

Determinants of Energy Use of Manufacturing Firms and Private Households

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Introduction

Modern energy policy emphasizes the importance of reducing energy consumption through energy efficiency improvements. This focus emerged not only since climate change is on the political agenda, but can be observed already since the oil crises of the 1970s, when attention to the demand side of the energy sector complemented traditional supply side policies. Policy makers, businesses and consumers sing the praise especially of energy demand policies that target energy efficiency. Energy efficiency improvements are increasingly regarded as a panacea, or as “everything that is good” (Convery 2011), for energy and climate policy challenges. They are supposed to reduce emissions of CO₂ and beyond, promote energy security, while at the same time not compromising economic efficiency and keeping energy prices low. Corresponding key demand-side policy instruments include energy tax schemes, subsidies for efficiency measures such as building insulation, facilitated access to financing for energy efficiency projects or corresponding research and development efforts. While the actual impact of energy efficiency measures is up to debate (for a summary see for example Gillingham and Palmer 2014), the International Energy Agency (IEA) in their current World Energy Outlook (WEO) acknowledge that, although not always as visible as supply-side options, measures to promote energy efficiency deliver relatively quickly and at the same time indeed foster competitiveness, reign in energy costs, and fight local and global pollution (IEA 2013).

Recently, the emergence of climate protection as an additional policy goal of energy policy reinforced the call for energy conservation. The IPCC in its fifth Assessment Report (AR5) has robust evidence that efficiency enhancements are a key mitigation strategy to keep climate change in manageable bounds (IPCC 2014). Energy efficiency improvements in the

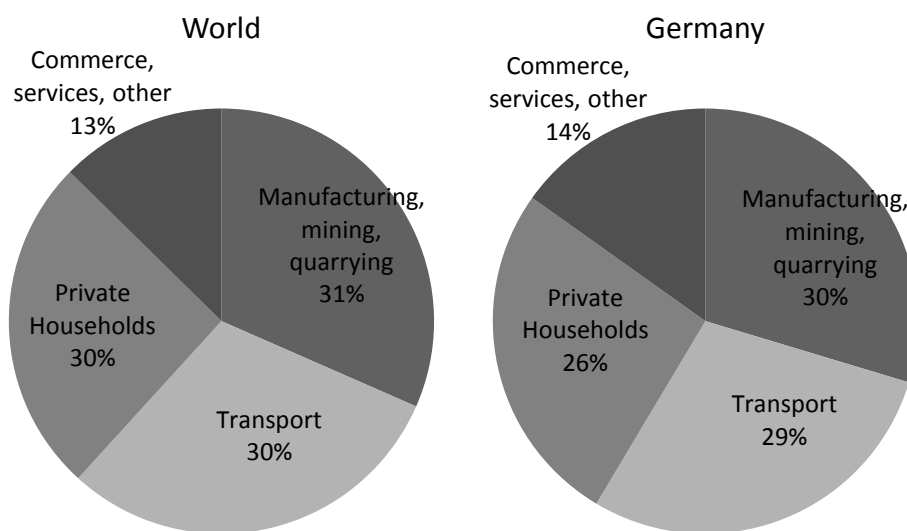
form of efficient buildings and power plants as well as efficiency improvements in the transport sector are also one of the five “stabilization wedges” using current technology to solve the climate problem put forward by Pacala and Socolow (2004). The need for political action to fight climate change also gave rise to additional policy instruments, such as emission trading schemes. The focus on climate protection draws attention to the trans-border dimension of energy policy, with carbon leakage and impacts on international competitiveness being of major concern.

Consequently, governments worldwide have turned or renewed their attention to energy efficiency. Sometimes induced by increased energy prices, the previously slow rate of improvement in global energy intensity has recently accelerated (IEA 2013). Countries as heterogeneous as the United States, Russia, and China were at the forefront of improving energy efficiency in the last years (based on 2011-2012 data, see IEA 2013).

All energy policy instruments mentioned above target energy or carbon efficiency at the end-use level. In the end, it is the final consumer that determines uptake and success of energy use policies, and the end-user also bears the cost of any such instrument. Energy policy targets three main end-use sectors, each of which faces a tailored policy mix adapted to the conditions of this sector. The industry sector, comprised by manufacturing, mining, and quarrying activities makes up around 30 % of final energy use, with the transport sector and the private household sector being almost as large (Figure 1). The remaining 15 % are made up by the “commerce, services, and other consumers” sector, which covers a heterogeneous group of activities. In this dissertation, I will concentrate on two of these sectors, the industry sector as well as the private household sector. These two sectors are of special importance. On the one hand, the industry sector is estimated to be the second largest single cause for the increase in anthropogenic CO₂

emissions between 2000 and 2014, right after the electricity sector (IPCC 2014). On the other hand, industry and buildings, including private homes, are believed to be the prime contributors to energy-efficiency related energy savings in the future, e.g. making up 63 % of all efficiency-related savings in the IEA’s New Policies Scenario (IEA 2013).

Figure 1: Sector shares in final energy use worldwide and in Germany (2011 data)



Source: IEA (2014), Arbeitsgemeinschaft Energiebilanzen (2013).

The importance of and policy interest in final energy consumption and end-use energy efficiency demands a better understanding of the determinants of energy consumption of final energy users, such as industry or private households. Therefore, this dissertation is dedicated to uncover and evaluate these determinants and their relative importance, including the assessment of the efficiency and efficacy of relevant policy instruments.

My dissertation is organized in two sections. The first and main section is concerned with the industry sector in Germany. Apart from the good data situation, the relatively large share of the manufacturing sector makes

Germany a particularly interesting case for analyzing end-use policies in the industry sector. The strong orientation of the German manufacturing sector toward export markets makes it an interesting case for investigating the validity of widespread concerns that unilateral regulation of European firms leads to a loss of competitiveness in international product markets. In the second section, I widen my focus and cover a multitude of countries, concentrating on the household sector. Within these two sections, my aim is the qualitative and quantitative analysis of the impact of key determinants of household and industrial energy use. In particular, I answer the following questions:

Section 1:

1. In how far does within- and between-sector firm heterogeneity shape industrial energy use?
2. How important are economic activity, technological progress, sector composition, intra-sector competition, and fuel mix in determining manufacturing energy use and CO₂ emissions? How is the relative importance of these determinants? How does the existing literature succeed or fail to correctly attribute changes in aggregate energy use to the individual determinants?
3. Using the example of one of the most prominent policy interventions in modern energy policy, the EU emission trading scheme, how successful is energy policy in inducing emission abatement and energy efficiency improvements in the manufacturing sector? What are potential detrimental side effects? And what channels are used by manufacturing firms to abate emissions?

Section 2:

4. How does temperature affect private households' energy consumption? What conclusions can we draw with regard to future temperature rises, e.g. because of climate change?

In Section 1, I add to existing research by demonstrating the importance of firm heterogeneity for aggregate industrial energy use and exploiting this heterogeneity to analyze the effects of the EU emission trading scheme, applying modern program evaluation econometrics. In Section 2, I add to the literature by shedding light on non-linearities in the effect of temperature changes on energy use in a global context, which is so far often not incorporated in global climate and integrated assessment models.

The four chapters of my dissertation follow the four sets of questions formulated above. The core of my work, i.e. the first three chapters, focusses on a variety of determinants of industrial energy use. In Chapter 1, my coauthors and I describe the immense effect of firm heterogeneity on different energy use patterns in industry. In particular, we address the fact that intra-sector variation of energy use patterns, e.g. with respect to energy efficiency levels or fuel mix, is often considerably larger than variation between sectors. This chapter serves at the same time to describe the data underlying the manufacturing-focused chapters of this dissertation. In Chapter 2, and building on the findings of Chapter 1, I use index decomposition methodology to discern the impact of technological progress, sector composition, intra-sector competition and fuel mix on industrial energy use and CO₂ emissions. In the central chapter of my dissertation, Chapter 3, we use program evaluation econometrics to quantify the effect of the EU emission trading scheme on firm-level energy use and emissions. We show the effectiveness of this corner stone of European climate and energy policy and analyze the side effects on industrial output, employment

and international competitiveness. A closer analysis of investment activities, fuel mix, and interview responses of plant managers reveal some information about the related transmission channels. As a final chapter, Chapter 4, we shed light on the long-term determinants of household energy use on a global scale. Using dynamic cross-country panel econometrics, we estimate the impact of temperature changes on households' energy consumption, paying special attention on non-linearities in the reaction of households to temperature changes. The following paragraphs give a more detailed outlook on the chapters to come and provide some answers to the questions posed above.

