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CO₂ Emission Intensity and Exporting: Evidence from German Firm-Level Data

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Abstract

This study analyses whether exporting firms produce less CO₂ emission-intensively than non-exporting competitors. It exploits a novel and unique dataset for Germany, a major exporting country. We make use of the particularity that CO₂ emissions are directly linked to the type of fuel consumed. This allows us to directly estimate CO₂ emission intensity within a production function framework. We show that such an integrated approach solves the issue of omitted variable bias that standard regressions approaches on CO₂ emission intensity of firms are exposed to. It furthermore enables us to apply latest econometric techniques from the productivity literature that solve the problem of endogeneity. Our findings suggest a positive relation between export intensity and CO₂ productivity—the inverse of emission intensity. This exporter’s environmental premium holds for most of the German manufacturing industries at the two-digit level.

JEL codes: F18; Q54; D22; D24; L60

Keywords: CO₂ emission intensity; export activity; productivity; firms; Germany

1 Introduction

Climate change is not only a global problem, it is a challenge that must to be understood within the context of a globalising world with increasing amounts of goods being traded. For multiple reasons international trade may affect carbon dioxide (CO₂) emissions. One reason is a trade-induced change in the average emission intensity.¹ Empirical evidence at the sector-level suggests that trade leads to a reduction in the average emission intensity, i.e. an environmentally beneficial partial effect (Antweiler et al., 2001, p. 894).² This finding is commonly explained by a trade-induced increase in income that strengthens the demand for a healthier environment and, therefore, the claim for tougher environmental regulation by the citizens. Recent findings reject this view (cf. Cherniwchan, 2013), hinting at firm-level explanations that drive sector-level changes in emission intensity.³

Hence, it is crucial to understand differences across firms. There is a small, but growing, literature that contrasts the environmental performance of exporting and non-exporting firms using micro-level data and micro-econometric techniques. So far, there is some initial empirical evidence for a negative link between a firm's export activity and its emission intensity, controlling for size and industry. To the best of our knowledge only two papers focus on CO₂ emission intensities: Cole et al. (2013) using Japanese and Forslid et al. (2015) using Swedish firm-level data. Both find a significant negative impact of the export status on emission intensity. Accordingly, exporting firms emit less CO₂ per output than non-exporting competitors—an exporter's environmental premium.⁴ As CO₂ emissions are the driving force in global warming, further analyses are needed to understand possible differences across firms as a vital contribution to the design of climate policy.

¹ This is the so-called *technique effect* (cf. Grossman and Krueger, 1993; Copeland and Taylor, 2004).

² See McAusland (2010) and Copeland (2011) for comprehensive surveys on the empirical literature. The overall impact of trade on the environment is estimated to be beneficial for local pollutants (cf. Antweiler et al., 2001; Frankel and Rose, 2005), but less so for CO₂ emissions. Cole and Elliott (2003) find that for CO₂, trade openness leads to an increase in emissions despite a reduced average emission intensity. This result is partly confirmed by Managi et al. (2009) for OECD countries. These papers all rely on sector-level data and, hence, abstract from firm differences and the unbalanced impact of trade on them.

³ Accordingly, it is argued that the trade-induced reduction in sector-level emission intensities potentially originates from the reallocation of factor inputs between firms (Kreickemeier and Richter, 2014). This micro perspective is in line with the recent trade literature that highlights the importance of changes at the firm-level due to trade that drive empirical observations at the sector-level (Melitz and Trefler, 2012). For instance, firms are differently affected by trade liberalization: low-productive firms are induced to exit the market (Trefler, 2004), while high-productive firms gain market shares (Pavcnik, 2002).

⁴ This positive environmental premium is partly confirmed for other pollutants than CO₂ by Holladay (2010), Cui et al. (2012) and Cui and Qian (2013) who all investigate firm-level emission intensities of toxic releases in the United States. See the next Section for a comprehensive literature survey on the "exceptional exporter performance" (Bernard and Jensen, 1999) in environmental and non-environmental characteristics.

In this paper, we test whether exporters produce less CO₂ emission-intensively than non-exporters, thereby contributing to the literature in various ways:

First, we exploit the particularity of CO₂ as being directly linked to the usage of fossil fuels as neither end-of-pipe filters exist, nor are methods to capture carbon generally utilised.⁵ While this link has been used for the calculation of CO₂ emissions before (cf. [Jaraité and Di Maria, 2016](#); [Forslid et al., 2015](#); [Petrick and Wagner, 2014](#)), we are the first to also take into account its important implications on the methodology applied. It allows to incorporate CO₂ emissions directly into the production function, similar to other input factors. Doing so, we are able to directly estimate CO₂ productivity—the inverse of CO₂ emission intensity—within a production function framework. Second, we show that such an integrated approach solves the potential omitted variable bias that the previous regression approaches were exposed to. Third, and implied by our first two contributions, we deviate from previous studies as we apply methods and ideas from the productivity literature to this new research field. More specifically, we are the first to apply an integrated approach to structurally estimate CO₂ productivity along the lines of [Akerberg et al. \(2006, 2015\)](#). This resolves the inherent endogeneity problem. In the spirit of [Aw et al. \(2011\)](#), [De Loecker \(2007, 2011, 2013\)](#), [De Loecker and Warzynski \(2012\)](#), and [Van Biesebroeck \(2005\)](#), we thereby include a measure of export activity directly in the estimation. Fourth and finally, we tackle this research question by means of novel and unique firm-level data for Germany, a major exporting country.⁶ To this end, we construct a panel dataset covering the years 2003 to 2011 that contains detailed information on CO₂ emissions at the plant-level as well as a multitude of firm characteristics.

Our main results show that exporting firms in Germany have a significantly higher CO₂ productivity than non-exporting competitors, controlling for narrowly defined sectors at the two-digit level. Hence, there is evidence for an exporter’s environmental premium for the German manufacturing industry. More specifically, we find that, on average across all industries, an increase in export intensity by one percentage point leads to improved CO₂ productivity by 0.21 percent. Our result is robust to the use of a simple export dummy, where results suggest an average export

⁵ The combustion of fossil fuels leads to an oxidation of carbon to CO₂. The amount of CO₂ per unit of fuel depends on the chemical structure of each type of fuel. This allows to derive fuel-specific CO₂ emission factors (cf. [Umweltbundesamt, 2013](#)).

⁶ Environmental characteristics of German manufacturing firms are also the topic of several studies. However, in contrast to [Petrick \(2013\)](#) and [Petrick and Wagner \(2014\)](#), we focus on the relation between a firm’s CO₂ emission intensity and its export status, controlling for the productivity of firms.

premium of about 9 percent. In addition, the finding of an exporter’s environmental premium holds for the vast majority of the two-digit manufacturing sectors. These results support the idea that firm-level differences may explain trade-induced changes in emission intensities at the sector-level as indicated above.

The remainder of this paper is organised as follows. Section 2 discusses the related literature, while the empirical strategy is explained in Section 3. Section 4 presents our dataset, which is constructed from a variety of sources. In Section 5 we discuss our empirical findings and present robustness checks. Section 6 concludes.

2 Related Literature and Hypothesis

2.1 Environmental Performance of Exporting Firms

A limited, but growing, literature tests whether exporting firms better perform environmentally than their non-exporting competitors.

Holladay (2010) is the first study that analyses this research question with respect to toxic releases. To this end, a panel dataset for US manufacturing plants is constructed consisting of key economic characteristics and information on toxic releases provided by the US Environmental Protection Agency (EPA). Controlling for industry and output, the study finds that exporters emit significantly fewer toxic chemicals—based on a composite of 500 different substances—both in terms of quantity and hazardousness: an exporter’s environmental premium.⁷ Similarly, Cui et al. (2012) and Cui and Qian (2013) investigate plant-level emission intensities of toxic releases in the USA. They focus on four local pollutants (SO₂, CO, O₃, and particulate matter). Both papers use the same dataset, but apply different empirical strategies. Relying on an OLS regression controlling for industry, time trends and productivity, Cui et al. (2012) find evidence for an exporter’s premium for all four analysed pollutants, i.e. lower emissions per value of sales. In contrast, there is mixed evidence across industries in Cui and Qian (2013), who use a matching approach to compare exporting and non-exporting firms.

Batrakova and Davies (2012), Roy and Yasar (2015) and Girma and Hanley (2015) investigate the difference between exporters and non-exporting firms relying on proxies for environmental performance, namely fuel purchases and responses to a survey, respectively. This is in contrast to

⁷ See Holladay (2015) for an updated version.

our data that allows for the calculation of CO₂ emission intensities, based on detailed information of fuel consumption, in terms of quantities of different fuel types consumed. Using data on Indonesian manufacturing plants, [Roy and Yasar \(2015\)](#) develop an IV-approach to show that exporters rely to a larger extent on electricity than on fuels (based on cost shares) relative to non-exporters. As the authors argue, this is consistent with an exporter's environmental premium as long as electricity generation is cleaner than direct use of fuel by the individual plants. [Batrakova and Davies \(2012\)](#) construct a panel dataset of Irish firms and rely on a quantile regression distinguishing firms according to their energy intensity. They find that export status is only negatively related to energy purchases for energy-intensive firms. Among firms that only rely to a small extent on energy, by contrast, export activity is related to an increase in fuel purchases. Furthermore, employing a matching approach, the authors reject the hypothesis that energy-efficient firms self-select into exporting.⁸ [Girma and Hanley \(2015\)](#), in turn, analyse data from a survey on environmental innovation conducted among UK firms, basing their empirical strategy on a probit model. They find evidence that exporters report with higher probability that their innovation has a positive impact on the environment and reduces energy use in output.⁹

Only two papers so far focus on the difference between exporters and non-exporters in CO₂ emissions. The first paper by [Cole et al. \(2013\)](#) makes use of a cross-section dataset on Japanese manufacturing firms. In their first specification, using a standard OLS approach, they find a significant negative relation between export activity and CO₂ emission intensity. In contrast to the previous literature, export activity is not represented by a binary variable but measured as the share of output sold abroad. Hence, they provide evidence for a continuous relation: the more a firm relies on exports, the lower its emission intensity. Furthermore, [Cole et al. \(2013\)](#) focus on spatial aspects and give four reasons why environmental performance at the firm-level may be spatially correlated: This is due to location specific regulation, industrial agglomeration, demonstration and imitation of best-practices, as well as due to local competition based on environmental performance (local public perception).¹⁰ The authors find that export activity of one firm also has a negative impact on the CO₂ emission intensities of neighbouring firms, in particular within the same industry. Coefficient

⁸ As noted by the authors, they also have to reject the hypothesis that it is the most productive firms that start to export. This is at odds with the vast majority of the literature (see the next section) and may be specific to the Irish dataset.

