Drivers of Energy Efficiency in German Manufacturing: A Firm-level Stochastic Frontier Analysis

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Abstract

Increasing energy efficiency is one of the main goals in current German energy and climate policies. We study the determinants of energy efficiency in the German manufacturing sector based on official firm-level production census data. By means of a stochastic frontier analysis, we estimate the cost-minimizing energy demand function at the two-digit industry level using firm-level heterogeneity. Apart from the identification of the determinants of the energy demand function, we also analyze potential drivers of energy efficiency. Our results suggest that there is still potential to increase energy efficiency in most industries of the German manufacturing sector. Furthermore, we find that in most industries exporting and innovating firms as well as those investing in environmental protection measures are more energy efficient than their counterparts. In contrast, firms which are regulated by the European Union Emissions Trading System are mostly less energy efficient than non-regulated firms.

Keywords: Stochastic Frontier Analysis, Stochastic Demand Frontier, Energy Efficiency, Climate Policy, Manufacturing

JEL-Classification: D22, D24, L60, Q41

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1 Introduction

Increasing energy efficiency is a cornerstone of current climate and energy policies in many countries around the world. The European Union (EU) has set the goal to increase energy efficiency by 20 percent by 2020 compared to 2008 in its 20-20-20 targets (EC, 2010).[1] Targets for increasing energy efficiency are set to reduce emissions resulting from the use of fossil fuels and enhance energy security by reducing import dependencies. Beyond 2020, the EU targets for the year 2030 include an increase in energy efficiency of at least 27 percent compared to 2008 (EC, 2014).

Germany, in particular, has set ambitious goals to increase energy efficiency in the framework of the Energy Transition. The main energy efficiency target consists in increasing final energy productivity[2] by 2.1 percent per year until 2050. From 2008 to 2015, final energy productivity, however, only increased by 1.3 percent per year on average, falling short of the target. To reach the objective by 2020 after all, an average increase of 3.3 percent per year is necessary, which requires Germany to increase its efforts to improve the energy efficiency in all sectors of the economy. (BMWi, 2016b; Löschel et al., 2016).

The German manufacturing sector accounts for around 30 percent of final energy demand and also has to contribute to the overall economy wide targets (BMWi, 2016a). Apart from final energy demand, the German manufacturing sector is of particular interest because it is seen as the backbone of the German economy with a share of 20 percent in employment and 25 percent in GDP in 2016 (Destatis, 2017). In addition, the German manufacturing sector accounts for around 20 percent of Germany's carbon dioxide emissions (BMWi, 2016a).

If future energy and climate policy objectives are to be met, efficient policy measures are of the essence. To evaluate the policy mix and the potential to further increase energy efficiency in the manufacturing sector, a better comprehension of energy efficiency and its drivers is crucial. This requires analyses based on comprehensive microdata of the manufacturing sector incorporating firm heterogeneity. After all, measures to reach the politically prescribed goals have to be implemented by the individual firms. Thus, we estimate the firm-level energy demand and energy efficiency for 14 two-digit industries in the German manufacturing sector using the stochastic frontier analysis (SFA) approach and data from the official German production census. Furthermore, we analyze different drivers of the estimated energy (in)efficiencies.

In our analysis, we focus on drivers which are based on policy instruments and firm characteristics. These drivers can be influenced by policy makers through different regulatory incentives, either costs or subsidies. Additionally, our analysis provides insights about the relationship of different firm characteristics and energy efficiency, which can

[1]The strategy also includes targets for the reduction of greenhouse gas emissions (GHG) and the increasing use of renewable energy sources (RES).

[2]Final energy productivity is defined as price adjusted gross domestic product divided by total final energy consumption.

be influenced by the firm itself and is thus of interest for managements. Consequently, our contribution includes not only the identification of the potential to increase energy efficiency at the industry level but also of the influence of different drivers, i. e. the relationship between the underlying energy efficiency and the European Union Emissions Trading System (EU ETS), the firms' export status, the firms' R&D expenditures, their investments in environmental protection measures, as well as their electricity generation from renewable energy sources.

We contribute to the literature by applying a parametric stochastic frontier function approach to the estimation of energy demand and energy efficiency. This is of great relevance because little is known about the drivers of energy efficiency in manufacturing based on sound econometric analysis of official microdata. We use official German production census data ("AFiD"), i. e. a full sample of all manufacturing firms with more than 20 employees for the period from 2003 to 2012. This data set is highly reliable and comprehensive. On top of firms' energy use, it includes a wide set of covariates allowing us to capture the firm-level heterogeneity. To our knowledge, there is no other study applying a stochastic energy demand frontier model to Germany and so far there are only very few applications to firm-level census data.

Energy efficiency can be estimated using a stochastic frontier function approach, in the course of which the "frontier" or benchmark of cost-minimizing energy demand is estimated (as adapted by Filippini and Hunt, 2011). By contrast, previous studies on energy productivity have usually used energy intensity, i. e. the ratio of total energy use to an output measure, as an approximation to energy efficiency, which, however, appears to be inadequate (Lundgren et al., 2016; IEA, 2012; Filippini and Hunt, 2011; Bhattacharyya, 2011).

That is, it is important to define these terms and distinguish between energy efficiency, as it is analyzed in our study using a SFA, and energy intensity or productivity. Energy intensity or productivity are often used in the political debate and also to set political targets as a proxy for energy efficiency. As aforementioned, the German "energy efficiency" target also refers to an increase in annual energy productivity. The definition of energy intensity is the ratio of energy consumption to GDP at the state or country level or energy use per output at the industry or firm level, or per square meter at the residential level. Energy productivity is the inverse of energy intensity.

Energy efficiency, as we estimate it, is defined as the difference between the actual and predicted energy use (Filippini and Hunt, 2011). Filippini and Hunt (2011) show – based on country-level data – that it is not clear if energy intensity is actually a good proxy for energy efficiency. Lundgren et al. (2016) show the same unclear relationship based on firm-level data for the Swedish manufacturing sector. The authors compare the energy efficiency scores derived from a SFA with calculated energy intensities using a simple correlation analysis. The relationship is expected to be perfectly negatively correlated, if both are perfectly comparable. The authors find negative correlations in most sectors, but with a relatively low magnitude. Thus, they cannot confirm that energy intensity is a clear-cut proxy for energy efficiency.[3]

While the stochastic frontier function approach has been applied to analyze energy demand and energy efficiency at the country or state level (Filippini and Hunt, 2011; Evans et al., 2013; Fillipini and Hunt, 2012; Filippini et al., 2014), the approach can be even more informative at the firm or plant level taking advantage of the underlying heterogeneity (Lundgren et al., 2016; Boyd and Lee, 2016). The estimation of the stochastic energy demand function at the firm level allows comparing firms to a "frontier" or benchmark of energy efficiency in each individual industry.

The use of individual plant- and firm-level data is very scarce in the literature regarding energy efficiency due to limited data availability and the novelty of the use of the research approach to identify energy efficiency and its drivers. However, the utilization of microdata is a very important step to exploit in-depth information and heterogeneity of plants and firms. In an early study, Boyd (2008) analyzes the energy efficiency of corn mills in the US empirically using publicly unavailable plant data. He uses the stochastic frontier analysis approach as an energy efficiency management tool. His results support the ENERGY STAR program by the U.S. Environmental Protection Agency (EPA), according to which a product or firm is eligible for the energy star if it falls above the 75^{th} percentile of energy efficiency "for comparable products or facilities" (Boyd, 2008).

The studies closest to ours are conducted by Lundgren et al. (2016) and Boyd and Lee (2016). Lundgren et al. (2016) analyze energy efficiency for 14 industries within Swedish manufacturing based on individual firm-level data for the years 2000 to 2008. The authors apply a parametric stochastic frontier approach and the "true random effects" model by Greene (2005a, 2005b), which allows for firm-specific heterogeneity. They find considerable inefficiencies, in particular in fuel use compared to electricity use. Boyd and Lee (2016) use a similar approach to analyze the energy efficiency of five different metal-based durable manufacturing industries in the United States. They apply the model to six repeated cross sections for each five-year census for the years 1987 to 2012 using confidential plant-level data on energy use and production from the quinquennial U.S. Economic Census. They also find considerable inefficiencies and consistently better electrical efficiency compared to fuel (thermal) efficiency.

Using German production census data, Petrick et al. (2011) analyze the energy use patterns and energy intensity in the German industry form 1995 to 2006. They find strong positive correlations between energy intensity, energy use, CO_2 emissions, and emission intensity. Apart from this study, there is no analysis on energy demand and energy intensity using panel plant- or firm-level data of the German manufacturing sector to our knowledge. In contrast to Petrick et al. (2011), we analyze the energy efficiency of the German manufacturing sector applying a SFA and on top of that contribute a more recent analysis for the years 2003 to 2012 to the literature.

Our results suggest that there is still potential to improve energy efficiency in most

[3]For a visual analysis of the covariation, see Lundgren et al. (2016). They conclude that one should be cautious about using energy intensity as a measurement for energy efficiency.

industries of the German manufacturing sector. Compared to results from the Swedish manufacturing sector, the potential, however, appears to be smaller. We identify heterogeneous levels of energy efficiency at the two-digit industry level. Our results for the mean time-variant energy efficiency scores range from 0.80 to 0.97, compared to 1 as the reference point with no inefficiencies present. Energy intensive industries, pulp & paper (0.85), chemicals (0.86), and basic metals (0.91), have a rather big potential to increase their energy efficiency. Specifically, energy intensive industries present a considerable lever regarding the effects of energy efficiency improvements on overall energy use and firms' energy costs. That is, policy makers should consider to incentivize energy efficiency increases especially in these industries by applying more comprehensive policy measures.

