The effect of climate policy on productivity and cost pass-through in the German manufacturing sector*

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Abstract

We investigate productivity and cost pass-through of German manufacturing firms using administrative data from 2001 to 2018. Our framework allows for the estimation of quantity-based production functions for multi-product firms while controlling for unobserved productivity shocks and unobserved input quality. Using our parameter estimates, we compute total factor productivity, markups and marginal costs, which in turn allows us to measure cost pass-through. We find that firms pass on shocks to materials costs almost completely, whereas pass-through of energy costs is around 30%. However, the level of energy cost pass-through is no different for firms in "trade-exposed" sectors that continue to receive free allowances. Our results add to the recent literature concerning the causal effects of climate policy on firms and are relevant for policymakers when defining the level of free allowance allocation to industry.

Keywords: *Productivity; production function; markup; cost pass-through; EU ETS; climate policy*

JEL Codes: *D24, H23, Q52, Q54*

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1 Introduction

To limit emissions of greenhouse gases, the global community has agreed on a series of international agreements such as the Kyoto Protocol and the Paris Agreement. However, these international agreements did not establish legally enforceable rules. As a consequence, individual countries and regions have instituted unilateral climate policies in their own jurisdictions. The single largest climate policy instrument to date is the EU Emissions Trading System (EU ETS).

The benefits of action against climate change are becoming increasingly obvious, but there remain concerns that instituting climate policies that are sufficiently stringent to decarbonize the economy will put EU firms at a disadvantage relative to their rivals overseas that face no -or less restrictive- legislation about greenhouse gas emissions. For this reason, the emissions cap in the EU ETS has remained relatively generous, and a significant share of the allowances have been allocated at no cost. On the other hand, there exist arguments that environmental regulation may lead firms to re-optimize their activities and thereby become more productive (Porter and Van der Linde, 1995; Ambec et al., 2013).

In this paper, we add to the recent literature about the consequences of climate policy at the firm level and investigate three questions: (i) How are productivity, markups and profits affected by the EU ETS; (ii) to what extent are ETS firms able to pass on their marginal costs to consumers; and (iii) what are the implications for free allowance allocation at the sector-level?

We answer these questions using rich firm data from Germany, Europe's largest emitter of greenhouse gases and home to an internationally competitive manufacturing sector. We estimate production functions in 4-digit manufacturing industries. A common feature in these industries is that firms produce more than one product. Previous approaches have relied on revenue-based production functions (e.g., De Loecker and Warzynski, 2012; Lutz, 2016), as these accommodate multi-product production quite naturally by simply adding up the revenue from different product lines. However, estimating revenue-based production functions may lead to biased estimates because the quantity and price effects cannot be individually identified (Foster et al., 2008; De Loecker, 2011). In other words, an increase in revenue could be the consequence of an increase in price and/or quantity. We exploit the rich information in our data and estimate a quantity-based production function following the methodology by De Loecker et al. (2016) that overcomes this problem. Our framework allows us to estimate total factor productivity (TFP), markups and marginal costs based on separately observed physical output quantities and product prices.

We quantify the extent of cost pass-through in the manufacturing sector by regressing prices on our estimate of marginal costs, using an instrumental variables (IV) approach to mitigate possible bias due to classical measurement error. By choosing different instruments, we exploit the variation of different types of costs. This allows us to estimate cost pass-through for materials, energy and carbon costs separately. We find close to complete pass-through for materials costs (measured by using lagged marginal costs as an instrument), and pass-through of around 30% for energy costs shocks (measured by using energy prices as instruments). Cost pass-through significantly varies over individual industries. This variation can likely be explained by the degree of competition with firms from outside the EU ETS.

Using our model results, we can further identify the causal effect of the EU ETS on economic outcomes (TFP, markups and profits) using a difference-in-difference approach, in which firms not covered by the system serve as the control group. To control for unobserved differences between treated and untreated firms we employ nearest-neighbor matching. We find that on average, EU ETS coverage did not affect TFP and profits. This is good news for climate policy, as firms appear not to suffer adverse economic consequences.

Our paper makes two main contributions to the literature. By estimating cost pass-through for manufacturing firms, we provide new and important information to policy makers about the incidence of climate policy. There is empirical evidence for high (or even complete) cost pass-through in the electricity sector (Fabra and Reguant, 2014; Fell et al., 2015; Hintermann, 2016), but very little is known about the other sectors of the economy. After power generation, manufacturing is the most emissions-intensive sector that is covered by the EU ETS and other carbon markets worldwide. An exception is a recent paper by Ganapati et al. (2020), who estimate the pass-through and incidence of energy costs for U.S. manufacturing firms that produce six distinct products. Our approach allows us to estimate cost pass-through for a much wider range of industries and products. Importantly, our estimates are based on an ex-post analysis of actual climate policy that has been put in place, rather than relying on variation in energy prices to infer the consequences of a climate policy that has yet to be implemented. The degree of pass-through of costs in general, and of carbon costs in particular, is crucial to determine the level of free allocation required to combat carbon leakage. We find that some of the industries that benefit from generous free allocation pass on a high share of their costs to consumers, implying that the EU's current rules are not optimal.

Second, we contribute to the literature on firm-level outcomes of climate policy. Unbiased estimates of the causal effect of the EU ETS on productivity, markups and profits is crucial for the future design of climate policy and the eventual decarbonization of the economy. Using a matching approach, we estimate the causal effect of the EU ETS on the main model outcomes (productivity and markups). Previous papers have focused on different outcomes, e.g., on emissions (Jaraite and Di Maria, 2016; Colmer et al., 2020), employment and revenue (Petrick and Wagner, 2014), innovation and adoption of new technology (Calel and Dechezleprêtre, 2016; Calel, 2020), whereas the ones that have focused on productivity do so within a revenue-based framework (Lutz, 2016; Calligaris et al., 2019). By using a state-of-the art framework to estimate a quantities-based production function, we obtain estimates about productivity and markups that avoid many of the econometric problems that have plagued the previous literature. Our framework controls for the "output price" bias of revenue-based approaches, the "simultaneity" bias associated with unobserved productivity shocks and the "unobserved input quality" bias, which is due to the recent contribution by De Loecker et al. (2016). We go beyond that paper and estimate the production on the 4-digit industrial level, thus allowing for more flexibility. We then use our estimates to investigate the effect of the EU ETS on firm-level total factor productivity and profits, which is important to understand the implications of climate policy for firms.

In the next section, we provide some more background information and review the literature that has studied the effect of this system on firms. Section 3 describes the data that are the basis for our analysis. Section 4 contains our empirical model and describes how we estimate total factor productivity, markups and cost pass-through, and section 5 presents our results.

2 Background

In this section, we briefly discuss the features of the EU ETS that are relevant for the current context and provide more details about the literature that has focused on the firm-level effects of this program and on cost pass-through.

2.1 The EU Emissions Trading System

The EU ETS is a cap-and-trade system in operation since 2005. It covers energy-intensive installations from all EU members and from additional countries that have linked into the system over time.[1] Of these 32 countries, Germany is the largest emitter. Installations covered by the EU ETS have to surrender one EU allowance, or EUA, for each metric ton of CO_2 equivalent that they emitted during the previous calendar year. Allowances are fully tradable across participating firms. The total number of allowances that are distributed each year, either for free or in auctions, constitutes the annual emissions cap in the EU ETS. This cap is reduced every year relative to the 2008-2012 period at a reduction rate of (currently) 2.4 percentage points. As the total number of EUAs available is limited by the cap, they represent valuable assets, which creates an opportunity cost for each ton of CO_2 emitted by regulated installations. This is true regardless of the method of allocation, because surplus allowances can be sold on the market. The market for allowances was established at the very beginning of the system, and liquidity has been high with the exception of the first two years. For an overview of the EU ETS, see

[1] Currently, the EU ETS includes 32 countries: The 27 EU countries plus the UK, Norway, Iceland, Liechtenstein and Switzerland.

Ellerman et al. (2016).

Participation in the EU ETS is mandatory for all combustion installations with a rated thermal input in excess of 20 MW. Industrial installations specializing in certain energy-intensive activities exceeding specific capacity thresholds are also regulated.[2] The inclusion criteria for the EU ETS apply at the installation level, whereas our unit of analysis is the firm. We define a firm as covered by the ETS if it owns at least one installation that is included in the system. This is somewhat problematic as firms may be exposed to different treatment intensities. On the other hand, it means that despite the inclusion thresholds that depend on size, treated and control firms are quite comparable with respect to the observable outcomes. For example, a firm owning two installations with 19 MW of installed capacity (and thus not covered by the EU ETS) will emit more emissions than a firm that owns a single installation with a rated thermal input of 25 MW. This similarity on the firm level is an attractive property and has been exploited in previous empirical work (see, e.g., Petrick and Wagner, 2014; Calel and Dechezleprêtre, 2016; Calel, 2020; Colmer et al., 2020).

The EU ETS has so far gone through three compliance periods, called "phases". Phase 1 covered the years 2005-2007 and served as a pilot for phase 2 (2008-2012), which matched the compliance period of the Kyoto Protocol. The (current) phase 3 ends in 2020, and phase 4 will cover the years 2021-2030. The analysis below focuses on the first two phases and most of the third, as we have access to data only for the period 2001-2018. The phases mainly differ in terms of their rules for banking (which is allowed since phase 2) and free allocation. In the first two phases, the allocation of permits was decentralized, relying on National Allocation Plans (NAP) and grandfathering. Since phase 3, allocation is carried out based on centralized benchmarking rules on the EU level, and an increasing number of allowances are auctioned.[3] Whereas power generators have had to purchase all of their allowances on the market since phase 3 (with some exceptions), manufacturing

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

[3] The benchmarking is based on the emissions intensity of the 10% most efficient firms in a given industry. This emission intensity is then multiplied by the historical level of output to obtain the benchmark level of free allocation for a particular firm. The non-EU countries in the EU ETS have retained some autonomy to determine their firms' level of free allocation. In practice, however, these rules are very similar to those in the EU.

firms continue to receive a significant share of their needed emissions allocated for free. In the course of phase 3, this share has been decreased, for most firms, from 80% of the benchmark in 2013 to 30 % in 2020, and to zero by 2027.

There are, however, special rules for manufacturing subsectors that are deemed to be exposed to carbon leakage. This classification is a function of a firm's emission intensity and its exposure to competition from outside the EU ETS.[4] Firms in these subsectors continue to receive up to 100% of their benchmark value allocated for free. The underlying reasoning is that they are not able to pass on their costs to their consumers. In this paper, we examine whether this is in fact the case.

