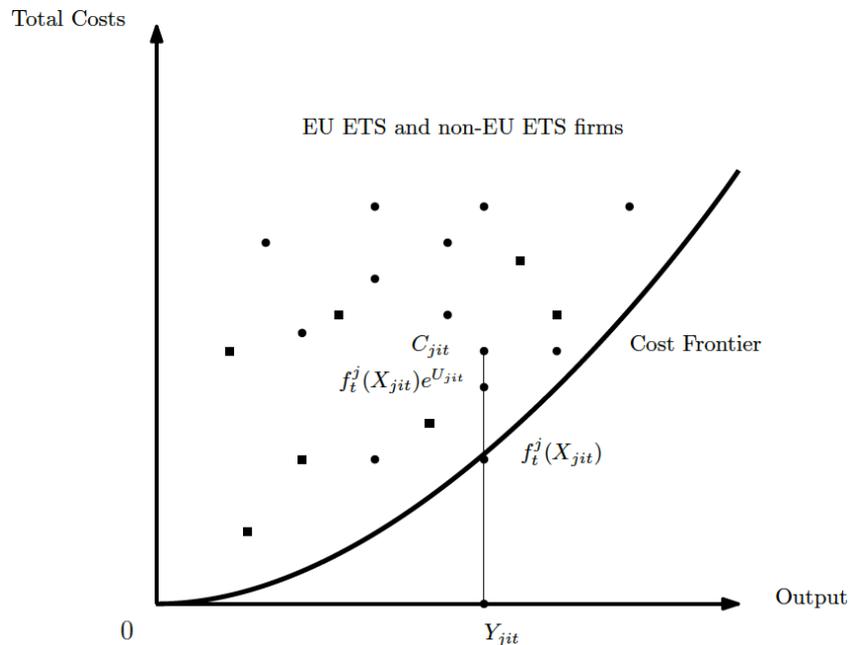


Figure 2: Use of stochastic frontier analysis for industry-specific cost frontier estimations, Source: Own depiction

3.2 Meta Frontier Analysis

There is often a considerable interest in measuring the performance of firms across different production groups.¹⁹ 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

¹⁸To estimate equations 1 and 2 with a single-stage approach, I use the Stata commands provided in Belotti et al. (2013).

¹⁹Nkamleu 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.

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 (Uzawa (1962), Shephard (2012)).²⁰ 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.

²⁰This was previously done by Chen et al. (2014) and Huang and Fu (2013), Huang et al. (2010), and Huang et al. (2010).

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.²¹ In this study, I use the SMFA for two purposes. First, as depicted in Figure 3, 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, by employing the method that was introduced by Huang et al. (2014), henceforth referred to as the HHL model.²² Contrary to prior efforts, the HHL model uses a conventional maximum likelihood method to

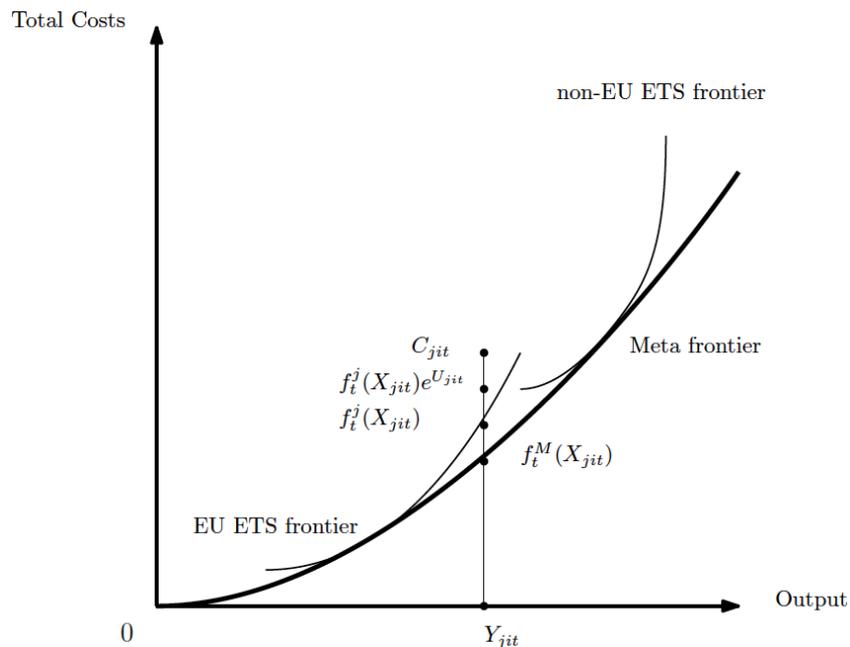


Figure 3: Use of meta-frontier analysis for intra-industry comparisons, Source: Own depiction

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

²¹In 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.