With our study, we are also among the first to estimate the own-price elasticities of energy demand for the German manufacturing sector. The estimated industry-specific elasticities appear to be rather small in comparison to recent studies of other countries, ranging from around -0.4 to -0.8. These elasticities give an indication about the responsiveness of firms to changes in energy prices and thus their reactions to price-based policy interventions, which is of interest for policy makers.

Additionally, we analyze different drivers of energy efficiency and find that exporting and innovating firms are more energy efficient than their counterparts in most industries of the manufacturing sector. Our study is one of the first empirical studies, in which this positive relationship is identified. Also firms that invest in environmental protection measures are more energy efficient than their counterparts in many industries. That is, clean technology adoption and energy efficiency also have a positive relation at the firm level. Apart from this, firms regulated by the EU ETS are mostly less energy efficient than non-regulated firms. Comparing our results to the current literature, does not allow us to draw a comprehensive conclusion about the relationship between the EU ETS and energy efficiency. Additionally, our analysis shows predominantly no significant relationship between firms' electricity self-generation from renewable energy sources and their energy efficiency.

The remainder of the paper is structured as follows. In Section 2, we describe the potential drivers of energy efficiency analyzed in more detail. In Section 3, we outline the methodology of the SFA approach. Section 4 describes the German production census and the additional data used. The results of our analysis are shown in Section 5 and their robustness in Section 6. In Section 7, we conclude with a discussion.

2 Potential drivers of energy efficiency

Energy efficiency is one key element in many energy and climate policies, but not the only one. This fact leads to an interplay with various other aspects and objectives. The reduction of greenhouse gas emissions as well as the increasing use of renewable energy sources are also important goals in the German energy and climate policy agenda (BMWi, 2016b; Löschel et al., 2016). To analyze the interactions between these measures, we study the relationship between energy efficiency and the European Union Emissions Trading System (EU ETS), the investments in environmental protection measures, and the use of renewable energy sources for electricity generation. Furthermore, innovation is not only an integral part of current energy and climate policies, i. e. to develop new technologies for a low carbon or sustainable economy, but also of Germany's industrial policy, which is based on the following paradigm: "Germany's economic strength is largely based on the efficiency of German industry, and particularly on its innovative strength." (BWMi, 2017) In addition, the "(i)ndustry is at the heart of Germany's strong export performance." (BWMi, 2017) To better understand the determinants in these key areas (innovation and export) of the German economy, we study their interplay with energy efficiency. Overall, we analyze the relationship of these different drivers with the energy efficiency development of firms in 14 two-digit industries of the German manufacturing sector. In this section, we shortly describe the determinants used in our analysis in more detail and additionally give an overview on possible relationships drawn from the literature.

First, we analyze the relationship between the EU ETS and firms' energy efficiency. The EU ETS is the most important climate policy instrument of the EU and its member states. With the help of the EU ETS, the EU aims at steering the European economy to a low carbon pathway. The EU ETS puts a price on the greenhouse gas emissions of the regulated installations and consequently on fossil fuel use. Theoretically, the use of fossil fuels should be reduced by this price signal and firms should face incentives to use energy more efficient (Linares and Labandeira, 2010; de Miguel et al., 2015). Thus, we would expect that regulated firms are more energy efficient than their counterparts. However, the empirical literature on the EU ETS and its impact on firms is scarce. Martin et al. (2016) as well as Joltreau and Sommerfeld (2016) give comprehensive overviews on the impacts of the EU ETS on firm behavior.

The empirical evidence specifically analyzing German manufacturing is even more limited. Petrick and Wagner (2014) investigate the causal effects of the EU ETS regarding emissions, output, employment, and exports. They find that the EU ETS reduced emissions of regulated firms, but had no significant impact on output, employment, and exports in the years 2007 to 2010. Lutz (2016) estimates the effects on firm-level productivity using a structural production function approach and data of the German production census from 1999 to 2012. He shows that the EU ETS had a significant positive impact on productivity during the first compliance period. Furthermore, Löschel et al. (2016) investigate the effects of the EU ETS on the technical efficiency of German manufacturing firms using data from 2003 to 2012. They apply a difference-in-differences approach combined with parametric conditioning strategies and find no significant effect of the EU ETS on the performance of regulated firms. They also analyze the treatment effects at the two-digit industry level for four different industries and only find statistically significant results for the paper industry. In this industry, the EU ETS had a significantly positive impact on the efficiency of the regulated firms. The empirical evidence on the relationship between the EU ETS and energy efficiency is even scarcer. Specifically regarding energy efficiency, Lundgren et al. (2016) find a mixed relationship with energy efficiency, that is in some industries positive, negative, or not significant at all. We add to this strand of literature and analyze the correlation between the EU ETS and energy efficiency in the different industries of the German manufacturing sector.

As a second determinant of energy efficiency, we analyze the influence of the exporting status of firms. Exporting could increase energy efficiency through different channels. Improved foreign market access could, for example, induce innovation or it may improve management practices (Roy and Yasar, 2015). From a broader perspective, there is literature regarding the relationship between exporting behavior and firm performance or productivity. Wagner (2012) gives an overview of the literature and summarizes that exporters are more productive than non-exporters. The higher productivity of exporters could also be related to higher energy efficiency. But there is no evidence yet on the relationship between export status and energy efficiency. There are, however, studies on the relationship between export status and energy use. Roy and Yasar (2015) find that exporting reduces the use of fuels relative to electricity. They analyze a firm-level panel data set for Indonesia. Batrakova and Davies (2012) show theoretically and empirically with Irish firm-level data that exporting increases energy use due to greater output. However, the effect can be offset by adopting more energy-efficient technologies and this reaction is stronger for firms with higher energy intensity. Cole et al. (2008), and Dardati and Saygili (2012) analyze Ghanaian and Chilean firms, respectively. They find that exporting is negatively related to energy intensity. To conclude, so far there is no study analyzing the association of exporting status to the underlying energy efficiency. There is, however, some indication for a negative relationship between energy intensity and exporting status.

Furthermore, we analyze the correlation between firms' R&D expenditures, as proxy for the innovation behavior of firms, and their energy efficiency. Innovations, policy incentives and high relative energy prices make new technologies often more energy efficient than older ones. Thus, innovative firms may also be more energy efficient. Popp (2001), for example, finds that one-third of the reduction of industrial energy consumption can be explained by innovation. He uses patent data to create a knowledge stock at the US industry level. We use the firms' R&D expenditures as proxy for innovation. However, it is unclear ex ante how the relationship between innovation and energy efficiency materializes for manufacturing firms. An overview of further literature on the relationship between energy and technological change can be found in Popp et al. (2010).

The same rationale for more energy efficient new technologies may also hold for investments in environmental protection measures. These investments account for the adoption of technologies, specifically green technologies. There are numerous studies on the determinants of green or clean technology adoption and firm performance; for a recent overview see Hottenrott et al. (2016). The relationship between environmental protection investments and energy efficiency, however, has not yet been studied to the best of our knowledge.

Finally, we analyze the relationship between energy efficiency and the usage of renewable energy sources to self-generate electricity. It is unclear how self-generation relates to energy efficiency and as far as we are aware there have been no studies analyzing this relationship so far. From the perspective of a firm, investments in renewable energy technologies increase its capital stock, but could crowd out other investments which could be favorable for the productivity as well as energy efficiency of the firm, as Boyd and McClelland (1999) suggest.[4] The effects on the other input factors of the production function are also not straightforward. Furthermore, the implications depend on the relative energy prices from self-generated electricity and purchased electricity from utilities, as well as possible cogeneration of process heat.

As the implications and the magnitude of the different drivers of energy efficiency are mostly unclear and never have been analyzed for the German manufacturing sector, we will study their relationships empirically.

3 The stochastic energy demand frontier approach

The measurement of energy efficiency based on economic foundations has evolved from the economic theory of production and the empirical methods for measuring productive efficiency. For a general overview of frontier, efficiency, and productivity analyses, we refer you to Coelli et al. (2005), Fried et al. (2008), or Kumbhakar and Lovell (2000). For an overview on the literature and methodology of energy efficiency measurement based on economic foundations, see Filippini and Hunt (2015).

The estimation of a measure of efficient use of energy can be based on a stochastic demand function of energy (Filippini and Hunt, 2011).[5] This is a parametric approach, which has higher discriminating power in energy efficiency performance measurement compared to its nonparametric frontier counterparts like the data envelopment analysis (DEA) (Zhou et al., 2012). The estimated energy demand function gives the cost-minimizing input combination to produce a given level of output, i. e. energy service. It indicates the minimum amount of energy that is necessary to produce a given level of output, given the technology, input prices, and other factors (Filippini and Hunt, 2015). The difference between the frontier and the actual energy use can be explained by allocative or technical inefficiencies.

Boyd (2008) is a prominent example of a study estimating an energy input requirement function using stochastic frontier analysis. He stresses the notion that energy efficiency should be measured relative to some benchmark (instead of simply measuring inputs to outputs), which is achieved by stochastic frontier analysis. He focuses on plant-level energy efficiency, illustrating his approach by using data on US corn mills.

[4] This could also be true for the investments in environmental protection discussed above.

[5] The basic stochastic frontier approach was introduced by Aigner, Lovell and Schmidt (1977) and in the same year by Meeusen and Van den Broeck (1977).

While an energy input requirement function uses input amounts in order to explain minimal requirements for output production (e. g. Boyd, 2008), by contrast, an energy demand frontier function uses input prices instead of input amounts as an explanatory variable for energy use (e. g. Filippini and Hunt, 2011, 2012; Evans et al., 2013; Filippini et al., 2014).[6] Thus, the frontier cost (minimizing) level of energy demand is based on energy prices, given the output and quasi-fixed inputs (Boyd and Lee, 2016).