The main topic of Chapter 1, *Energy Use Patterns in German Industry: Evidence from Plant-level Data* (Petrick et al. 2011)¹, is the description of a comprehensive plant-level data on the German manufacturing sector. The dataset described here is used throughout the remaining chapters of my dissertation, in varying aggregation levels and sample periods. I, together with my co-authors, present in detail the data sources as well as a collection of descriptive statistics that can be used to draw first conclusions on the role of firm heterogeneity for the interpretation of energy use statistics and on major trends in industrial energy use after the German reunification.

We show that heterogeneity among manufacturing plants is constituent for a number of well-known trends in manufacturing energy use. The increasing trend in energy use that dominated the post-reunification era² was driven mainly by the large energy consumers in the upper tail of a right-skewed distribution. Because the accompanying even more expansive trend in

¹ This paper is joint work with Katrin Rehdanz and Ulrich Wagner. We agreed collectively on the idea and conceptual design of the analysis. Implementation of the concept into program code was mostly done by me. All three co-authors contributed substantially to writing the paper.

² I.e. after 1995, the beginning of harmonized collection of industrial energy use data for East and West Germany.

industrial activity, energy intensity declined over the sample period. Analogue to the increase in energy use, which was driven by the largest consumers, this decline in intensity was more pronounced in the most energy intensive plants.

Additional to energy use trends over time, we examine energy use patterns in a recent cross-section of plants. Using data from 2006, we document that both energy use and intensity are highly dispersed. When isolating the between-sector variation in energy intensity, we find a strong positive correlation with energy use, CO₂ emissions and emission intensity, yet there is no evidence that the scale of an industry determines its energy intensity.

The central outcome of the first chapter was that acknowledging heterogeneity among plants is conditional to understanding developments in the aggregate, in my case energy use in the German manufacturing sector. In Chapter 2, *Carbon Efficiency, Technology, and the Role of Innovation Patterns: Evidence from German Plant-Level Microdata* (Petrick 2014), I build on the previous chapter and take the argument even further. I argue that heterogeneity or, more precisely, shifts in the composition between heterogeneous firms, even shapes the trends in any aggregate looked at. Using the examples of industrial CO₂ emissions and energy intensity, I illustrate how disregard of changes in the composition of firms leads to erroneous policy conclusions. I use conventional index decomposition methodology to show that improvements in firm-level energy efficiency, as a measure of technological progress, play a negligible role in reducing industrial CO₂ emissions. This is in contrast to previous results from the sector level that identified energy efficiency improvements, labelled as technological progress, as a main driver of emission reductions.

The difference between my firm-level analysis and previous sector-level studies stems from the (usually data-imposed) ignorance of shifts of within-

sector market shares in sector-level analyses. I show that these shifts in market shares are on average in favour of relatively energy efficient (“green”) firms and on the cost of relatively energy inefficient (“dirty”) firms. In other words, new entries or relatively small and growing efficient firms push out relatively large and shrinking inefficient firms. I show that this competition effect was one of the most powerful drivers of reductions in CO₂ emissions after 1995, compared to structural change, changes in firm-level energy efficiency, shifts towards cleaner fuels in the industry sector, and less carbon-intensive electricity production upstream. I argue that the disregard of this effect may potentially lead to the imposition of ineffective policies if those policies are targeted at established firms. Because innovative prowess lies with new entrants or rising stars, policies with the aim of sector-specific “greening” are likely to achieve more emission savings if targeted at these firms.

Based on sector-level results of the previous decomposition analysis, I identify sectors where policies targeted at firm-level energy efficiency are likely to be effective, as well as sectors where they are more prone to fail, the latter including a number of energy intensive industries, such as the ceramics sector.

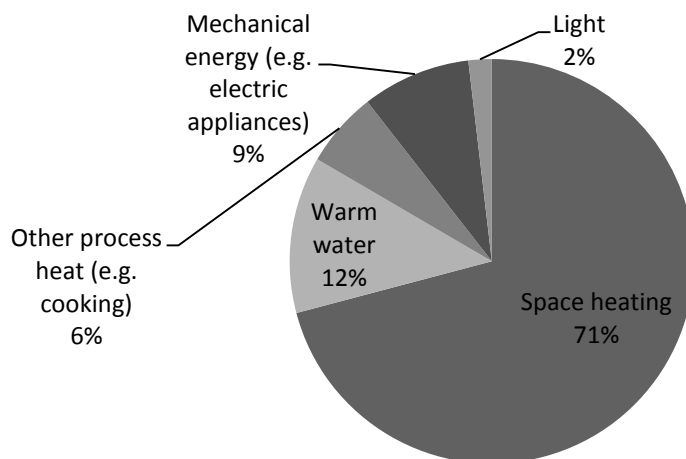
In the previous chapters, I have shown that including heterogeneity of firms is important and failing to do so may even result in erroneous conclusions. In Chapter 3, *The Impact of Carbon Trading on Industry: Evidence from German Manufacturing Firms* (Petrick and Wagner 2014),³ I, together with my co-author, exploit this heterogeneity to identify the causal effect of a

³ This paper is joint work with Ulrich Wagner, who came up with the original idea. The conceptual design of the analysis was done in discussions between both co-authors. I designed the underlying program code. Both co-authors contributed substantially to writing the paper. Subsection 6.2, “Technology upgrades and other emissions reducing measures” was completely designed, analyzed and written by Ulrich Wagner, apart from the brief introduction based on AFiD data.

central policy instrument of German and European climate and energy policy, the EU Emission Trading Scheme (EU ETS). The EU ETS is implemented as a classical cap-and-trade system for CO₂ emissions. Participating firms receive emission permits that are fully tradable across firms in all participating countries. Independently of international efforts to curb greenhouse gas emissions beyond the EU, the ETS is the centrepiece of the EU's unilateral climate policy, which stipulates a 20% reduction of GHG emissions in 2020 relative to 1990. The EU Emissions Trading Scheme (EU ETS) covers more than 2 billion tons of CO₂ in 31 countries, making it the most significant market-based instrument of climate policy implemented to date, the first trans-boundary cap-and-trade system, and the world's largest carbon pricing experiment per se. Although the EU ETS is a prime candidate for evaluating the effectiveness and economic consequences of cap-and-trade in the real world, causal evidence on these issues is still very scant, owing to the recency of the policy and a lack of suitable emissions data. While post-treatment data on participants in the scheme is recorded via the EU ETS's transaction database, the "Community Independent Transaction Log" (CITL), data on non-treated firms as well as pre-treatment data is scarce. Our dataset, as described in Chapter 1, fills this gap. By linking our dataset with the CITL, we are able to identify firms that participate in the EU ETS and compare them, both pre- and post-treatment, with their non-treated counterparts. Since treatment is not random, we need to resort to suitable econometric program evaluation procedures. We construct a pseudo-experimental control group by exploiting heterogeneity among firms and matching non-treated firms that are as similar as possible to the program participants. The matching takes place via a variety of standard semi-parametric and parametric propensity score matching techniques.

We find robust evidence that the EU ETS caused treated firms to abate one-fifth of their CO₂ emissions between 2007 and 2010 relative to non-treated firms. This reduction was achieved predominantly by improving energy efficiency, by curbing the consumption of natural gas and petroleum products, but not electricity use and by more efficient use of heat. Contrary to widespread concerns of policy makers and business lobbyists, we find no evidence that emission trading lowered employment, gross output or exports of treated firms. Our contribution supports calls for a reform of the EU ETS that is more stringent and strengthens the supra-national cap-and-trade system, potentially on the cost of less efficient national legislation, such as the German Renewable Energy Act (EEG).

Figure 2: Energy uses of German households (2011 data).



Source: Statistisches Bundesamt (2013).

While the energy use of firms, or, to be precise, manufacturing firms, was in the focus of previous parts of this dissertation, I turn to residential energy use in the final chapter, *The Impact of Temperature Changes on Residential*

Energy Consumption (Petrick et al. 2014).⁴ This chapter is aimed at quantifying key determinants of household energy use. The determinants of energy use in the household sector are structurally different from those of the manufacturing sector. While firms may be able to adjust crucial parts of their technology, such as electrical motors, with short or medium time horizon (as described in Chapter 2), space heating is the largely dominant source of household's energy use, at least in moderate or cold climate (see Figure 2 for the case of Germany).