⁹ The survey questions are more broadly. Apart from the pure environmental innovation the relevant question also refers to reduced usage of materials and to innovation-induced improvements in health or safety aspects.

¹⁰ [Cole et al. \(2013\)](#) use three different spatial weighting matrices: Based on the industry which the firm belongs to, the region the firm is located in, and a combination of both.

estimates, however, are only weakly significant.

The second paper analysing exporters' emission intensities of CO₂, and most closely related to our work, is [Forslid et al. \(2015\)](#). The authors use an extensive panel dataset constructed from manufacturing census data from Statistics Sweden for the years 2005-2011.¹¹ CO₂ emissions are calculated from fuel use and fuel-specific emissions factors. In a first step, [Forslid et al. \(2015\)](#) estimate total factor productivity (TFP) based on value added production functions at the two-digit level, relying on the approach of [Levinsohn and Petrin \(2003\)](#). In a second step, CO₂ emission intensity is regressed on export status controlling for the estimated firm productivity and accounting for exposure to the EU-ETS by means of firm-year fixed effects. As laid out in Section 3, we argue that this empirical strategy resembles an estimation of production functions in disguise. [Forslid et al. \(2015\)](#) find that exporting firms emit almost 12 percent less per sales than non-exporting competitors within the same sector. However, differentiating between energy-intensive and non-energy intensive sectors, estimated coefficients become smaller and lose significance; this particularly holds for energy-intensive industries.¹²

In summary, the literature finds evidence for an exporter's environmental premium. This leads us to expect that it also holds for German manufacturing firms that exporting firms emit less CO₂ per output than non-exporting competitors within the same sector. Hence, we postulate and test the following hypothesis:

Hypothesis. *Exporters produce less CO₂ emission-intensively than non-exporting competitors within the same narrowly defined sector.*

2.2 Exporters vs Non-exporters

While the literature on exporting and the environmental performance of firms is still emerging, there already exists an established empirical literature on the systematic difference between exporters and non-exporters as well as on the relationship between exporting and firm productivity. Initiated by the seminal paper of [Bernard and Jensen \(1995\)](#), it is by now well-established in the literature that exporters are not representative for their industry but rather share distinct characteristics:¹³

¹¹ This time period is specific to the analysis on CO₂. In addition to CO₂ emissions, the authors test for firm differences in SO₂ and NO_x emissions as well as in investments in emission abatement and environmentally-friendly technology.

¹² In a second set of estimations, [Forslid et al. \(2015\)](#) further investigate the difference in investments in emission abatement technology. They find a significantly positive relation between export status and these investments. Similarly to emission intensities, the positive relation is more pronounced for non-energy intensive industries.

¹³ See [Greenaway and Kneller \(2007\)](#) and [Bernard et al. \(2012\)](#) for recent discussions as well as [Bernard and Wagner \(1997\)](#) and [Wagner \(2007b\)](#) for evidence on Germany.

They are found to be larger and more capital- and skill-intensive; exporters are also found to pay higher wages controlling for differences in employees' characteristics (cf. [Schank et al., 2007, 2010](#)).

Moreover, the literature provides overwhelming evidence that exporters are significantly more productive.¹⁴ This empirical evidence is crucial for any study analyzing the relationship between CO₂ emission intensity and export activities of firms. It makes clear that any analysis of CO₂ emission intensity must appropriately control for firm productivity in order to avoid biased estimates.

In the literature on export and firm performance, productivity is usually measured in terms of output per worker, or value added per worker. Taking into account that factor intensities usually differ across firms, this one-factor productivity measure is at best incomplete. An alternative productivity concept is TFP, which is not specific to one input factor but measures how efficiently firms use a bundle of inputs (cf. [Syverson, 2011](#)). A recent development in the literature allows for the estimation of TFP while overcoming the inherent simultaneity and endogeneity issues by means of structural approaches initiated by [Olley and Pakes \(1996\)](#), [Levinsohn and Petrin \(2003\)](#), and [Akerberg et al. \(2015\)](#) (henceforth ACF). Building on this literature, [Aw et al. \(2011\)](#), [De Loecker \(2007, 2013\)](#), [De Loecker and Warzynski \(2012\)](#), and [Van Biesebroeck \(2005\)](#) show how to integrate export activities directly in the estimation procedure.

3 Model and Empirical Strategy

3.1 CO₂ Emissions Intensity and Production Functions

We argue that a firm's CO₂ emission intensity, as indicator for environmental performance, and the production function under which it operates are directly linked. This link requires the application of estimation approaches that resolve the issues of simultaneity and endogeneity associated with the econometric estimation of production functions. The link between output and CO₂ emissions also casts doubts about those approaches previously used in the literature, that regress some company characteristics or policy variables on CO₂ emission intensity of firms without including basic production function inputs, such as labour or capital.

Consider a Cobb-Douglas production function with gross output or sales as dependent variable that requires material as input in addition to labour and capital such as in [Levinsohn and Petrin](#)

¹⁴ For a comprehensive literature survey, including the question whether more productive firms tend to self-select into exporting or whether exporters increase their productivity through learning, see [Wagner \(2007a, 2012\)](#), and [Silva et al. \(2012\)](#).

(2003) or [Petrin et al. \(2004\)](#). Generally, the material variable also includes energy. If energy and material can be observed separately, however, the production function becomes:

$$Y_{it} = L_{it}^{\beta_l} K_{it}^{\beta_k} M_{it}^{\beta_m} E_{it}^{\beta_e} \tilde{\omega}_{it} e^{\epsilon_{it}}, \quad (1)$$

where Y_{it} is sales, L_{it} denotes labour input, K_{it} capital input, M_{it} material input, and E_{it} energy input for firm i in year t . Furthermore, $\tilde{\omega}_{it}$ is considered the total factor productivity (TFP), while ϵ_{it} is the i.i.d. error component. Notably, both the last two terms $\tilde{\omega}_{it}$ and ϵ_{it} are unobserved to the econometrician. Taking logs and subtracting the corresponding input, Eq. (1) can be transformed into a function of labour productivity, capital productivity or into a function of energy productivity:

$$y_{it} - e_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + (\beta_e - 1)e_{it} + \tilde{\omega}_{it} + \epsilon_{it}, \quad (2)$$

where small case letters denote the logarithmic value of a particular input.

At this point, the special relationship between CO₂ and fossil fuels plays a decisive role. Fossil fuels are hydrocarbons, i.e. chemical combinations of hydrogen and carbon, whose combustion leads to an oxidation of carbon to CO₂. This is a proportional link and fuel-specific emissions factors depend on the carbon content of the particular fuel. For instance, natural gas, mainly composed of methane (CH₄), has a lower content of carbon—and thus a lower emission intensity—than coal products per unit of energy generated (cf. [IPCC, 2006](#)). From this chemical relationship it follows that the use of different forms of fuel and energy can be linearly transformed into CO₂ emissions. This specific link between energy consumption and CO₂ emissions is well established and has been exploited lately in other studies such as [Jaraitė and Di Maria \(2016\)](#), [Forslid et al. \(2015\)](#) and [Petrick and Wagner \(2014\)](#) in order to calculate CO₂ emissions at the firm-level. However, in contrast to the literature, we are the first to also take into account the implication of this link for the estimation approach that has to be used.

By exploiting the link between energy and CO₂, we can thus substitute e_{it} by $co2_{it}$, and CO₂ emissions can be treated like a direct input in the production function:

$$y_{it} - co2_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + (\beta_c - 1)co2_{it} + \tilde{\omega}_{it} + \epsilon_{it}. \quad (3)$$

Note that CO₂ productivity, as shown in Eq. (3), is the inverse of CO₂ emission intensity—the com-

only used indicator for measuring the environmental performance of firms. Consequently, both the empirical analyses of CO₂ productivity, and CO₂ emission intensity respectively, is hampered by the simultaneity and endogeneity issues accompanying the estimation of production functions.

Before turning to the question of how to solve these issues, we show how any analysis of the determinants of CO₂ emission intensity of firms may suffer from omitted variable bias, if it relies on a regression approach and ignores the underlying production function.

Let us suppose we are interested in measuring the effect of some variables on the environmental performance of firms. This could be the effect of export activity or the effect of a certain trade or environmental policy. The corresponding estimation function could look like the following:

$$co2_{it} - y_{it} = \alpha_0 + \alpha_x X_{it} + \alpha_{pol} POL_{it} + \eta_{it}, \quad (4)$$

where X_{it} is a measure of export activity, POL_{it} is a dummy taking the value one if the firm is exposed to a certain policy, e.g. to an ETS, and η_{it} is the error term. Regardless of the additional control variables one has in mind, comparing Eq. (4) with Eq. (3)—while keeping in mind that CO₂ emission intensity is just the inverse of CO₂ productivity—reveals that such a function is a production function in disguise, with omitted variables, however. These omitted variables are the standard variables of any production function such as labour and capital input or TFP, all just subsumed in the error-term η_{it} . This becomes more obvious when rewriting Eq. (4) such that the underlying production function Eq. (3) becomes explicit:

$$co2_{it} - y_{it} = \alpha_0 + \alpha_x X_{it} + \alpha_{pol} POL_{it} + \underbrace{-\beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it} - (\beta_c + 1)co2_{it} - \tilde{\omega}_{it} - \epsilon_{it}}_{\eta_{it}}. \quad (5)$$

As textbook econometrics shows, the coefficients α_0 , α_x and α_{ets} are at risk of suffering from omitted variable bias if we estimate Eq. (4) instead of Eq. (5). This holds, as long as one of the omitted variables has explanatory power for y_{it} or $co2_{it}$ and the covariance between an observed and an omitted variable is significantly different from zero (Greene, 2012; Schiersch, 2015).

It becomes immediately clear that a two stage approach, with TFP being estimated in a first stage, and a second stage that regresses TFP and additional control variables on $co2_{it} - y_{it}$, is also hard to justify. After all, if the control variables from the second stage regression, such as export

activity, have explanatory power for $co2_{it} - y_{it}$, they should also be relevant for $co2_{it}$ or y_{it} in the first stage estimation. Likewise, estimating TFP in a first stage, while omitting relevant variables, can lead to biased estimates of TFP. In other words, the omission of a relevant variable in the first stage, e.g. of export activities, can also distort the second stage estimation, because estimates from the first stage, e.g. of TFP, may suffer from omitted variable bias, thus being incorrect even before being used in the second stage.