Filippini and Hunt (2011) and Evans, Filippini and Hunt (2013) estimate an energy demand function at the country level for a panel of 29 OECD countries. Filippini and Hunt (2012), Filippini et al. (2014) and Weyman-Jones et al. (2015) build on the approach by Filippini and Hunt (2011) while adding a Mundlak correction for unobserved heterogeneity (Mundlak, 1978).

Early panel models for the stochastic frontier function approach did not differentiate between transient and persistent inefficiencies (for an overview see Filippini and Greene, 2016). We employ the “true random effects” model (TRE) proposed by Greene (2005a, 2005b). It is based on the pooled model of Aigner, Lovell and Schmidt (1977) and extended by firm-specific time-invariant random effects. This model’s error term subsumes three different components: a term for time-invariant unobserved firm-level heterogeneity (ψ_i), a firm-specific time-varying inefficiency term (u_{it}), and a random noise term (ν_{it}). Thus, the TRE model allows estimating the firm-specific time-variant, “transient” energy inefficiency u_{it}. A similar approach is used by Lundgren et al. (2016) with Swedish firm-level data as well as by Boyd and Lee (2016) with US plant-level data.

Our estimation incorporates both the energy demand function (Equation 1) and the drivers of its inefficiencies (Equation 2) within a single-stage approach using maximum simulated likelihood. We estimate the following short-run stochastic cost-minimizing energy demand function for firm i in period t separately for each two-digit industry within the manufacturing sector:

$$e_{it} = \beta_0 + \beta_1 y_{it} + \beta_2 k_{it} + \beta_3 l_{it} + \beta_4 m_{it} + \beta_5 p^e_{it} + \tau T + \psi_i + \nu_{it} + u_{it}. \tag{1}$$

In Equation 1, y denotes the gross value of produced output, and k, l, and m denote capital, labor, and materials, respectively. p^e refers to the energy price and T is a time trend variable, which captures technological change. ψ_i as introduced by Greene (2005a and 2005b) is a firm specific random effect and allows for time-invariant heterogeneity at the individual level, which is assumed to be uncorrelated with the other input factors, the prices and the time trend.

We identify ν_{it} and u_{it} by making assumptions about their functional forms. u_{it} can be referred to as the conditional energy inefficiency. It is assumed to have a non-negative truncated normal distribution $u_{it} \sim N^+(\mu_{it}, \sigma^2_{u_i})$. Intuitively, inefficiencies can only take positive values as no firm can be any more efficient than the frontier. Furthermore, ν_{it} is the usual error term, which is assumed to have a normal distribution $\nu_{it} \sim N(0, \sigma^2_{\nu_i})$. The complete error term can also be written as ϵ_{it} with $\epsilon_{it} = \nu_{it} + u_{it}$.

[6] For a detailed overview and comparison of different economic models see Filippini and Hunt (2015).

Our variables representing the drivers of energy efficiency are placed in the mean (μ_{it}) of the non-negative truncated normal distribution of u_{it}, which represents the inefficiency. We use the status of regulation by the EU ETS (ETS), the export status (EXP), the R&D activity status ($R\&D$), the investment activity in environmental protection (EPI), and the self-generation of electricity from renewable energy sources ($RENEW$) as variables in our conditional inefficiency model.

The estimation of the conditional inefficiency follows the model:

$$u_{it} = \gamma_1 ETS_{it} + \gamma_2 EXP_{it} + \gamma_3 R\&D_{it} + \gamma_4 EPI_{it} + \gamma_5 RENEW_{it} + \zeta_{it}, \tag{2}$$

where ζ_{it} is a random error term.

To get an indication of efficiency or inefficiency, we use two indicators. First, we calculate λ, which is defined as $\lambda_i = \sigma_{u_i}/\sigma_{\nu_i}$, and provides information on the relative contributions of the error term (ν_{it}) and the energy efficiency term (u_{it}) to the decomposed error term. If λ is significant, it means that the variance of the conditional energy inefficiency term (u_{it}) is significantly greater than 0. Consequently, it indicates that there are significant differences in energy efficiency between the firms within the respective two-digit industry. Second, the energy efficiency of every analyzed industry can be translated into an energy efficiency score EE_{it}, which is given by $EE_{it} = exp\{-\hat{\mu}_{it}\}$. It represents the distance of every firm to the frontier in the respective industry. An energy efficiency score of one indicates an industry on the frontier, which would mean that all firms and thus the industry are 100 percent energy efficient.

It is assumed that markets are perfectly competitive and firms minimize costs (Lundgren et al., 2016). Under these assumptions, the estimated efficiency scores will fully capture time-variant inefficiency. Note that time-constant, "persistent" firm-specific inefficiencies are part of the time-invariant heterogeneity term ψ_i in the TRE model. In this case, the firm-specific inefficiency term u_{it} does not capture the "persistent" part of inefficiencies and should therefore be considered as a conservative estimate.

4 Data

Our analysis is based on data from the German production census AFiD (Amtliche Firmendaten für Deutschland – Official firm data for Germany) provided by the Federal Statistical Office and the Statistical Offices of the Länder. The data is confidential and only accessible for scientific purposes. The participation is mandatory by law and the quality of the results is monitored by the Statistical Offices. It is also used as a basis for official government statistics. The structure of this longitudinal data set is modular. Below we describe the different data modules that we combine for our analysis.

The core data set is the Cost Structure Survey (CSS), which contains comprehensive annual information about output produced and inputs used by firms in the manufacturing sector. The CSS includes all manufacturing firms with more than 500 employees and a random sample of firms with more than 20 and less than 500 employees. The random

Table 1: Descriptive statistics of variables in the energy demand functions

Industry	ISIC Rev. 4	Output (EUR 1,000)	Energy use (MWh)	Energy price (EUR/kWh)	Capital stock (EUR 1,000)	Number of employees	Materials (EUR 1,000)	Number of firms
Food	10	52,800	25,100	0.1427	13,800	183	36,300	3,493
		(137,000)	(121,000)	(1.1676)	(35,200)	(347)	(106,000)	
Textiles	13	18,700	12,100	0.1001	7,171	128	9,443	836
		(32,200)	(29,600)	(0.2481)	(13,400)	(168)	(17,500)	
Wood	16	25,800	41,600	0.1812	9,924	122	14,900	940
		(49,600)	(163,000)	(1.6779)	(24,300)	(185)	(30,400)	
Pulp & paper	17	61,500	145,000	0.1277	29,500	243	30,800	850
		(109,000)	(447,000)	(1.4664)	(77,000)	(364)	(57,200)	
Chemicals	20	116,000	294,000	0.3956	53,500	357	57,600	1,453
		(482,000)	(2,610,000)	(15.8516)	(244,000)	(1,510)	(233,000)	
Pharmaceuticals	21	128,000	31,400	0.1905	71,800	562	42,400	343
		(399,000)	(98,400)	(1.7417)	(273,000)	(1,511)	(101,000)	
Rubber & plastics	22	40,600	17,600	0.1421	15,700	240	20,100	2,165
		(98,000)	(54,900)	(1.8538)	(37,900)	(534)	(51,000)	
Basic metals	24	131,000	397,000	0.1398	34,300	360	81,900	1,076
		(474,000)	(3,480,000)	(1.8505)	(142,000)	(1,028)	(308,000)	
Fabricated metal products	25	25,900	7,630	0.1333	9,711	167	12,200	4,710
		(54,500)	(28,100)	(1.0905)	(22,100)	(286)	(31,800)	
Computer/electronics	26	47,300	7,562	0.2780	22,800	274	33,100	1,717
		(164,000)	(33,800)	(4.9128)	(129,000)	(688)	(179,000)	
Electrical equipment	27	68,800	10,200	0.1579	20,700	426	39,300	2,150
		(529,000)	(72,100)	(0.7625)	(180,000)	(3,891)	(354,000)	
Machinery	28	54,600	7,590	0.1444	14,000	287	28,000	5,581
		(177,000)	(44,700)	(0.6146)	(73,300)	(1,141)	(109,000)	
Other transport equipment	30	109,000	16,700	0.2105	28,700	528	64,900	420
		(420,000)	(69,500)	(3.7269)	(159,000)	(1,835)	(248,000)	
Other manufacturing	32	24,800	4,612	0.1511	10,700	173	9,132	1,244
		(71,700)	(25,800)	(0.2325)	(40,200)	(383)	(28,600)	
Repair & installation	33	32,500	2,685	0.7371	4,730	193	16,200	999
		(154,000)	(17,000)	(5.0764)	(18,300)	(617)	(79,200)	

Notes: Mean values from 2003 to 2012. Standard deviation in parentheses. Source: Research Data Centres of the Federal Statistical Offices and the Statistical Offices of the Länder (2014), own calculations.

sample is changed every few years. In our sample period from 2003 to 2012, the sample was renewed in 2003, 2008, and 2012. It is stratified by the number of employees and economic activity affiliation. The firms are classified according to ISIC Rev. 4. Appendix A includes additional information on the industry classification.

Additionally, we use the database AFiD-Panel Industrial Units, which contains annual data from the Monthly Report on Plant Operation, the Census on Production, and the Census on Investment. This data set is a full sample of all plants in manufacturing which belong to firms with a minimum number of 20 employees. This data is combined at the plant level with the AFiD-Module Use of Energy and the AFiD-Module Environmental Protection Investments. The Energy Use Module includes comprehensive data on electricity and fuel purchase, sale, and use. It also distinguishes between electricity generation from fossil or renewable energy sources. The AFiD-Module Environmental Protection Investments contains information on various investment categories regarding environmental protection. These categories are waste management, water conservation, noise abatement, air pollution control, nature and landscape preservation, and soil remediation. We aggregate this information on firm level to be able to combine all data sets described.