Figure 1 shows the EUA price over time. At the beginning of phase 1, the price was above 25 Euro, but later converged to zero as it became clear that the market overall was over-allocated. After the start of Phase 2, the price recovered, but the decline in economic activity due to the financial crisis once again resulted in a price collapse during the second half of 2008. At the time, prices were also affected by the heavy use of Kyoto offsets.[5] As banking was allowed in Phase 2, EUA prices did not converge to zero, remaining at around 15 Euro until another price plunge below 10 Euro in the second half of 2011. In the aftermath of the latest round of reforms in February 2018, the EUA price has appreciated to over 20 Euro, but this increase happened only at the end of our sample period.[6]

2.2 The effect of climate policy on firms

There is a growing literature about the effect of the EU ETS on firms, with recent reviews by Martin et al. (2016) and Joltreau and Sommerfeld (2019).[7] In what follows, we focus on the effects related to cost pass-through, productivity and profits which is the subject of

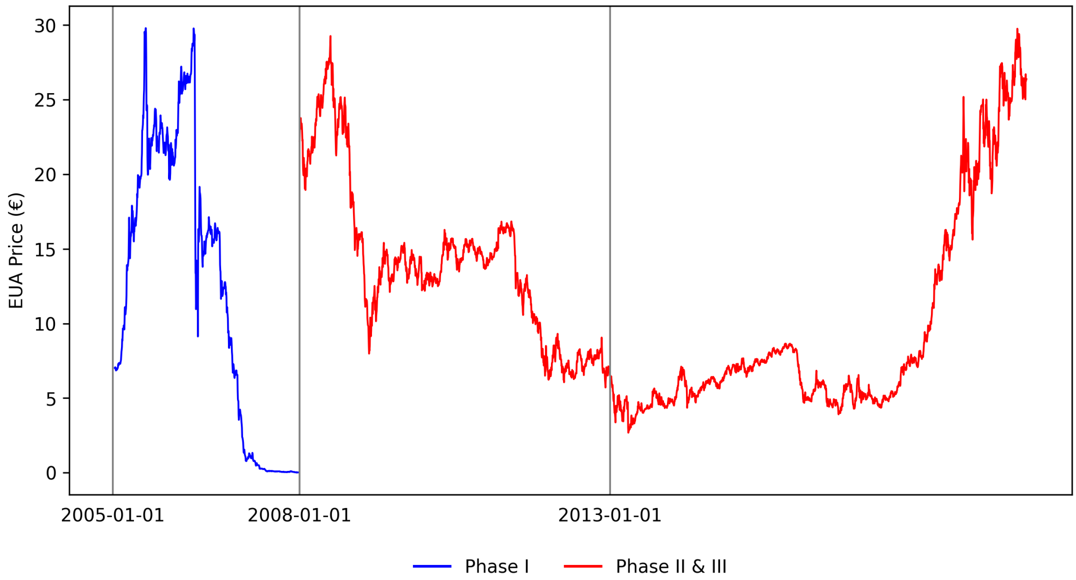
[4] Specifically, firms for which the value of emissions exceed 5% of their gross value added and whose trade exposure to competitors from outside the EU ETS exceeds 10% are deemed to be at risk. An intensity of either emissions or trade exposure of above 30 % alone also places sectors in the carbon leakage risk group. In addition, there are qualitative criteria that can lead to an inclusion. The rules for free allocation in the EU ETS are defined in European Commission (2010).

[5] For a review of the literature on price determination in the EU ETS, see Hintermann et al. (2016).

[6] In these reforms, the long-term cap was reduced by increasing the annual reduction factor from 1.74% to 2.2%, and by introducing a rule whereby a portion of the allowances located in the "Market Stability Reserve" (MSR) are not just temporarily removed, but actually invalidated. See Perino (2018); Gerlagh and Heijmans (2019) for a discussion about the recent MSR reforms.

[7] For a more general literature on the worldwide consequences of environmental regulation on firms, see Dechezleprêtre and Sato (2017).

Figure 1: Daily EUA prices in phases 1-3; Source: Thomson Reuters Eikon.



our paper. Our data could also be used to examine the effect of the EU ETS on emissions and employment of German manufacturing firms, but this is being done in other, ongoing work (Lehr et al., 2020).

The most direct consequence is that covered firms have to submit allowances for their emissions. However, most ETS firms do not need to purchase all of the required allowances. With a sufficiently high level of cost pass-through, this means that firms may get compensated for allowances they never had to buy. This implies a transfer from taxpayers to firms, as well as a degree of second-order inefficiency due to the lost revenue that cannot be used to reduce existing taxes or to increase redistribution. So far, most of the papers examining cost pass-through have focused on the power sector due to the availability of high-frequency price data and the high emission intensity of this sector. Power generators were found to pass on their emissions costs fully to consumers (Sijm et al., 2008; Jouvet and Solier, 2013; Fabra and Reguant, 2014; Fell et al., 2015; Hintermann, 2016). Free allowance allocation in the first two market phases, in combination with inframarginal profits, led to significant windfall gains for power producers (Neuhoff et al., 2006; Sijm et al., 2006). In general, the higher the rate of cost pass-through and the share of inframarginal profits are, the lower will be the amount of free allocation that keeps profits unchanged relative to the situation before the regulation.[8]

While there is a growing body of literature about cost pass-through in the power sector, cost pass-through in manufacturing has received little attention in empirical research so far, despite the importance it has for carbon leakage and, indirectly, for employment and profits. The reason for the sparse empirical evidence lies in the multitude of products produced in the manufacturing sector, which have a range of different production costs and are traded on diverse markets. For this reason, the previous literature has focused on individual products using a mixture of theory and empirical work.

For example, Smale et al. (2006) use a theory approach to examine the effect of the EU ETS on firms profits in the cement, newsprint, steel, aluminum and petroleum sectors. Their model assumes Cournot competition and linear demand which, along with the distribution of rivals across EU and non-EU countries, determine the extent of cost pass-through. With full grandfathering of allowances, all sectors except for aluminium are expected to benefit from the introduction of the EU ETS. Demailly and Quirion (2006) use a similar model for the cement sector and show that profit neutrality could be achieved with 50% of free allocation. However, the rate of cost pass-through in these models is not measured empirically but follows from the assumptions about the demand curve and the market structure. Hepburn et al. (2013) and Nicolaï (2019) determine the profit-neutral level of free allocation in an oligopolistic setting (which is appropriate, e.g., for the power, steel and cement sectors) and conclude that due to the likely presence of cost pass-through, very low levels of free allocation can be sufficient to maintain profit neutrality.[9]

De Bruyn et al. (2010) also rely on cointegration to estimate the effect of allowance prices on the prices for eight generic products in the manufacturing sector (two types of steel, three refinery products and three chemicals). Besides the EU prices for these goods, the model also includes product prices from outside the EU to incorporate international

[8] In the case of power generators, this level of "profit-neutral" free allocation is negative for most large power producers, as a significant share of generation is carbon-free (Hintermann, 2017).

[9] This finding is robust to different assumptions about the curvature of demand. The shape of the demand curve matters because it co-determines the rate of cost pass-through. Nicolaï and Zamorano (2018) show that if demand is iso-elastic and firms engage in Cournot competition, a cost shock that affects all firms will generally increase profits.

price adjustments. Using the average carbon content of these products, the authors conclude that carbon costs are passed on fully to steel and refinery products, and to a large extent also to chemicals. However, the confidence intervals are quite large. Using a cointegration framework, Alexeeva-Talebi (2010) estimates the relationships between domestic (in this case, German) and foreign output prices for manufacturing goods, along with prices for materials, labor and electricity. Her results imply positive rates of cost pass-through. However, since these are reduced-form relationships, the degree of cost pass-through cannot be established. Miller et al. (2017) estimate cost pass-through for the Portland cement industry in the USA. They combine a reduced-form approach with outside information about product markups and compute a rate of fuel cost pass-through that exceeds unity.

Some previous papers have focused on the question of carbon leakage in manufacturing, which is a closely related concept. Carbon leakage occurs when firms relocate some of their production capacity abroad in response to unilateral climate policy. The underlying reason is that they are not able to pass on their carbon costs to their customers if they are competing with rivals that are subject to a less stringent climate policy (or no policy at all). The threat of carbon leakage is the main reason for the free allowance allocation in the EU ETS and other carbon markets. Based on a theoretical model complemented with a survey of manufacturing firms covered by the EU ETS, Martin et al. (2014) demonstrate that the current amount of free allocation significantly exceeds the level that would be required if the goal were to limit the expected damage of relocation (including both the probability and the magnitude of a potential downsize). The marginal effect of free allocation on relocation risk varies significantly across firms depending on their ability to pass on their costs to consumers. D'Arcangelo (2019) finds that the introduction of carbon pricing has a statistically significant effect on the expected profits, and thus on the investment decisions, of manufacturing firms in Europe. But since the effect is small, he concludes that the scope of carbon leakage due to unilateral climate policy is rather limited. This finding is consistent with at least some cost pass-through.

The paper closest to ours is by Ganapati et al. (2020). They compute marginal costs for six manufacturing products (boxes, bread, cement, concrete, gasoline and plywood) using a quantities-based production function similar to ours. Given the homogeneity of their products, they do not control for unobserved input quality. They find cost pass-through rates between 24 % (gasoline) and 99 % (boxes). The variation in pass-through rates can be explained by differences in market structure.

Muehlegger and Sweeney (2020) show that besides differing industry structures, a variation in the degree of cost pass-through can also be explained by the nature of the cost shock. They exploit the variation in fracking-induced costs shocks that vary locally or regionally, and examine their effects on the output prices of petroleum refineries in the USA. If the shock is idiosyncratic and only affects a particular firm, a lower share of costs is passed on to consumers. In contrast, if more firms or even the entire industry is affected, cost pass-through is higher, which is intuitive.

Besides cost pass-through, our paper is related to the literature that focuses on firm productivity. Franco and Marin (2017) find beneficial effects of environmental regulation on a productivity index for manufacturing firms in eight EU countries. The index is an approximation of TFP based on growth accounting methods and is part of the EU-KLEMS database. Marin et al. (2018) estimate the effect of the EU ETS on a range of firm outcomes in 19 EU countries. They estimate a value-added production function and find no adverse effects on TFP and a positive effect on labor productivity and on (absolute) markups. The latter suggests that firms pass on at least some of their carbon costs to consumers.

Calligaris et al. (2019) use administrative data from Italy to investigate the consequences of the EU ETS on total factor productivity and find preliminary evidence for a positive effect. Using the same administrative data on German manufacturing firms as this paper, Lutz (2016) also reports an increase in TFP as a consequence of the EU ETS. Klemetsen et al. (2020) examine Norwegian manufacturing firms and find a positive impact on (labor) productivity in the second phase. In all three papers, productivity measures are based on revenue and thus potentially subject to the price bias in the sense that an increase in revenue could be due to either an increase in price or in quantity.

Dividing the revenue by an industry-wide price index does not solve the problem if firms differ with respect to their marginal costs and their markups, such that TFP will be over-estimated for some firms and under-estimated for others. We tackle this issue head-on by using a quantities-based approach. Löschel et al. (2019) estimate firms' distances to a common stochastic production frontier and find that the EU ETS did not move firms away from this frontier, and in some subsectors even moved them towards it, which can be interpreted as an increase in productive efficiency.

Overall, the available evidence on suggests positive cost pass-through for manufacturing firms and a (modest) increase in the productivity of firms as a consequence of the EU ETS.

3 Data

This study is based on a unique dataset, obtained by combining several micro-datasets and modules from AFiD.[10] The AFiD data are provided by the German Federal Statistical Office and the Statistical Offices of the German Federal States. Importantly, this is not a voluntary survey, as the information disclosure is mandatory for all surveyed firms and plants. AFiD data provide very detailed information on plant- and firm-level characteristics, production and energy inputs. The individual AFiD modules are merged based on plant and firm identifiers. All monetary variables are deflated to 2015 Euros. For additional information on the merging procedure, see section A in the Appendix.

The AFiD Panel Manufacturing Plants ("Industriebetriebe" in German) contains information on foreign sales, salaries and investments for all German manufacturing plants with more than 20 employees. For a detailed description of this module, see Koch and Migalk (2007) and Wagner (2010). We follow Lutz (2016) and use the perpetual inventory method and investment information to calculate capital stocks. This method also involves the use of external datasets. The procedure is described in detail in Appendix B.

The AFiD Module on Energy Use ("Energieverbrauch") contains detailed information

[10]AFiD stands for "Amtliche Firmendaten für Deutschland", which translates to "Official Firm Data for Germany".

on the annual fuel and electricity use at the plant-level. The data is provided in units of energy content (kWh), which allows us to calculate firm-level energy use from 15 different fuels including electricity, district heat and primary fuels (e.g. natural gas and different types of oil and coal). For more information about this module, see Petrick et al. (2011).

The AFiD Module on Products ("Produkte") includes the information extracted from the production surveys of the goods manufactured in the manufacturing sector. It can be linked to other AFiD modules at both plant and firm-level. 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). In addition to providing production sales values, it also includes the quantities produced for sales and further processing. We deflate the sales values using two-digit NACE Rev. 2. deflators. An example of product classification for leather and leather-products industry is listed in the Appendix in Table A.11.