The problem of omitted variables is still relevant if TFP is estimated in a first stage by means of a value added production function. In this case, CO₂ cannot enter the production function because it is the substitute for energy which is an intermediate input and therefore not part of a value added production function. However, even in such a case all variables with explanatory power for the dependent variable have to enter the estimation equation.¹⁵ Referring to our example, export activity would need to be included in the estimation procedure (cf. [Aw et al., 2011](#); [De Loecker, 2007, 2013](#); [De Loecker and Warzynski, 2012](#); [Van Biesebroeck, 2005](#)). The same holds for any policy measured by POL_{it} , because it is hard to justify why this policy should not have explanatory power for the output of firms (y_{it}) or their CO₂ emissions ($co2_{it}$) but still affects CO₂ emissions intensity ($co2_{it} - y_{it}$).

The fact that estimating CO₂ emission intensity of firms with a regression approach essentially means to estimate a production function—explicitly as in Eq. (3) or implicitly as in Eq. (4)—has a further implication: such estimation would be exposed to the issue of simultaneity and endogeneity that is inherent to any production function estimation. In order to overcome the simultaneity and endogeneity issue, we propose to use a structural approach along the lines of [Akerberg et al. \(2015\)](#).

3.2 Estimation Strategy

In line with [Aw et al. \(2011\)](#) and [Van Biesebroeck \(2005\)](#) we assume that firms' productivity is determined by its past productivity, ω_{it-1} , an innovation component, ξ_{it} , and the export market participation in the previous period, X_{it-1} . Export activities are expected to be relevant for TFP directly because, "the export market is a source of knowledge or expertise that can improve future productivity" ([Aw et al., 2011](#), p. 1317). In addition, and along the lines of [De Loecker \(2007, 2011\)](#),

¹⁵ The dependent variable implicitly includes CO₂ because energy expenditure are deducted from sales when calculating value added. Hence, if a variable explains CO₂ usage, it explains also at least a part of the variation of value-added.

we assume that ω_{it} can be decomposed such that $\tilde{\omega}_{it} = \omega_{it} + \beta_x X_{it-1}$. Using this decomposition, we can transform Eq. (3) such that our estimation equation becomes

$$y_{it} - co2_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + (\beta_c - 1)co2_{it} + \beta_x X_{it-1} + \omega_{it} + \epsilon_{it}. \quad (6)$$

In order to account for the difference between random or one-time export activities and significant export orientation of companies, X_{it} is defined as export intensity of companies (export sales divided by total sales) as done by [Cole et al. \(2013\)](#). We assume that knowledge transfer and learning effects are stronger with continuous and intensive exchange through exports. Nevertheless, we test for robustness of our results by alternatively using a binary variable to express export activity.

The simultaneity and endogeneity problems inherent to production function estimations need to be resolved to obtain consistent parameters for Eq. (6), such as our coefficient of interest β_x . These issues arise because productivity is unobserved by the econometrician, while firms eventually know about their productivity and take it into account when choosing inputs. The seminal studies of [Olley and Pakes \(1996\)](#), [Levinsohn and Petrin \(2003\)](#) and [Akerberg et al. \(2015\)](#) advocate a structural approach for identifying the parameters.

These structural approaches rely on the existence of an investment demand function or intermediate input demand function ([Olley and Pakes, 1996](#); [Levinsohn and Petrin, 2003](#)), which is strictly monotonic in ω_{it} ; and in which ω_{it} is the only unobserved state variable. The monotonicity assumption allows us to invert out ω_{it} . Accordingly, the unobserved productivity is approximated by a non-parametric function of observed variables. As we discuss in detail below, we use the 'input demand function' of CO₂ emission. The inverted function $f_t^{-1}(l_{it}, k_{it}, m_{it}, co2_{it}, X_{it-1})$ can be substituted into Eq. (6) for ω_{it} . This yields:

$$y_{it} - co2_{it} = \varphi_t(l_{it}, k_{it}, m_{it}, co2_{it}, X_{it-1}) + \epsilon_{it}, \quad (7)$$

where we define $\varphi_t(\dots) \equiv \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + (\beta_c - 1)co2_{it} + \beta_x X_{it-1} + f_t^{-1}(l_{it}, k_{it}, m_{it}, co2_{it}, X_{it-1})$. By means of OLS we estimate Eq. (7) as the first stage of the estimation routine ([Olley and Pakes, 1996](#)). The regressors have to be included in φ_{it} due to the functional dependency with f_t^{-1} . They are thus not identified in the first stage estimating Eq. (7).

The second stage of the estimation routine relies on the assumption that the firms' expectation about its productivity in t is determined by its information set I_{it-1} and some uncertain "innovation"

component ξ_{it} . I_{it-1} contains all past information about productivity and its development, while the innovation term is assumed to be uncorrelated with the past information set ($E[\xi_{it}|I_{it-1}] = 0$). It is further assumed that ω_{it} follows a first-order Markov process that yields $\omega_{it} = E[\omega_{it}|I_{it-1}] + \xi_{it} = E[\omega_{it}|\omega_{it-1}] + \xi_{it}$ (Akerberg et al., 2007). Following Petrin et al. (2004), we approximate this equality by an AR1-process with a polynomial of order 2:

$$\omega_{it} = \gamma_0 + \gamma_1\omega_{it-1} + \gamma_2\omega_{it-1}^2 + \varepsilon_{it}, \quad (8)$$

where ε_{it} consists of an i.i.d. error term and the unobserved innovation term ξ_{it} . Because $\omega_{it} = f_t^{-1}$ and we have defined $\varphi_t = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + (\beta_c - 1)co2_{it} + \beta_x X_{it-1} + f_t^{-1}$, we can substitute ω_{it} in Eq. (8) by $\varphi_t - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it} - (\beta_c - 1)co2_{it} - \beta_x X_{it-1}$. Likewise for ω_{it-1} . We make use of GMM to obtain the coefficients for labour, capital, materials, export participation and CO₂. However, for a consistent estimation it is imperative to find orthogonal relations between these variables and ξ_{it} , which is unobserved by the econometrician and therefore part of ε_{it} . This is ensured by the timing assumptions regarding decisions on inputs.

Since the seminal study by Olley and Pakes (1996), it is assumed that the capital stock in t is the result of the firms' investment decision in $t - 1$ and the capital stock of period $t - 1$. In other words, while the investment decision in t is influenced by the observed productivity ω_{it} , k_{it} is not. Given this timing assumption, k_{it} and ξ_{it} are uncorrelated and the moment condition $E[\xi_{it}|k_{it}] = 0$ can be used for estimating β_k . ACF show that the moment condition for labour needs to be different because labour is a flexible input, almost like material, which causes a problem of functional dependency. ACF introduced the assumption that labour can be "less variable" than material and that therefore the decision on labour is taken before the firm decides about material (Akerberg et al., 2015). But even if the decision on labour is made in $t - b$ ($0 < b < 1$), thus after $t - 1$ but before t when the firm orders material, it is not completely independent from ξ_{it} , because the firm might have observed part of the innovation in productivity at $t - b$. ACF recommend to use lagged labour in the moment condition, because it is determined by all information up to and including $t - 1$, but not by I_{it} , and is therefore uncorrelated with ξ_{it} . The second moment condition is hence given by $E[\xi_{it}|l_{it-1}] = 0$.

Since our production function includes CO₂ emissions in addition to material, it is necessary to deviate from the approach in ACF as subsequently demonstrated: Let us start by assuming that $co2_{it}$ and m_{it} are both non-dynamic fully variable inputs. In that case, firms decide simultaneously

about $co2_{it}$ and m_{it} while knowing their ω_{it} . Consequently, the demand function for $co2_{it}$ includes the same variables as the demand function for m_{it} :

$$co2_{it} = f_t(l_{it}, k_{it}, X_{it-1}, \omega_{it}) \quad (9)$$

$$m_{it} = h_t(l_{it}, k_{it}, X_{it-1}, \omega_{it}). \quad (10)$$

If the monotonicity assumption regarding ω_{it} holds for both functions, we can invert h_t and use it to substitute ω_{it} in function f_t . This results in $co2_{it} = f_t(l_{it}, k_{it}, X_{it-1}, h_t^{-1}(l_{it}, k_{it}, X_{it-1}, m_{it}))$, and $co2_{it}$ is described by a function that includes m_{it} . As a consequence, β_c is not identified, because one cannot estimate the coefficient for $co2_{it}$, which is a function of l_{it}, k_{it}, X_{it-1} and m_{it} , simultaneously with a non-parametric approximation of the function h_t^{-1} , which includes the same variables (cf. [Akerberg et al., 2006](#)).

We solve this issue by following the idea behind the ACF approach. Accordingly, we solve the problem of functional dependency and avoid the simultaneity by introducing an additional sub-period and an additional timing assumption. We assume that firms decide one m_{it} after they have chosen l_{it} but before t , i.e. at $t - d$ where $0 < d < b < 1$. The idea is that material must be ordered and delivered before the actual production process starts. By contrast, energy is used in the moment in which the goods are produced, i.e. in t . Now the decision about $co2_{it}$ still depends on m_{it} , but the firms' decision on m_{it} is based on the existing information at $t - d$ and thus $co2_{it}$ has variance that is independent of m_{it} . Of course, β_m cannot be consistently estimated in the first stage of the estimation procedure because it is correlated with parts of ξ_{it} and also due to the functional dependency between m_{it} and f_t^{-1} . However, lagged material is uncorrelated with ξ_{it} . this allows us to use the moment condition $E[\xi_{it}|m_{it-1}] = 0$ for identifying β_m in the second stage of the estimation routine ([Levinsohn and Petrin, 2003](#)). The same reasoning holds for $co2_{it-1}$. Thus, the fourth moment condition that is applied is $E[\xi_{it}|co2_{it-1}] = 0$.

This leaves the question whether β_x is identified in the first stage and whether it is part of the demand function for $co2_{it}$. Due to the assumption that export activities can affect firm's overall productivity, X_{it-1} consequently has to enter the demand function f_t ([De Loecker and Warzynski, 2012](#); [Van Biesebroeck, 2005](#)). In this way export activities can effect the optimal choice of firms regarding CO₂ emissions. Since X_{it-1} is part of f_t^{-1} , we encounter again a functional dependency problem in the first stage and therefore β_x need to be identified in the second stage. But as the

decision to export is made already in $t - 1$, X_{it-1} is uncorrelated with ξ_{it} . Consequently, the required moment condition is given by $E[\xi_{it}|X_{it-1}] = 0$.

Summing up, the coefficients are obtained by non-parametrically regressing ω_{it} on ω_{it-1} , Eq. (8), by means of the GMM using the moment condition

$$E[\xi_{it}|Z_t] = 0, \quad (11)$$

where Z_t is a vector containing $\{k_{it}, l_{it-1}, m_{it-1}, co2_{it-1}, X_{it-1}\}$. In the computations, we use k_{it-1} , l_{it-2} , m_{it-2} , $co2_{it-2}$ and X_{it-2} as additional instruments in order to improve the efficiency of the estimation.¹⁶ Candidate value for the parameters, which are needed to calculate the start values for ω_{it} and ω_{it-1} for the iterative process, are obtained from an OLS regression of the inputs on φ_t (cf. [Levinsohn and Petrin, 2003](#)).