Households' energy use is thus mainly determined by temperature and the heating technology, which is in turn determined by the heating fuel, or cooling if temperature is warmer. In order to analyze the effects of temperature and fuel choice on energy use of private households, we specify econometric models of coal, electricity, natural gas, and oil use with, among others, temperature as an explanatory variable. Since heating equipment is a long-term investment and, even if replacing private heating equipment is cost efficient, households are frequently faced with tighter financing opportunities compared to enterprises, we use a relatively long panel from the 1970s until 2002. Since the effect of temperature is the focus of our investigation, we rely on sufficient variation in temperature levels. This is one reason for using a global cross-country panel for our analysis, covering up to 176 countries (our key results are based on data on 62 countries, from 1978 to 2002). That way, we can also account for different income levels, which adds to the overall validity of our results. In order to reconcile the yearly frequency of our data with the need to depict differences in seasonal variation, we construct an innovative temperature measure, regionalized heating and cooling degree months. These measures allow us to take into

⁴ This paper is joint work with Katrin Rehdanz and Richard S.J. Tol, who came up with the original idea and the original dataset as well as supported me in developing the conceptual design of the analysis. I performed the analysis and wrote most of the paper. Final polishing was done by all three authors.

account both periods without any demand for heating or cooling as well as differences in temperature level between different climate zones in a fine regional (i.e. sub-country level) resolution.

Unsurprisingly, we find that warmer temperatures lead to a reduction in energy use. We find, however, that this effect is non-linear – the speed of the decrease also declines with rising temperature levels. We do not find a significant effect of temperature changes on the global demand of energy for cooling. Our findings are also a contribution to the discussion on the impacts of climate change. The climate change impact literature discusses changes in the level of energy consumption as one important consequence of global warming. Our results may be used as an input for relevant modelling efforts, e.g. in the framework of integrated assessment models, and thus add to a better understanding of climate change impacts.

All chapters together, I draw a number of conclusions relevant for decision makers and researchers in energy economics. I highlight the importance of firm heterogeneity for shaping industrial energy use in Chapters 1 and 2. While energy economists usually think in terms of sectors, concentrating on the most energy intensive ones such as the paper and pulp industry, the glass and cement industry, or metal manufacturing, the fruits in sectors outside these classical targets of energy policy may actually hang lower. Energy intensive outliers in usually “unsuspicious” sectors might be a target of effective and efficient energy policy. Concentrating on generating competitiveness advantages for energy efficient firms may be one policy lever that exploits intra-market heterogeneity in energy efficiency. As I show in Chapter 2, competition has in the past been a major driver of energy efficiency improvements. At the same time it uses decentralized organization, limiting the necessary depth of engagement of regulation. I hypothesize that this finding is transferable to other sectors, both

commercial and beyond. As a matter of fact, the EU ETS is such a policy instrument that sets the guidelines and targets in which firms self-organize in a decentralized way. Despite the general sentiment that the EU ETS has actually failed to deliver, given that the price for emission allowances has been low for most of the time, I argue that this is not due to a general failure of the policy instrument, but “merely” due to an under-ambitious setting of the political particulars of the regulation, namely the cap. As we show in Chapter 3 for the first years of the first commitment phase, when prices were comparably high, emission trading is actually effective, with manageable side effects on industrial activity, employment, and competitiveness. Climate change continues to force political interventions in the way energy is used, and even changes the way energy is used directly, as I show in Chapter 4. Energy policy makers will have to react to this force by developing stringent and efficient legislation that builds on economic agents’ ingenuity in responding to change.

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Statistisches Bundesamt (2013): *Tabellen zu den Umweltökonomischen Gesamtrechnungen*. Table 3.3.6.1.

Energy Use Patterns in German Industry: Evidence from Plant-level Data^{*}

Sebastian Petrick[†] Katrin Rehdanz[‡] Ulrich J. Wagner[§]

Abstract

This paper analyzes energy use and CO₂ emissions of more than 78 000 German industrial plants between 1995 and 2006. It is the first study to exploit exceptionally rich energy data that were recently matched to official micro datasets. We document that both energy use and intensity are highly dispersed across plants. When isolating the between-sector variation in energy intensity, there is a strong positive correlation with energy use, CO₂ emissions and emission intensity. Yet there is no evidence that the scale of an industry determines its energy intensity. The dispersion of energy use across plants of a given sector, normalized by the median, is positively correlated with that of gross output, but not with the median energy use. Similarly, there is no evidence that the median energy intensity is correlated with the within-sector dispersion of energy intensity or with that of CO₂ emissions. Looking at the fuel mix across sectors, we find that more energy intensive industries rely more on fuels other than electricity, although the variability among plants in those industries is extremely high. We also demonstrate that average fuel shares are sensitive to the skewness of the underlying distribution and recommend the use of median fuel shares for better representativeness.

^{*} This paper would not have been possible without the exceptional efforts of Alexander Vogel of the research data centre in Kiel who also ran the estimation code and performed the confidentiality checks. The staff of the research data center of the Statistical Offices of the Länder made the data provision possible. Special thanks go to Diane Zabel and to Michael Rößner of the research data centres in Bremen and Halle (Saale) who gave their expert input regarding the various AFiD datasets and modules, as well as to several members of the Federal Statistical Office for information and advice on various statistical products. The paper benefits from comments from two anonymous reviewers. Ulrich Wagner gratefully acknowledges financial support from the Spanish Ministry for Science and Innovation under grant SEJ2007-62908.

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1 Introduction

As the main engine of economic growth, the industry sector has traditionally been at the heart of economic analyses. Despite the transformation of modern economies into service economies, the industry sector remains one of the main pillars of income and employment in developed economies like Germany.¹ In 2006, the industry sector made up for 29 % of overall German gross value added and 30 % of jobs in Germany compared to OECD averages of 26% and 25 % respectively (World Bank 2009).

In recent years, the industry sector has received increasing attention from researchers in the fields of energy economics and climate policy due to its role as a major energy consumer and emitter of the main greenhouse gas carbon dioxide (CO₂). In 2006, the industry sector was responsible for 22 % of total final energy use and for 14 % of total CO₂ emissions in Germany. This compares to OECD averages of 23 % and 15 %, respectively. The respective world averages are 27 % and 20% (IEA 2008, 2009). Future regulation reducing these emissions could require industrial companies to increase their use of renewable energy and to limit their use of fossil fuels, or to adopt more energy efficient ways of production. Clearly, governments intending to implement such measures need detailed information on the patterns of industrial energy use in order to be able to assess the impacts of such measures.

This paper sheds new light on this issue using official microdata on energy use of more than 70 000 German industrial plants covering 97 different sectors between 1995 and 2006. Ours is the first study based on detailed energy data from an extended survey, which was only made available in 2009 by the Research Data Centres of the Federal Statistical Office and the

¹ Under industry, we subsume the manufacturing as well as mining and quarrying sectors (ISIC codes C and D).

statistical offices of the *Länder*. Previous studies on industrial energy use and emission patterns in Germany have been limited to analyses at the aggregate level. These studies are commonly based on the energy balances published by the Working Group on Energy Balances (AGEB 2009) and the environmental accounting datasets such as input-output tables or on the underlying primary statistics of the Statistical Offices (e.g. Statistisches Bundesamt 2009). Both data sources contain information on final energy use of two-digit (and sometimes also three-digit) industrial sectors. While being more aggregated, data from the energy balances provides particularly detailed information on the fuels used.

A number of research publications are based on these datasets, and so are most energy use models for Germany, including for example the PANTARHEI model covering 59 aggregated sectors (see e.g. Frohn et al. 2003, Frohn et al. 1998, GWS 2010, Lutz 2000, Lutz et al. 2005, Meyer 2001, Meyer/Ewerhart 1998, Meyer/Welfens 2001, Schleich et al. 2002) or the model system used by RWI and later EEFA consulting (see e.g. Buttermann/Hillebrand 2000, Frohn et al. 2003, Frohn et al. 1998, Hillebrand 1996, Hillebrand/Buttermann 2003, Hillebrand/Löbke 2008) which differentiates between 60 sectors. The data have also been used by industry associations such as BDEW (2009), Statistik der Kohlenwirtschaft e.V. (2009), VIK 2010, Wirtschaftsvereinigung Stahl (2009), to name just a few.