As measure for output, we use the gross value of production of the firm. This is taken from the Census on Production and deflated using two-digit ISIC deflators.[7] The measure for labor input is calculated as the annual average of the number of employees reported monthly in the production census. This annual average of monthly data offers more detailed information on employment compared to the number of employees collected at the reporting date of the CSS. To compute the firm's capital stock, we use the perpetual inventory method. A detailed description of the method and its application to AFiD data can be found in Lutz (2016). Material expenditures are taken from the CSS and deflated in the same manner as our output variable. We also include the firm specific average energy price in our energy demand frontier function. The energy price is calculated by dividing the firm's total energy expenditures by its total energy use, including fuels and electricity, for each year and firm. In Table 1, we report the descriptive statistics for the aforementioned variables of the energy demand function. More detailed descriptive statistics are presented in Appendix B.

The drivers of energy efficiency are obtained as followes: in order to identify firms which are regulated by the EU ETS (ETS), we match the production census with the European Union Transaction Log (EUTL) from 2005 to 2012. We use information on the commercial register number and the VAT number for the merger. This data is also used in Lutz (2016) and Löschel et al. (2016). More information on the methodology of the merger is available in Appendix A. The production census provides information on revenues from exports at the firm level. We identify a firm as exporting if the export revenues are positive (EXP). Furthermore, we create a dummy variable for the firm's

[7]The data on price indexes was retrieved from the Federal Statistical Office and has already been used for example by Lutz (2016).

Table 2: Descriptive statistics of drivers of energy efficiency

Industry	ISIC Rev. 4	ETS	EXP	R&D	EPI	RENEW
Food	10	0.028	0.485	0.160	0.127	0.028
Textiles	13	0.014	0.906	0.313	0.120	0.021
Wood	16	0.039	0.698	0.145	0.092	0.042
Pulp & paper	17	0.179	0.901	0.242	0.207	0.021
Chemicals	20	0.067	0.934	0.591	0.314	0.030
Pharmaceuticals	21	0.040	0.908	0.480	0.224	0.026
Rubber & plastics	22	0.013	0.880	0.364	0.156	0.020
Basic metals	24	0.055	0.915	0.285	0.319	0.024
Fabricated metal products	25	0.001	0.773	0.248	0.148	0.028
Electrical equipment	27	0.005	0.857	0.531	0.142	0.045
Machinery	28	0.003	0.897	0.492	0.124	0.027
Other transport equipment	30	0.022	0.806	0.389	0.164	0.013
Other manufacturing	32	0.005	0.737	0.335	0.089	0.024
Repair & installation	33	0.001	0.596	0.164	0.060	0.032

Notes: Shares over the years from 2003 to 2012. Source: Research Data Centres of the Federal Statistical Offices and the Statistical Offices of the Länder (2014), own calculations.

R&D activity ($R\&D$) differentiating between firms with zero or positive expenditures for R&D. This data is taken from the CSS and includes all cost of internal R&D activities as well as joint activities with external research centers or laboratories. The dummy variable for Environmental Protection Investments (EPI) reflects whether firms have zero or positive investment expenditures in any of the aforementioned investment categories. The information about the self-generation of electricity with renewable energy sources ($RENEW$) is obtained from the production census. The dummy variable represents whether firms produce electricity from renewable energy sources (i. e. water, wind, geothermal, or solar photovoltaics) or not. We report the descriptive statistics for the efficiency determinants at the two-digit industry level in Table 2. The yearly descriptive statistics of the efficiency determinants can also be found in Appendix B.

5 Results

In this section, we present the estimated energy demand stochastic frontier as well as the simultaneously estimated relationships of different drivers and energy efficiency. In Table 3, we show the main estimation results. The first six columns show the estimated parameters of the frontier. The following five columns present the relation between several determinants and energy efficiency. The last two columns contain the estimated variance parameters of σ_u and λ. The estimates of λ denote the relative contribution of the variance in energy efficiency (σ_u) compared to the variance of the error (σ_ν). The statistical significance of λ indicates the presence of energy inefficiency in the respective industry.

The results of the estimated energy demand frontier in Table 3 show plausible signs for the short-run elasticities from an economic point of view. The positive signs for labor, capital, output and materials can be interpreted as follows: Given the technology a respective increase in these variables would require an increasing energy demand. The positive and highly statistically significant time trend hints at the fact that the energy

Table 3: Estimation results for the energy demand frontier

Industry	ISIC	Parameters						Drivers					Variance parameters	
	Rev. 4	ln L	ln K	ln p^e	ln y	ln m	Time trend	ETS	EXP	R&D	EPI	RENEW	σ_u	$\lambda = \sigma_u/\sigma_\nu$
Food	10	0.157***	0.261***	-0.541***	0.325***	0.064***	0.042***	2.058***	-	-0.021	-	0.052**	-	-
Textiles	13	0.411***	0.207***	-0.634***	0.142***	0.128***	0.042***	2.992***	-0.886***	-0.255 ***	-0.119	0.119	0.373***	2.495***
Wood	16	0.358***	0.280***	-0.802***	0.229***	0.155***	0.058***	1.702***	-0.012	-0.125*	0.124***	0.018	0.249***	1.211***
Pulp & paper	17	0.366***	0.210***	-0.679***	0.413***	0.046**	0.043***	2.196***	-0.130	-0.013	-0.068***	0.000	0.016	0.082***
Chemicals	20	0.503***	0.246***	-0.678***	0.246***	0.030***	0.052***	-1.179***	-2.975***	-2.100***	0.189	-0.912	0.800***	4.908***
Pharmaceuticals	21	0.547***	0.289***	-0.614***	0.052***	0.078***	0.062***	-2.087	-1.225***	-0.295*	0.114	-1.267	0.523***	3.840***
Rubber & plastics	22	0.299***	0.220***	-0.612***	0.320***	0.130***	0.038***	-0.026	-1.292***	-0.943***	-0.284***	-0.163	0.549***	5.268***
Basic metals	24	0.620***	0.112***	-0.733***	0.171***	0.176***	0.040***	-0.280	-0.625***	-0.539***	-0.092	0.223	0.275***	1.517***
Fabricated metal products	25	0.532***	0.193***	-0.477***	0.223***	0.046***	0.034***	0.912***	-0.388***	-0.235***	-0.125***	0.021	0.267***	1.550***
Electrical equipment	27	0.534***	0.256***	-0.430***	0.148***	0.068***	0.027***	-8.250	-0.729***	-0.465***	-0.257***	0.011	0.438***	2.548***
Machinery	28	0.674***	0.159***	-0.520***	0.075***	0.082***	0.031***	0.013	-1.205***	-0.489***	-0.299***	-0.356*	0.458***	2.896***
Other transport equipment	30	0.594***	0.211***	-0.591***	0.029*	0.094***	0.046***	0.104	-0.544**	-0.354	-0.048	0.953***	0.208***	0.845***
Other manufacturing	32	0.571***	0.266***	-0.394***	0.092***	0.051***	0.028***	2.608***	-0.384***	-0.019	0.117**	0.159	0.280***	1.575***
Repair & installation	33	0.533***	0.348***	-0.491***	-0.037	0.080***	0.058***	3.551***	0.158***	0.146***	0.047	-0.109	0.011	0.034

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Source: Research Data Centres of the Federal Statistical Offices and the Statistical Offices of the Länder (2014), own calculations.

use increased over time in all industries. It ranges from 0.027 in the electrical equipment industry (27) to 0.062 in the pharmaceutical industry (21). These coefficients can be translated into an increase of energy use of 2.7 to 6.2 percent per year. In contrast to this, Lundgren et al. (2016) find more heterogeneous results for the time trend in the Swedish industry. In their analysis, fuel demand decreases in most industries from 2000 to 2008, however, electricity demand increases in many industries.[8]

Furthermore, we find an economically plausible relationship between energy prices and energy demand: the negative relationship means that rising energy prices reduce the energy demand. The own-price elasticities of energy demand range from -0.39 to -0.80 in our analysis. When we compare these elasticities to results from the literature, the elasticities in the German manufacturing sector seem generally to be quite low, especially in comparison to more recent studies. They are, however, in the range of what Kleijweg et al. (1989) find for Dutch firms. They use a panel of Dutch firms for the years 1978 to 1986 and find an own-price elasticity of energy of -0.56. Nguyen and Streitwieser (2008), in contrast, find much higher own-price elasticities in the range of -1.68 to -7.27 for two-digit US manufacturing industries, but note that they use a cross section for the year 1991. In a more recent study, Haller and Hyland (2014) find an own-price elasticity of -1.46 using a long panel of Irish industrial firms from 1991 to 2009. Bardazzi et al. (2015) analyze the energy demand of the Italian manufacturing sector utilizing a panel covering the years 2000 to 2005. They estimate an own-price elasticity of -1.13 for energy. Note that there are more studies analyzing own-price elasticities in the manufacturing sector, but in many studies it is possible to split energy use into fuel and electricity use. We are not able to disentangle the energy use due to our underlying data and therefore the comparison to these results seems not feasible, cf. Woodland, 1993; Bjørner et al., 2001; Arnberg and Bjørner, 2007; Boyd and Lee, 2016; Lundgren et al., 2016; Abeberese, 2017.

Regarding the drivers of energy efficiency,[9] our analysis suggests that exporting firms are more energy efficient than non-exporting firms in most industries. Exporting firms are less energy efficient only in the repair and installation industry (33). The same holds for innovating firms. These are generally more energy efficient except in the repair and installation (33) industry. Our results are in line with analyses on different productivity and efficiency measures presented in Section 2. However, we can show for the first time that there is a positive relationship between exporting or innovating and the energy efficiency of manufacturing firms.