4 Data

We construct a novel and unique panel dataset for German manufacturing firms for the 2003 to 2011 period, which has not been used in this form by researchers before. It is created from four datasets: the "*AFiD Panel Industriebetriebe*," the "*AFiD Modul Energieverbrauch*," the "*Kostenstrukturerhebung (KSE)*," and the "*Unternehmensregister (URS)*," which are provided by the German *Federal Statistical Office* and the *Statistical Offices of the States*.¹⁷ All firms and plants that participate in these surveys or full censuses are legally obliged to deliver the requested data. Our dataset contains information on economic characteristics as well as plant-specific energy usages of different fuel types. It is combined with external data to calculate firm-specific CO₂ emission intensities and to estimate capital stocks.

We abstain from discussing all datasets in detail and refer to [Konold \(2007\)](#) and [Wagner \(2010b\)](#) for a description of "*AFiD Panel Industriebetriebe*" as well as [Fritsch et al. \(2004\)](#) for a description of the *KSE*. A comprehensive description of the *URS*, in turn, is provided by [Koch \(2007\)](#), while [Petrick et al. \(2011\)](#) provide detailed information about the "*AFiD Modul Energieverbrauch*." In

¹⁶ We follow [Schiersch \(2015\)](#) and also make use of l_{it} . This is possible in case of a sufficiently rigid labour market, as it is the case for Germany ([OECD, 2015](#)), since then labour is no longer a fully flexible input. Using l_{it} in such environment then "often generates more efficient estimates" ([Ackerberg et al., 2006](#), p. 21).

¹⁷ [Petrick \(2013\)](#) and [Petrick and Wagner \(2014\)](#) use the "*AFiD Panel Industriebetriebe*" together with the "*AFiD Module Energieverbrauch*" for their analyses. They do not merge this data with the *URS* and the *KSE*; a necessity for our analysis as we utilize estimated capital stocks in our integrated production function approach.

the following, we present those data elements and variables used for our analysis. The datasets are merged at the firm-level using unique company IDs as identifier.¹⁸

4.1 Data on Energy Consumption and CO₂ Emissions

Like others, e.g. [Jaraité and Di Maria \(2016\)](#), [Forslid et al. \(2015\)](#) and [Petrick and Wagner \(2014\)](#), we calculate CO₂ emissions from fuel usage, thereby exploiting the following characteristic: Fossil fuels are hydrocarbon, i.e. chemical combinations of hydrogen and carbon, whose combustion leads to an oxidisation of carbon to CO₂. This is a proportional link and fuel-specific emissions factors depend on the carbon content of the particular fuel.¹⁹ Consequently, CO₂ emissions can be quite accurately computed with detailed information on fuel consumption (cf. [IPCC, 2006](#)). Detailed data on the usage of 15 different fuels (including electricity and fossil fuels like natural gas or different types of coal, e.g. lignite) are taken from the "*AFiD Modul Energieverwendung*" (AFiD module energy usage). We follow [Petrick et al. \(2011\)](#) and calculate CO₂ emissions at the plant-level by means of annual fuel-specific CO₂ emission factors provided by the German Federal Environment Agency ([Umweltbundesamt, 2013](#)). We use average annual CO₂ emissions of the German electricity mix in order to calculate emissions factors for electricity consumption in a given year. The emissions factor for district heating is derived from information provided by the *AG Energiebilanzen*²⁰ that assigns the different fuels used for district heating. Table 1 provides annual data on emissions factors by fuel in gCO₂/kWh, updating and extending the work of [Petrick et al. \(2011\)](#).

4.2 Data on Firm Characteristics

The "*AFiD Panel Industriebetriebe*" (AFiD panel manufacturing plants) dataset contains economic data for all German manufacturing plants with more than 20 employees, counting about 45,000 plants each year. This dataset provides (among others) annual information on sales within Germany and abroad, on the number of employees, as well as the number of products made by a plant. Furthermore, plants are characterized by a plant and a company ID, and the assigned industrial sector. We use the information of this dataset to classify firms as exporters and non-exporters.

The "*Kostenstrukturhebung (KSE)*" (Cost Structure Survey) in turn provides detailed data on

¹⁸ Combining firm- with plant-level data has been done before, e.g. by [Schiersch and Schmidt-Ehmcke \(2011\)](#).

¹⁹ CO₂ emissions for the chemical industry may be overestimated as our data do not allow to exclude process usage of fuels.

²⁰ Personal communication with Ingrid Wernicke (AG Energiebilanzen).

Table 1: CO₂ emission factors by type of energy in gCO₂/kWh

	2003	2004	2005	2006	2007	2008	2009	2010	2011
Natural Gas / Associated Gas	201.6	201.6	201.6	201.6	201.6	201.6	201.6	201.6	201.6
Light fuel oil	266.4	266.4	266.4	266.4	266.4	266.4	266.4	266.4	266.4
District heating	286.3	286.2	261.3	248.5	268.9	256.7	253.5	257.9	264.4
Hard Coal	338.4	338.4	338.4	339.1	338.8	339.5	339.5	339.1	339.1
Coke	378.0	378.0	378.0	378.0	378.0	378.0	378.0	378.0	378.0
Lignite	403.2	402.8	401.0	398.2	401.8	398.5	398.2	396.0	394.2
Lignite briquets	358.9	358.9	358.9	358.9	358.6	358.6	359.3	359.3	359.6
Other coal products	352.6	352.5	353.1	353.5	352.9	353.3	353.2	353.3	353.3
LPG	234.0	234.0	234.0	234.0	234.0	234.0	234.0	234.0	234.0
Heavy fuel oil	280.8	280.8	280.8	280.8	280.8	280.8	280.8	280.8	280.8
Other oil products	259.8	265.8	257.1	262.0	270.0	270.0	267.2	270.1	272.0
Renewables	4.2	21.7	15.1	19.3	10.3	11.3	12.7	7.7	12.0
Other gases	147.8	150.4	152.5	161.7	166.4	170.9	182.2	170.8	179.8
Waste and other fuels	256.0	256.0	256.1	256.1	256.1	256.1	256.0	256.0	256.0
Electricity	631.0	610.0	607.0	611.0	626.0	592.0	573.0	563.0	570.0

Source: [Umweltbundesamt \(2013\)](#) and other sources; own calculations.

the structure and the different types of costs and inputs (from number of employees to salaries to tax payments). The data is collected annually for a selection of manufacturing firms. The survey is representative at the two-digits industry and at the state level. Being legally obliged, all firms with more than 500 employees constantly participate in the survey, while smaller firms, with employees ranging from 20 to 500, are selected as to guarantee the representativeness. The subsample of SMEs is held constant for four years, before a new subsample is drawn. This dataset is indicative for factor inputs into the production process of firms. It is the source of labour and material input as well as of firm sales.²¹ From this dataset we also derive the capital stock using the method that [Wagner \(2010a\)](#) proposes for the *KSE*.²²

By means of the "*Unternehmensregister (URS)*" (company register) that lists all German manufacturing firms we can properly account for the non-trivial change in the sector classification in Germany in 2008. All monetary variables are deflated using a price deflator at the 4-digits industry level.²³

²¹ We observe material expenditures with and without energy costs, ultimately using material costs excluding energy.

²² For a comprehensive description see Appendix A.1

²³ Data is taken from www.destatis.de/en, accessed on September 10, 2014.

4.3 Data Preparation and Descriptive Statistics

The merged and unprocessed dataset covers 2003 to 2011 and contains 131,117 observations. In the initial step of the data cleaning process, we delete all observations with missings in the dependent and independent variables, leaving 125,980 observations. Subsequently we aim to exclude obvious outliers. To this end we delete all observations with values above the 99.5 and below the 0.5 percent percentile in any of the variables except export. In addition we drop observations with values above the 99 and below the 1 percent percentile in the variables $CO2_{it}/L_{it}$ and $CO2_{it}/K_{it}$. The remaining dataset contains 116,300 observations. Finally we have to drop the observations for sections ISIC 12 (*Manufacturing of tobacco products*) and ISIC 19 (*Manufacture of coke and refined petroleum products*) due to a lack of observations which causes a potential violation of the privacy policy rules of the statistical offices.²⁴ The remaining dataset contains 115,898 observations.

Table 2: Descriptive statistics

Variable	Description (unit)	Median	p1	p99	Std. Dev.	N
X_{it}	Export (in percent of sales)	0.19	0	0.94	0.26	115,898
R_{it}	Sales (1000 Euro)	14,096.18	1,269.66	623,375.06	260,689.25	115,898
L_{it}	Employees (number)	93	23	1,952	580.73	115,898
K_{it}	Capital stock (1000 Euro)	6,642.04	175.12	361,812.16	151,271.58	115,898
M_{it}	Material (1000 Euro)	5,097.9	144.83	303,779.75	143,666.58	115,898
$CO2_{it}$	CO ₂ emissions (kg)	848,034.13	35,626.41	119,000,000	64,500,000	115,898
E_{it}	Energy use (1000 kWh)	2,059.94	84	384,196.03	191,113.12	115,898

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder, 2003-2011; own calculations.

Tables 2 provides the main descriptive statistics and reveals that the median firm in the dataset has a real turnover of 14 million Euro (in 2005 prices), of which 19 percent is generated through exports. It employs 93 workers, has a capital stock of 6.6 Million Euro, and uses material in the value of 5 million Euro (in 2005 prices). Moreover, the median firm emits 848 tons of CO₂.

Tables A.2 to A.8 in the appendix provide the descriptive statistics for each variable by industry. This shows that the variation in all variables is considerable, both within sector and between sectors.

²⁴ Section ISIC 12 has 118 observation from 22 firms and section ISIC 19 has 284 observations from 48 firms. In addition, both sectors are unique because mainly headquarter activities are located in Germany while the production is largely outsourced to other countries. Consequently, the average labour productivity is between 200 and 550 percent larger than the average labour productivity of the remaining 22 two-digit industries (see also Schiersch, 2015).

5 Results

5.1 Enhanced Correlation Analysis

In order to derive some stylized facts on the difference between exporters and non-exporting competitors, we first estimate exporters' premia by regressing different firm characteristics on an export dummy while controlling for sector, year and firm size²⁵ as shown in Eq. (12)

$$Z_{it} = \beta_0 + \beta_x X_{it} + \gamma \mathcal{A}_{it} + \epsilon_{it}, \quad (12)$$

where the indices i and t denote firms and years. Z_{it} is a place holder for different firm characteristics such as sales or CO₂ emission intensities. X_{it} describes a firm's export activity defined as binary variable that is equal to one if the particular firm has exported in the given year.²⁶ Finally, \mathcal{A} collects the control variables industry, year, and size.