Depending on the research question, the use of aggregate data requires that an implicit assumption be made on the distribution of energy use across plants *within* a sector. For example, an energy intensity measure calculated as aggregate energy use divided by aggregate gross output is equivalent to the weighted mean of energy intensities across plants. This is a meaningful statistic provided that energy intensities are distributed symmetrically

around the mean. Conversely, if the distribution is skewed the median is more informative. Neglecting this type of heterogeneity in ex-ante assessments of energy and climate policies can give rise to misjudgements with costly consequences.

This paper takes heterogeneity of energy use and carbon emissions across plants seriously. Based on the new microdata, we document considerable heterogeneity in energy use, energy intensity, carbon emissions and in the fuel mix of plants even within sectors defined at the three-digit level. Furthermore, we explore the determinants of this heterogeneity both within and across sectors. In particular, we compute measures of dispersion for each of these variables at the sector level and examine whether they are correlated with each other or with sector medians. Deriving this evidence on the empirical distribution of plant-level energy use and carbon emissions is an important prerequisite for developing useful theoretical models as well as for conducting further empirical analyses.

The paper is structured as follows. The next section describes the dataset. Section 3 presents the main results on energy use, energy intensity, carbon emissions and on the fuel mix. Section 4 concludes.

2 Data description

2.1 The AFiD panel datasets

The AFiD panels² are microdatasets provided by the German research data centres. They comprise observations at the plant and enterprise level from various sectors, including industry. For this paper, we use the AFiD panel “industrial plants” (FDZ 2010a) in combination with a module on energy use (FDZ 2010b). The former comprises the principal measures of economic

² AFiD: “Amtliche Firmendaten für Deutschland“, English: “Official Firm Data for Germany“.

activity such as gross output, workforce, payroll, export share, and others. The latter contains data on plant-level energy use. The matching of the AFiD panel “industrial plants” to the energy demand module was done by staff at the research data centres. The resulting dataset contains annual observations for up to 68 000 plants per year from 1995 to 2008. Since the energy module is not yet available for 2007 and 2008 the analysis in this paper is based on data for the years from 1995 until 2006. The dataset covers more than 78 000 individual plants of which 28 000 are reported in each of the 12 years.

An important feature of the data at hand is that it is based on a mandatory survey that each industrial plant with more than 20 employees is required to answer. Therefore, a lack of representativeness is not a concern for this dataset.³ By virtue of its size and representativeness, the dataset in principle lends itself to detailed analyses even of small sectors or small geographical units. In practice, what limits such analyses is the legal requirement to preserve the confidentiality of data on individual plants. For this reason, all research output has to be approved by staff at the research data centre before it is published. Details on the different modes of data access can be found in Konold (2007) or Malchin and Voshage (2009).

2.2 Production data

The economic activity variables in our dataset stem from the AFiD panel “industrial plants”, which comprises data from four individual official surveys: the annual results of the “monthly report on manufacturing, mining and quarrying plants”, the annual results of the “quarterly production survey for manufacturing plants”, the “annual investment survey for

³ We drop observations with a total yearly turnover below 10 000 Euro and those with missing information on electricity consumption. In total, 33 761 out of 596 793 observations were dropped over all years (5.7 %). In the last year (2006), 3 586 out of 47 666 observations were dropped (7.5 %).

manufacturing, mining and quarrying plants” and the “annual report on small industrial plants” (only until 2002).⁴ These data have been described in great detail elsewhere, see for example Konold (2007), Malchin and Voshage (2009) and Wagner (2000, 2010a).

Plant-level data from these sources have been used in a number of studies on topics such as international trade (e.g. Fryges/Wagner 2010, ISGEP 2008, Wagner 2009a or Wagner 2007a), firm performance (e.g. Mangelsdorf 2007, Wagner 2010b) or employment dynamics (e.g. Wagner 2007b). Other studies have analyzed different topics at the enterprise level, i.e. after aggregating the different plants of each enterprise (e.g. Girma et al. 2009, Görzig/Pohl 2007, Görzig et al. 2005, Wagner 2009b). In contrast, prior to the creation of the research data centres, empirical studies were usually conducted at the regional level, i.e. for plants within a single German *Bundesland* (for an overview, see Wagner 2006).

A comprehensive list of all available variables in the “industrial plants” panel can be found in FDZ (2010c, only in German). In our analysis we use information on gross annual turnover (gross output), number of employees and payroll data from the “monthly report on manufacturing, mining and quarrying plants” and the annual results of the “quarterly production survey for manufacturing plants”. Since these variables have already been used extensively in previous work, we abstain from describing them in detail here. The main focus of this paper is on the patterns of energy use across plants.

⁴ German titles are as follows: “Monatsbericht für Betriebe des Verarbeitenden Gewerbes sowie des Bergbaus und der Gewinnung von Steinen und Erden”, “Vierteljährlichen Produktionserhebung im Verarbeitenden Gewerbe“, “Investitionserhebung bei Betrieben des Verarbeitenden Gewerbes sowie des Bergbaus und der Gewinnung von Steinen und Erden“ and “Industrielle Kleinbetriebserhebung“.

2.3 Energy data

In contrast to the production data in the panel, the energy demand module has not been analyzed before. This module is based on data collected as part of the “monthly report on manufacturing, mining and quarrying plants” until 2002. Since 2003 energy data are gathered through a stand-alone “survey on energy use of manufacturing, mining and quarrying plants”. The expanded questionnaire includes a larger variety of fuels and also additional fuels and thus provides a much more detailed picture of energy use at the plant level since 2003 compared to the data until 2002. For example, the consumption of non-standard oil, gas and coal products was removed from the aggregate fuel use after 2003 and put into own categories. Newly added fuels include heat and renewable energy sources. On the downside, the switch in reporting requirements is also partly responsible for a structural break in the data between 2002 and 2003. Apart from the change in surveys, the industry classification scheme changed as well during this period which resulted in a number of plants being dropped from the survey.

Throughout the entire period, the energy use module contains annual information at the plant level on both inventories and usage of different types of oil, gas, coal and other fuels, as well as on on-site generation of electricity vs. purchases from other sources, and electricity usage. A complete list of the variables available as well as those used in our analysis can be found in Table A 1 in the appendix.

Since detailed data on energy use are available, we are able to calculate a plant's CO₂-emissions from energy use very precisely using emission coefficients for the different fuel types. For electricity, district heating, hard coal, lignite, lignite briquets and other coal products we use average emission coefficients for Germany (Umweltbundesamt 2010). All emission

factors used for the conversion of energy into CO₂-emissions are listed in Table A 2 in the appendix.

3 Results

3.1 Aggregate Energy Use and Energy Intensity of the Industry Sector as a Whole

Figure 1 shows that energy use increased considerably between 1995 and 2006. According to official statistics, total final energy use increased by 97 TWh (10 %), starting from 968 TWh in 1995. While energy use declined smoothly during the late 1990s and levelled off by 2002, the graph also shows a sharp increase between 2003 and 2006. Plants that do not report electricity consumption and plants with an extremely low annual turnover below 10 000 EUR are considered as reporting implausibly and are dropped from the panel (cf. footnote 3). After cleansing the data in this way, total final energy use reported by all plants in our panel increased by 80.2 TWh (9.2 %), starting from 870 TWh in 1995.⁵ About one quarter of the change, 21 TWh, occurred between 2002 and 2003. In the original data before data cleansing, 64 % of the change, 62 TWh, occurred between 2002 and 2003. Unfortunately, it is hard to distinguish precisely how much of these large one-year changes is an artifact of the aforementioned modifications to the statistical reporting and how much of it corresponds to a real change in energy usage.

~ Figure 1 about here ~

Turning to the distribution of energy use among different industrial plants, the median energy use follows a similar pattern. The median plant used

⁵ The difference between the official statistics and the data we are using is mainly due to the data cleansing process, but also due to the fact that, in contrast to our approach, the official statistics include non-energetic use of several fuels. Non-energetic use is reported from 2003 onwards.