The Cost Structure Survey ("Kostenstrukturerhebung") reports annual information on various types of costs and inputs at the firm-level. The participation in the survey is mandatory for all German manufacturing firms with more than 500 employees. Information on smaller and medium firms (20 - 500 employees) are collected from a large random sample, stratified at the two-digit industry level and size class level. This random sample is redrawn every four years, and some SMEs are surveyed every time if they operate in certain concentrated industries. We obtain our revenue, total costs, materials (including energy) and labor expenditures from the CSS and deflate them using two-digit NACE deflators.[11] We also obtain information on the number of employees from this survey. The cost structure survey is explained in more detail by Fritsch et al. (2004) and Lutz (2016).

We add data from the German company register ("Unternehmensregister"), which is described in Koch and Migalk (2007), and from the European Union Transaction Log (EUTL) in order to identify which German manufacturing firms are regulated by the EU ETS and other external data to estimate capital stocks in accordance with Lutz (2016).

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

Table 1: Summary statistics of the German manufacturing sector

Nr.	Industry description	Output share (%)	All Firms (Nr)	Single-product firms (Nr.)	EU ETS firms (Nr.)	Products (Nr.)
10	Food products	14.15	9'242	1'471	39	361
11	Beverages	2.28	981	274	18	59
13	Textiles	1.34	1'278	711	7	259
14	Wearing apparel	0.05	246	99	0	44
16	Wood and products of wood and cork	1.98	2'230	1'128	25	81
17	Paper and paper products	4.16	1'428	985	114	120
20	Chemicals and chemical products	11.91	1'939	721	100	597
22	Rubber and plastic products	7.18	4'682	2'193	21	229
23	Other nonmetallic mineral products	3.57	3'181	1'664	185	227
24	Basic metals	6.85	1'410	644	68	247
25	Fabricated metal products	10.05	9'606	5'890	14	463
26	Computer, Electronic and optical prod.	4.7	2'695	1'664	< 4	250
27	Electrical equipment	7.27	3'266	1'760	11	310
28	Machinery and equipment n.e.c.	22.29	9'741	4'592	20	815
32	Other manufacturing	2.2	2'507	1'874	< 7	176
	Overall	100	53'432	25'670	629	4'238

Notes: Columns 4, 5 and 6 report the number of all firms, firms being ever single-product and ever took part in the EU ETS, respectively. Column 7 reports the number of distinct products by industry. < 4 denotes redacted information during the data security check for observations between one and three. Given that we report the overall number of observations, the second smaller number (< 7) was also redacted to ensure that the former remains unidentifiable. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2018).

Table 1 shows the subsectors on the 2-digit NACE Rev. 2 level that together constitute the manufacturing sector in Germany, along with the summary statistics for total output share, the number of firms, the number of single-product firms, and the number of products produced by these industries. More than half of the firms in our sample produce more than one product, implying that focusing on single-product firms would miss an important part of the sector. Further information on industry level classification can be found in Appendix A.

4 Empirical strategy

In this section, we describe our methodology to estimate the parameters of the production function, total factor productivity, markups and marginal costs. The exposition is intended to convey the economic intuition. A more detailed, step-by-step description is provided in Appendix C. The methodology is based on De Loecker et al. (2016), and accordingly we borrow some of their notation.

4.1 Model overview

Let Q_{fjt} refer to the physical output quantity (in tons) of product j produced by firm f in year t. Output is produced with three inputs: Capital K, labor L and materials M, which includes energy.[12] We write the production function as

$$Q_{fjt} = F_j(K_{fjt}, L_{fjt}, M_{fjt}) \cdot \Omega_{fjt}\,, \tag{1}$$

where Ω_{fjt} is a Hicks-neutral term that captures total factor productivity (TFP). The production function is specific for each product and could in theory vary across time.[13] Estimating production functions in the presence of a productivity shock that is known to the firm, but unobserved to the researcher, has been the focus of the recent literature on productivity analysis (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015). De Loecker et al. (2016) extend the methodology to allow for unobserved input quality.

Denoting V^X_{fjt} as the price for input $X \in (K, L, M)$, which the firm treats as given at time t, the firm's cost minimization problem for product j can be written as

$$\begin{aligned}\min_{K_{fjt},L_{fjt},M_{fjt}} \quad & V^K_{fjt}K_{jft} + V^L_{fjt}L_{fjt} + V^M_{fjt}M_{fjt} \\ s.t. \quad & Q_{fjt} \leq Q_{fjt}(K_{fjt}, L_{fjt}, M_{fjt}; \Omega_{fjt}) \;\forall\; j\end{aligned}$$

This specification allows for the possibility that different firms pay different prices for the same input, and that input quality (and thus the input price) varies across products. Solving this problem leads to the following first-order condition, e.g., for material inputs:[14]

$$V^M_{fjt} = \lambda_{fjt}\frac{\partial Q_{fjt}}{\partial M_{fjt}} \tag{2}$$

[12] Naturally, this model could be expanded to include an arbitrary number of factors.

[13] Given our relatively short sample, we abstain from estimating time-specific production functions and thus omit the subscript t in $F(\cdot)$.

[14] The production function could include more than three inputs, and the first-order condition can be derived using any of them. However, in terms of interpretation, it makes sense to choose an input that is variable in the short run. We follow most of the production literature by assuming that there is at least one input that is freely adjustable. In our setting, the most adjustable factor is material expenditure, which includes all energy inputs.

The interpretation of λ_{fjt}, which is the multiplier of the firm's production constraint in the cost minimization problem, is the cost of producing another unit of Q_{fjt}, i.e., the marginal cost. Multiplying both sides by $\frac{M_{fjt}}{Q_{fjt}}$ and dividing by λ_{fjt} yields:

$$\frac{1}{\lambda_{fjt}} \frac{V_{fjt}^{M} M_{fjt}}{Q_{fjt}} = \frac{\partial Q_{fjt}}{\partial M_{fjt}} \frac{M_{fjt}}{Q_{fjt}}$$

If we denote the product price by P_{fjt} and define the proportional markup as $\mu_{fjt} \equiv P_{fjt}/\lambda_{fjt}$ and substitute, we obtain the following expression:

$$\mu_{fjt} = \left(\frac{\partial Q_{fjt}}{\partial M_{fjt}} \frac{M_{fjt}}{Q_{fjt}} \right) \left(\frac{V_{fjt}^{M} M_{fjt}}{P_{fjt} Q_{fjt}} \right)^{-1} \tag{3}$$

The markup has two components: The first term on the right-hand side is the elasticity of output with respect to material inputs, which can be estimated using standard econometric methods. The second term is the share of materials expenditure on product Q_{fjt} relative to the firm's revenue from that product. For single-product firms, this share collapses to the firm's share of materials expenditures (or any other input used to derive the first-order condition) relative to its revenue, which is observable. However, for multi-product production, the share of inputs used for particular products is not recorded even in highly disaggregated data such as AFiD. Assuming that the physical input-output relationship is the same between single- and multi-product firms that produce the same good, we circumvent this issue by relying on single-product firms only to obtain estimates of the production function, as in De Loecker et al. (2016). However, we depart from their approach by using products' revenue shares as a proxy for their expenditure share, instead of computing the expenditure share independently of the revenue share. Indeed, using products' revenue shares has three important advantages.

First, it allows us to use the full sample, which enables us to estimate the production function at the 4-digit rather than the 2-digit level as is usually done. This is important especially in the context of a quantity-based production function, since the technology to convert capital, labor and materials into tons of output can be expected to vary across product groups.[15] Second, identifying the expenditure shares with the revenue shares allows us to derive TFP at the product level (as opposed to the firm-level), which increases the power of estimating the effect of the ETS on TFP, and which could also be useful in the context of studying endogenous product selection (since firms presumably add products that they can produce efficiently and drop those that they produce inefficiently). And third, the computation of the shares requires around 17 hours of computing and, in addition, can lead to multiple competing solutions per run. This renders a bootstrap based on replicating the endogenous-share procedure impractical.[16]

Based on the estimated markup $\hat{\mu}_{fjt}$, we can compute marginal costs λ_{fjt} as

$$\hat{\lambda}_{fjt} = \frac{P_{fjt}}{\hat{\mu}_{fjt}}\,. \tag{4}$$

This marginal cost serves as the explanatory variable in our cost pass-through regressions, which are discussed in more detail below.

We also use our estimates to learn something about the effect of the EU ETS on productivity. Having estimated the production function, we derive an estimate for TFP by dividing output by the production function estimate:

$$\hat{\Omega}_{fjt} = \frac{\hat{Q}_{fjt}}{\hat{F}_f(K_{fjt}, L_{fjt}, M_{fjt}|\,\hat{\beta})} \tag{5}$$

The vector $\hat{\beta}$ contains parameter estimates of the production function, and $\hat{Q}_{fjt}$ is an estimate of the output that is purged of idiosyncratic shocks. Using a difference-in-difference framework and matching based on observable firm characteristics, we investigate whether markups, TFP and profits are affected by the ETS.

[15] Ideally, we would estimate production functions at the most disaggregated level, which is 9 digits in our data. However, this is impractical because there are not enough observations for most product codes for the estimation procedure to converge.

[16] The Indian data, on which De Loecker et al. (2016) ran this procedure, includes much fewer firms than our data set.

4.2 Estimating the production function

We estimate Cobb-Douglas specifications of the production function (1) for each 4-digit NACE industry. Estimating the production function using OLS is subject to two different types of bias. The first is the well-known simultaneity bias first noted by Marschak and Andrews (1944), which assumes that firms observe the productivity shock before choosing (some of) their inputs. This implies that the input amounts and the error term in an OLS regression (which includes ω_{fjt}) may be correlated.[17] The resolution of this econometric problem is the focus of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015). We follow the latter to address the simultaneity bias. We assume that materials can be adjusted in the short run and that productivity is a strictly increasing function of material inputs. This allows for inverting materials demand and express productivity as an increasing function of materials input. We then set up an equation of motion for productivity and solve for the production parameters using the method of moments.

Besides the simultaneity bias, there is a second econometric challenge that needs to be overcome. The actual input quantity is not recorded in the data (with the exception of energy inputs) but has to be imputed by deflating input expenditure using an industry-wide price index. But firms may use different input qualities for different products, and the actual prices paid are presumably a function of this quality. De Loecker et al. (2016) show that unobserved input quality lead to additional terms in the production function, which precludes the identification of the production coefficients using standard methods. This is particularly important when estimating quantity-based production functions because the quantity of the output may well be a function not only of the quantity, but also the quality of the input.[18]

[17] If all inputs were pre-determined, this would not be an issue. But in this case, the firm would not have control over its current output, which is an assumption that seems highly implausible. In addition, the coefficients of the production function are identified off different timing assumptions about various inputs.

[18] As an example, consider the production of garments, which can be based on very different qualities of materials and labor. Suppose that two firms purchase inputs of 1 million Euro each, but one mass-produces T-shirts whereas the other produces haute couture. Without an input price correction, we would translate the input expenditure into the same quantity (in tons) of garments, which is not correct. The input price correction function uses the fact that haute couture is more expensive than T-shirts, by introducing an adjustment factor to each firm's input expenditure that reduces (increases) the quantity

The solution proposed by De Loecker et al. (2016), and which we follow here, is to add additional terms to the estimating equation to account for the unobserved input quality. We assume that high-quality inputs are related to high-quality outputs, which tend to cost more (see, e.g., Kugler and Verhoogen, 2011; Manova and Zhang, 2012). Moreover, we assume that a firm will use high-quality inputs throughout, in the spirit of the "O-ring theory" (Kremer, 1993), rather than mixing inferior inputs of one kind with high-quality inputs of another. This assumption justifies the application of the same price correction to all inputs. Based on these arguments, we use the output price as our main proxy for input quality. In addition, we include the market share of a product, the export status (as exporting firms may have different opportunities to obtain inputs on the international market), ETS coverage (to control for the fact that covered firms have to pay for emissions allowances and therefore have higher energy costs than non-ETS firms) and a series of product and measurement unit dummies. Because the output price and the market share could be jointly determined with the input demand, we instrument for these variables by using their lags. Based on the coefficients of the price control variables we then compute an input price correction by which we adjust the input expenditure recorded in the raw data. The exact steps are given in Appendix section C. In addition, variables for labor and materials expenditures encompass a broader set of activities that are not linked to firms' main operations. If left unadjusted, those variables would not reflect the true costs allocated to manufacturing, and we scale them down with the share of revenue from firms' operating plants. This decision and procedure are explained in Appendix section D.