Table 3: Average exporter's premium by firm characteristic

Characteristic (Z)	Coefficient β_x	Std.Dev.
Sales	0.451***	(0.00558)
Capital	0.313***	(0.00795)
Employees	0.036***	(0.00222)
Material	0.642***	(0.00842)
Capital labour ratio	0.276***	(0.00748)
Sales per worker	0.415***	(0.00499)
Energy use	0.441***	(0.00860)
CO ₂ emissions	0.424***	(0.00827)
CO ₂ per worker	0.388***	(0.00784)
CO ₂ per unit of capital	0.111***	(0.00804)
Sales per CO ₂	0.027***	(0.00741)
CO ₂ per sales	-0.027***	(0.00741)

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder, 2003-2011; own calculations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As depicted in Table 3, we find that, on average, exporters within the same industry have higher sales (+45 percent), a larger capital stock (+31 percent), employ more workers (+4 percent) use

²⁵ The dataset comes with 5 predefined size classes: 20-49, 50-99, 100-249, 250-499, 500 and more employees.

²⁶ Export activity can be defined by an export dummy (cf. Holladay, 2010; Cui et al., 2012; Forslid et al., 2015), or alternatively be represented by the proportion of output that is exported to incorporate the export intensity (cf. Cole et al., 2013). We stick at this point to the binary export variable.

more material (+64 percent), they produce more capital intensive than non-exporting competitors (+28 percent) and have higher labour productivity (+42 percent). This is well in line with the literature (Bernard et al., 2007, 2012). Moreover, exporters use more energy (+44 percent) and consequently generate more CO₂ emission (+42 percent). They also emit more CO₂ per worker (+39 percent) and per unit of capital (+11 percent). However, exporters can generate more sales per unit of CO₂ emission (+3 percent). They, hence, use emissions more productively and produce on average less CO₂ emission-intensively. This supports the hypothesis of an exporter’s environmental premium. However, as discussed above, results from this enhanced correlation analysis are biased due to endogeneity problems. We hence turn to the integrated structural approach in what follows to validate the results.

5.2 Integrated Approach

We conduct the empirical analysis as outlined in Section 3 by estimating Eq. (6) with CO₂ productivity as the dependent variable. Accordingly, a positive coefficient for the export variable indicates that an increase in the export orientation of a company leads to higher CO₂ productivity. Or, in other words, a positive coefficient for X_{it-1} indicates that exporters produce less CO₂ emission-intensively per unit of output.

We conduct the analysis separately for the entire manufacturing industry and for each of the 22 two-digit sub sectors. The estimation on the two-digit sector level is conducted for two reasons: First, as we estimate a production function, it is less restrictive to assume that all firms within a two-digit sector produce under the same production frontier, applying the same technology, than assuming that all manufacturing firms use the same technology, e.g. that chemical firms produce under the same production frontier as furniture producers. Second, it serves as a robustness check, as we split the sample into 22 subsamples. If we find positive coefficients for export intensity in most of the 22 two-digit industries, it seems robust to conclude that export activity is positively related to CO₂ productivity.

Table 4 shows our estimation results, with the first row depicting results for the entire manufacturing industry. All coefficients are significant and have the expected sign. They are, apart from the coefficient of material, lower but in the neighborhood of the corresponding OLS coefficients (see Table A.9 in the appendix). This is in line with the expectation that structural approaches reduce the magnitude of coefficients (cf. Doraszelski and Jaumandreu, 2013; Olley and Pakes, 1996). Ex-

Table 4: CO₂ productivity with export intensity

Ind. Code	N	L	K	M	CO ₂	X	Hansen-Test		
		(Std.Err)	(Std.Err)	(Std.Err)	(Std.Err)	(Std.Err)	Chi ²	df	p-value
10t33	64,704	0.294*** (0.014)	0.078*** (0.002)	0.620*** (0.023)	-0.922*** (0.009)	0.217*** (0.008)	120.18	3	0.00
10	7,697	0.260*** (0.018)	0.072*** (0.006)	0.636*** (0.039)	-0.903*** (0.019)	0.137* (0.056)	7.22	5	0.20
11	1,160	0.458*** (0.035)	0.193*** (0.01)	0.315*** (0.05)	-0.958*** (0.066)	-0.301** (0.095)	2.70	4	0.61
13	1,851	0.577*** (0.046)	0.053*** (0.005)	0.342*** (0.05)	-0.926*** (0.03)	0.217*** (0.047)	2.27	4	0.69
14	1,076	0.492*** (0.051)	0.088*** (0.015)	0.276*** (0.077)	-0.814*** (0.141)	0.505*** (0.082)	6.68	5	0.25
15	500	0.395*** (0.065)	0.173*** (0.021)	0.454*** (0.060)	-0.874*** (0.057)	0.207*** (0.062)	6.45	4	0.17
16	1,590	0.375*** (0.02)	0.036*** (0.005)	0.545*** (0.039)	-0.927*** (0.028)	0.042 (0.021)	3.99	5	0.55
17	1,766	0.394*** (0.035)	0.032*** (0.006)	0.506*** (0.051)	-0.816*** (0.038)	0.139*** (0.04)	10.84	4	0.03
18	1,312	0.458*** (0.044)	0.021 (0.015)	0.050 (0.123)	-0.555*** (0.079)	0.233* (0.093)	8.93	5	0.11
20	3,771	0.340*** (0.038)	0.086*** (0.009)	0.517*** (0.072)	-0.879*** (0.036)	0.118** (0.043)	0.44	3	0.93
21	867	0.573*** (0.032)	0.156*** (0.012)	0.368*** (0.042)	-1.017*** (0.02)	0.122*** (0.028)	0.40	4	0.98
22	3,678	0.374*** (0.009)	0.071*** (0.006)	0.542*** (0.013)	-0.964*** (0.005)	0.206*** (0.011)	6.34	5	0.27
23	3,447	0.332*** (0.048)	0.089*** (0.013)	0.488*** (0.054)	-0.903*** (0.012)	0.091 (0.083)	5.94	3	0.11
24	2,916	0.271*** (0.015)	0.043*** (0.005)	0.609*** (0.009)	-0.933*** (0.009)	0.064*** (0.018)	4.42	3	0.22
25	7,359	0.602*** (0.02)	0.042*** (0.004)	0.335*** (0.014)	-0.950*** (0.009)	0.273*** (0.017)	23.84	4	0.00
26	3,143	0.306*** (0.077)	0.126*** (0.019)	0.538*** (0.062)	-0.796*** (0.069)	0.263*** (0.027)	24.67	3	0.00
27	3,774	0.389*** (0.013)	0.064*** (0.005)	0.533*** (0.022)	-0.948*** (0.009)	0.159*** (0.015)	4.68	5	0.46
28	9,902	0.497*** (0.012)	0.05*** (0.002)	0.429*** (0.011)	-0.942*** (0.007)	0.163*** (0.007)	10.61	4	0.03
29	2,999	0.379*** (0.06)	0.062*** (0.006)	0.486*** (0.08)	-0.913*** (0.034)	0.113*** (0.031)	12.10	5	0.03
30	878	0.558*** (0.06)	0.066*** (0.017)	0.303*** (0.065)	-0.863*** (0.106)	0.052 (0.029)	2.55	4	0.64
31	1,442	0.351*** (0.061)	0.023* (0.009)	0.601*** (0.091)	-0.810*** (0.037)	0.134** (0.048)	7.41	4	0.12
32	2,124	0.595*** (0.027)	0.08*** (0.007)	0.264*** (0.049)	-0.945*** (0.025)	0.252*** (0.039)	0.92	4	0.92
33	1,452	0.704*** (0.061)	0.069*** (0.009)	0.312*** (0.061)	-0.990*** (0.05)	0.314*** (0.035)	1.49	5	0.91

Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder, 2003-2011; own calculations *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Names of industries can be found in Table A.1 in the appendix.

port intensity proves to have a positive impact on environmental efficiency: CO₂ productivity in the manufacturing industry increases on average by 0.21 percent when the share of export sales on total sales increases by one percentage point. Or in other words, CO₂ emission intensity decreases with increasing export participation.

Unfortunately, the p -value of the Hansen-tests of overidentifying restrictions is below 0.01. We can therefore not rule out that one of the instruments is endogenous.²⁷ However, a possible cause for the rejection of the null of the Hansen test could be heterogeneities within the sample, i.e. the rejection might be driven by some specific industries, as previously observed for the *KSE* dataset (Nielen and Schiersch, 2014).

The finding of a positive impact of export activity on environmental efficiency is reinforced when separately estimating the production function for each of the 22 two-digit sectors. The estimations for 18 out of the 22 sectors reveal that export intensity positively affects CO₂ productivity. The export coefficient is between 0.06 and 0.51. Hence, CO₂ productivity increases, depending on the industry, by 0.06 to 0.51 percent as export intensity increases by one percentage point. This strongly supports the hypothesis of an exporter’s environmental premium.

However, as Table 4 also reveals, there is quite some heterogeneity in the coefficients between sectors. We must also note that we have two sectors with rather problematic results. First, the coefficient for export intensity is negative and significant in the *beverage industry* (Ind.Code 11). It would suggest that firms in the beverage industry become less CO₂ productive the more they generate sales abroad. This is surprising and also contrary to the OLS results.²⁸ In addition, we consider the results of sector *Printing & reprod. of recorded media* (Ind.Code 18) as non-credible, since the coefficients for capital and material are insignificant. This is contrary to the OLS results. In addition, tests with subsamples for this sector find significant and credible coefficients for both inputs. Hence, we assess the results in Table 4 for the media sector and the beverage industry as being not robust and interpretable.

The coefficients for labour, capital, material and CO₂ are, apart from industry 18, significant and generally lower but in the neighbourhood of the corresponding OLS coefficients, as it is to be expected (Doraszelki and Jaumandreu, 2013). The Hansen-tests also perform well for most estimations. If we include those sectors in which the Hansen-test is not rejected at the 1 percent

²⁷ Various combinations of instruments and lags have been tested, but the Hansen-test is always rejected. However, in most estimations the coefficients do not change significantly to the ones presented here.

²⁸ This deviating result seems not to be driven by the choice of instruments. All tests with different instruments and also with smaller samples for this industry provide similar results.

level, the null hypothesis cannot be rejected in 18 of the 20 sectors. Only the instruments in two of the sector estimations are potentially endogenous. In fact, it seems reasonable to assume that these two sectors are also causing the rejection of the null hypothesis of the Hansen-test in the estimation for the entire manufacturing industry. However, as the tests perform well in the remaining 18 sectors, it follows that not only the coefficients for exporting have the expected sign and are significant, the unbiasedness of estimates is also given: firstly, in terms of the potential endogeneity bias inherent to production function estimation which we tackle using a structural approach; secondly, with regard to the potential endogeneity of the instruments used, which proved to be exogenous in our estimations.