92 MWh less in 2002 compared to 1995 (starting from 717 MWh), but 72 MWh more in 2006 compared to 2003 (2003: 904 MWh). Compared to the median plant it is interesting to note that in every single year the average plant used more than 20 times more energy, exceeding the 90th percentile (see Figure 2). Unlike the information provided by published statistics, these numbers demonstrate that significant differences in energy use within the industry sector exist, which call for further investigation.

Figure 2 illustrates this fact in more detail. The distance between the 10th percentile and the median is much smaller than the distance between the median and the 90th percentile. This implies that the distribution of energy use across plants is extremely right skewed, and becomes even more so following the inclusion of additional fuels in 2003.

~ Figure 2 about here ~

Since we have combined data on energy use with production data we are able to analyze the distribution of energy intensity, i.e. of the ratio between energy input and monetary or physical output. We follow the approach used in official statistics based on the same data (e.g. Statistisches Bundesamt 2009, 2010a) and calculate energy intensity as the ratio between energy input (in kWh) and gross output (in 1 000 €). This variable is interesting because it can be interpreted as the inverse of a simple energy efficiency measure. It is also more informative on structural changes in the economy than total energy use which is sensitive to macro-economic fluctuations.

While total energy use remained constant or increased over time, energy intensity declined almost monotonically, except for an early peak in 1996 and the switch of statistics between 2002 and 2003 (Figure 3). The median industrial plant in Germany used 18 kWh less per 1 000 EUR in 2002

compared to 1995 (at current prices).⁶ Between 2003 and 2006, a saving of similar magnitude occurred mainly caused by a considerable drop in intensity levels in 2006.

Again, the spread in distribution is large. The 90th percentile is around five times higher than the median. The general trend of a decline in energy intensity can be observed for all plants. However, plants in the upper tail of the distribution decreased their energy intensity by much more than those in the lower tail. At the 10th percentile, energy intensity, on average, decreased by 0.7 and 1.3 kWh/1 000 EUR per year for the periods 1995-2002 and 2003-2006, respectively, while at the 90th percentile energy intensity decreased on average by 21 and 29.1 kWh/1 000 EUR per year for the periods 1995-2002 and 2003-2006, respectively.

It is noteworthy that after 2003 mean energy intensity peaks twice, in 2004 and 2006, exceeding the 90th percentile. These two sharp increases are caused by one-time events in single sectors. The increase in 2004 is caused by an extraordinary drop in average gross output in a few plants of the mining sector (100) while the increase in 2006 is due to an exceptional boost in consumption of heavy fuel oil in a few plants of the cement articles industry (266). This, again, demonstrates the limited usefulness of arithmetic means due to its vulnerability towards the occurrence of outliers, even in single plants.

~ *Figure 3 about here* ~

⁶ Under inflation, the use of gross output in current prices instead of deflated gross output implies that decreases in energy intensity are overrated. Applying a common price deflator does not solve this problem because differences in the development of prices between sectors and even products have been large during the observation period (cf. Statistisches Bundesamt 2010c). Constructing sector or even plant specific deflators is beyond the scope of this study and will be a topic for future research. Since the main focus of this paper is on the 2006 cross section, we refrain from deflating gross output altogether. Doing so is inconsequential for the cross-sectional results but may cause bias in the results obtained for the longitudinal dimension.

The reader should bear in mind that defining energy intensity as the ratio of energy use and gross output is not neutral with respect to changes along the value chain. While energy input takes into account only the particular step in the value chain, the output measure takes into account output from all preceding steps. For example, in industries with low or decreasing depth of added value, this implies that our measure of energy intensity is too low or too rapidly decreasing, respectively. A common solution to this problem is to divide energy use by value added. Unfortunately, we cannot calculate value added at the plant level for lack of information on intermediate inputs.⁷ Alternative measures like the ratio of energy use to employees are very sensitive to changes in labour productivity over the observation period (Statistisches Bundesamt 2010d), and hence would not allow us to disentangle the underlying trends in energy intensity.

Conceptually, the dispersion in energy use across plants and over time illustrated by the above figures can be decomposed into variation between and within sectors. The next section aims at disentangling the dispersion in energy use generated by differences between less and more energy intensive sectors from the dispersion arising from differences across plants even within more narrowly defined sectors.

3.2 Energy Intensity and Energy Use of Selected Sectors

Figure 4 shows the ten sectors whose plants had the highest median energy intensity in German industry in 2006, the most recent year in our dataset.⁸ At the top of the list are the sectors of the ceramics and cement industry (i.e.

⁷ Firm-level data on cost structures are available for a large sample of companies (FDZ 2010d). In future research, energy use over value added could be calculated after aggregating plant-level energy data to the company level and matching the aggregated dataset to the cost structure data.

⁸ A similar figure for the five sectors with the lowest median energy intensity can be found in the appendix (Figure A 1).

WZ code 265: manufacture of cement, lime and plaster; 264: manufacture of bricks, tiles and construction products, in baked clay and 263: manufacture of ceramic tiles and flags).⁹ Lime, plaster and cement manufacturers (265) use on average more than 9 MWh to generate 1 000 EUR of gross output. Other energy intensive industries are the pulp and paper industry (211), the chemical industry (247: manufacture of man-made fibres) and the metal casters (275). Textile manufacturing is among the top ten as well. Some sectors that are – on the basis of aggregate statistics – usually classified as energy intensive are missing from our list, such as coke ovens and refineries (230), some chemical industry sectors (240 ff.) and the metal manufacturing industry (270 ff.). One reason for this is that their gross output is often disproportionately higher than their gross value added, which is known from published statistics on the sectoral level (cf. Statistisches Bundesamt 2010e). Hence, our ranking is most accurate when the share of intermediate inputs in an industry's gross output is not too high.¹⁰

~ *Figure 4 about here* ~

In what follows, we characterize the joint distributions of energy intensity and other variables by examining (i) the correlation between the median of different variables across sectors, and (ii) the correlation between the median and the dispersion of a variable across sectors. Our goal is to derive a set of stylized facts that can serve as a reference for the development of theoretical models that explain the heterogeneity across plants, and to set the stage for further empirical research, especially a multivariate analysis of these relationships.

⁹ WZ codes are the German derivative of the NACE classification scheme. A complete list of sector codes and descriptions can be found in Table A 3 in the appendix.

¹⁰ Information on average energy use and production features of the individual sectors can be found in Table A 4.

We start by investigating how the median energy intensity correlates with the median of other key energy and production variables across sectors. The focus on the median allows us to isolate the drivers of *between*-sector heterogeneity in energy use patterns, and to abstract from heterogeneity *within* sectors. Figure 5 shows simple bivariate correlations for these variables. As expected, energy and carbon intensities are highly correlated, although there are subtle differences at the plant level due to a changing energy mix, as will be explained below. The positive correlation between energy intensity, total energy use and total CO₂ emissions is intuitive, especially since we use gross output where monetary costs of energy are included, contrary to a value added term. At the same time, however, energy intensity is not correlated with gross output itself or with any of the other production variables proxying for plant size (workforce and payroll). This appears to refute the notion that some sectors are more energy intensive than others because they operate at a different scale.

To characterize the energy mix we use the share of electricity in total energy use as an indicator. Energy intensity and electricity share are negatively correlated, meaning that energy intensive sectors in particular rely more on primary energy sources like natural gas, petroleum products or coal. Prominent examples are the iron and steel industry (270), which has an aggregated coal share of about 60 %, the coke, petroleum products and nuclear fuel industry (230), which has a share of oil products of 74 % or the glass industry (261) which has a natural gas share of 69 %.

Most of the above results could have been derived from published aggregate statistics at the two-digit level. However, such statistics fail to characterize the heterogeneity of energy use within sectors. In the next paragraphs, we describe this heterogeneity and demonstrate the implications for the assessment of sectoral energy use, emissions and intensities by analysing

parallels between heterogeneity and the corresponding medians. Figure 4 visualizes this heterogeneity by displaying the range between the top and bottom quartiles (hatched bars) and deciles (grey bars) of the distribution of energy intensity across plants within a sector. The large bandwidth of some sectors demonstrates that aggregate statistics reporting the mean or median of a sector in many cases mask a great deal of heterogeneity across plants of that sector. An additional problem is that results on the basis of sector aggregates are vulnerable to outliers, even more so if the total number of plants is small. Outliers matter because they cause large differences between arithmetic mean and median. In some cases the mean is more than ten times the size of the median. For example, in the textiles sectors in Figure 4 (173 and 171) the mean is about four and twelve times the size of the median, respectively. The number of companies included in that sector is 113 and 57, respectively.