4.3 Causal effects of the EU ETS on profits and productivity

Although our chief interest in this paper is the quantification of cost pass-through in manufacturing, it is worth noting that our estimation methodology yields estimates of markups and TFP. Since these "by-products" are also policy relevant, we estimate the effect of the EU ETS on them. The effect of the EU ETS on markups and TFP is an important piece of information to evaluate the full societal impacts of unilateral climate

of expensive (cheap) inputs.

policy (besides the effect on emissions). To control for unobservable differences between ETS and non-ETS firms that might bias our results, we use a semi-parametric matching procedure in the spirit of Fowlie et al. (2012) and Colmer et al. (2020). We match on the industry classification, emission intensity, capital, number of employees and energy use. We perform a nearest-neighbor matching without replacement, as suggested by Abadie and Spiess (2019).

For the effect on markups, the null hypothesis of no effect depends on whether we are referring to a proportional (μ) or an absolute ($P - \lambda$) concept of markup. If firms have an internal rule of adding a margin of, say, 30% to marginal costs to recover their fixed costs, then we would not expect the EU ETS to change this. In other words, we expect no effect on μ. However, since marginal costs increase with the policy, a constant proportional markup translates to an increasing absolute markup.

We use the same framework to examine the effect on firm profits. These could be negatively affected by the ETS due to the cost increase as a consequence of having to pay for allowances. Profits could furthermore be affected via changes in markups and/or TFP, and due to the combination of free allowance allocation and cost pass-through to which we turn next.

4.4 Identifying cost pass-through

By definition, the output price is equal to marginal costs plus the markup:

$$P_{fjt} = \lambda_{fjt} + MU_{fjt} \tag{6}$$

Here, MU_{fjt} refers to the absolute markup given by $MU_{fjt} \equiv P_{fjt} - \lambda_{fjt}$. We can re-write (6) as

$$P_{fjt} = \overline{MU}_{fj} + \lambda_{fjt} + \left[MU_{fjt} - \overline{MU}_{fj}\right] , \tag{7}$$

where $\overline{MU}_{fj} \equiv \sum_{t=1}^{T} MU_{fjt}/T$ denotes the average markup needed to recover the fixed costs in the long run. The term in brackets is the deviation from this average; if the markup is constant at all times, this term is zero. This is the case of complete cost pass-through: If marginal costs increase by one Euro (e.g., due to an increase in energy prices), the product price increases by the same amount, but the markup remains constant. A special case is the situation where $MU_{fjt} = \overline{MU}_{fj} = 0$, such that price equals marginal costs at all times. In this "textbook" example, however, firms would not be able to recover their fixed costs.

If markups are variable, then $\lambda_{fjt} = P_{fjt} - MU_{fjt}$ is correlated with the error term in brackets and pass-through is different from unity. If the price elasticity of demand increases with the price, then an increase in marginal costs (and thus in the product price) leads to an increase in the price elasticity of demand, and thus a reduction of the markup. In other words, the firm will absorb a part of the cost shock by lowering the markup, rather than passing the full cost increase to the product price. If, on the other hand, the elasticity of demand decreases sufficiently with the price (for example, if demand is iso-elastic), then an increase in marginal costs will increase the markup, leading to more than complete pass-through.[19]

Besides the curvature of demand, the nature of the cost shock is relevant for cost pass-through. All else equal, firms pass on less of an idiosyncratic cost shock to consumers, as full pass-through would hurt their market share given that their competitors' costs remain constant. In contrast, if all firms in the market experience the same cost shock, pass-through will be higher (Muehlegger and Sweeney, 2020). The case of incomplete pass-through is more likely in the context of German manufacturing, given that many firms have competitors located outside the EU that are not subject to the same cost shocks. For example, an increase in the allowance price leads to an increase in the production costs for firms covered by the EU ETS, but not in the cost of firms that are not in the system, which includes all firms from outside the 31 ETS countries. In order to protect their market share, firms may not pass on the full carbon cost to the product price. This is the main reason why manufacturing firms receive a proportion of their needed emissions allowances allocated for free. The magnitude of the free allocation required to keep firms'

[19] For a discussion about the demand conditions under which we expect pass-through rates beyond one, see Seade (1985).

profits constant depends directly on the extent to which firms can pass on their carbon costs to product prices.

If marginal costs were known, we could simply regress product prices on a set of firm-product dummies and the marginal cost to identify the rate of cost pass-through:

$$P_{fjt} = a_{fj} + \gamma\lambda_{fjt} + \epsilon_{fjt} \tag{8}$$

The fact that $E[\lambda_{fjt} \cdot \epsilon_{fjt}] \neq 0$ is not a problem we need to be concerned about because (7) is an identity. The "bias" in the coefficient on marginal costs, if markups are variable, is precisely what we aim to capture when we estimate a cost pass-through regression. In this sense, the endogeneity of marginal costs and variable markups is a feature rather than a bug.[20] However, we do not actually observe marginal costs but estimate them with error. Let $\hat{\lambda}_{fjt} = \lambda_{fjt} + u_{fjt}$ where u_{fjt} is the measurement error. Substituting into (8) yields

$$P_{fjt} = a_{fj} + \gamma\hat{\lambda}_{fjt} + [\epsilon_{fjt} - u_{fjt}] \tag{9}$$

The presence of measurement error leads to a bias in the estimation of (9), as $E[\hat{\lambda}_{fjt} \cdot (\epsilon_{fjt} - u_{fjt})] < 0$. To address this problem, we use an instrumental variable approach. We rely on three different instruments that we use separately in different regressions. Because the IV estimate identifies the local effect of the exogenous variation in the underlying instrument, the interpretation of the resulting cost pass-through depends on the choice of the instrument. Our first instrument is the lagged marginal cost, which is appropriate as long as the measurement error is not correlated over time. The interpretation based on lagged marginal costs is that of materials costs pass-through, since we have constructed marginal costs based on the markup derived from the materials elasticity. Second, we use energy prices as instrument for energy costs. Those are the European prices for fuels (coal, natural gas and oil) and the German wholesale price for electricity. The underlying assumption is that these prices are unlikely to be influenced by individual firms. Because

[20] See De Loecker et al. (2016), p. 486f, for a more detailed explanation.

this approach exploits the variation of energy prices, we interpret the estimate in the sense of energy cost pass-through.

For the firms that are subject to the EU ETS, we employ a further instrument that speaks to the extent of carbon cost pass-through, which is relevant in the context of free allowance allocation as discussed above. To do this, we use the allowance price as the instrument, multiplied by the share of allowance costs within total energy costs in the first year of the system. To investigate whether cost-pass-through varies with export status and coverage by the EU ETS, we also run regressions where we interact marginal costs with dummies for being regulated under the EU ETS, exposed to carbon leakage and for exporting goods to areas outside the Euro zone, respectively.

Because our procedure involves multiple steps which are nonlinear, the standard errors on the coefficients of cost pass-through have to be computed using a bootstrap. (Note: this has not been done so far; the reported standard errors are possibly biased).

The above theory applies if the benchmark theory is that of perfect competition. If we instead live in a world of monopolisic competition, then the theory applies to proportional markups instead (Atkeson and Burstein, 2008; Amiti et al., 2019). This framework states that if costs increase by x%, small firms will increase their prices exactly by x%, whereas larger firms may deviate from this rule. The constant vs. proportional markup theories can be tested by specifying equations (6)-(9) in levels vs. logs.

5 Results

5.1 Average output elasticities, TFP and markups, by industry

Table 2 shows the average elasticities of output with respect to the three inputs labor, capital and materials for each 2-digit industry. The column labeled RTS (returns to scale) displays the sum of the elasticities. Some industries appear to be operating near constant returns to scale, with exceptions.

The last column in the table shows the average proportional markups. They are well in excess of unity, which is needed to recover the fixed costs that firms incur. The

Table 2: Average elasticities, TFP and markups, by industry

Nr.	Industry	Labour	Capital	Materials	RTS	TFP	Markup
10	Food products	-0.17	0.05	0.89	0.77	0.82	1.89
11	Beverages	0.1	0.41	0.82	1.32	-4.43	2.57
13	Textiles	0.06	-0.09	0.44	0.41	4.92	1.62
14	Wearing apparel	-0.11	0.26	0.34	0.49	3.47	0.93
16	Wood and products of wood and cork	0.33	0.13	0.55	1	-4.7	1.24
17	Paper and paper products	-0.04	0.02	0.73	0.72	-1.18	1.62
20	Chemicals and chemical products	0.02	0.04	0.49	0.55	2.93	1.29
22	Rubber and plastic products	0.12	0.18	0.45	0.75	1.13	1.12
23	Other nonmetallic mineral products	0.18	0.08	0.3	0.56	2.34	0.88
24	Basic metals	0.28	0.02	0.5	0.8	-5.13	1.1
25	Fabricated metal products	0.24	-0.09	0.37	0.52	1.81	1.17
26	Computer, electronic and optical prod.	0.38	-0.1	0.39	0.67	-1.44	1.09
27	Electrical equipment	0.25	0.12	0.4	0.77	-1.78	1.08
28	Machinery and equipment n.e.c.	0.32	0.15	0.44	0.9	-6.25	1.24
32	Other manufacturing	0.43	-0.27	0.29	0.44	5.82	1.36

Note: This table reports the average output elasticities from the production function, their sum (returns to scale), total factor productivity (demeaned) and the proportional markup. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2018).

average proportional markup ranges from 24 to 77%. Our estimates for the capital output elasticity are very low and even negative for some industries. One possible explanation for this may be the method we use to compute the capital stock. The AFiD data only includes information about investments. To derive the capital stock, we use the perpetual inventory approach (see Appendix). This approach is somewhat sensitive to fluctuations in the per-period investment and the assumed depreciation rate. If the variation in the imputed capital stock is significantly larger than the variation in the output quantity, then this would lead to a low estimate of the capital elasticity, or even a negative one if output surges in the years after an investment, but in which no new investment takes place. To test for the sensitivity of our results to the method used to compute the capital stock, we also employed an alternative method proposed by Wagner (2010). This methodology relies on the average life span of machinery and buildings, coupled with industry-specific information about shares of these types of investments, and with firm-specific information about depreciation rates. Overall, this did not lead to more credible estimates for the materials elasticity, and we therefore rely on the perpetual inventory method for the remainder of the paper.[21]

[21] We obtain negative materials elasticity estimates for 2% of the firm-product-year observations, which we remove by trimming on both sides. Moving towards the methodology by Wagner (2010) leads to more

5.2 The effect of the EU ETS on profits and TFP

[This subsection is unfortunately outdated as the new results are going through a data security check. Results will be updated upon reception.]

The first set of post-estimation analyses pertains to the causal effect of the EU ETS on productivity (measured by our methodology) and profits.[22] We do this for the subset of industries that have a sufficient number of ETS firms. Figure 2 shows the development of these outcomes over time. We see that matching on observable characteristics reduces the absolute difference between the treated and untreated firms. While we cannot reject the assumption of equal pre-treatment trends for profits after matching, matching actually leads to diverging pre-trends for TFP. Since the assumption of parallel trends is essential in a difference-in-differences analysis, we carry out the analysis on the full (i.e., non-matched) sample for TFP, and use the matched sample for profits.

Tables 3 and 4 contain the results of a difference-in-difference regression of total factor productivity on a treatment dummy and including firm and year fixed effects. The reported coefficients correspond to the average treatment effect on the treated (ATET).[23] The results imply that the ETS had no statistically significant effect overall.[24] For industry 24 (metals) we find a positive effect. In tables A.1-A.6 in the Appendix, we show the results from regressions that additionally include the ETS price as an interaction term. The qualitative results remain unchanged.