²²The 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.

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.

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) :

$$\ln \hat{T}C_{it} = \alpha + \beta_1 \ln Y_{it} + \beta_2 \ln P_{L_{it}} + \beta_3 \ln P_{K_{it}} + \beta_4 \ln P_{E_{it}} + \tau T + v_{it}^M + u_{it}^M \quad (4)$$

where $\hat{T}C_{it}$ 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:

$$u_{it} = a_0 + a_1 \text{RANDD}_{it} + a_2 \text{EX}P_{it} + \epsilon_{it} \quad (5)$$

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.²³ 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,

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

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

²³The 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).

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), Gerster et al. (2020), Calel and Dechezleprêtre (2016), Löschel et al. (2019)). 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. (2019). This way I do not have to pose any parametric assumptions on the relation between the cost efficiency and the explanatory variables z_{it} .²⁴ 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

²⁴Remaining 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: $0 < P[ETS_i = 1|X] < 1$.

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

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

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.²⁵

4 Data

My analysis relies on the use of the AFiD dataset for the period 2003-2014.²⁶ It contains information on annual general characteristics and cost structure, and it is particularly detailed in terms of fuel and electricity use.²⁷ I construct this unique dataset by combining several microdatasets and modules: the "AFiD Panel Industriebetriebe" (AFiD Panel Manufacturing Plants), the "AFiD Modul Energieverbrauch" (AFiD Module on Energy Use), "AFiD Modul Produkte" (AFiD Module on Products), the "Kostenstrukturerhebung" (Cost Structure Survey) and the "Unternehmensregister" (Company Register). These modules are provided by the German Federal Statistical Office and the Statistical Offices of the German Federal States and the information disclosure is mandatory for all surveyed firms and plants.²⁸ I additionally

²⁵In a future version of the paper we will implement nearest-neighbour matching without replacement as an additional matching techniques. As suggested by Abadie and Spiess (2019), this technique allows for a robust post-matching inference by clustering the standard errors on matched-pair level .

²⁶I 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.

²⁷AFiD stands for "Amtliche Firmendaten für Deutschland", English: Official Firm Data for Germany.

²⁸Detailed descriptions of the AFiD Panel Manufacturing Plants are provided by Koch and Migalk (2007) and Wagner (2010). Cost structure survey is explained in depth by Fritsch et al. (2004) and Lutz (2016). Additional information on Company Register can be found in Koch and Migalk (2007). Petrick et al. (2011) thoroughly

combine the European Union Transaction Log (EUTL) data in order to identify which German manufacturing firms are regulated by the EU ETS and other external data to calculate CO₂ emissions and estimate capital stocks. The datasets are merged at the firm-level via plant and firm-level identifiers. All monetary variables are deflated to 2010 Euros. For additional information on the merger, see section C in the Appendix.²⁹

4.1 SCF and SMF variables

My measure of total costs (TC) comes from the CSS.³⁰ My measure of output (Y) is the gross value of production of the firm, retrieved from the AFiD Module on Products. The production data is provided at the 9-digit product code level, which are listed in the List of goods from production statistics by Statistisches Bundesamt (2019). We deflate the sales values using two-digit ISIC Rev. 4. deflators.³¹ 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 annual emissions in tCO₂ with the respective EUA price. Annual emissions are calculated using energy use and related CO₂ emission factors. All monetary values are deflated to the 2010 base value.³² 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 drivers are obtained in the following way: Based on the commercial register number and the VAT number, I first match the European

inform on the AFiD Module on Energy Use.

²⁹The AFiD data was previously used in the context of the EU ETS by Gerster et al. (2020), Lutz (2016), Lutz et al. (2017), Richter and Schiersch (2017), Löschel et al. (2019).

³⁰This measure does not include the material consumption nor the use of external energy and water.

³¹I 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.

³²Consumer Price Indices for Germany are retrieved from the World Bank Group. The base year is 2010.

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.

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.

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.

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 intra-industry comparisons. I conclude with preliminary results of the DD analysis.