~ Figure 5 about here ~

In order to compare the within-sector dispersion of a given variable across different sectors, we normalize the interquartile range by the median.¹¹ Figure 6 plots the interquartile-range-to-median-ratio of several key variables for the ten most and five least energy intensive sectors. At first glance, there are no eye-catching patterns of correlation between the variation in energy intensity and the variation in energy use or other production variables. Sectors whose plants vary with respect to energy intensity do not necessarily vary with respect to total energy use (or, in other words, size) and vice versa. Examples are the sectors 263, 264 and 268, which differ a lot with respect to variation in energy intensity, but not much with respect to variation in energy use. Comparing the pulp and paper

¹¹ We normalize the interquartile range or the range between the 10th and 90th percentile by the median to obtain a variation measure that is comparable across different distributions with different means, similarly to the variation coefficient. Since the distributions of the variables at hand are usually highly skewed, the variation coefficient is not appropriate.

industry (211) and the mineral industry sectors 265 and 268, their degree of heterogeneity in energy intensity is similar, but not so for energy use.

Furthermore, the level of heterogeneity in variables that proxy for the size of a plant such as gross output or workforce is not a perfect predictor of the heterogeneity in energy use. Although the correlation coefficient between the heterogeneity of energy use and the heterogeneity of gross output reaches 0.79 for all sectors, there are a number of sectors that exhibit a lot of dispersion in energy use but much less in terms of gross output. Examples are the cement industry (265), the pulp and paper industry (211), the man-made fibres manufacturers but also manufacture of transmitters and telephones (322). In most of these cases – and especially when energy intensity is high – energy intensity is also quite heterogeneous. The correlation between the heterogeneity of energy use and of the workforce is much lower with a correlation coefficient of only 0.34. Even if the plants within a sector are relatively homogeneous with respect to gross output or workforce, they are not necessarily homogeneous with respect to energy use.

~ Figure 6 about here ~

In general, it is not the case that sectors with particularly energy intensive plants are also especially diverse in their plants' energy intensity. None of the sectors that were identified above as being the most dispersed (in terms of the ratio between the top-to-bottom-decile range and the median) are among the top ten sectors with the highest median energy intensities (Figure 7). A correlation between median energy intensity and variation of energy intensity of a sector, if at all present, is negative: Three of the five sectors with the smallest variation (264, 275 and 263) are among the top ten sectors with the highest median energy intensities. This negative correlation turns out to be even weaker when the actual correlation is used instead of the rank

correlation. While Spearman's rank correlation coefficient is -0.18, Pearson's correlation coefficient is only -0.06.

~ Figure 7 about here ~

Looking at energy use instead of energy intensity, we find that most of the energy intensive sectors are also large energy users. Figure 8 presents the ten sectors whose plants have the highest median total energy consumption,¹² including manufacture of basic chemicals, pesticides and other agro-chemical products (240), manufacture of dairy products (155), manufacture of motor vehicles (341) and manufacture of coke oven products, refined petroleum products and nuclear fuel (230). Most of these industries exhibit substantial heterogeneity in energy use, and several of them have been traditionally regarded as energy intensive, such as mineral products (263-265), pulp and paper (211), chemicals (240; 247) or metal manufacturing (274).

~ Figure 8 about here ~

This raises the question whether there is an empirical link between a sector's median energy use and how dispersed the distribution of energy use is among its plants. Figure 7 shows the top ten and bottom five sectors in terms of the dispersion of energy intensity. Among the top ten we identify three sectors that also made the top ten for energy use (Figure 9), namely manufacture of coke, refined petroleum products and fossil fuel (230), manufacture of motor vehicles (341) and manufacture of basic chemicals, pesticides and other agro-chemical products (240). However, there are two sectors from the top ten energy users among the five most homogeneous energy users (the ceramic and cement sectors 264 and 263). Hence there

¹² A similar figure for the five sectors with the lowest median total energy use can be found in the appendix (cf. Figure A 3).

does not appear to be a clear relationship between the level of energy use in a sector and the degree of heterogeneity of energy use amongst plants in that sector.

~ Figure 9 about here ~

3.3 Energy Mix

It stands to reason that not all fuel types are equally important for the running of a business. All plants in our dataset use electricity¹³ (44 080 plants in 2006) next to natural gas, followed by oil products. Less common fuels are heat, renewables, coal and other fuels, including waste (Figure 10). Regarding the amount of energy used from those sources, gas and coal are most important. In terms of aggregate use, gas is even slightly more important than electricity. Aggregate coal use almost equals the use of petroleum products, although only 378 plants actually use coal, compared to 18 786 plants using oil. The exact number of users and the aggregate use of the different fuels are reported in Table A 7 in the appendix.

~ Figure 10 about here ~

The transformation towards a cleaner fuel mix is an essential ingredient of a solution to the climate change issue, and a prerequisite for a sustainable future energy system. In the medium and long term climate and energy policies aim at fostering the substitution of natural gas and renewable energy sources for petroleum products and coal. Our data provides information on which sectors are especially reliant on coal and oil products and which sectors have an especially high share of natural gas and renewables in their energy mix. Oil and coal reliant sectors are supposed to

¹³ This is by construction because we drop plants that report zero electricity use, as described in footnote 3.

suffer most from the aforementioned transformation while gas and renewables reliant sectors are better prepared to face the challenge.

Table 1 presents examples of both sectors with highly concentrated fuel mixes and sectors with very balanced ones (top ten and bottom five). Overall, the numbers confirm our earlier result (cf. Figure 5) that sectors with high median energy intensities consume less electricity and more gas, oil or coal. In general, the reverse is also true, i.e. less energy intensive sectors use more electricity, although there are a few sectors among the top electricity consumers that have an above-average energy intensity, such as manufacture of plastic products (252) or manufacture of accumulators, primary cells and primary batteries (314).

The low electricity share of energy intensive sectors is due to high shares of gas and oil use, even though some other sectors also use these fuels, usually sectors with low overall energy use and a small number of plants. Heat, coal and other fuels (including mainly waste) are more rare. Not many sectors use them and for those that do, use is often closely linked to production technology, which is reflected in the shares. Consider the manufacture of man-made fibres (247) as an example for heat and metal manufacturers (e.g. 270, 275) or mining (100) as an example for coal. The emergence of manufacture of musical instruments as the sector with the highest share of coal consumption is due to one important outlier that dominates the small number of other observations in that sector.

Renewable energy sources are a special case. In 2006, only 973 plants used renewables. They only play a major role in the wood manufacturing sectors (201-205), in furniture manufacturing (361) and in the recycling industry (non-metal recycling, 372). All these sectors have a share of renewables above 20 %, in some of the wood manufacturing sectors (203, 204) the

share exceeds 70 %. Common to these sectors is that they can use biogenic by-products of production as energy sources.¹⁴

~ *Table 1* about here

In the remainder of this section, we analyze the variability in the use of different fuel types within sectors. The analysis is restricted to electricity and natural gas as the two most important fuel types. Figure 11 shows the ten sectors with the highest median electricity share. The list of sectors is different from the list in Table 1 – only three sectors (252, 321 and 372) are on both lists. One reason for this discrepancy is that Table 1 is based on the aggregate electricity share of a sector which is vulnerable to outliers, whereas the median share provides for a more representative assessment given the skewness of the underlying distribution apparent in Figure 11. Moreover, all of the sectors in Figure 11 exhibit considerable heterogeneity. There are many plants that report a 100 % electricity share whereas the electricity share in plants belonging to the bottom decile is often less than 20 %, as is the case with quarrying of sand and clay (142), sawmilling and planing of wood; impregnation of wood (201) or recycling of metal waste and scrap (371).

When looking at the five sectors with the smallest median electricity shares, there is less heterogeneity (Figure 12). Only one of the bottom five sectors, manufacture of cement, lime and plaster, is as heterogeneous as the top ten sectors. This might in part explain why the correspondence between the lists in Table 1 and Figure 12 is higher for the bottom five than for the top ten.