Our findings thus do not support the Porter Hypothesis, nor do they imply that German manufacturing firms have become less productive as a consequence of the EU ETS. This is consistent with the neoclassic assumption that firms have optimized their

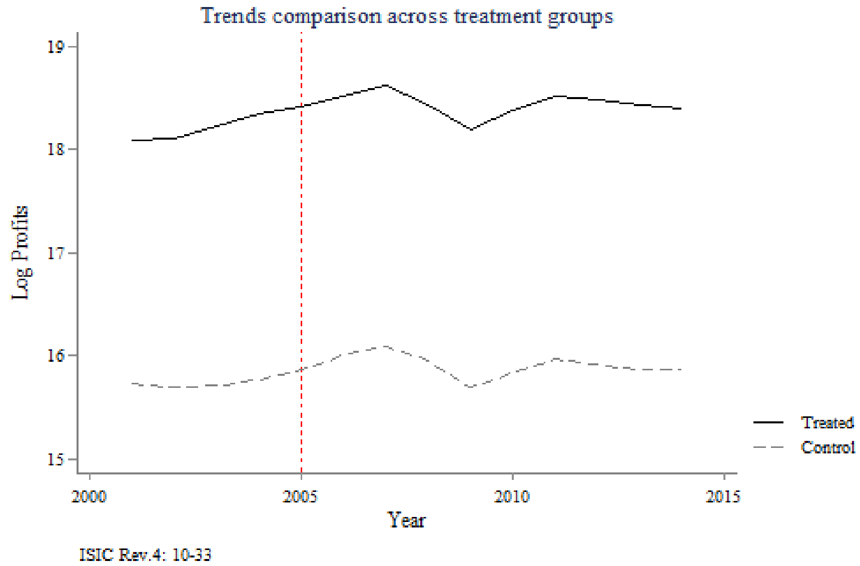
negative estimates.

[22] AfiD data does not provide information on profits directly, so we calculate them by subtracting total costs from total revenues for each firm. Total revenue includes sales from own products, sales from merchandise, sales from commissions through commercial brokerage and sales from other activities. Total costs comprise gross wages paid, social costs, costs for contract workers and costs for contract work carried out by other companies. Additional costs include costs for insurance, repairs, rental and leasing costs, taxes as well as public fees and contributions, tax depreciation on property, plant and equipment and interest on borrowed capital. This data is provided by the Cost Structure Survey.

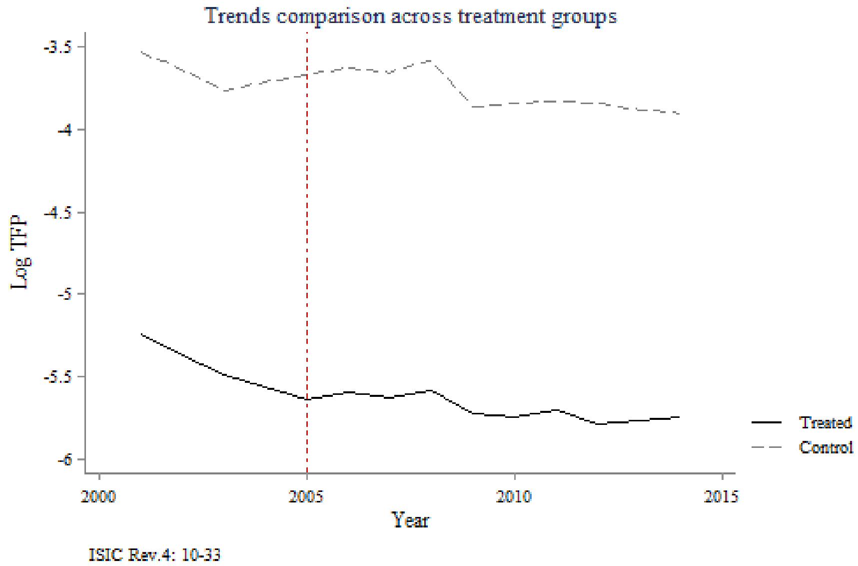
[23] Strictly speaking, this is a *differential* effect because the ETS affects all firms to some extent via its effect on electricity prices (Hintermann, 2016), such that the Stable Unit Treatment Assumption (SUTVA) is likely violated. The effect we identify is thus the difference between being treated directly by the ETS, and treated indirectly via electricity prices and possibly other market mechanisms.

[24] We note at this point that the standard errors have not yet been bootstrapped.

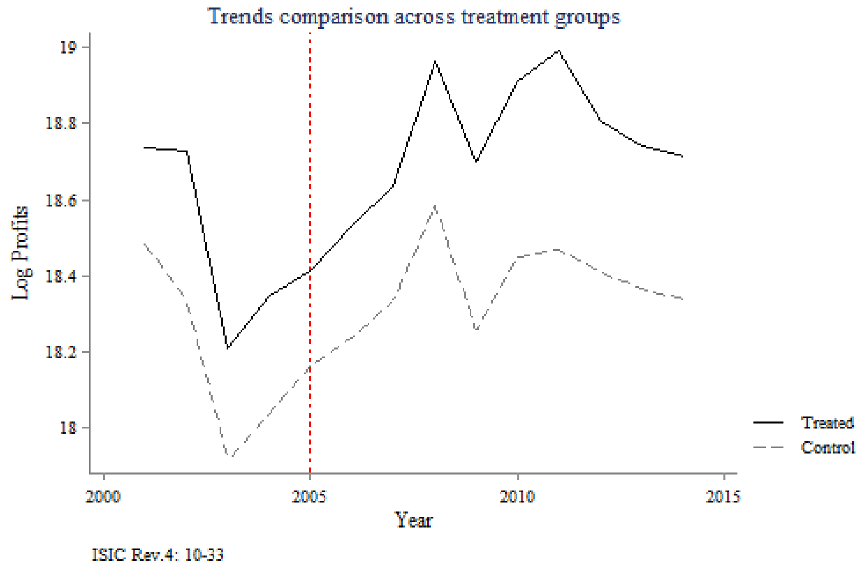
Figure 2: Trends in profits and TFP, with and without matching



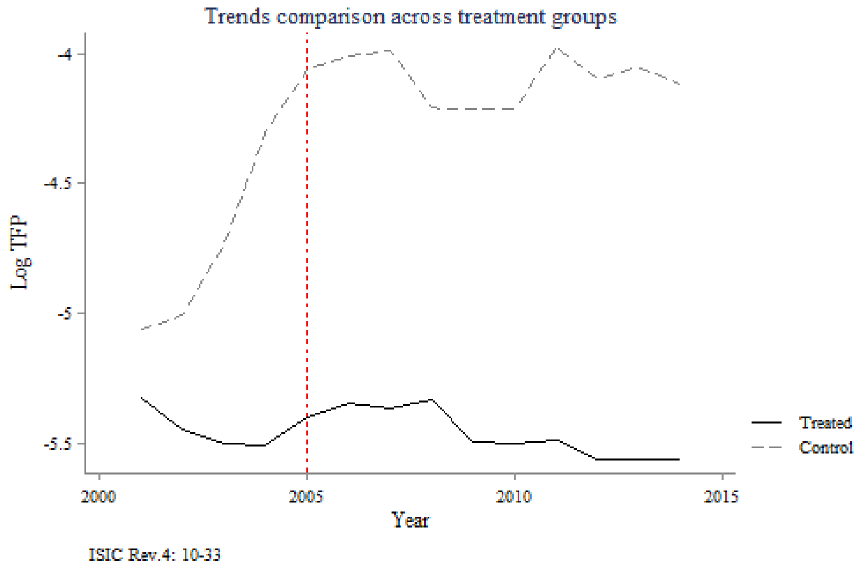
(a) Profits, before matching



(b) TFP, before matching



(c) Profits, after matching



(d) TFP, after matching

Table 3: The effect of the EU ETS on Profits

	Two-digit Industry					
	All	10	17	20	23	24
ETS	0.054	0.246	0.022	0.057	-0.019	0.187***
	(0.037)	(0.162)	(0.074)	(0.117)	(0.078)	(0.060)
Matching	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
N	6'874	504	980	1'380	1'238	1'114

Note: This table displays the results of the fixed-effect difference-in-difference analysis regressions of the EU ETS' impact on profits. Standard errors (in parentheses) are clustered on the matched pair. Industry codes: 10 – Food products, 17 – Paper and paper products, 20 – Chemicals and chemical products, 23 – Other nonmetallic mineral products, 24 – Basic metals. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2014). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: The effect of the EU ETS on TFP

	Two-digit Industry					
	All	10	17	20	23	24
ETS	-0.087	-0.138	-0.137	-0.037	-0.230	0.266**
	(0.0966)	(0.419)	(0.124)	(0.101)	(0.356)	(0.107)
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
N	466'073	97'480	13'885	73'049	19'660	23'208

Note: This table displays the results of the fixed-effect difference-in-difference analysis regressions of the EU ETS' impact on TFP for the full sample. Standard errors in parentheses. Industry codes: 10 – Food products, 17 – Paper and paper products, 20 – Chemicals and chemical products, 23 – Other nonmetallic mineral products, 24 – Basic metals. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2014). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

production process, and that being covered by an ETS does not fundamentally alter firm's profit-maximizing behavior. The lack of a negative impact on profits can be explained by the countervailing effect that partial free allowance allocation, combined with cost pass-through, has on profits. We turn to this next.

5.3 Estimates for cost pass-through

Table 5 reports the IV results from regressing product prices on a set of firm-by-product dummies (to capture the average markup) and the marginal cost, instrumented for with its lag. Because our marginal costs are based on materials, the results can be interpreted as materials cost pass-through.

We estimate (9) in logs.[25] Regressing the log price on log marginal costs yields an estimate of the elasticity. To transform this elasticity into a marginal effect, we multiply the respective elasticities in each industry by the industry-specific average markup. The log regression results without this adjustment (and which therefore show the proportional rather than additive markups) are shown in Tables A.7 and A.8 in the Appendix.

Table 5: Material cost pass-through (whole manufacturing sector)

mc	0.818***	0.820***	0.820***	0.824***
	(0.022)	(0.022)	(0.022)	(0.024)
mc × ETS		-0.011*		
		(0.006)		
mc × ETS × CLE			-0.015***	
			(0.006)	
mc × EXP				0.017***
				(0.004)
Observations	404'929	404'929	404'929	376'548
R-squared	0.504	0.505	0.505	0.504
F-statistic	3'670	1'806	1'817	226

Notes: The marginal effects have been computed based on a log specification. All regressions include firm-product fixed effects and lagged marginal costs as instruments. Standard errors (in parentheses) are clustered at the firm-level. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2018).

The results show that the average materials cost pass-through in the manufacturing

[25] When estimating it in levels, the first stage does not reach statistical significance, such that we focus on the log regressions.

sector is on the order of 80%, with relatively tight confidence intervals. We can easily reject the null hypotheses of zero and complete pass-through.

In some regressions we also interact marginal costs with an ETS dummy and an export dummy, which is equal to one for firms that belong to the top quartile in terms of exports outside the EU. The coefficient on the ETS dummy is weakly statistically significant, indicating that treated and non-treated firms may engage in differential cost pass-through. The significance and coefficient size both increase when we focus on treated firms deemed to be carbon leakage-exposed (CLE) by the EU, and confirms that firms affected by carbon-leakage have more difficulties to pass on their costs to consumers. For this column, we will next add an interaction with ETS firms in order to disentangle this effect between treated and non-treated carbon leakage firms. The coefficient on the export dummy is statistically significant, and surprisingly positive, as exporting firms should in theory have greater difficulties to pass-on their costs due to international competition.

Table 6 shows materials cost pass-through for selected industries, based on the models without interaction terms. The cross-industry variation shows that firms producing nonmetallic mineral products (23) and basic metals (24) have much lower pass-through, averaging half of their counterparts'.