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

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.

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.

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.

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 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.

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.

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. As mentioned above, the results of inter-industry comparisons are shown in the Appendix in Tables A.1

5.2.1 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 tech-

nologies. 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 use

Table 7: 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 (0,1816)	0,6259 (0,1767)	0,5309 (0,2168)	0,7023 (0,2264)	0,8415 (0,0515)	0,5915 (0,1915)
2005	0,8015 (0,2162)	0,6382 (0,1753)	0,5292 (0,2365)	0,6878 (0,2107)	0,8268 (0,0670)	0,5714 (0,1825)
2010	0,7732 (0,2416)	0,6972 (0,1500)	0,5573 (0,2444)	0,6865 (0,2357)	0,8011 (0,1069)	0,5662 (0,2103)
ISIC Rev. 4 (21)		treatment group			control group	
2003	0,5709 (0,1265)	0,5917 (0,1577)	0,3378 (0,1124)	0,6714 (0,1673)	0,9773 (0,0024)	0,6563 (0,1638)
2005	0,6228 (0,1544)	0,6719 (0,1794)	0,4190 (0,1536)	0,6832 (0,1536)	0,9776 (0,0024)	0,6680 (0,1503)
2010	0,6431 (0,1429)	0,6638 (0,2128)	0,4259 (0,1553)	0,6899 (0,1365)	0,9786 (0,0018)	0,6752 (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.

of heterogeneous frontiers for the treated and non-treated group is superior to using a homogeneous/pooled stochastic cost frontier. Table 7 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 8 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 8 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 8: 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 \times 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 9 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

Table 9: Non-parametric DD approach with matching: treatment effects for the full sample

Dependent Variable:	Cost efficiency in logs		
	one neighbor	five neighbors	twenty neighbors
Full sample			
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 \times 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.

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 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 8 and 9 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

Table 10: Parametric DD approach treatment effects for selected 2-digit industries

Dependent Variable:	Cost efficiency in logs			
	19	21	22	24
ISIC Rev.4				
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.

analysis in Table 10 confirm the 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 11 shows the

Table 11: 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.

results of non-parametric DD approach for a subsample of 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 10. 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 11, 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 industries (19) and (21). As expected, Table 12 indicates drastically different results. The average treatment effect of the EU ETS on firms in industry (19) is now much smaller, positive, and statistically

Table 12: 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.

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).

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 14 two-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 between treatment groups within industries, I employed SMF analysis. 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.

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 via 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 (1996) 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.³³ Recently, Karakaplan and Kutlu (2015) and 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 empirical 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,

³³For more information, see Terza et al. (2008) and Garrido et al. (2012).

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.

Note: Parts of this work are still in progress and as such subject to change. I kindly ask the reader to refer to the most recent updates of our work by using the external [link](#) provided at the beginning of the document.

Appendix

A Additional Results

A.1 Inter-Industry Comparison

The results in Table A.1 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), (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