We can therefore draw at this point first conclusions: the majority of estimations confirm the hypothesis that exporters produce less CO₂ emission-intensively than non-exporting competitors within the same narrowly defined sector.

Conducting the analysis separately for sector by sector allows not only to assess the robustness of the results. It also allows to compare energy-intensive and non-energy intensive sectors.²⁹ According to Table 4, the coefficients of export intensity are positive and significant also for energy-intensive sectors, except for sector 23. Hence, there is evidence for an exporter’s environmental premium in those sectors that use energy most intensively and that are thus most emission-intensive. Our results suggest, however, that this positive relation between export intensity and CO₂ productivity is smaller than in non-energy-intensive sectors, ranging between 0.06 and 0.14 compared to the industry average of 0.21. This is well in line with previous findings. While we find a lower than average exporter’s environmental premium, Forslid et al. (2015) do not find any significantly positive effects for energy-intensive sectors using Swedish data.

5.3 Robustness Check

Although we view the separate estimates for each sector as a standalone robustness check, we conducted an additional robustness check. To this end, and in line with Aw et al. (2011), we use a binary variable for export. Accordingly, we test whether exporters produce more CO₂ productively, regardless of the size of their export activity.

With respect to the entire manufacturing industry, we find that export continues to have positive and significant effect on CO₂ productivity: CO₂ productivity in the manufacturing industry is on

²⁹ Energy-intensive industries are the sectors 17, 19 (which is excluded from the analysis; see above), 20, 23, and 24.

Table 5: CO₂ productivity with export dummy

Ind. Code	N	L (Std.Err)	K (Std.Err)	M (Std.Err)	CO ₂ (Std.Err)	X (Std.Err)	Hansen-Test		
							Chi ²	df	p-value
10t33	64,704	0.36*** (0.006)	0.084*** (0.002)	0.540*** (0.009)	-0.947*** (0.004)	0.093*** (0.003)	69.96	4	0.00
10	7,697	0.275*** (0.018)	0.071*** (0.006)	0.643*** (0.038)	-0.927*** (0.021)	0.088*** (0.008)	8.48	5	0.13
11	1,160	0.421*** (0.038)	0.191*** (0.011)	0.305*** (0.048)	-0.931*** (0.071)	0.174*** (0.019)	1.75	4	0.78
13	1,851	0.549*** (0.047)	0.052*** (0.006)	0.363*** (0.061)	-0.908*** (0.034)	0.147*** (0.019)	4.67	5	0.46
14	1,076	0.475*** (0.042)	0.101*** (0.014)	0.265*** (0.076)	-0.770*** (0.096)	0.312*** (0.033)	3.94	5	0.56
15	500	0.423*** (0.043)	0.169*** (0.019)	0.442*** (0.038)	-0.921*** (0.052)	0.148*** (0.026)	4.40	4	0.35
16	1,590	0.358*** (0.026)	0.034*** (0.005)	0.561*** (0.042)	-0.931*** (0.028)	-0.006 (0.01)	3.64	5	0.60
17	1,766	0.437*** (0.03)	0.044*** (0.005)	0.455*** (0.054)	-0.878*** (0.042)	0.020 (0.022)	8.59	4	0.07
18	1,312	0.454*** (0.024)	0.025** (0.009)	0.357*** (0.094)	-0.841*** (0.077)	0.011 (0.019)	1.99	5	0.85
20	3,771	0.254*** (0.05)	0.086*** (0.01)	0.633*** (0.087)	-0.862*** (0.046)	0.161*** (0.019)	2.93	4	0.57
21	867	0.488*** (0.054)	0.158*** (0.009)	0.397*** (0.062)	-1.031*** (0.023)	0.091 (0.052)	1.38	5	0.93
22	3,678	0.189*** (0.038)	0.068*** (0.008)	0.701*** (0.042)	-0.854*** (0.022)	0.105*** (0.012)	72.15	4	0.00
23	3,447	0.328*** (0.052)	0.086*** (0.012)	0.497*** (0.066)	-0.908*** (0.02)	0.034 (0.021)	7.30	4	0.12
24	2,916	0.265*** (0.024)	0.047*** (0.005)	0.620*** (0.019)	-0.904*** (0.014)	0.028 (0.017)	18.05	4	0.00
25	7,359	0.581*** (0.018)	0.042*** (0.004)	0.317*** (0.017)	-0.949*** (0.017)	0.064*** (0.005)	40.64	5	0.00
26	3,143	0.344*** (0.093)	0.182*** (0.047)	0.435*** (0.029)	-0.763*** (0.061)	0.194*** (0.039)	12.53	3	0.01
27	3,774	0.372*** (0.013)	0.063*** (0.005)	0.554*** (0.014)	-0.948*** (0.007)	0.100*** (0.005)	4.17	4	0.38
28	9,902	0.369*** (0.017)	0.046*** (0.003)	0.524*** (0.012)	-0.803*** (0.018)	0.065*** (0.006)	83.92	5	0.00
29	2,999	0.506*** (0.044)	0.064*** (0.008)	0.348*** (0.063)	-0.982*** (0.05)	0.029* (0.013)	4.28	4	0.37
30	878	0.552*** (0.059)	0.071*** (0.017)	0.335*** (0.056)	-0.904*** (0.058)	-0.020 (0.027)	2.07	4	0.72
31	1,442	0.331*** (0.056)	0.026** (0.008)	0.593*** (0.075)	-0.790*** (0.039)	0.027* (0.012)	15.67	5	0.01
32	2,124	0.606*** (0.023)	0.079*** (0.007)	0.299*** (0.044)	-0.961*** (0.019)	0.130*** (0.015)	1.32	4	0.86
33	1,452	0.619*** (0.07)	0.074*** (0.01)	0.368*** (0.067)	-0.931*** (0.057)	0.015 (0.011)	0.33	4	0.99

Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder, 2003-2011; own calculations *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Names of industries are found in Table A.1 of the appendix.

average by 9.5 percent larger in exporting firms than non-exporting firms within the same industry (Table 5).³⁰ This is pretty much the average of the two extremes that we can derive from the results in Table 4. According to the linearly extrapolated results therein, firms with an export intensity of 100 percent would have a CO₂ productivity that is 21 percent larger than that of non-exporting firms. Hence, as the export dummy measures just an average effect, the coefficient of 0.09 is in line with the expectation. As with the estimation using export intensity, the null-hypothesis of the Hansen-test needs to be rejected at the 0.01 level. As before, however, this is due to only a few sub-sectors.

The results of the sub-sectors in Table 5 draw a similar picture as the results in Table 4 with minor difference in the number of significant export coefficients. Accordingly, the results of Table 4 with regard to the significance and the non-significance of export coefficient are confirmed for 18 of the 22 sectors. A further difference concerns the sectors *beverage industry* (Ind.Code 11) and *Printing & reprod. of recorded media* (Ind.Code 18). First, the coefficient of the export dummy is now positive and significant in case of the *beverage industry*. Given the negative coefficient in Table 4, this might suggest that the effect of export in this sector is non-linear. Second, the coefficients for capital and material in the estimation for sector *Printing & reprod. of recorded media* are now significant and have a reasonable magnitude. This suggests that the export intensity in the previous estimation (Table 4) is strongly correlated to both variables which in that sector and captures a lot of the variation. However, both sectors were previously labelled as problematic and, therefore, have not been taken into consideration for the assessment of the relationship between export and CO₂ productivity. When assessing the quality of the estimation by means of the Hansen-test, we must conclude that the null hypothesis needs to be rejected for six sectors. Hence, the robustness check by means of export dummies draws a similar picture and confirms the results for most of the sectors, but not for all. This is partly because the Hansen-test of overidentifying restrictions is more often rejected when using export dummies compared to estimations with export intensity.

All in all, however, the results in Table 5 support the previous findings which is why we conclude: Regardless of the way in which we include export in the estimations, we find strong support for the hypothesis that exporting firms, on average, produce less CO₂ intensively than non-exporting firms.

³⁰ The percentage differences is calculated as suggested in Kennedy (1981) for a semilogarithmic equation. Hence, it is defined by the coefficient of the dummy variable and its variance.

6 Conclusions

In this paper we test the hypothesis that exporting firms perform better environmentally than non-exporting competitors within the same industry. We focus on CO₂, the most important greenhouse gas for climate change, and exploit the particularity of CO₂ emissions that these are proportionately linked to energy input. For this reason, we argue that CO₂ productivity—the inverse of CO₂ emission intensity—can be estimated within a production function framework. To this end, we propose an integrated approach to structurally estimate CO₂ productivity, thereby overcoming the problem of omitted variable bias in previous studies. We are the first to apply the method of [Akerberg et al. \(2015\)](#) to this research field and include a measure of export activity directly in the estimation along the lines of [Aw et al. \(2011\)](#), [De Loecker \(2007, 2011, 2013\)](#), [De Loecker and Warzynski \(2012\)](#), and [Van Biesebroeck \(2005\)](#). We tackle our research question and apply the developed integrated approach using novel and unique firm-level data for Germany, a major exporting country. To this end, we construct a panel dataset containing detailed information on CO₂ emissions at the plant-level as well as a multitude of firm characteristics for the years 2003 to 2011.

Our main finding suggests the existence of an exporter’s environmental premium for manufacturing firms in Germany. Put differently, exporters can generate more sales with the same amount of CO₂ being emitted than non-exporting competitors within the same narrowly defined sector. Specifically, a one percentage point increase in a firm’s export intensity leads to an average increase in CO₂ productivity by 0.21 percent. An exporter’s environmental premium is found not only for the aggregated manufacturing industry but also for the majority of two-digit sub-sectors ranging between 0.06 percent and 0.51 percent. Moreover, we show that this positive relationship holds, regardless of whether we use export intensity or an export dummy to operationalise exports within our production function framework.

This paper contributes to the debate on the environmental impact of globalisation and whether free trade is beneficial or harmful for the environment. In particular, we provide evidence that firm-level differences may explain the trade-induced sector-level reductions in CO₂ emission intensity as found in the literature. In this literature, one of the explanations for the decreasing emission intensity at the sector-level is the *reallocation effect* (cf. [Kreickemeier and Richter, 2014](#)). According to this effect, high-productive exporters gaining market shares leads to a lower aggregate emission intensity conditional on exporters having lower CO₂ emission intensities.