Table 6: Material cost pass-through (selected industries)

	All	10	17	20	23	24
mc	0.818***	0.803***	0.766***	0.882***	0.413***	0.310***
	(0.022)	(0.093)	(0.097)	(0.043)	(0.051)	(0.053)
Observations	404’929	87’199	9’061	62’917	18’370	19’661
R-squared	0.504	0.334	0.284	0.6	0.348	0.268
F-statistic	3’670	587	183	584	344	362

Notes: The marginal effects have been computed based on a log specification. All regressions include firm-product fixed effects and lagged marginal costs as instruments. Standard errors (in parentheses) are clustered at the firm-level. Industry codes: 10 – Food products, 17 – Paper and paper products, 20 – Chemicals and chemical products, 23 – Other nonmetallic mineral products, 24 – Basic metals. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2018).

An alternative interpretation of our results is that firms may choose a proportional markup strategy. If firms keep this proportional markup constant, then a one-Euro increase in marginal costs will lead to a price increase by the extent of the markup (e.g., 1.40 Euro). The IV coefficient from the log model (i.e., the elasticities) are not statistically different from one, thus confirming the proportional markup strategy. In this sense, our results are consistent with a *constant proportional* markup, which translates to more than complete pass-through in an absolute sense. As far as we are aware, the distinction between absolute and proportional markup cost pass-through has not received much attention in the literature. If a firm has an average proportional markup of $\mu > 1$, and its marginal costs increase by one unit, then complete cost pass-through in an absolute sense implies a price increase by one unit, whereas complete cost pass-through in a proportional sense implies a price increase by μ units. The choice is not obvious, and different authors have used different interpretations. For example, Fabra and Reguant (2014) Ganapati et al. (2020) use the former interpretation, whereas De Loecker et al. (2016) use the latter.

Next, we turn to the IV estimates where we use energy prices as the instrument, and which therefore can be interpreted as energy cost pass-through. Table 7 shows the results for the whole sector, again in absolute terms. The tables without the adjustment with markups are shown in the Appendix in Tables A.9 and A.10. As above, the levels-regressions do not result in a valid first stage, and we therefore focus on the estimates from the log model. The interaction terms involving the ETS and carbon leakage firms are not statistically significant, indicating that ETS coverage and leakage status do not meaningfully affect the degree of pass-through for energy costs. The model interacting marginal costs with export status yielded a weak F-statistic and negative R-squared, thus was temporarily omitted from the table until the next round of results.

We find that on average, firms pass on only between 27 and 32 % of an energy cost shock to consumers. This is significantly less than cost pass-through for materials. A possible explanation for this result is that energy cost are more local or regional in nature compared to material inputs, which are traded on global markets. As argued by Muehlegger and Sweeney (2020), the geographic scale of a cost shock can explain the degree of cost pass-through and thus reconcile different empirical estimates. Intuitively, if a cost shock only affects a small share of the overall market, the potential for cost pass-through

Table 7: Energy cost pass-through (whole manufacturing sector)

mc	0.274***	0.308***	0.324***
	(0.058)	(0.057)	(0.050)
mc × ETS		-0.001	
		(0.003)	
mc × ETS × CLE			-0.000
			(0.001)
Observations	531'165	531'165	321'165
R-squared	0.299	0.325	0.339
F-statistic	60.1	33.6	32.4

Notes: The marginal effects have been computed based on a log specification. All regressions include firm-product fixed effects and energy prices as instruments. Standard errors (in parentheses) are clustered at the firm-level. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2018).

is more limited compared to a cost shock that is global and thus affects all firms. In other words, firms fully pass on costs if their competitors are subject to the same shock, but absorb a part of a more local cost shock by decreasing their margin.

Our estimates of cost pass-through are lower than the average values reported by (Ganapati et al., 2020), who specifically rely on the regional disaggregation of energy cost shocks to identify cost pass-through. In that paper, the average rate of marginal cost pass-through is 51-72%, depending on the specification. However, there is a large variation in cost pass-through across the six considered products, which ranged from 24 to 99%.

Table 8 reports results for the food, paper, and nonmetallic product industries to highlight the pronounced heterogeneity across industries. Despite lower F-statistic, we observe some variation where the food industry weights much than the sector average, with a pass-through averaging almost 50 %. The other industries show much lower pass-through, and are prone to insignificance.

In regards to the third IV strategy outlined in Section 4.4 above, none of the models that use the carbon price as the instrument survives the first stage. In other words, carbon prices are not significantly related to the marginal costs as computed in our model. This somewhat surprising result led us to investigate the way carbon costs are reflected in the

Table 8: Energy cost pass-through (selected industries)

	All	10	17	23
mc	0.274***	0.486***	0.159	0.155*
	(0.058)	(0.144)	(0.196)	(0.82)
Observations	531’165	112’189	11’891	24’062
R-squared	0.299	0.3	0.156	0.252
F-statistic	60.1	11.2	5.05	14.9

Notes: The marginal effects have been computed based on a log specification. All regressions include firm-product fixed effects and energy prices as instruments. Standard errors (in parentheses) are clustered at the firm-level. Industry codes: 10 – Food products, 17 – Paper and paper products, 23 – Other nonmetallic mineral products. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2018).

AFiD data. As it turns out, emission allowances are listed not among energy costs, but under financial assets and are thus part of capital. Since our marginal cost estimates are based on materials costs, they do in fact not reflect the opportunity cost of carbon emissions.[26]

Based on our estimates for energy cost pass-through, and assuming that the geographic scope of carbon cost shocks is comparable to that of energy cost shocks, our analysis implies that carbon costs are passed on to product prices to an extent of around 30 %. Considering that firms, on average, received more than 80% of their allowances allocated for free during our sample period, this means that German manufacturing firms nevertheless were over-compensated for the carbon costs that they had to incur as a consequence of the EU ETS.

6 Conclusions and outlook

There are concerns that unilateral climate policy may adversely affect firms. In this paper we show that these concerns are unfounded for German manufacturing firms covered by the EU ETS for the first ten years of the system. We find that the program had no effect on profits and productivity for the sector overall, and even a positive effect for some

[26]This is work in progress. In a future update of our paper, we will transfer the value of emission allowances (i.e., verified emissions times the allowance price) from capitals to materials and re-estimate the model. This will hopefully lead to a valid first stage for carbon cost pass-through.

industries.

We further estimate the degree of different types of cost pass-through. Our findings indicate that firms use a fixed proportional markup and pass on materials costs fully in a proportional sense, and more than completely in an absolute sense. In contrast, the rate of absolute cost pass-through for energy cost shocks is on the order of 30 %. The lower rate of pass-through could be explained by the more local nature of energy cost shocks, relative to shocks to materials costs that tend to be traded more globally. Assuming that carbon cost pass-through is similar to energy cost pass-through, our estimates imply that manufacturing firms passed on their carbon costs sufficiently to insulate themselves from profit losses during our sample period. On the other hand, the reduction of free allocation to 30% of benchmark emissions by 2020 will likely lead to profit losses for the average firm, which, given our current estimates, is able to pass on less than 70% of its carbon costs to consumers.

Some (sub-)industries will continue to receive a much larger share free allocation due to concerns of carbon leakage. We show that in the context of energy costs, firms deemed to be "carbon leakage exposed" pass-on their costs to consumers in the same way, calling in question the allowance allocation rules of the European Commission.

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Appendix

A Additional tables

Table A.1: The effect of the EU ETS on Profits

Nr.	10				17			
ETS	0.007	0.246	0.136	0.256	0.123**	0.022	0.143**	0.058
	(0.058)	(0.162)	(0.093)	(0.190)	(0.049)	(0.751)	(0.056)	(0.093)
ETS × PRICE			-0.059**	-0.005			-0.009	-0.017
			(0.065)	(0.924)			(0.150)	(0.059)
Matching	✗	✓	✗	✓	✗	✓	✗	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
N	21698	504	21698	504	6225	980	6225	980

Note: This table displays the results of the fixed-effect difference-in-difference analysis regressions of the EU ETS' impact on firm profits. Standard error in parentheses. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2014). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: The effect of the EU ETS on Profits

Nr.	20				23			
ETS	-0.023	0.057	-0.048	0.071	0.110**	0.019	0.118*	-0.071
	(0.061)	(0.117)	(0.070)	(0.142)	(0.053)	(0.078)	(0.062)	(0.095)
ETS × PRICE			-0.011	-0.006			-0.004	0.024*
			(0.041)	(0.171)			(0.285)	(0.040)
Matching	✗	✓	✗	✓	✗	✓	✗	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
N	10667	1380	10667	1380	8799	1238	8799	1238

Note: This table displays the results of the fixed-effect difference-in-difference analysis regressions of the EU ETS' impact on firm profits. Standard error in parentheses. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2014). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: The effect of the EU ETS on Profits

Nr.	24				Sector			
ETS	0.203***	0.187***	0.229***	0.166**	0.070***	0.054	0.088***	0.050
	(0.000)	(0.060)	(0.000)	(0.072)	(0.025)	(0.037)	(0.028)	(0.044)
ETS × PRICE			-0.012	0.009			-0.009*	0.002
			(0.162)	(0.227)			(0.047)	(0.147)
Matching	✗	✓	✗	✓	✗	✓	✗	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
N	8437	1114	8437	1114	150286	6874	150286	6874

Note: This table displays the results of the fixed-effect difference-in-difference analysis regressions of the EU ETS' impact on firm profits. Standard error in parentheses. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2014). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: The effect of the EU ETS on TFP (industries nr. 10-17)

Nr.	10				17			
ETS	-0.138	0.744	0.060	0.937*	-0.137	0.044	-0.060	0.151
	(0.419)	(0.458)	(0.454)	(0.502)	(0.124)	(0.165)	(0.120)	(0.179)
ETS × PRICE			-0.090*	-0.087			-0.036	-0.049
			(0.049)	(0.055)			(0.023)	(0.034)
Matching	✗	✓	✗	✓	✗	✓	✗	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
N	97480	5960	97480	5960	13885	3251	13885	3251

Note: This table displays the results of the fixed-effect difference-in-difference analysis regressions of the EU ETS' impact on total factor productivity. Standard error in parentheses. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2014). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: The effect of the EU ETS on TFP (industries nr. 20-23)

Nr.	20				23			
ETS	-0.037	0.048	-0.067	0.076	-0.230	0.040	-0.285	0.091
	(0.101)	(0.134)	(0.111)	(0.155)	(0.356)	(0.417)	(0.377)	(0.455)
ETS × PRICE			0.014	-0.013			0.025	-0.023
			(0.014)	(0.025)			(0.035)	(0.045)
Matching	✗	✓	✗	✓	✗	✓	✗	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
N	73049	27266	73049	27266	19660	4407	19660	4407

Note: This table displays the results of the fixed-effect difference-in-difference analysis regressions of the EU ETS' impact on total factor productivity. Standard error in parentheses. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2014). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: The effect of the EU ETS on TFP (industry nr. 24 and overall)

Nr.	24				Sector			
ETS	0.266**	0.353***	0.332**	0.401***	-0.087	0.121	-0.097	0.144
	(0.107)	(0.119)	(0.131)	(0.153)	(0.097)	(0.119)	(0.107)	(0.139)
ETS × PRICE			-0.031	-0.022			0.004	-0.010
			(0.220)	(0.480)			(0.241)	(0.277)
Matching	✗	✓	✗	✓	✗	✓	✗	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
N	23208	5018	23208	5018	466073	62004	466073	62004

Note: This table displays the results of the fixed-effect difference-in-difference analysis regressions of the EU ETS' impact on total factor productivity. Standard error in parentheses. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2014). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Material cost pass-through (whole manufacturing sector): Proportional CPT

mc	0.588***	0.589***	0.589***	0.592***
	(0.016)	(0.016)	(0.016)	(0.017)
mc × ETS		-0.008*		
		(0.004)		
mc × ETS × CLE			-0.011***	
			(0.004)	
mc × EXP				0.012***
				(0.003)
Observations	404’929	404’929	404’929	376’548
R-squared	0.504	0.505	0.505	0.504
F-statistic	3’670	1’806	1’817	226

Notes: These are the results from regression in logs such that the coefficients represent elasticities. All columns include firm-product fixed effects and lagged marginal costs as instruments. Standard errors (in parentheses) are clustered at the firm-level. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2018).