Table A.1: 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 (0,1701)	0,7367 (0,0929)	0,7328 (0,1593)	0,5405 (0,1369)	0,6323 (0,1648)	0,7349 (0,0959)	0,7387 (0,1574)	0,5423 (0,1339)	0,6223 (0,1683)	0,7322 (0,0934)	0,7305 (0,1606)	0,5352 (0,1389)
13	0,6746 (0,1205)	0,7509 (0,1033)	0,7758 (0,0647)	0,5828 (0,0926)	0,6810 (0,1292)	0,7527 (0,1136)	0,7811 (0,0647)	0,5884 (0,1005)	0,6853 (0,1231)	0,7535 (0,1065)	0,7966 (0,0632)	0,6008 (0,0974)
16	0,7041 (0,1273)	0,6503 (0,1544)	0,9228 (0,0250)	0,5998 (0,1419)	0,7068 (0,1233)	0,6549 (0,1509)	0,9222 (0,0254)	0,6033 (0,1377)	0,7010 (0,1271)	0,6493 (0,1506)	0,9190 (0,0281)	0,5962 (0,1376)
19	0,6895 (0,2743)	0,5834 (0,2751)	0,9125 (0,1683)	0,5598 (0,2835)	0,6633 (0,2597)	0,5540 (0,2588)	0,9211 (0,1515)	0,5309 (0,2665)	0,6378 (0,2616)	0,5349 (0,2767)	0,9297 (0,1358)	0,5126 (0,2774)
20	0,7004 (0,1486)	0,6667 (0,1523)	0,9363 (0,0145)	0,6241 (0,1424)	0,7103 (0,1455)	0,6731 (0,1492)	0,9423 (0,0141)	0,6340 (0,1400)	0,7139 (0,1500)	0,6619 (0,1573)	0,9522 (0,0117)	0,6301 (0,1495)
21	0,6658 (0,1597)	0,6675 (0,1703)	0,8790 (0,0528)	0,5870 (0,1568)	0,6721 (0,1541)	0,6790 (0,1571)	0,8748 (0,0543)	0,5941 (0,1447)	0,6703 (0,1404)	0,6859 (0,1403)	0,8554 (0,0563)	0,5879 (0,1307)
22	0,6904 (0,1180)	0,7403 (0,1086)	0,8454 (0,0412)	0,6256 (0,0952)	0,7037 (0,1136)	0,7506 (0,1038)	0,8519 (0,0382)	0,6393 (0,0921)	0,7126 (0,1124)	0,7495 (0,1069)	0,8678 (0,0343)	0,6501 (0,0940)
24	0,7101 (0,1256)	0,8053 (0,0864)	0,8682 (0,0505)	0,6970 (0,0680)	0,7297 (0,1219)	0,7969 (0,1071)	0,8846 (0,0451)	0,7021 (0,0836)	0,7352 (0,1234)	0,7896 (0,1142)	0,9015 (0,0378)	0,7096 (0,0948)
25	0,7353 (0,1080)	0,7257 (0,1227)	0,9204 (0,0178)	0,6675 (0,1116)	0,7299 (0,1123)	0,7257 (0,1240)	0,9133 (0,0194)	0,6625 (0,1127)	0,7131 (0,1079)	0,7232 (0,1153)	0,8889 (0,0243)	0,6427 (0,1029)
26	0,7164 (0,1322)	0,6574 (0,1511)	0,9485 (0,0110)	0,6236 (0,1437)	0,7283 (0,1296)	0,6700 (0,1490)	0,9497 (0,0124)	0,6362 (0,1418)	0,7413 (0,1282)	0,6797 (0,1481)	0,9540 (0,0084)	0,6485 (0,1415)
27	0,6829 (0,1312)	0,6734 (0,1384)	0,9061 (0,0234)	0,6106 (0,1286)	0,7076 (0,1195)	0,6915 (0,1293)	0,9175 (0,0200)	0,6348 (0,1208)	0,7392 (0,1110)	0,6998 (0,1273)	0,9422 (0,0115)	0,6593 (0,1200)
28	0,7422 (0,1066)	0,7305 (0,1282)	0,9409 (0,0114)	0,6874 (0,1218)	0,7547 (0,0998)	0,7520 (0,1183)	0,9371 (0,0121)	0,7048 (0,1121)	0,7367 (0,1047)	0,7413 (0,1221)	0,9285 (0,0149)	0,6883 (0,1144)
29	0,6938 (0,1317)	0,7225 (0,1250)	0,8871 (0,0271)	0,6414 (0,1143)	0,7067 (0,1307)	0,7334 (0,1245)	0,8897 (0,0260)	0,6527 (0,1135)	0,7111 (0,1343)	0,7324 (0,1290)	0,8990 (0,0233)	0,6587 (0,1180)
30	0,6863 (0,1654)	0,5967 (0,1996)	0,9327 (0,0384)	0,5558 (0,1851)	0,6837 (0,1721)	0,6011 (0,2070)	0,9310 (0,0543)	0,5606 (0,1930)	0,6986 (0,1400)	0,5924 (0,1849)	0,9451 (0,0304)	0,5590 (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.

between different industries, one could 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 A.1 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 A.2. The development of mean meta cost-efficiency scores over time is depicted in Figure 6 in the Appendix.

Table A.2: The comparison of rankings using SCF and MCF analyses across years

Ranking	2003		2005		2010	
	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.