While we do not explicitly focus on the *reallocation effect*—because (i) our econometric approach focuses on a production function framework that aims at appropriately controlling for firm productivity and export participation; (ii) our data does not provide any trade liberalisation to exploit; (iii) we do not observe exiting firms; and because (iv) we cannot control for market shares because we use an unbalanced panel constructed from survey data—we nevertheless provide some support for the *reallocation effect* as we find evidence that exporters have lower CO₂ emission intensities.

Furthermore, we find CO₂ emission intensity not just being lower because of higher productivity, as assumed in [Kreickemeier and Richter \(2014\)](#). Indeed, we find, while appropriately controlling for a firm’s productivity and export participation, CO₂ emission intensity is lower the more a firm is involved in global trade through exporting. This suggests that export participation itself is relevant, in addition to a potential *reallocation effect*.

It remains an open question, however, what underlying channels explain the exporter’s environmental premium that we found. Furthermore, it would be desirable to exploit an episode of trade liberalisation to properly tackle the question of whether more liberal trade can have an overall positive effect on the environment through the analysed firm-level difference. Both are left for further research.

Appendix

A.1 Calculation of capital stocks

In order to estimate the capital stock of a particular firm, we use its annual depreciation provided by the *KSE* and multiply it with a sector-specific average economic lifetime (AEL) of capital following [Wagner \(2010a\)](#). This method is similar to the approach that [Mueller \(2008\)](#) develops for the plant data of the *IAB establishment panel* and is used in [Nielen and Schiersch \(2014\)](#) and [Schiersch \(2015\)](#). We apply the method of [Wagner \(2010a\)](#) and [Mueller \(2008\)](#) to derive the AEL of capital for the two-digit industry level for the years 2003 to 2011, extending the period covered by [Wagner \(2010a\)](#). For this purpose, we use data on capital stocks, divided into "buildings" and "equipment," that the *Federal Statistical Office*, ([Bundesamt für Statistik, 2014](#)), provides for each sector and year. Additionally, we use information on the average lifetimes of these two types of capital on the economy-wide level.³¹ Forming the harmonic mean then gives us the AEL of capital per sector.

We furthermore use an alternative approach in order to test for the robustness of our estimates.³² In contrast to the first approach, here, the calculation of sector-specific AEL of capital does not rely on information of just two types of capital stocks and their average economy-wide lifetime but it relies on available sector-level depreciation rates. This has the advantage of implicitly using more detailed information on the capital stock within a sector than just the information on the stock of buildings and equipment.

There are two critical assumptions underlying both methods to estimate a firm's capital stock. First, both the composition and AEL of the capital stock is assumed identical across firms within a sector. Second, the already depreciated but still utilised capital is assumed of minor importance in the overall stock as we infer a firm's capital stock only from new annual depreciation. Despite these shortcomings, however, these methods are more robust to fluctuations than using data on annual investments, which, in addition, is also lumpy.

³¹ We refer to [Schmalwasser and Weber \(2012, p. 941\)](#), who provide investment data for 2010, which we use as proxy for the capital stocks. Accordingly, we assume an average lifetime for equipment of 15 years, and an average lifetime of buildings ("Sonstige Nichtwohnbauten") of 53 years.

³² We thank Oda Schmalwasser of the *Federal Statistical Office* for proposing this alternative method in a personal communication.

A.2 Variables and Descriptive Statistics

Table A.1: Sector codes

Industry	Industry Code ISIC Rev. 4
Manufacturing	10t33
Manufacturing of food products	10
Manufacturing of beverages	11
Manufacturing of textiles	13
Manufacturing of wearing apparel	14
Manufacturing of leather & related prod.	15
Manufacturing of wood & prod. of wood etc.	16
Manufacturing of paper & paper prod.	17
Printing & reprod. of recorded media	18
Manufacturing of chemicals & chemical prod.	20
Manufacturing of basic pharm. prod. & pharm. prep.	21
Manufacturing of rubber & plastics prod.	22
Manufacturing of other non-metallic mineral prod.	23
Manufacturing of basic metals	24
Manufacturing of fabricated metal prod., exc. mach. & equip.	25
Manufacturing of computer, electronic & optical prod.	26
Manufacturing of electrical equipment	27
Manufacturing of machinery & equipment	28
Manufacturing of motor vehicles, trailers & semi-trailers	29
Manufacturing of other transport equipment	30
Manufacturing of furniture	31
Other Manufacturing	32
Repair & installation of machinery & equipment	33

Source: [UN \(2008\)](#).

Table A.2: Export intensity per sector

Ind. Code	Mean	Median	p1	p99	Std.Dev.	N
10	0.10	0.00	0.00	0.80	0.17	13,234
11	0.05	0.00	0.00	0.58	0.12	2,022
13	0.31	0.27	0.00	0.91	0.24	3,248
14	0.23	0.19	0.00	0.78	0.21	1,835
15	0.29	0.24	0.00	0.94	0.24	8,33
16	0.18	0.07	0.00	0.91	0.23	3,015
17	0.27	0.21	0.00	0.82	0.24	3,104
18	0.08	0.01	0.00	0.73	0.15	2,640
20	0.41	0.41	0.00	1.00	0.27	6,120
21	0.33	0.26	0.00	1.00	0.29	1,431
22	0.27	0.23	0.00	0.88	0.23	6,909
23	0.21	0.11	0.00	0.86	0.24	5,948
24	0.29	0.25	0.00	0.93	0.23	4,699
25	0.20	0.13	0.00	0.84	0.22	14,124
26	0.38	0.35	0.00	0.97	0.29	5,712
27	0.28	0.25	0.00	0.89	0.24	6,842
28	0.40	0.39	0.00	0.96	0.29	18,177
29	0.27	0.22	0.00	0.93	0.24	5,103
30	0.35	0.29	0.00	1.00	0.31	1,390
31	0.17	0.09	0.00	0.84	0.20	2,780
32	0.30	0.25	0.00	0.98	0.29	4,000
33	0.15	0.03	0.00	0.93	0.23	2,732
10t33	0.26	0.19	0.00	0.94	0.26	115,898

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder, 2003-2011; own calculations. Export intensity is measured as sales abroad over total sales.

Table A.3: Sales per sector (in 1000 Euro)

Ind.	Mean	Median	p1	p99	sd	N
10	51,055.04	14,406.47	1,086.45	479,189.22	99,602.27	13,234
11	50,038.15	18,347.20	2,264.28	414,644.13	82,996.89	2,022
13	19,263.2	9,409.53	824.48	107,952.20	24,859.17	3,248
14	22,607.15	10,272.09	657.76	173,966.20	34,091.89	1,835
15	17,675.06	7,501.74	886.89	140,632.77	29,086.26	833
16	24,964.88	8,833.24	1,367.92	203,403.20	40,453.27	3,015
17	61,246.15	23,086.39	1,805.15	456,787.28	95,170.13	3,104
18	20,098.54	7,869.52	1,114.43	163,787.56	31,416.92	2,640
20	104,316.12	29,585.31	2,285.08	1,310,000.00	250,142.64	6,120
21	141,816.45	28,964.29	1,927.18	2,400,000.00	422,805.32	1,431
22	41,022.11	15,818.89	1,664.21	365,134.09	69,324.71	6,909
23	33,066.39	13,279.07	1,431.08	27,9902.22	53,600.64	5,948
24	105,892.48	29,148.54	2,162.32	1,470,000.00	252,680.44	4,699
25	25,863.79	9,707.97	1,443.16	226,469.83	42,895.69	14,124
26	45,304.34	11,724.31	851.28	498,147.91	108,131.91	5,712
27	54,782.38	15,457.19	1,403.81	614,902.25	118,006.82	6,842
28	51,945.26	15,432.71	1,725.81	598,794.50	109,168.28	18,177
29	209,349.49	25,366.60	1,652.55	2,480,000.00	1,080,000.00	5,103
30	125,286.08	18,103.27	1,463.49	1,940,000.00	328,053.68	1,390
31	27,681.38	11,226.88	1,442.07	224,330.89	42,911.87	2,780
32	23,006.71	6,667.04	944.93	257,812.24	49,074.10	4,000
33	39,000.45	9,468.61	1,375.51	531,459.06	92,340.65	2,732
10t33	56,033.68	14,096.18	1,269.66	623,375.06	260,689.25	115,898

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder, 2003-2011; own calculations.

Table A.4: Employment per sector

Ind.	Mean	Median	p1	p99	sd	N
10	195	102	23	1,371	267	13,234
11	143	72	22	897	185	2,022
13	122	72	23	706	132	3,248
14	126	71	22	821	167	1,835
15	107	74	23	511	102	833
16	114	58	21	843	148	3,015
17	228	125	23	1,287	272	3,104
18	134	76	22	900	165	2,640
20	269	105	24	2,542	534	6,120
21	463	175	23	8,024	1,119	1,431
22	219	107	24	1,595	310	6,909
23	172	82	22	1,213	238	5,948
24	296	121	24	3,313	528	4,699
25	153	78	23	1,146	209	14,124
26	229	100	24	2,043	383	5,712
27	267	105	23	2,237	466	6,842
28	240	103	23	2,079	408	18,177
29	627	147	24	8,005	2,061	5,103
30	480	114	23	6,533	1,218	1,390
31	163	82	22	1,118	215	2,780
32	153	68	22	1,314	238	4,000
33	198	71	23	1,701	364	2,732
10t33	228	93	23	1,952	581	115,898

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder, 2003-2011; own calculations.

Table A.5: Capital stock per sector (in 1000 Euro)

Ind.	Mean	Median	p1	p99	sd	N
10	22,502.60	6,737.88	166.37	232,991.52	454,72.33	13,234
11	50,671.28	17,835.52	889.73	443,004.25	85,721.79	2,022
13	14,259.18	5,713.09	98.38	114,373.39	22,547.02	3,248
14	7,900.10	2,544.26	50.36	85,549.69	14,855.49	1,835
15	6,817.68	2,724.32	80.32	52,261.65	10,584.02	833
16	17,940.54	4,062.41	132.16	234,344.94	42,072.71	3,015
17	48,291.27	14,394.14	189.05	525,030.00	98,915.39	3,104
18	17,560.25	6,011.88	169.5	163,821.08	31,540.70	2,640
20	65,484.22	14,239.81	351.86	899,399.75	17,7469.16	6,120
21	93,414.09	20,195.39	564.68	1,650,000.00	294,053.65	1,431
22	27,475.97	8,158.07	254.29	262,524.59	51,893.13	6,909
23	28,677.72	8,977.77	263.06	295,324.25	57,394.54	5,948
24	52,407.24	11,794.41	220.81	694,038.06	130,224.82	4,699
25	16,607.57	5,115.49	124.51	157,978.94	30,647.75	14,124
26	25,524.16	4,955.52	180.94	406,371.25	80,772.13	5,712
27	28,380.01	5,660.72	217.72	331,785.03	73,175.13	6,842
28	23,138.55	6,154.94	236.45	291,999.31	55,372.00	18,177
29	106,330.84	11,954.47	158.04	1,730,000.00	604,344.08	5,103
30	58,318.24	9,472.01	220.81	981,050.56	208,508.70	1,390
31	15,200.63	4,492.11	118.66	161,369.45	32,549.82	2,780
32	16,309.94	3,307.74	116.81	175,441.99	39,134.69	4,000
33	9,430.98	2,727.27	146.42	110,240.43	20,676.38	2,732
10t33	31,150.28	6,642.04	175.12	361,812.16	151,271.58	115,898

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder, 2003-2011; own calculations.