~ *Figure 11* about here ~

~ *Figure 12* about here ~

¹⁴ The share of renewables in the electricity mix is not covered by our data as long as the plant does not have their own renewable electricity plant.

Compared to electricity shares, heterogeneity is even higher in the case of natural gas shares in the ten sectors with the highest gas shares (Figure 13).¹⁵ In practically each of the sectors a considerable number of plants do not use natural gas at all, despite the high median gas share. At the same time, in almost all top ten sectors the 90th percentile exceeds a share of 80 %. In two cases, baked clay (264) and manufacture of ceramic tiles and flags (263), almost half of the plants use more than 90 % natural gas in their energy mix. The correspondence between the aggregated and the median perspective (cf. also Table 1) is slightly higher.

In sum, the evidence shows that intra-sectoral variation is especially high for variables characterizing the fuel mix at the plant level, and that this heterogeneity causes the mean (which aggregates fuel use across all firms) and the median (which does not require aggregation of fuel use) to diverge substantially in many sectors. Thus, statistical data on the energy mix which are based on aggregation across plants should be interpreted with caution.

Heterogeneity in the fuel mix across plants within a sector can arise for several reasons. First, the product mix may vary across plants. Second, fuels may be easily substitutable without major changes of the production process. For example, if large amounts of process heat are required in the production process, the plant can choose between a range of fuels to generate it – in fact, heterogeneity could even arise within a single plant. Third, fuels may be substitutable in the long run if there are alternative technologies for producing the same final product, and if these technologies employ different fuels. Once the plant is set up, the fuel cannot be changed, but different plants in a given sector may choose different technologies. An example for this is steel production, which uses either coke in basic oxygen furnaces or electricity in electric arc furnaces.

¹⁵ We do not show the bottom five sectors with respect to the natural gas share in energy mix since the majority of plants in those sectors does not use gas at all.

~ Figure 13 about here ~

3.4 Emissions

The increasing awareness of global warming has led policymakers and scientists to focus on greenhouse gas emissions, in particular CO₂ emissions. In order to solve a long-term problem like climate change, it is of critical importance to reduce the carbon intensity of industrial output. This motivates our interest in CO₂ emissions. We calculate total emissions as described in section 2.3 above and measure carbon intensity as the ratio of CO₂ emissions to gross output.¹⁶ Figure 14 shows the ten sectors with the highest median carbon intensity and the corresponding variation.¹⁷ The ranking given in this figure is roughly the same as in the one given for energy intensity in Figure 4.

~ Figure 14 about here ~

While the absolute levels of the different percentiles of carbon and energy intensities are not directly comparable, Figure 15 demonstrates that the variation of carbon intensity moves in lockstep with the variation of energy intensity (cf. Figure 7 for relative variation of energy intensity). However, variation in carbon intensity tends to be lower than variation in energy intensity for the most energy intensive sectors and in particular for mining and quarrying of energy producing materials and ores (100) as well as for manufacture of glass and glass products (261). The reason for this is the dominance of a particular fuel type in these sectors. For instance, the mining sector relies heavily on coal, the coke, petroleum products and nuclear fuels sector relies heavily on oil and the glass sector relies heavily on natural gas, as has been shown Section 3.3. The importance of a single fuel type for the

¹⁶ Naturally, the same caveats regarding the construction of carbon intensity on the basis of gross outputs as in the case of energy intensity apply.

¹⁷ A similar figure for the five sectors with the lowest median carbon intensity can be found in the appendix (cf. Figure A 4).

production process entails a more homogeneous fuel mix within these sectors. Some of the variation in energy intensity appears to be attenuated by this effect and does not carry through to carbon intensity.

~ Figure 15 about here ~

4 Conclusions

In this paper we draw on different sources of official microdata to analyze the patterns of energy use and carbon dioxide emissions at more than 78 000 plants in the German mining, quarrying and manufacturing sectors. In particular, we combine data on production and energy use from the AFiD panels and energy modules for the years from 1995 until 2006. The energy data for the later years are based on an extended questionnaire that has been used since 2003 and allow us to characterize energy use and carbon emissions at a level of detail heretofore unfeasible.

Our analysis sheds new light on the role of heterogeneity in energy usage both across sectors and across plants within more narrowly defined sectors. We find that the increasing trend in energy use over the sample period was driven mainly by the large energy consumers in the upper tail of a right-skewed distribution. In contrast, energy intensity declined over the sample period and this decline was more pronounced in the most energy intensive plants.

We examine energy use patterns in a cross-section of plants at the end of our sample period and document that both energy use and intensity are highly dispersed. When isolating the between-sector variation in energy intensity, we find a strong positive correlation with energy use, CO₂ emissions and emissions intensity, yet there is no evidence that the scale of an industry determines its energy intensity. Further, we investigate the

dispersion within plants of a given sector, measured as the ratio of the range between the top and bottom quartiles to the median. There is a positive correlation between the dispersion of energy use and that of gross output, but not with the median energy use. Similarly, there is no evidence that, looking across sectors, the median energy intensity is correlated with the dispersion of energy intensity or with that of CO₂ emissions within a sector. Finally, we examine the fuel mix across sectors and found a negative correlation between a sector's energy intensity and the electricity share. More energy intensive industries tend to rely more on fuels other than electricity, although the variability among plants in those industries is extremely high. We document the sensitivity of average fuel shares (i.e. the ratio of aggregate electricity to aggregate total energy use) with respect to the skewness of the underlying distribution and recommend the use of median fuel shares for better representativeness.

In sum, this paper presents a first set of empirical facts on energy use patterns in German industrial plants based on an exceptionally detailed dataset. The bottom line emerging from these results is that the heterogeneity of energy use and carbon emissions both within and across sectors is poorly understood so far and deserves further attention. One line of future work on this topic would be to conduct empirical research on the determinants of the within-sector heterogeneity of energy and carbon intensities as well as the structure of the energy mix. This kind of work should also pay attention to how and why these distributions change over time and how these changes are related to intra-industrial structural change, e.g. by decomposition analysis or similar exercises. Finally, the stylized facts coming out of such empirical efforts might motivate research into theoretical models of the distribution of energy use, carbon emissions and the associated intensities in the cross section and over time, which could subsequently be subjected to empirical testing.

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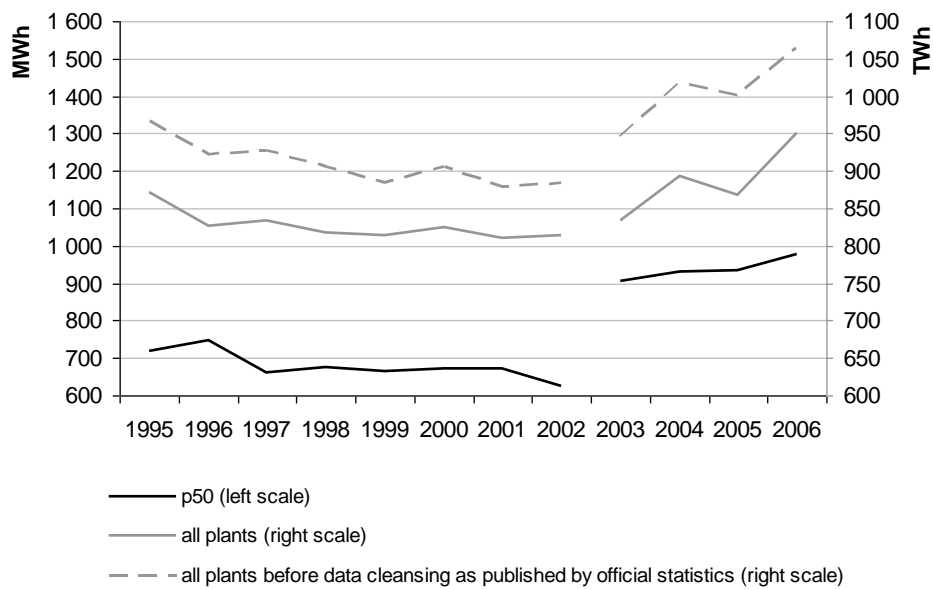
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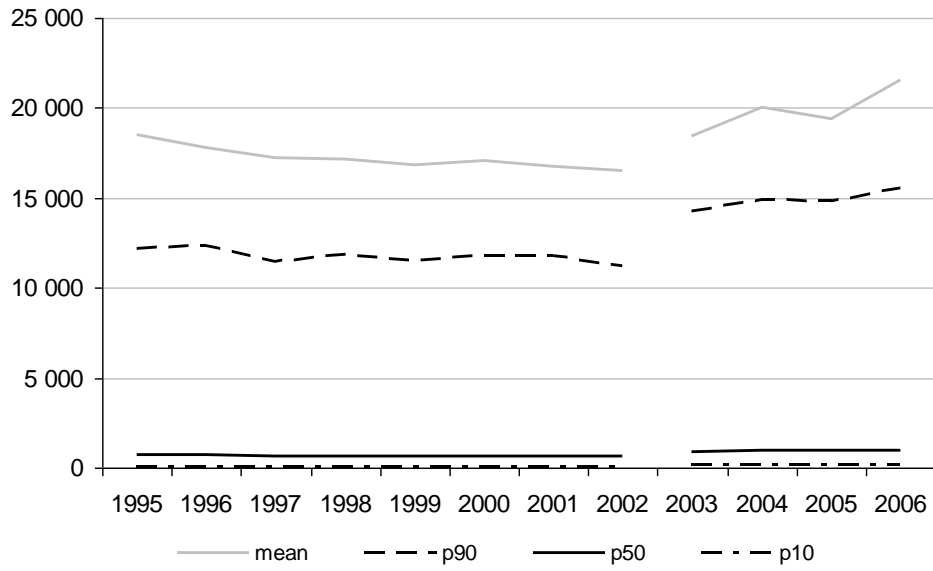
Tables and Figures