EU ETS regulated firms, on the other hand, are less energy efficient in most industries than their non-regulated counterparts. Only EU ETS regulated firms in the chemical industry (20) are more energy efficient than non-regulated ones. The lower energy efficiency of regulated firms is counterintuitive to our expectations formulated in Section 2. Our

[8]Note that we cannot disentangle fuel and electricity demand.

[9]The results of the regression of the determinants presented in Table 3 can be interpreted as follows. A negative sign means that the firms with variable status 1 are more energy efficient compared to the group with variable status 0.

results are not in line with the results of Lundgren et al. (2016) for the Swedish manufacturing sector; they find ambiguous results and no clear-cut trend regarding regulated and non-regulated firms. For the chemical industry, for example, they find that regulated firms are less fuel efficient, which is in contrast to our results. On the other hand, for the pulp and paper industry they find a similar effect, namely that regulated firms are also less fuel efficient than their counterparts. Thus, the EU ETS seems to regulate less energy efficient firms. The incentives for firms to become more energy efficient, which should exist due to the price signal as we stated above, might, however, materialize in the long term, when the signal is more salient to firms.

The results for environmental protection investments suggest that firms which invest are also more energy efficient. This positive result applies to the pulp and paper (17), rubber and plastics (22), fabricated metal products (25), electrical equipment (27), and machinery (28) industries. Nevertheless in the wood (16) and other manufacturing (32) industries the picture is negative for firms which invested in environmental protection. Thus, overall our results suggest that energy efficiency and clean technology adoption seem to be positively related to each other.

The association of energy efficiency and the use of renewable energy sources is only statistically significant in three industries. Thus, firms which self-generate electricity by using renewable energy are more energy efficient in the machinery (28) industry and less energy efficient in the food (10) and other transport equipment (30) industries. That is, we cannot draw clear conclusions from our analysis on the relationship between energy efficiency and the self-generation of electricity with renewable energy sources.

Table 4: Energy efficiency and energy intensity

		Energy efficiency (EE)		Energy intensity (EI)	
Sector	ISIC Rev. 4	EE_{mean}	EE_{median}	EI_{mean}	EI_{median}
Food	10	0.973	0.999	0.630	0.303
Textiles	13	0.871	0.900	0.721	0.376
Wood	16	0.803	0.835	0.852	0.220
Pulp & paper	17	0.845	0.998	1.176	0.262
Chemicals	20	0.857	0.888	1.152	0.196
Pharmaceuticals	21	0.849	0.878	0.357	0.184
Rubber & plastics	22	0.848	0.881	0.417	0.299
Basic metals	24	0.914	0.925	0.961	0.462
Fabricated metal products	25	0.882	0.898	0.343	0.181
Electrical equipment	27	0.850	0.875	0.179	0.089
Machinery	28	0.874	0.896	0.309	0.098
Other transport equipment	30	0.925	0.942	0.398	0.140
Other manufacturing	32	0.856	0.880	0.226	0.098
Repair & installation	33	0.888	0.854	0.129	0.049

Notes: Energy intensity is measured in kWh/EUR (energy use/output). Source: Research Data Centres of the Federal Statistical Offices and the Statistical Offices of the Länder (2014), own calculations.

There are two indicators for energy efficiency in our model. The first one as mentioned above is λ, which is shown in the last column of Table 3. We can identify energy inefficiencies for most industries in the German manufacturing sector. λ is statistically significant in almost all analyzed industries. This means that we can reject the null hypothesis of $\lambda = 0$, i. e. there are time-variant differences in energy efficiency between the firms within the respective two-digit industry. The variance of the conditional energy inefficiency term u is significantly greater than 0.

The second indicator is the energy efficiency score: $EE_{it} = exp\{-\hat{\mu}_{it}\}$. These scores are presented in Table 4. The highest possible score is 1, which would indicate that there is no potential for time-variant energy efficiency improvements in the respective industry. The mean energy efficiency scores in our analysis range from 0.803 in the wood industry (16) to 0.973 in the food industry (10). The results for the median scores range from 0.835 to 0.999 in the respective industries. These results are fairly high, which hints at the fact that there is actually not much potential to increase energy efficiency. Note, that this is the time-variant part of the energy efficiency and considered in relation to the industry's own benchmarking technology. Furthermore, the median is larger than the mean in most industries, except for repair & installation (33). The mass of the distribution is therefore concentrated above the mean. That is, most firms in the respective industries are relatively closer to the frontier and therefore the 100 percent energy efficient firm in each industry.

Policy makers are particularly concerned about energy intensive firms and industries. On the one hand, most energy efficiency goals are set to reduce energy intensity in the future. On the other hand, there is a concern that especially energy intensive firms and industries might lose competitiveness through energy and climate policies as they face high shares of energy costs. In Table 4, we also include the mean and median energy intensities measured in energy use per output (kWh/EUR) at the two-digit industry level. The industries with the highest mean energy intensity in our sample are the pulp & paper (17), chemicals (20), and basic metals (24) industries. The pulp & paper industry, as the most energy intensive industry (1.176) in our sample, has one of the lowest mean energy efficiencies (0.845). Thus, compared to other industries, there is a high potential to increase the time-variant energy efficiency and many firms are far from utilizing the optimal cost-minimizing energy demand function of the best performing firm on the frontier. The chemicals industry has a medium rank energy efficiency score compared to other industries in our sample, but still a relatively low mean energy efficiency score of 0.857 after all. The basic metal industry has in comparison a rather high energy efficiency score, which leads to the conclusion that there is not as much potential for increases in energy efficiency. However, there is some potential, because the mean energy efficiency score of the basic metals industry amounts to 0.914.

6 Robustness check

A concern that could be raised regarding our estimation might be a simultaneity or timing problem between the energy demand function and the drivers of energy efficiency. Thus, we also use a specification with lagged values of different determinants. The determinants are lagged for one year, so the results can be interpreted as the effect of the status of the determinant from year $t-1$ on the energy efficiency in year t. We lag

Table 5: Estimation results for the energy demand frontier - Lagged efficiency drivers

Industry	ISIC	Parameters						Drivers					Variance parameters	
	Rev. 4	ln L	ln K	ln EnP	ln y	ln m	Time trend	ETS	EXP_{t-1}	$R\&D_{t-1}$	EPI_{t-1}	$RENEW_{t-1}$	σ_u	$\lambda = \sigma_u/\sigma_\nu$
Textiles	13	0.399***	0.194***	-0.636***	0.132***	0.143***	0.043***	-0.256	-1.279***	-0.418***	-0.677***	-0.645	0.501***	4.822***
Wood	16	0.437***	0.303***	-0.798***	0.267***	0.108***	0.067***	1.360***	0.143***	-0.115***	0.020	-0.054	0.006	0.026
Chemicals	20	0.502***	0.304***	-0.660***	0.267***	0.038***	0.051***	-1.638***	-3.423***	-1.846***	0.157	-2.486**	0.795***	5.083***
Pharmaceuticals	21	0.469***	0.334***	-0.588***	0.122***	0.057***	0.063***	-0.612	-1.225***	-0.179	0.008	-1.018	0.466***	3.763***
Rubber & plastics	22	0.306***	0.239***	-0.627***	0.256***	0.153***	0.045***	0.114	-1.095***	-0.556***	-0.379***	-0.247	0.489***	6.850***
Fabricated metal products	25	0.468***	0.222***	-0.489***	0.248***	0.041***	0.038***	-2.939	-0.440***	-0.095**	-0.109***	0.119**	0.279***	2.016***
Computer & electronics	26	0.633***	0.307***	-0.527***	0.057***	0.064***	0.039***	1.773***	-1.262***	-0.407***	-0.179	0.818***	0.553***	3.579***
Machinery	28	0.638***	0.190***	-0.550***	0.079***	0.094***	0.032***	0.567	-1.084***	-0.409***	-0.313***	-0.169	0.438***	3.227***
Repair & installation	33	0.491***	0.336***	-0.469***	-0.039	0.081***	0.058***	0.978	0.131***	0.072	0.047	-0.045	0.013	0.043

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Source: Research Data Centres of the Federal Statistical Offices and the Statistical Offices of the Länder (2014), own calculations.

the exporting status (EXP_{t-1}), the expenditures in R&D ($R\&D_{t-1}$), the investments in environmental protection (EPI_{t-1}) and the electricity generation from renewable energy sources ($RENEW_{t-1}$). For the EU ETS, we suppose no lagged influence, because for most firms the regulatory status should be clear for a longer period. The results for the lagged model specification are presented in Table 5. A comparison of the results of the contemporaneous and lagged analyses is presented in Appendix C.

The estimation with lagged energy efficiency determinants reveals that exporting firms are for the most part more energy efficient than non-exporting firms. This confirms the results from our former estimation. The same result holds for the R&D activities of firms. Thus, innovating firms are more energy efficient than their counterparts in mostly all estimated industries. The lagged specification of environmental protection investments suggests that firms which invested are more energy efficient than firms which did not invest in environmental protection measures. All statistically significant industries (textiles (13), rubber & plastics (22), fabricated metal products (25), and machinery (28)) show this result. The results of the electricity generation from renewable energy sources are mixed. Firms in the chemical (20) industry are more energy efficient, if they generated electricity with renewable energy sources in the year before. But in the fabricated metal product (25) and computer & electronics (26) industries firms with renewable energy electricity generation are less energy efficient than firms without.

Table 6: Energy efficiency - Lagged efficiency drivers

Industry	ISIC Rev. 4	EE_{mean}	EE_{median}
Textiles	13	0.861	0.890
Wood	16	0.890	0.867
Chemicals	20	0.869	0.896
Pharmaceuticals	21	0.869	0.894
Rubber & plastics	22	0.856	0.889
Fabricated metal products	25	0.878	0.897
Computer & electronics	26	0.841	0.869
Machinery	28	0.875	0.898
Repair & installation	33	0.909	0.877

Notes: Source: Research Data Centres of the Federal Statistical Offices and the Statistical Offices of the Länder (2014), own calculations.