Table A.6: Material input per sector (in 1000 Euro)

Ind.	Mean	Median	p1	p99	sd	N
10	28,075	5,426	194	291,049	59,604	13,234
11	15,879	4,594	280	132,379	26,285	2,022
13	8,186	3,909	97	58,812	11,449	3,248
14	7,965	3,511	5	57,282	11,481	1,835
15	6,847	2,662	54	50,563	11,899	833
16	12,311	3,761	217	115,680	22,133	3,015
17	26,585	9,890	388	211,214	42,226	3,104
18	7,564	2,054	19	75,294	13,984	2,640
20	41,535	12,564	271	520,928	92,965	6,120
21	33,147	7,265	184	422,270	77,657	1,431
22	17,287	6,341	345	180,064	31,576	6,909
23	9,935	3,873	122	83,652	16,387	5,948
24	58,341	12,276	428	918,267	154,154	4,699
25	10,056	3,174	130	100,184	19,435	14,124
26	17,370	4,071	142	212,694	44,679	5,712
27	22,710	6,250	268	305,774	51,834	6,842
28	22,477	5,783	242	284,487	52,773	18,177
29	116,062	11,783	109	1,520,000	620,930	5,103
30	59,433	6,766	75	872,499	152,876	1,390
31	12,222	4,473	367	102,683	20,518	2,780
32	6,343	1,745	99	77,062	14,169	4,000
33	13,902	2,462	48	220,278	41,289	2,732
10t33	25,211	5,098	145	303,780	143,667	115,898

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder, 2003-2011; own calculations.

Table A.7: CO₂ emission per sector (in kg)

Ind.	Mean	Median	p1	p99	sd	N
10	5,080,000	1,310,000	84,258	49,500,000	10,800,000	13,234
11	5,500,000	1,940,000	126,130	48,400,000	9,320,000	2,022
13	3,640,000	1,170,000	44,132	27,200,000	5,820,000	3,248
14	587,403	231,795	23,966	5,230,000	1,060,000	1,835
15	706,178	309,698	26,039	6,950,000	1,270,000	833
16	4,360,000	602,842	32,501	86,900,000	14,200,000	3,015
17	31,600,000	2,640,000	72,865	472,000,000	87,000,000	3,104
18	2,800,000	612,153	43,299	29,000,000	6,340,000	2,640
20	29,000,000	2,130,000	65,585	490,000,000	123,000,000	6,120
21	7,830,000	1,810,000	65,165	138,000,000	21,500,000	1,431
22	6,350,000	1,990,000	69,045	69,700,000	12,600,000	6,909
23	15,800,000	1,890,000	68,059	235,000,000	51,700,000	5,948
24	46,200,000	4,330,000	122,744	560,000,000	261,000,000	4,699
25	2,410,000	723,994	47,113	24,200,000	4,800,000	14,124
26	2,080,000	376,735	25,710	35,000,000	6,470,000	5,712
27	2,570,000	471,850	28,212	34,000,000	6,850,000	6,842
28	2,070,000	536,142	44,356	26,900,000	5,210,000	18,177
29	10,000,000	1,370,000	55,742	138,000,000	42,400,000	5,103
30	5,010,000	805,916	42,054	76,000,000	13,500,000	1,390
31	1,430,000	523,056	58,286	14,100,000	2,490,000	2,780
32	1,090,000	226,574	21,147	13,300,000	2,840,000	4,000
33	873,663	191,351	8,569	11,200,000	2,210,000	2,732
10t33	7,970,000	848,034	35,626	119,000,000	64,500,000	115,898

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder, 2003-2011; own calculations.

Table A.8: Energy usage per sector (in 1000 kWh)

Ind.	Mean	Median	p1	p99	sd	N
10	14,736	3,442	191	157,900	34,606	13,234
11	16,121	5,681	351	141,018	28,548	2,022
13	10,013	2,956	122	73,275	16,686	3,248
14	1,687	643	61	15,691	3,653	1,835
15	2,008	819	57	23,650	4,009	833
16	25,432	1,712	60	469,403	109,598	3,015
17	113,538	6,400	200	1,670,000	349,332	3,104
18	6,669	1,253	85	84,973	18,770	2,640
20	89,940	5,308	181	1,750,000	395,940	6,120
21	23,289	4,554	139	511,707	74,464	1,431
22	14,152	3,946	188	175,097	30,307	6,909
23	54,699	5,062	163	862,842	186,652	5,948
24	121,012	10,752	278	1,560,000	718,587	4,699
25	5,870	1,683	131	60,449	12,286	14,124
26	4,390	880	51	64,870	12,997	5,712
27	5,864	1,145	68	75,639	15,824	6,842
28	5,048	1,323	115	68,365	12,565	18,177
29	23,657	3,092	138	296,375	105,195	5,103
30	12,623	2,009	104	178,691	34,258	1,390
31	4,550	1,423	114	43,108	9,232	2,780
32	2,538	585	38	28,986	6,556	4,000
33	2,307	539	17	29,164	5,882	2,732
10t33	23,248	2,060	84	384,196	191,113	115,898

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder, 2003-2011; own calculations.

A.3 Additional Result Tables

Table A.9: OLS estimates for production function with export intensity

Ind. Code	N	Constant (Std.Err)	L (Std.Err)	K (Std.Err)	M (Std.Err)	CO ₂ (Std.Err)	X (Std.Err)	R-squared
10t33	64,704	4.495*** (0.019)	0.381*** (0.002)	0.106*** (0.002)	0.479*** (0.001)	-0.943*** (0.001)	0.185*** (0.005)	0.91
10	7,697	2.51*** (0.053)	0.276*** (0.005)	0.085*** (0.004)	0.557*** (0.003)	-0.871*** (0.005)	0.088*** (0.02)	0.83
11	1,160	4.865*** (0.258)	0.367*** (0.027)	0.164*** (0.02)	0.534*** (0.011)	-1.03*** (0.019)	0.032 (0.101)	0.83
13	1,851	5.49*** (0.108)	0.495*** (0.014)	0.047*** (0.008)	0.483*** (0.007)	-0.982*** (0.007)	0.215*** (0.029)	0.93
14	1,076	5.679*** (0.285)	0.5*** (0.029)	0.147*** (0.015)	0.416*** (0.01)	-1.009*** (0.02)	0.344*** (0.064)	0.80
15	500	4.492*** (0.309)	0.415*** (0.036)	0.217*** (0.021)	0.460*** (0.021)	-1.022*** (0.02)	0.068 (0.074)	0.85
16	1,590	4.449*** (0.1)	0.414*** (0.013)	0.059*** (0.009)	0.512*** (0.008)	-0.940*** (0.007)	0.090*** (0.031)	0.93
17	1,766	4.726*** (0.105)	0.464*** (0.014)	0.056*** (0.008)	0.441*** (0.01)	-0.911*** (0.006)	0.152*** (0.03)	0.95
18	1,312	5.096*** (0.149)	0.460*** (0.018)	0.044*** (0.009)	0.236*** (0.009)	-0.767*** (0.013)	0.108* (0.059)	0.79
20	3,771	4.526*** (0.077)	0.375*** (0.009)	0.137*** (0.007)	0.443*** (0.005)	-0.933*** (0.005)	0.120*** (0.021)	0.93
21	867	6.049*** (0.243)	0.583*** (0.025)	0.136*** (0.019)	0.397*** (0.014)	-1.017*** (0.017)	0.054 (0.046)	0.84
22	3,678	4.706*** (0.073)	0.398*** (0.008)	0.085*** (0.005)	0.513*** (0.006)	-0.972*** (0.005)	0.202*** (0.018)	0.92
23	3,447	4.341*** (0.082)	0.372*** (0.009)	0.119*** (0.007)	0.424*** (0.005)	-0.902*** (0.004)	0.046** (0.022)	0.95
24	2,916	3.939*** (0.079)	0.285*** (0.009)	0.06*** (0.006)	0.575*** (0.005)	-0.933*** (0.005)	0.033 (0.021)	0.94
25	7,359	5.499*** (0.067)	0.47*** (0.007)	0.058*** (0.004)	0.419*** (0.004)	-0.933*** (0.004)	0.259*** (0.016)	0.90
26	3,143	5.526*** (0.128)	0.516*** (0.014)	0.136*** (0.009)	0.459*** (0.007)	-1.036*** (0.008)	0.246*** (0.023)	0.88
27	3,774	4.581*** (0.089)	0.405*** (0.01)	0.088*** (0.006)	0.494*** (0.006)	-0.952*** (0.006)	0.165*** (0.02)	0.89
28	9,902	5.313*** (0.07)	0.454*** (0.007)	0.061*** (0.004)	0.481*** (0.003)	-0.967*** (0.004)	0.175*** (0.01)	0.89

Table continues on next page ...

Table A.9: (continued)

Ind. Code	N	Constant (Std.Err)	L (Std.Err)	K (Std.Err)	M (Std.Err)	CO ₂ (Std.Err)	X (Std.Err)	R-squared
29	2,999	5.504*** (0.118)	0.475*** (0.012)	0.106*** (0.007)	0.444*** (0.006)	-0.987*** (0.008)	0.111*** (0.025)	0.88
30	878	5.253*** (0.261)	0.494*** (0.026)	0.071*** (0.014)	0.412*** (0.012)	-0.926*** (0.017)	0.078** (0.038)	0.84
31	1,442	4.472*** (0.181)	0.407*** (0.018)	0.042*** (0.008)	0.534*** (0.011)	-0.944*** (0.011)	0.075** (0.035)	0.87
32	2,124	5.743*** (0.135)	0.569*** (0.016)	0.094*** (0.009)	0.37*** (0.008)	-0.961*** (0.01)	0.319*** (0.027)	0.84
33	1,452	4.495*** (0.019)	0.381*** (0.002)	0.106*** (0.002)	0.479*** (0.001)	-0.943*** (0.001)	0.185*** (0.005)	0.91

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Names of industrial sectors can be found in Table [A.1](#).

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