Table A.8: Material cost pass-through (selected industries): Proportional CPT

	All	10	17	20	23	24
mc	0.588***	0.425***	0.473***	0.684***	0.470***	0.281***
	(0.016)	(0.049)	(0.062)	(0.032)	(0.058)	(0.048)
Observations	404’929	87’199	9’061	62’917	18’370	19’661
R-squared	0.504	0.334	0.284	0.6	0.348	0.268
F-statistic	3’670	587	183	584	344	362

Notes: These are the results from regression in logs such that the coefficients represent elasticities. All regressions include firm-product fixed effects and lagged marginal costs as instruments. Standard errors (in parentheses) are clustered at the firm-level. Industry codes: 10 – Food products, 17 – Paper and paper products, 20 – Chemicals and chemical products, 23 – Other non-metallic mineral products, 24 – Basic metals. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2018).

Table A.9: Energy cost pass-through (whole manufacturing sector): Proportional CPT

mc	0.197***	0.221***	0.233***
	(0.042)	(0.041)	(0.043)
mc × ETS		-0.001*	
		(0.002)	
mc × ETS × CLE			-0.000
			(0.002)
Observations	531'165	531'165	321'165
R-squared	0.299	0.325	0.339
F-statistic	60.1	33.6	32.4

Notes: These are the results from regression in logs, such that the coefficients represent elasticities. All models include firm-product fixed effects and energy prices as instruments. Standard errors (in parentheses) are clustered at the firm-level. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2018).

Table A.10: Energy cost pass-through (selected industries): Proportional CPT

	All	10	17	23
mc	0.197***	0.257***	0.098	0.176*
	(0.042)	(0.076)	(0.121)	(0.093)
Observations	531'165	112'189	11'891	24'062
R-squared	0.299	0.3	0.156	0.252
F-statistic	60.1	11.2	5.05	14.9

Notes: These are the results from regression in logs such that the coefficients represent elasticities. All regressions include firm-product fixed effects and energy prices as instruments. Standard errors (in parentheses) are clustered at the firm-level. Industry codes: 10 – Food products, 17 – Paper and paper products, 23 – Other nonmetallic mineral products. Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder (survey years 2001-2018).

B Further Data Description

In the periods 1995-2018, the industry classification in our dataset ("Wirtschaftszweig") has changed three times. During the last change in our sample after 2008, the classification has changed in accordance with the European implementation NACE Revision 2 (Statistical Classification of Economic Activities in the European Community) of the UN classification ISIC Revision 4. We reclassify the years before 2008 using official reclassification guide of the German Statistical Offices at the four-digit industry code level, to be able to use the NACE Rev. 2 classification throughout.[27]

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

As the AFiD dataset does not provide explicit capital stock information, we use the perpetual inventory method to compute capital stocks on firm-level. In what follows we borrow from Lutz (2016). The 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. We derive the initial capital stock K_1 from the equation (A.1):

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

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

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

We assume the real investments grow at rate g:

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

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

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

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

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

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

For information on investment in machinery and equipment, investment in buildings, and investment in properties without buildings. we use firm-level investment data from the AFiD-Panel Industriebetriebe ("AFiD Panel Manufacturing Plants"). We deflate investments using industry-specific deflators for machinery and equipment as well as general deflators for buildings and property without buildings. We start from K1 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 we observe annual firm-level investment data for the period 2003-2018, 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.

We use the same source for the deflators information.[28] 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.

[28]For more information on this data, visit the Destatis portal GENESIS at https://www-genesis.destatis.de/genesis/online.

Table A.11: An example of product-level classification in the leather industry

2-digit code	4-digit code	6-digit code	9-digit code	Main Description	Additional Description
15	1520	1520 11	1520 11 000	Waterproof shoes with outsoles and uppers of Rubber or plastic	
15	1520	1520 12	1520 12 100	Other shoes with outer soles and uppers made of rubber or plastic	Sandals
15	1520	1520 12	1520 12 310	Other shoes with outer soles and uppers made of rubber or plastic	Street shoes (boots, ankle boots, loafers)
15	1520	1520 12	1520 12 370	Other shoes with outer soles and uppers made of rubber or plastic	Slippers
15	1520	1520 13	1520 13 300	Shoes with uppers made of leather with a main sole made of wood	
15	1520	1520 13	1520 13 510	Shoes with outer soles made of rubber, plastic, leather or reconstituted leather	for men
15	1520	1520 13	1520 13 522	Shoes with outer soles made of rubber, plastic, leather or reconstituted leather	for women
15	1520	1520 13	1520 13 529	Shoes with outer soles made of rubber, plastic, leather or reconstituted leather	unisex
15	1520	1520 13	1520 13 530	Shoes with outer soles made of rubber, plastic, leather or reconstituted leather	for children
15	1520	1520 13	1520 13 610	Shoes with outer soles made of rubber, plastic, leather or reconstituted leather	Sandals for men
15	1520	1520 13	1520 13 620	Shoes with outer soles made of rubber, plastic, leather or reconstituted leather	Sandals for women and unisex
15	1520	1520 13	1520 13 630	Shoes with outer soles made of rubber, plastic, leather or reconstituted leather	Sandals for children
15	1520	1520 13	1520 13 700	Shoes with outer soles made of rubber, plastic, leather or reconstituted leather	Slippers
15	1520	1520 13	1520 13 800	Shoes with outer soles made of rubber, plastic, leather or reconstituted leather	Other shoes
15	1520	1520 14	1520 14 440	Shoes with textile uppers	Slippers
15	1520	1520 14	1520 14 450	Shoes with textile uppers	Shoes with outer soles made of rubber, plastic, leather or reconstituted leather
15	1520	1520 14	1520 14 460	Shoes with textile uppers	Other shoes
15	1520	1520 21	1520 21 000	Sports shoes	Tennis, basketball, gymnastics, training shoes
15	1520	1520 29	1520 29 000	Sports shoes	Other sports shoes (excluding ice skates and roller skates)
15	1520	1520 31	1520 31 200	Secured shoes with a metal protection in the toe cap	with outsoles or uppers made of rubber or plastic(including waterproof shoes
15	1520	1520 31	1520 31 500	Secured shoes with a metal protection in the toe cap	with upper part made of leather and with outer soles made of rubber, plastic or leather
15	1520	1520 32	1520 32 000	Other secured shoes, n.e.s.	
15	1520	1520 40	1520 40 200	Parts of leather shoes; Insoles, heel pieces, etc. exempt goods	from leather
15	1520	1520 40	1520 40 500	Parts of leather shoes; Insoles, heel pieces, etc. exempt goods	from other fabrics
15	1520	1520 40	1520 40 800	Parts of leather shoes; Insoles, heel pieces, etc. exempt goods	Other shoe parts, insoles, etc. removable goods

Note: This table shows an example of product classification in the Official Production Statistics of Germany. The codes are in accordance with the NACE Rev. 2 classification. Each product can be assigned to a 9-digit code. The first two digits of the product code represent the industry in which this products are produced. This table shows only a subset of all product codes in the leather industry as a whole, relating to shoe products specifically, denoted with the 4-digit code 1520. Source:Statistisches Bundesamt (2019).

C Estimating markups, marginal costs and TFP

C.1 Estimating the production function

We use lower case variables to denote the natural logarithm of a variable and collapse the three factors into the vector $x = (k, l, m)$. This leads us to the following production function:

$$q_{fjt} = f_j(x_{fjt}; \beta) + \omega_{fjt} + \epsilon_{fjt} \tag{A.8}$$

The vector β contains the production coefficients, ω_{fjt} is the log of TFP and ϵ_{fjt} is an i.i.d. error term. We specify a Cobb-Douglas production function that takes as arguments the physical input quantities:

$$f_j(x_{fjt}; \beta) = \beta_l l_{fjt} + \beta_k k_{fjt} + \beta_m m_{fjt} \tag{A.9}$$

We do not observe actual input quantities, but only input expenditures. Let x^e_{ft} be the log of firm f's expenditure on input x, and v_{fjt} is the unobserved input price that this firm pays in the production of product j. To deflate input expenditures, an industry-wide price index $\bar{v}_{jt}$ is used. The deflated log input expenditure is denoted by $\tilde{x}_{ft} \equiv x^e_{ft} - \bar{v}_{jt}$, which can be computed from the data. Furthermore, let ρ_{fjt} refer to the log share of inputs used in the production of product j. In our base specification, we approximate this with the revenue share and compute $\tilde{x}_{fjt} = \rho_{fjt} + \tilde{x}_{ft}$. As an extension, we use the methodology by De Loecker et al. (2016), who treat ρ_{fjt} as endogenous (see below).

We can then express the log physical quantity of input x used in the production of j by

$$\begin{aligned} x_{fjt} =& \rho_{fjt} + x^e_{ft} - v_{fjt} \\ =& \rho_{fjt} + (x^e_{ft} - \bar{v}_{jt}) + (\bar{v}_{jt} - v_{fjt}) \\ =& \tilde{x}_{fjt} - vd_{fjt} \end{aligned} \tag{A.10}$$

Here, $vd_{fjt} \equiv v_{fjt} - \bar{v}_{jt}$ is the deviation of the firm- and product-specific input price vector v_{fjt} from the industry price index; if $vd_{fjt} = 0$, the firm pays exactly the industry average for input x in the production of good j. If it pays more, then a given amount of input expenditure will lead to a lower input quantity, and vice versa.

Substituting (A.10) into (A.8), we can express the production function as

$$q_{fjt} = f_j(\tilde{x}_{fjt}; \beta) + C(v_{fjt}; \delta) + \omega_{fjt} + \epsilon_{fjt} \quad . \tag{A.11}$$

The term $C(\cdot)$ captures all components that are related to the unobserved input quality, captured by the firm-product specific price v_{fjt}. Estimating this equation with OLS would be problematic even abstracting from the simultaneity bias as v_{fjt} is endogenous. We therefore need to resort to a control function approach similar to that used for the simultaneity bias.

To control for unobserved input quality, we need observable proxies. As discussed in the main text, will assume complementarity such that high-quality products rely exclusively on high-quality inputs and thus use the output price p_t (along with its square) as our main proxy for input quality.[29] In addition, we include the market share of a product ms_{fjt} (by itself and interacted with the product price); a EU ETS membership dummy ETS_{ft} that is equal to one if a firm is included in the market and zero otherwise; and a series of product and measurement unit dummies PD_{fjt}. The firm-specific price (and thus quality premium) in input prices can be written as

$$v_{fjt} = v\left(p_{fjt}, ms_{fjt}, ETS_{ft}, PD_{fjt}; \delta\right) \tag{A.12}$$

When substituting (A.12) into (A.11), we instrument for the current price and market share with their lags, as well as with the lagged price interacted with the vector of input expenditures $\tilde{x}_{fjt}$ in order to facilitate identification of the parameter vectors β (for the production function) and δ (for the price correction).

We follow the methodology by Wooldridge (2009) and Ackerberg et al. (2015) to

[29] For a detailed rationalization of this approach, see De Loecker et al. (2016, Appendix A).

identify the coefficients of the production function. Specifically, we assume that materials are the input that is best adjustable in the short run, whereas labor adjusts a little more slowly, and capital is a dynamic input in the sense that the stock of capital in period t can be treated as given. Besides labor and capital, materials demand also depends on the productivity shock and on the unobserved input price quality v_{ft}:

$$\tilde{m}_{fjt} = m\left(\omega_{fjt}, \tilde{k}_{fjt}, \tilde{l}_{fjt}, p_{fjt}, ms_{fjt}, ETS_{ft}, PD_{fjt}\right) , \tag{A.13}$$

where the tilde refers to the fact that these are expenditures (rather than amounts), and the subscript j indicates that these have been converted to the product-level by multiplying by ρ_{fjt}.