The energy efficiency indicators λ and EE show results in a similar range as in the non-lagged specification above. λ is statistically significant in most industries. The mean energy efficiency scores EE range from 0.841 in the computer & electronics (26) industry to 0.909 in the repair & installations (33) industry. The comprehensive results are shown in Table 6 and a comparison to the results of the estimation with contemporaneous variables can be found in in Appendix C.

7 Concluding discussion

Increasing energy efficiency plays a crucial role in current energy and climate policies. However, little is known about the determinants and drivers of industrial energy demand and energy efficiency. Therefore, insights into these developments are needed. This can help to improve the efficiency of current and future policy instruments and thus to achieve the overarching climate and energy policy targets. The manufacturing sector, with its considerable energy use and carbon dioxide emissions, is an important sector when it comes to contributing to these goals and increasing energy efficiency. Moreover, the manufacturing sector is very heterogeneous. We acknowledge this by analyzing energy efficiency at the industry level capturing the firm-level heterogeneity.

We analyze the determinants of energy efficiency in the German manufacturing sector by means of a stochastic energy demand frontier analysis. We estimate the energy demand function at the two-digit industry level allowing for firm heterogeneity by using official firm-level production census data. Furthermore, we analyze potential drivers of energy efficiency. The selection of drivers in our analysis is based on the relevance for research and policy. Except for the EU ETS, our analysis is the first to analyze these drivers. For our analysis, we focus on the following policies and firm characteristics: regulation under the European Union Emissions Trading Scheme (EU ETS), exporting status, R&D activity, investments in environmental protection and electricity generation with renewable energy sources.

First of all, our analysis shows that there is potential to increase the energy efficiency in all analyzed industries of the German manufacturing sector, although the energy efficiency scores are in general quite high. The variety in energy efficiency scores at the industry level reflects the heterogeneity of the manufacturing sector as a whole. The mean of the energy efficiency scores in some industries is quite high and many firms are close to the optimal cost-minimizing energy demand function within the industry, i. e. in the food industry. On the other hand there are industries with lower mean energy efficiency scores, which indicate that many firms are further away from the cost-minimizing frontier in the respective industry, i. e. manufacturing wood products. Thus, the time-varying energy efficiency might be increased by optimizing production processes according to an industry benchmark.

Furthermore, energy intensive industries of the German manufacturing sector (pulp & paper, chemicals, and basic metals industries) seem to have quite a vast potential to increase their energy efficiency in comparison with less energy intensive industries. The potential is estimated compared to the cost-minimizing frontier at the industry level. Reaching the frontier could lead to more efficient use of energy, supposably without harming the competitive position of these industries. Additionally, the changes in energy demand and efficiency in energy intensive industries have larger impacts on the overall goals than those in industries with low energy intensities. Thus, the increase in energy efficiency in energy intensive industries is of high importance to reach the underlying energy and climate policy goals.

Additionally, we find that there is also heterogeneity regarding the influences of the analyzed drivers of energy efficiency. Exporting and innovating firms are in general more energy efficient than non-exporting and non-innovating firms. Thus, we show that these measures are positively correlated to higher energy efficiency in almost all industries in the manufacturing sector. Also, in most industries firms that invest in environmental protection measures are more energy efficient than their counterparts which do not invest. Our results suggest that clean technology adoption and energy efficiency are closely related in many industries in the manufacturing sector.

However, EU ETS regulated firms are mostly less energy efficient than non-regulated firms. The chemical industry is an exception; EU ETS regulated firms in the chemical industry are more energy efficient than non-regulated firms. Comparing our results to earlier studies, does not allow us to draw a clear conclusion about the relationship between energy efficiency and the EU ETS. Apart from that, our analysis shows predominantly no significant relationship between firms' electricity self-generation from renewable energy sources and energy efficiency. Our results are generally also robust, if we use one year lagged variables in the conditional energy efficiency function to avoid timing or simultaneity problems.

In future research, the contemporaneous identification of time-variant and time-invariant firm-specific inefficiencies could be of interest (cf. Filippini and Greene, 2016). This could help to better understand the underlying sources of energy (in)efficiency in the manufacturing sector and thus to tailor policy instruments according to the specific requirements of the different industries.

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References

Abeberese, A. B. (2017): "Electricity Cost and Firm Performance: Evidence from India," *The Review of Economics and Statistics*, 99(5), 839–852.

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

Arnberg, S., and T. B. Bjørner (2007): "Substitution between energy, capital and labour within industrial companies: A micro panel data analysis," *Resource and Energy Economics*, 29(2), 122–136.

Bardazzi, R., F. Oropallo, and M. G. Pazienza (2015): "Do manufacturing firms react to energy prices? Evidence from Italy," *Energy Economics*, 49, 168–181.

Batrakova, S., and R. B. Davies (2012): "Is there an environmental benefit to being an exporter? Evidence from firm-level data," *Review of World Economics*, 148(3), 449–474.

Bhattacharyya, S. C. (2011): *Energy economics: concepts, issues, markets and governance*. Springer Science & Business Media.

Bjørner, T. B., M. Togeby, and H. H. Jensen (2001): "Industrial companies' demand for electricity: evidence from a micropanel," *Energy Economics*, 23(5), 595–617.

BMWi (2016a): *Energy Data: Complete Edition*. The Federal Ministry for Economic Affairs and Energy (BMWi), Available at: http://www.bmwi.de/Redaktion/EN/Artikel/Energy/energiedaten.html. Update: November 2016.

——— (2016b): *Fifth "Energy Transition" Monitoring Report - The Energy of the Future - 2015 Reporting Year - Summary*. The Federal Ministry for Economic Affairs and Energy (BMWi).

——— (2017): *A modern industrial policy*. The Federal Ministry for Economic Affairs and Energy (BMWi), Available at: http://www.bmwi.de/Redaktion/EN/Dossier/modern-industry-policy.html, last accessed on December 2nd 2017. The Federal Ministry for Economic Affairs and Energy (BMWi).

Boyd, G. A. (2008): "Estimating plant level energy efficiency with a stochastic frontier," *The Energy Journal*, pp. 23–43.

Boyd, G. A., and J. M. Lee (2016): "Measuring Plant Level Energy Efficiency and Technical Change in the U.S. Metal-Based Durable Manufacturing Sector Using Stochastic Frontier Analysis," *US Census Bureau Center for Economic Studies Paper No. CES-WP- 16-52*, Available at SSRN: https://ssrn.com/abstract=2881611.

Boyd, G. A., and J. D. McClelland (1999): "The Impact of Environmental Constraints on Productivity Improvement in Integrated Paper Plants," *Journal of Environmental Economics and Management*, 38(2), 121–142.

Coelli, T. J., D. S. P. Rao, C. J. O'Donnell, and G. E. Battese (2005): *An introduction to efficiency and productivity analysis*. Springer Science & Business Media.

Cole, M. A., R. J. Elliott, and E. Strobl (2008): "The environmental performance of firms: The role of foreign ownership, training, and experience," *Ecological Economics*, 65(3), 538–546.

Dardati, E., and M. Saygili (2012): "Multinationals and environmental regulation: are foreign firms harmful?," *Environment and Development Economics*, 17(02), 163–186.

de Miguel, C., X. Labandeira, and A. Löschel (2015): "Frontiers in the economics of energy efficiency," *Energy Economics*, 52, 1–4.

Destatis (2017): *Volkswirtschaftliche Gesamtrechnung.* Available at: https://www.destatis.de/DE/ZahlenFakten/GesamtwirtschaftUmwelt/VGR/VolkswirtschaftlicheGesamtrechnungen.html. Last accessed on January 31st 2017.

EC (2010): *Energy 2020: A strategy for competitive, sustainable and secure energy.* Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions, COM(2010) 639 final.

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

Evans, J., M. Filippini, and L. C. Hunt (2013): "The contribution of energy efficiency towards meeting CO2 targets," in *Handbook of Energy and Climate Change*, ed. by R. Fouquet, pp. 175–223. Edward Elgar Publishing.

Filippini, M., and W. Greene (2016): "Persistent and transient productive inefficiency: a maximum simulated likelihood approach," *Journal of Productivity Analysis*, 45(2), 187–196.

Filippini, M., and L. C. Hunt (2011): "Energy Demand and Energy Efficiency in the OECD Countries: A Stochastic Demand Frontier Approach," *Energy Journal*, 32(2), 59–80.

——— (2012): "US residential energy demand and energy efficiency: A stochastic demand frontier approach," *Energy Economics*, 34(5), 1484–1491.

——— (2015): "Measurement of energy efficiency based on economic foundations," *Energy Economics*, 52, S5–S16.

Filippini, M., L. C. Hunt, and J. Zorić (2014): "Impact of energy policy instruments on the estimated level of underlying energy efficiency in the EU residential sector," *Energy Policy*, 69, 73–81.

Fried, H. O., C. A. K. Lovell, and S. S. Schmidt (eds.) (2008): *The Measurement of Productive Efficiency and Productivity Growth.* Oxford University Press.

Greene, W. (2005a): "Fixed and Random Effects in Stochastic Frontier Models," *Journal of Productivity Analysis*, 23(1), 7–32.

——— (2005b): "Reconsidering heterogeneity in panel data estimators of the stochastic frontier model," *Journal of Econometrics*, 126(2), 269–303.

Haller, S. A., and M. Hyland (2014): "Capital–energy substitution: Evidence from a panel of Irish manufacturing firms," *Energy Economics*, 45, 501–510.

Hottenrott, H., S. Rexhäuser, and R. Veugelers (2016): "Organisational change and the productivity effects of green technology adoption," *Resource and Energy Economics*, 43, 172–194.