B Additional Figures

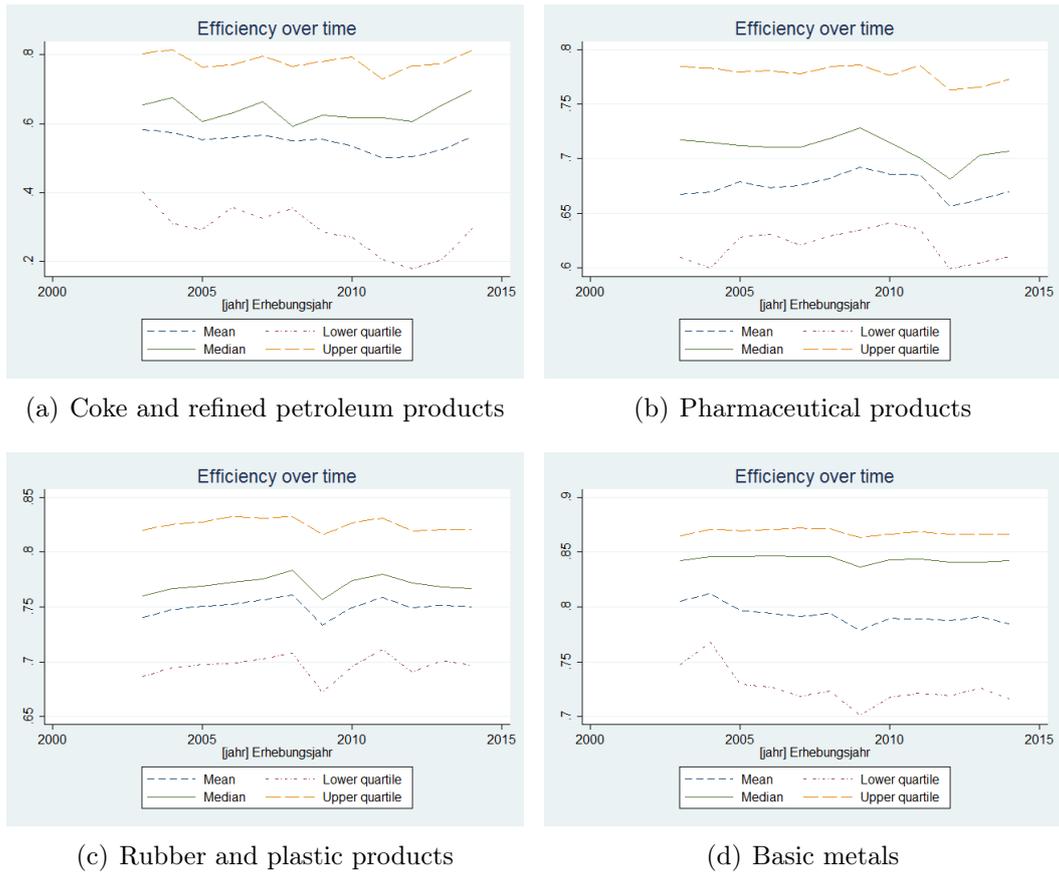


Figure A.1: Mean cost efficiency scores across the years for selected 2-digit industries (19), (21), (22), (24). Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