Inverting the function $m(\cdot)$ leads to

$$\omega_{fjt} = h(\tilde{x}_{fjt}, p_{fjt}, ms_{fjt}, ETS_{ft}, PD_{fjt}) \tag{A.14}$$

Following Ackerberg et al. (2015), we use the following equation of motion for the productivity shock:

$$\omega_{fjt} = g(\omega_{fjt-1}, EXP_{ft-1}, NP_{ft-1}) + \xi_{fjt} , \tag{A.15}$$

To predict the productivity shock, we include the export status as exporting firms have been found to be more productive in many contexts (Melitz, 2003; Wagner, 2007; De Loecker, 2013), including the German manufacturing sector (Arnold and Hussinger, 2005; Richter and Schiersch, 2017). In addition, we include the (lagged) number of products (NP_{ft-1}) that a firm produces to control for the possibility that high-productivity firms produce more products (or that they, by producing more products, become more productive).

Identification is achieved via timing assumptions in a general methods of moments framework. We assume that materials and labor are static inputs in the sense that they can be adjusted in the short run, whereas the stock of capital is pre-determined at time

t. In practice, this means that we include current capital as a pre-determined regressors, whereas we instrument for materials and labor by using their lags.

To form moments on the innovation ξ_{fjt}, the productivity has to be expressed as a function of data and estimable parameters. To do this, we first purge output from unobserved shocks by regressing it on all variables in $f(\cdot)$ and $C(\cdot)$, using lags wherever an endogeneity problem may be expected and a series of product and unit dummies. This semi-parametric regression yields an estimate for output, $\hat{q}_{fjt}$, that is independent of idiosyncratic shocks ϵ_{fjt} in (A.11). The productivity shock can then be expressed as

$$\omega_{fjt}(\beta,\delta) = \hat{q}_{fjt} - f(\tilde{x}_{fjt};\beta) - C(p_{fjt}, ms_{jft}, ETS_{ft}, PD_{fjt};\delta) \tag{A.16}$$

The parameters are estimated by forming moments based on the error term in the law of motion for ω_{fjt}:

$$\xi_{fjt}(\beta,\delta) = \omega_{fjt}(\beta,\delta) - E\left[\omega_{fjt}(\beta,\delta)\,|\,\omega_{fjt-1}(\beta,\delta), EXP_{ft-1}, NP_{ft-1}\right] \tag{A.17}$$

$$E\left[\xi_{fjt}(\beta,\delta)\cdot Y_{fjt}\right] = 0 \tag{A.18}$$

The vector Y_{fjt} includes current capital, lagged materials and labor, as well as lagged output prices and market shares, lagged export and ETS dummies, the lagged number of products and a series of product dummies.

More precisely, we estimate the production function using an IV procedure based on two-step GMM that contains two sets of endogenous regressors. The dependent variable is the quantity of output. The set of endogenous regressors in the production function contains input terms for material and labor. The endogenous regressors in the price control function are the output price and its square, the market share, the market share interacted with the output price and the ETS status. The set of (excluded) instruments are the corresponding lagged variables, the interaction of the lagged output price with labor, capital and materials, and the lagged export status. Finally, the included exogenous regressors include current and lagged capital, squared and cubic lagged output price, the export status and a series of year and product dummies.

Having the regression estimates for β and δ, we can first compute the price correction using (A.12) and then the productivity shock in (A.16). We compute the price correction by

$$\hat{v}_{fjt} = \gamma_p \cdot p_{fjt} + \gamma_{p2} \cdot p_{fjt}^2 + \gamma_{ms} \cdot ms_{fjt} + \gamma_{pms} \cdot p_{fjt} \times ms_{fjt} + \gamma_{ETS} \cdot ETS_{ft} \tag{A.19}$$

$$\gamma_y \equiv \frac{-\hat{\delta}_y}{\bar{\theta}_m + \bar{\theta}_l + \bar{\theta}_k} \qquad \text{for} \quad y \in (p, p2, ms, pms, ETS) \tag{A.20}$$

$$\bar{\theta}_m \equiv \hat{\beta}_m \tag{A.21}$$

$$\bar{\theta}_l \equiv \hat{\beta}_l \tag{A.22}$$

$$\bar{\theta}_k \equiv \hat{\beta}_k \tag{A.23}$$

The correction parameters γ_y are equal to the negative of the coefficient estimates $\hat{\delta}$ on the respective endogenous variables in (A.19) divided by the returns to scale evaluated at the average values, as dented by the bars. Recall that we estimate the regressions on the 4-digit level, such that the averages are taken within these subsectors. Intuitively, we model a better input quality as if the firm had fewer inputs to generate a given output, relative to a firm with a worse input quality. This input quantity adjustment (over all inputs) affects the output quantity to the extent of the returns to scale. Suppose, for simplicity, that the price correction only consisted in the output price. The marginal effect of the (instrumented) price on the output quantity is then

$$\frac{\partial q_{fjt}}{\partial p_{fjt}} = -\delta_p = \frac{\partial q_{fjt}}{\partial v_{fjt}} \frac{\partial v_{fjt}}{\partial p_{fjt}} = (\bar{\theta}_m + \bar{\theta}_l + \bar{\theta}_k) \cdot \gamma_p < 0 \tag{A.24}$$

The first equality represents the IV regression where we regress the quantity, among other things, on the (instrumented for) product price. The coefficient on this is $-\delta_p$, where the negative sign is due to the specification of (A.10). In the second equality we simply expand the marginal effect of price on quantity into a marginal effect of the output price on the input price times the marginal effect of the input price on the output quantity. The latter is given by the returns to scale, and the former by the coefficient γ_p as shown in (A.19).

We estimate the regression using the ivreghdfe command (Correia, 2018) in Stata 15, using the option gmm2s. The code is available upon request. The estimation takes place at the 4-digit-level, such that the estimates for β and δ are the same for all firms that share the same 4-digit-code.

Having estimated $\hat{v}_{fjt}$, we de-mean it and derive the adjusted input quantities $\hat{x}_{fjt}$ by dividing the deflated input expenditures by $\hat{v}d_{fjt}$, as shown in (A.10). Last, having the production coefficients and the adjusted input amounts, we obtain TFP by

$$\hat{\omega}_{fjt} = \hat{q}_{fjt} - f(\hat{x}_{fjt}; \hat{\beta}) \quad , \tag{A.25}$$

where $\hat{q}_{fjt}$ is the output quantity that has been purged of idiosyncratic shocks via semi-parametric regression.

C.2 Endogenous input shares

In our base model, we use revenue shares to approximate the input shares. The methodology proposed by De Loecker et al. (2016) uses the structural form to derive an independent estimate for the input shares. This method only allows for the estimation of TFP only on the firm level (not the firm-product level) as will become clear below.

The key of this methodology is to divide the production function into two sub-functions: One that contains the (unknown) input shares, and one that does not:

$$q_{fjt} = f_1(\tilde{x}_{ft}, \hat{\beta}, \hat{vd}_{fjt}) + f_2(\tilde{x}_{ft}, \hat{\beta}, \hat{vd}_{fjt}, \rho_{fjt}) + \omega_{ft} \tag{A.26}$$

The vector of deflated input expenditures, $\tilde{x}_{ft}$ does not have a product-subscript, as the input quantities are given at the firm-year level only. The price correction is computed as discussed above.The specification of f_1 and f_2 depends on the functional form of the production function. For purposes of exhibition we will omit the “hats” in what follows, with the understanding that all parameters are estimates.

For the Cobb-Douglas production function, f_1 and f_2 are given by[30]

$$f_1(\cdot) = k_{ft}\beta_k + l_{ft}\beta_l + m_{ft}\beta_m \tag{A.27}$$

$$f_2(\cdot) = (\beta_k + \beta_l + \beta_m) \cdot \rho_{fjt} \tag{A.28}$$

The definition of vd_{fjt} is as in (A.19)-(A.23). Subtracting $f_1(\cdot)$ from both sides in (A.26) leads to a system of $J+1$ equations in as many unknowns for each firm-year combination:

$$q_{f1t} - f_1(vd_{f1t}) = (\beta_k + \beta_l + \beta_m) \cdot \rho_{f1t} + \omega_{ft} \tag{A.29}$$

$$\ldots$$

$$q_{fJt} - f_1(vd_{fJt}) = (\beta_k + \beta_l + \beta_m) \cdot \rho_{fJt} + \omega_{ft} \tag{A.30}$$

$$\sum_{j=1}^{J} \rho_{fjt} = 1 \tag{A.31}$$

This system can be solved for the ρ_{fjt} and ω_{ft}. Here, it becomes clear why TFP is restricted to the firm, rather than the firm-product level. If TFP were allowed to vary across products as well, there would be (J+1) equations in (2J) unknowns. In this sense, the restriction that ω_{ft} applies to all products of firm f allows for the identification of the unobserved input shares.

Finally, having the input shares we can compute the corrected input quantities and proceed as in the base model.

D Correction of expenditure shares

Firms in our sample may endure costs other than through their manufacturing operations, and generate revenues for services provided to third parties alongside their main activity. If left unadjusted, some of the variables we observe at the firm level will overestimate operational activity and hence bias our production estimates. This is the case for labor,

[30]To derive this, express the product-level inputs, corrected for input quality, as $m_{fjt} = \rho_{fjt} + m_{ft} - vd_{ft}$, $l_{fjt} = \rho_{fjt} + l_{ft} - vd_{ft}$ and $k_{fjt} = \rho_{fjt} + k_{ft} - vd_{ft}$ and use these terms in the production function. Multiplying out and collecting terms yields the given expression.

materials, and energy expenditures that we take from the Cost Structure Survey, for which the AFiD dataset does not provide more granular information than at the level of the whole firm. To this extent, we aggregate plant-level information on revenues from operations only and divide it by total revenues. This information is taken from the annual results of the Monthly Report survey, which is available in the Panel for Industry Plants. To our knowledge, this is the most disaggregated level of revenues we can observe at the plant level. For each firm f in year t, we construct the following scaling factor:

$$xmfgshare_{ft} = \sum_{p} \frac{mb\_20_{pft} + mb\_24_{pft}}{mb\_27_{pft}} \tag{A.32}$$

The numerator reflects the total operational revenue, by taking the sum domestic (mb_20) and export (mb_24) revenue for each plant p belonging to firm f. The denominator denotes plants' total revenues (from the construction sector, manufacturing, and other parts of the economy).[31] De Loecker et al. (2016) faces the same issue and also applies a similar correction. Using this revenue share factor, we hope to capture the share of expenditures related to firms' manufacturing activity only. More specifically, it rules out revenues from the construction sector and other parts of the economy, including:

- Third-party services provided in their own name
- Turnover of construction-related parts of the economy
- Purchased products, unprocessed and without manufacturing
- Maintenance and repair of motor vehicles and goods
- Software development
- Rental and leasing of equipment
- Residential leases, excluding income from land leases
- Patents and granting of licenses

[31] For more information, we refer to the official metadata report available at this address (part two, only in German) `https://www.forschungsdatenzentrum.de/de/10-21242-42111-2021-00-01-1-1-0`

- Provision of employees to other legal entities
- Non-industrial services and transport services for third-parties
- Employee facilities (e.g., canteens, restaurants)
- Own agricultural products

Even though, the numerator still contains other revenues that we would also want to avoid:

- Goods produced by subcontracting to another legal entity
- Value of contract work performed for third-parties
- Self-generated electricity, district heating, gas, steam and water
- By-products from the production
- Saleable production residues (e.g., scrap, castings)
- Other industrial services (e.g., repairs, maintenance, installations, assemblies)
- Rental and leasing of goods produced

We apply this scaling factor to labor and materials (including energy) expenditures, which are then used in the production function estimation. This not only impacts the production function estimates β_l and β_m and the resulting output elasticities, but also TFP and markups, which both depend on β_m.