IEA (2012): *Progress implementing the IEA 25 Energy Efficiency Policy Recommendations: 2011 Evaluation. Report from the International Energy Agency.* International Energy Agency (IEA).

Joltreau, E., and K. Sommerfeld (2016): "Why Does Emissions Trading Under the EU ETS not Affect Firms' Competitiveness? Empirical Findings from the Literature," *ZEW Discussion Paper No. 16-062.*

Kleijweg, A., G. Van Leeuwen, R. Huigen, and K. Zeelenberg (1989): "The demand for energy in Dutch manufacturing; a study using panel data of individual firms, 1978-1986," *Research Paper 8906, Research Institute for Small and Medium-sized Business in the Netherlands, Department of Fundamental Research.*

Kumbhakar, S. C., and C. A. K. Lovell (2000): *Stochastic Frontier Analysis.* Cambridge University Press, United Kingdom: Cambridge University Press.

Linares, P., and X. Labandeira (2010): "ENERGY EFFICIENCY: ECONOMICS AND POLICY," *Journal of Economic Surveys*, 24(3), 573–592.

Löschel, A., G. Erdmann, F. Staiss, and H.-J. Ziesing (2016): *Expert commission on the Energy of the Future Monitoring Process, Statement on the Fifth Monitoring Report of the Federal Government for 2015, Berlin, Mannheim, Stuttgart.*

Löschel, A., B. J. Lutz, and S. Managi (2016): "The Impacts of the EU ETS on Efficiency - An Empirical Analyses for German Manufacturing Firms," *ZEW Discussion Paper No. 16-089.*

Lundgren, T., P.-O. Marklund, and S. Zhang (2016): "Industrial energy demand and energy efficiency – Evidence from Sweden," *Resource and Energy Economics*, 43, 130–152.

LUTZ, B. J. (2016): "Emissions Trading and Firm Productivity: Firm-level Evidence from German Manufacturing," *ZEW Discussion Paper No. 16-067*.

MARTIN, R., M. MUÛLS, AND U. J. WAGNER (2016): "The Impact of the European Union Emissions Trading Scheme on Regulated Firms: What Is the Evidence after Ten Years?," *Review of Environmental Economics and Policy*, 10(1), 129–148.

MEEUSEN, W., AND J. VAN DEN BROECK (1977): "Efficiency estimation from Cobb-Douglas production functions with composed error," *International Economic Review*, pp. 435–444.

MUNDLAK, Y. (1978): "On the pooling of time series and cross section data," *Econometrica*, 46, 69–85.

NGUYEN, S. V., AND M. L. STREITWIESER (2008): "Capital-Energy Substitution Revisited: New Evidence from Micro Data.," *Journal of Economic and Social Measurement*, 33(2-3), 129 – 153.

PETRICK, S., K. REHDANZ, AND U. J. WAGNER (2011): "Energy Use Patterns in German Industry: Evidence from Plant-level Data," *Jahrbücher für Nationalökonomie und Statistik*, 3(231), 379–414.

PETRICK, S., AND U. WAGNER (2014): "The Impact of Carbon Trading on Industry: Evidence from German Manufacturing Firms," Available at SSRN: https://ssrn.com/abstract=2389800.

POPP, D., R. G. NEWELL, AND A. B. JAFFE (2010): "Energy, the Environment, and Technological Change," in *Handbook of the Economics of Innovation- Vol-II*, ed. by B. H. Halland, and N. Rosenberg, pp. 873–938. Burlington: Academic Press.

POPP, D. C. (2001): "The effect of new technology on energy consumption," *Resource and Energy Economics*, 23(3), 215–239.

RESEARCH DATA CENTRES OF THE FEDERAL STATISTICAL OFFICE AND THE STATISTICAL OFFICES OF THE LÄNDER (2014): "AFiD-Panel Industrial Units, AFiD-Module Use of Energy, AFiD-Module Environmental Protection Investments and Cost Structure Survey 2003-2012," Further information: http://www.forschungsdatenzentrum.de/en/index.asp.

ROY, J., AND M. YASAR (2015): "Energy efficiency and exporting: Evidence from firm-level data," *Energy Economics*, 52, 127–135.

WAGNER, J. (2012): "International trade and firm performance: a survey of empirical studies since 2006," *Review of World Economics*, 148(2), 235–267.

WEYMAN-JONES, T., J. M. BOUCINHA, AND C. F. INÁCIO (2015): "Measuring electric energy efficiency in Portuguese households: A tool for energy policy," *Management of Environmental Quality: An International Journal*, 26(3), 407–422.

Woodland, A. D. (1993): "A Micro-Econometric Analysis of the Industrial Demand for Energy in NSW," *The Energy Journal*, 14(2), 57–89.

Zhou, P., B. Ang, and D. Zhou (2012): "Measuring economy-wide energy efficiency performance: a parametric frontier approach," *Applied Energy*, 90(1), 196–200.

Appendix

A Further data description

Industry classification: The underlying industry classification in the data set is based on the European implementation NACE Rev. 2 (Statistical Classification of Economic Activities in the European Community) of the UN classification ISIC Rev. 4. From 2003 to 2008 the industry classification based on NACE Rev. 1.1 was used in the data sets. To transfer these from NACE Rev. 1.1 to NACE Rev. 2, we use the official reclassification guide of the statistical offices at the four-digit industry code level.

Matching AFiD, CSS, and EUTL: The different internal data sets of the Statistical Offices of Germany, such as AFiD and CSS, can easily be merged via plant- and firm-level identifiers. However, it requires some effort to match external data to AFiD and CSS, since the information on firm identifiers and names is not accessible for researchers. We match AFiD data at the firm level with aggregated data from the EUTL for the years from 2005 to 2012 using the commercial register number and the VAT number. We are able to match 77 percent (813 firms) of the firms in the EUTL with AFiD. The 238 firms that are not matched mainly belong to the energy, public, or service sector and thus are not part of the production census for manufacturing.

B Further descriptive statistics

Table 7: Detailed descriptive statistics (2003–2012)

Industry	ISIC Rev. 4	Mean	SD	Skewness	Kurtosis	P10	P50	P90	N
Output (EUR 1,000)									
Food	10	52,800	137,000	6.97	70.00	1,571	11,900	127,000	16,796
Textiles	13	18,700	32,200	5.74	50.10	1,967	8,327	44,700	3,922
Wood	16	25,800	49,600	4.28	28.49	1,868	7,477	67,200	3,899
Paper	17	61,500	109,000	3.96	23.91	3,326	20,800	165,000	3,944
Chemicals	20	116,000	482,000	14.74	282.51	4,231	24,500	203,000	7,727
Pharmaceuticals	21	128,000	399,000	6.34	52.28	3,169	24,200	227,000	1,774
Rubber/plastic	22	40,600	98,000	8.37	96.77	2,889	13,600	95,600	8,615
Basic metals	24	131,000	474,000	11.23	169.02	4,170	25,400	241,000	5,920
Fabricated metal products	25	25,900	54,500	6.91	85.74	2,377	8,700	61,500	17,792
Computer/electronics	26	47,300	164,000	11.43	178.36	2,115	10,500	93,300	7,178
Electrical equipment	27	68,800	529,000	26.33	751.50	2,680	12,800	113,000	8,577
Machinery	28	54,600	177,000	15.86	457.76	2,806	13,500	114,000	22,630
Other transport equipment	30	109,000	420,000	8.82	97.65	2,460	11,700	190,000	2,217
Other manufacturing	32	24,800	71,700	7.40	74.43	1,387	5,761	50,500	5,001
Repair and installation	33	32,500	154,000	18.00	383.98	2,079	8,205	61,100	2,758
Energy use (MWh)									
Food	10	25,100	121,000	15.83	324.20	419	3,532	44,600	16,757
Textiles	13	12,100	29,600	11.03	209.32	296	3,033	34,100	3,946
Wood	16	41,600	163,000	7.09	70.08	200	1,751	58,300	3,877
Paper	17	145,000	447,000	5.43	40.96	499	6,192	385,000	3,935
Chemicals	20	294,000	2,610,000	19.12	425.00	509	5,172	205,000	7,740
Pharmaceuticals	21	31,400	98,400	5.44	35.79	428	4,317	54,500	1,829
Rubber/plastic	22	17,600	54,900	9.34	116.05	508	3,791	36,800	8,579
Basic metals	24	397,000	3,480,000	16.17	317.07	870	10,400	225,000	5,903
Fabricated metal products	25	7,630	28,100	37.75	2,678.01	316	1,704	17,300	17,761
Computer/electronics	26	7,562	33,800	13.76	314.35	141	864	12,700	7,102
Electrical equipment	27	10,200	72,100	22.41	606.30	165	1,107	15,500	8,528
Machinery	28	7,590	44,700	27.07	1,020.43	265	1,280	12,700	22,475
Other transport equipment	30	16,700	69,500	11.67	185.63	267	1,872	31,600	2,220
Other manufacturing	32	4,612	25,800	12.38	176.42	103	608	6,660	4,981
Repair and installation	33	2,685	17,000	16.17	290.99	75	387	3,918	2,647
Energy price (EUR/kWh)									
Food	10	0.1427	1.1676	80.94	7506.11	0.0485	0.0944	0.2032	16753
Textiles	13	0.1001	0.2481	27.09	853.94	0.0459	0.0786	0.1340	3945
Wood	16	0.1812	1.6779	43.61	2052.12	0.0201	0.0963	0.2450	3872
Paper	17	0.1277	1.4664	51.75	2865.76	0.0344	0.0775	0.1409	3935
Chemicals	20	0.3956	15.8516	61.48	3831.34	0.0373	0.0815	0.1616	7740
Pharmaceuticals	21	0.1905	1.7417	37.71	1527.65	0.0518	0.0879	0.1885	1829
Rubber/plastic	22	0.1421	1.8538	59.42	3814.25	0.0541	0.0908	0.1449	8579
Basic metals	24	0.1398	1.8505	49.55	2753.45	0.0402	0.0765	0.1370	5903
Fabricated metal products	25	0.1333	1.0905	89.43	8743.03	0.0552	0.0954	0.1649	17759
Computer/electronics	26	0.2780	4.9128	64.08	4448.72	0.0602	0.1061	0.2424	7090
Electrical equipment	27	0.1579	0.7625	42.54	2356.68	0.0566	0.0980	0.1946	8521
Machinery	28	0.1444	0.6146	39.04	2203.85	0.0571	0.0956	0.1732	22467
Other transport equipment	30	0.2105	3.7269	46.77	2198.03	0.0522	0.0923	0.1851	2220
Other manufacturing	32	0.1511	0.2325	13.79	299.72	0.0561	0.1056	0.2493	4981
Repair and installation	33	0.7371	5.0764	20.78	536.07	0.0684	0.1379	0.8357	2641
Capital stock (EUR 1,000)									
Food	10	13,800	35,200	7.88	91.09	412	3,700	33,500	16,769
Textiles	13	7,171	13,400	5.73	50.78	380	2,685	17,700	3,945
Wood	16	9,924	24,300	5.27	38.19	418	2,269	23,800	3,853
Paper	17	29,500	77,000	7.10	70.99	976	7,612	68,200	3,930
Chemicals	20	53,500	244,000	13.68	250.15	1,063	8,142	87,300	7,754
Pharmaceuticals	21	71,800	273,000	6.53	48.36	1,020	10,000	94,600	1,849
Rubber/plastic	22	15,700	37,900	7.34	74.66	664	4,583	37,500	8,584
Basic metals	24	34,300	142,000	15.27	298.34	815	6,061	67,100	5,903
Fabricated metal products	25	9,711	22,100	7.73	103.67	453	2,870	24,500	17,828
Computer/electronics	26	22,800	129,000	14.19	244.84	388	2,617	30,600	7,222
Electrical equipment	27	20,700	180,000	25.63	711.85	353	2,568	31,500	8,594
Machinery	28	14,000	73,300	40.89	2,320.69	522	3,272	26,100	22,652
Other transport equipment	30	28,700	159,000	12.64	178.67	450	2,887	39,700	2,251
Other manufacturing	32	10,700	40,200	8.83	94.16	245	1,634	19,800	5,009
Repair and installation	33	4,730	18,300	11.50	161.89	273	1,208	8,045	2,742