C 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

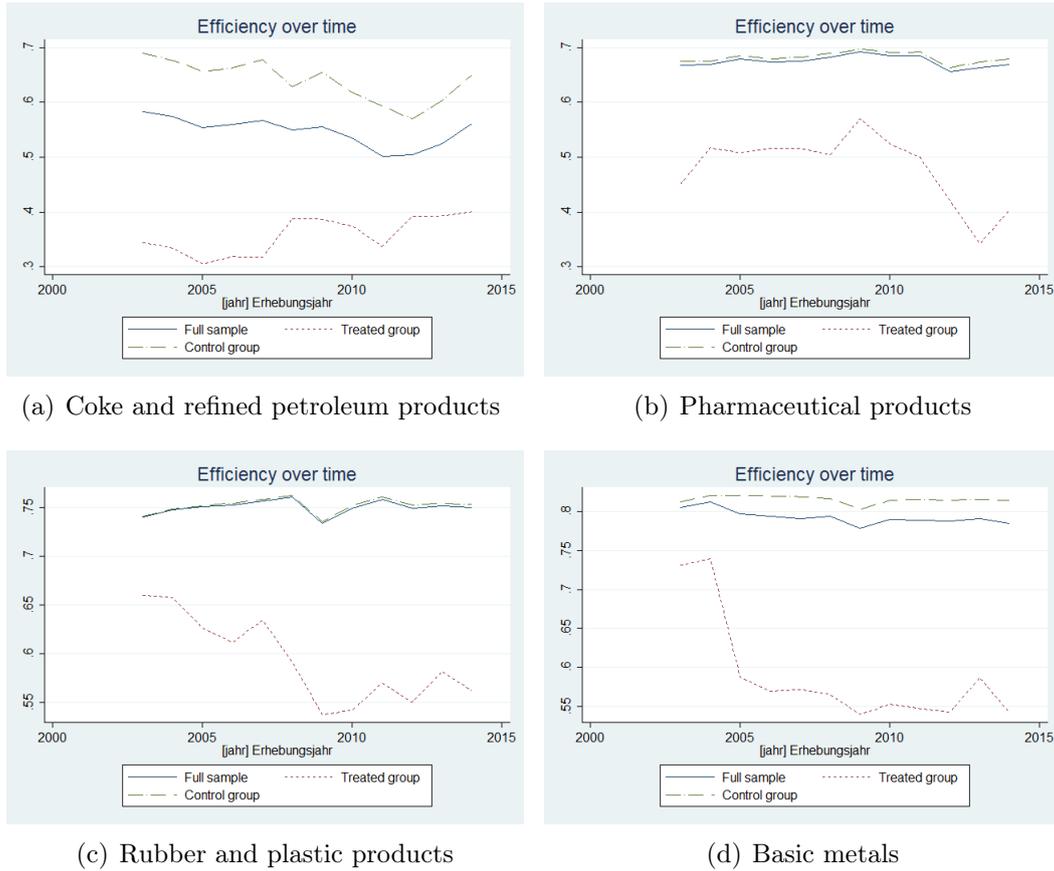


Figure A.2: Regulated firms and unregulated firms mean cost efficiency scores across the years for selected 2-digit industries (19), (21), (22), (24). Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

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.

D Perpetual Inventory Method for Capital Stock Estimation

As is standard whenever data does not provide explicit capital stock information, I use perpetual inventory method to compute capital stocks at the firm-level. In what follows we borrow from

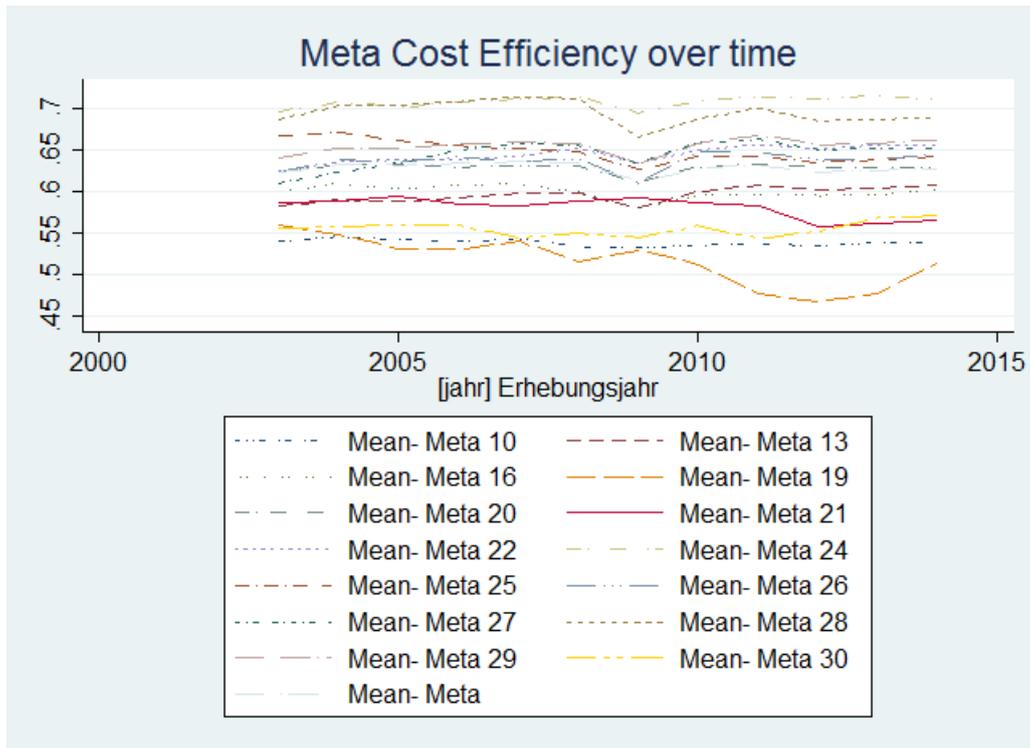


Figure A.3: Inter-industry comparison of yearly mean meta-cost efficiency scores. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