Table 7: (continued)

Industry	ISIC Rev. 4	Mean	SD	Skewness	Kurtosis	P10	P50	P90	N
Number of employees									
Food	10	183	347	7.33	86.55	27	83	394	16,872
Textiles	13	128	168	4.66	36.52	30	71	272	3,990
Wood	16	122	185	4.55	33.62	25	56	287	3,906
Paper	17	243	364	4.84	39.88	33	121	588	3,947
Chemicals	20	357	1,510	16.85	354.58	33	101	605	7,785
Pharmaceuticals	21	562	1,511	5.43	33.96	34	171	928	1,850
Rubber/plastic	22	240	534	8.59	100.22	32	98	544	8,624
Basic metals	24	360	1,028	12.29	214.17	34	115	708	5,933
Fabricated metal products	25	167	286	5.47	48.32	29	75	388	17,912
Computer/electronics	26	274	688	10.67	180.17	31	96	600	7,280
Electrical equipment	27	426	3,891	27.86	807.83	31	101	639	8,645
Machinery	28	287	1,141	35.63	1841.11	31	99	560	22,803
Other transport equipment	30	528	1,835	7.99	80.10	32	99	839	2,261
Other manufacturing	32	173	383	7.88	91.40	27	67	357	5,048
Repair and installation	33	193	617	13.75	233.04	28	70	387	2,784
Materials (EUR 1,000)									
Food	10	36,300	106,000	8.88	128.69	529	5,516	91,800	16,885
Textiles	13	9,443	17,500	6.25	67.32	569	3,906	23,800	3,992
Wood	16	14,900	30,400	4.33	31.06	718	3,730	39,700	3,910
Paper	17	30,800	57,200	4.13	25.90	1,234	9,855	78,600	3,952
Chemicals	20	57,600	233,000	13.14	226.64	1,169	11,900	106,000	7,789
Pharmaceuticals	21	42,400	101,000	3.71	17.56	724	7,977	89,800	1,853
Rubber/plastic	22	20,100	51,000	8.43	101.69	1,014	6,087	46,400	8,636
Basic metals	24	81,900	308,000	11.01	172.94	1,333	11,900	146,000	5,936
Fabricated metal products	25	12,200	31,800	9.74	187.67	502	3,118	27,800	17,926
Computer/electronics	26	33,100	179,000	17.28	432.01	856	4,957	50,000	7,284
Electrical equipment	27	39,300	354,000	28.56	889.79	938	6,056	58,300	8,654
Machinery	28	28,000	109,000	23.42	1003.32	807	5,625	54,100	22,818
Other transport equipment	30	64,900	248,000	9.55	124.29	485	5,224	125,000	2,262
Other manufacturing	32	9,132	28,600	8.70	113.70	248	1,871	18,100	5,048
Repair and installation	33	16,200	79,200	11.35	148.99	378	2,391	26,200	2,785

Notes: Source: Research Data Centres of the Federal Statistical Offices and the Statistical Offices of the Länder (2014), own calculations.

Table 8: Descriptive statistics of drivers of energy efficiency (II)

Year	ETS	Exports	R&D	EPI	RENEW
2003	0.026	0.772	0.341	0.130	0.014
2004	0.027	0.772	0.339	0.135	0.011
2005	0.028	0.780	0.342	0.108	0.011
2006	0.029	0.788	0.352	0.173	0.013
2007	0.031	0.809	0.359	0.171	0.017
2008	0.027	0.787	0.344	0.158	0.022
2009	0.028	0.791	0.347	0.146	0.028
2010	0.029	0.794	0.352	0.166	0.040
2011	0.029	0.798	0.357	0.183	0.051
2012	0.029	0.797	0.347	0.171	0.065

Notes: Shares over industries, included industries (ISIS Rev. 4): 10, 13, 16, 17, 20-22, 24-28, 30, 32, 33. Source: Research Data Centres of the Federal Statistical Offices and the Statistical Offices of the Länder (2014), own calculations.

C Comparison of results

Table 9: Comparison of estimation results with contemporaneous and lagged energy efficiency drivers

Industry	ISIC	Energy efficiency drivers										Energy efficiency indicators			
	Rev. 4	ETS		EXP		R&D		EPI		RENEW		$\lambda = \sigma_u/\sigma_\nu$		EE_{mean}	
		I	II	I	II	I	II	I	II	I	II	I	II	I	II
Food	10	2.058***	-	-	-	-0.021	-	-	-	0.052**	-	-	-	0.973	-
Textiles	13	2.992***	-0.256	-0.886***	-1.279***	-0.255***	-0.418***	-0.119	-0.677***	0.119	-0.645	2.495***	4.822***	0.871	0.861
Wood	16	1.702***	1.360***	-0.012	0.143***	-0.125*	-0.115***	0.124***	0.020	0.018	-0.054	1.211***	0.026	0.803	0.890
Pulp & paper	17	2.196***	-	-0.130	-	-0.013	-	-0.068***	-	0.000	-	0.082***	-	0.845	-
Chemicals	20	-1.179***	-1.638***	-2.975***	-3.423***	-2.100***	-1.846***	0.189	0.157	-0.912	-2.486**	4.908***	5.083***	0.857	0.869
Pharmaceuticals	21	-2.087	-0.612	-1.225***	-1.225***	-0.295*	-0.179	0.114	0.008	-1.267	-1.018	3.840***	3.763***	0.849	0.869
Rubber & plastics	22	-0.026	0.114	-1.292***	-1.095***	-0.943***	-0.556***	-0.284***	-0.379***	-0.163	-0.247	5.268***	6.850***	0.848	0.856
Basic metals	24	-0.280	-	-0.625***	-	-0.539***	-	-0.092	-	0.223	-	1.517***	-	0.914	-
Fabricated metal products	25	0.912***	-2.939	-0.388***	-0.440***	-0.235***	-0.095**	-0.125***	-0.109***	0.021	0.119**	1.550***	2.016***	0.882	0.878
Computer & electronics	26	-	1.773***	-	-1.262***	-	-0.407***	-	-0.179	-	0.818***	-	3.579***	-	0.841
Electrical equipment	27	-8.250	-	-0.729***	-	-0.465***	-	-0.257***	-	0.011	-	2.548***	-	0.850	-
Machinery	28	0.013	0.567	-1.205***	-1.084***	-0.489***	-0.409***	-0.299***	-0.313***	-0.356*	-0.169	2.896***	3.227***	0.874	0.875
Other transport equipment	30	0.104	-	-0.544**	-	-0.354	-	-0.048	-	0.953***	-	0.845***	-	0.925	-
Other manufacturing	32	2.608***	-	-0.384***	-	-0.019	-	0.117**	-	0.159	-	1.575***	-	0.856	-
Repair & installation	33	3.551***	0.978	0.158***	0.131***	0.146***	0.072	0.047	0.047	-0.109	-0.045	0.034	0.043	0.888	0.909

Notes: * p<0.10, ** p<0.05, *** p<0.01. All estimation results of Model I are presented in Tables 3 and 4. All estimation results of Model II including lagged energy efficiency drivers are presented in Tables 5 and 6.
Source: Research Data Centres of the Federal Statistical Offices and the Statistical Offices of the Länder (2014), own calculations.