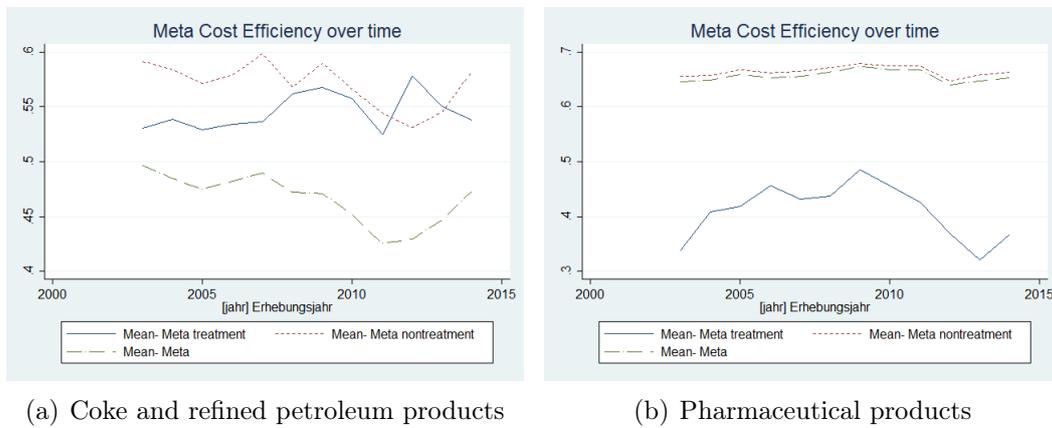


Figure A.4: Intra-industry comparison of yearly mean meta cost efficiency scores across treatment groups for selected 2-digit industries (19), (21). Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [survey years 2003-2014], own calculations.

Lutz (2016).

Perpetual inventory method relies on the following fundamental formula:

$$K_t = K_{t-1}(1 - \delta) + I_t, \tag{A.1}$$

where K denotes capital stock, δ the geometric depreciation rate and I the investment. I derive

the initial capital stock K_1 from the equation (A.1):

$$K_1 = I_0 + I_{-1}(1 - \delta) + I_{-2}(1 - \delta)^2 + \dots \quad (\text{A.2})$$

$$K_1 = \sum_{s=0}^{\infty} I_s(1 - \delta)^s \quad (\text{A.3})$$

I assume the real investments grow at rate g :

$$K_1 = I_0 \sum_{s=0}^{\infty} \left[\frac{(1 - \delta)}{(1 + g)} \right]^s \quad (\text{A.4})$$

$$K_1 = I_0 \frac{(1 + g)}{(g + \delta)} \quad (\text{A.5})$$

I can therefore define the capital stock in the first period as:

$$K_1 = I_1 \frac{1}{(g + \delta)} \quad (\text{A.6})$$

Lutz (2016) points out that in the "AFiD Panel Manufacturing Plants" investments fluctuate greatly over time and this complicates the computation of initial capital stocks. To overcome this, I need to compute the average I_t over all periods available and estimate I_1 :

$$\hat{I}_1 = \frac{\sum_{t=0}^n \frac{I_{t+1}}{(1+i)^t}}{n} \quad (\text{A.7})$$

D.1 Data preparation

For information on investment in machinery and equipment, investment in buildings, and investment in properties without buildings. I use firm-level investment data from the AFiD-Panel Industriebetriebe ("AFiD Panel Manufacturing Plants"). I deflate investments using industry-specific deflators for machinery and equipment as well as general deflators for buildings and property without buildings. I start from K_1 and plug in firm-specific investments and the industry specific time-varying depreciation rates into equation (A.1) to compute the entire time series of the firm's capital stock. As I observe annual firm-level investment data for the period

2003-2014, the growth rate of capital g and the depreciation rate δ can either be assumed to take a certain value or estimated using aggregated data, e.g. industry-level data. We compute industry-specific average growth and depreciation rates using aggregate data from the Destatis portal GENESIS. I use the same source for the deflators information.³⁴ In particular we use the statistics with the following codes: 81000-0107 National Accounts Depreciation, 81000-0115 Gross Investment, 81000-0116 Gross Capital Stock, 81000-0117 Net Capital Stock, and 61262-0001 Price Index Property.

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³⁴For more information on this data, visit the Destatis portal GENESIS at <https://www-genesis.destatis.de/genesis/online>.

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