Figure 1: Aggregate energy use of the whole industry sector and the median plant.



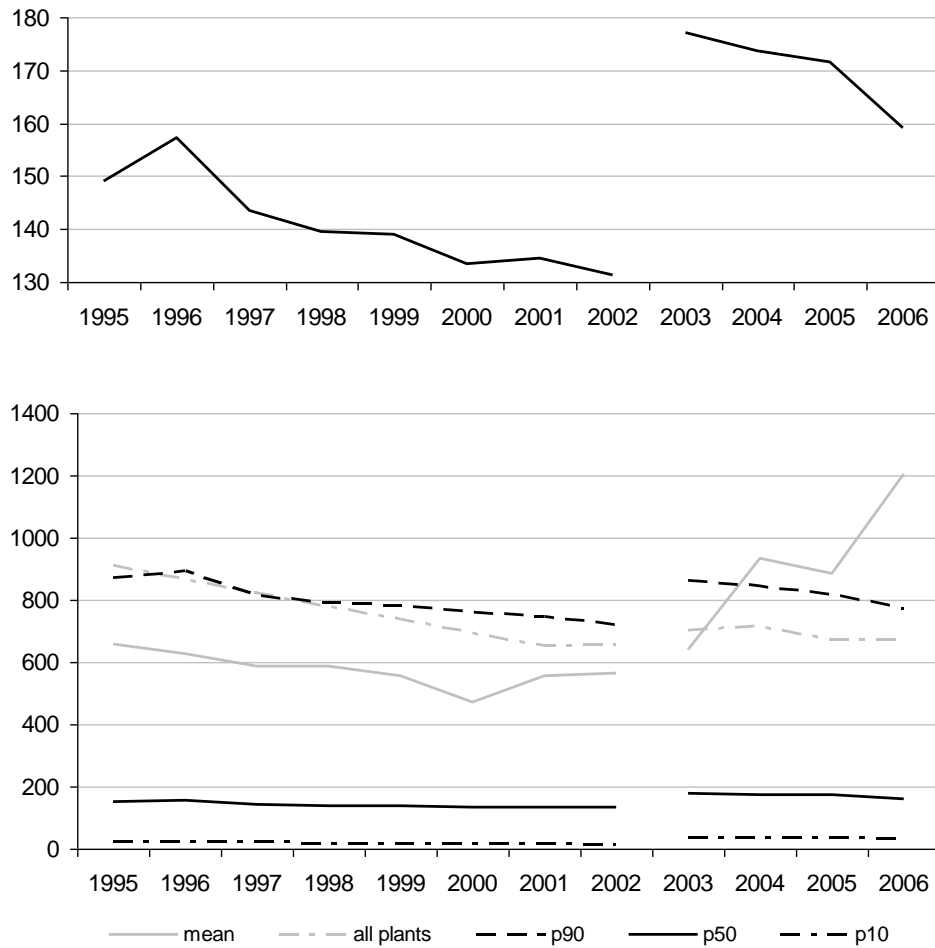
Own calculations. "All plants as published by official statistics": Statistisches Bundesamt (2002, 2010a).

Figure 2: Mean, median and dispersion of total energy use by industrial plants between 1995 and 2006 (in MWh).



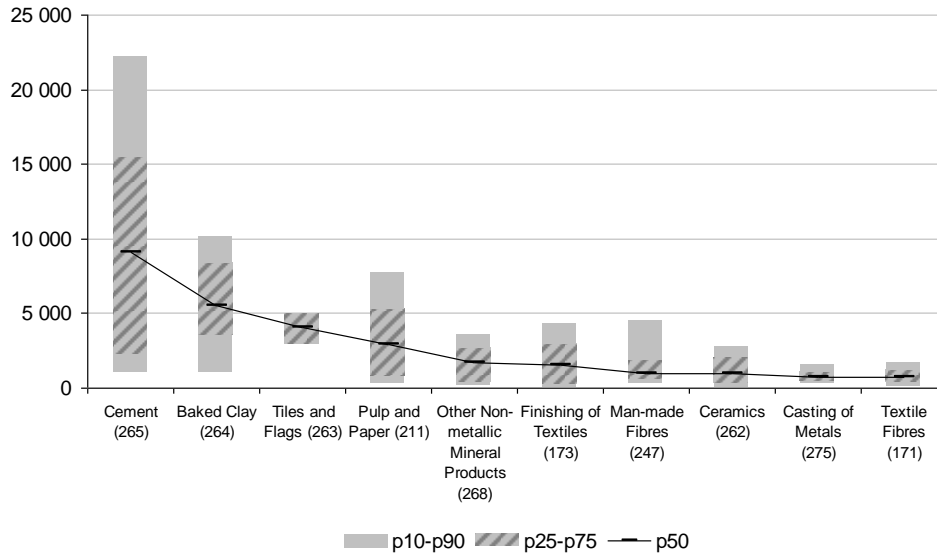
Own calculations.

Figure 3: Aggregate energy intensity of all plants across sectors (mean, median, top and bottom percentiles, in kWh/1000 EUR).



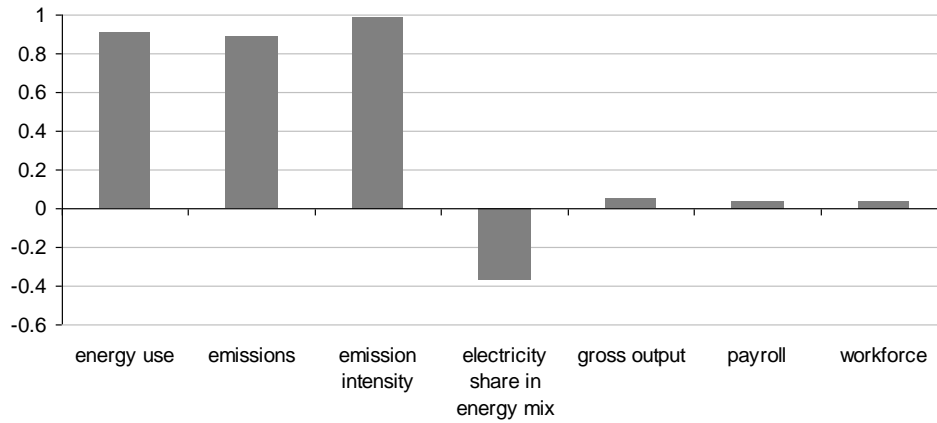
Own calculations. The upper part of the figure matches the p50 series of the lower part on a more detailed scale. The series “all plants” is taken from published official statistics (own calculations based on Statistisches Bundesamt 2002, 2010a, b) and not from our microdataset because calculations using the microdataset could not be done for 1995 and 2001 to ensure confidentiality.

Figure 4: The ten sectors with the highest median energy intensity in 2006 (in kWh/1000 EUR).



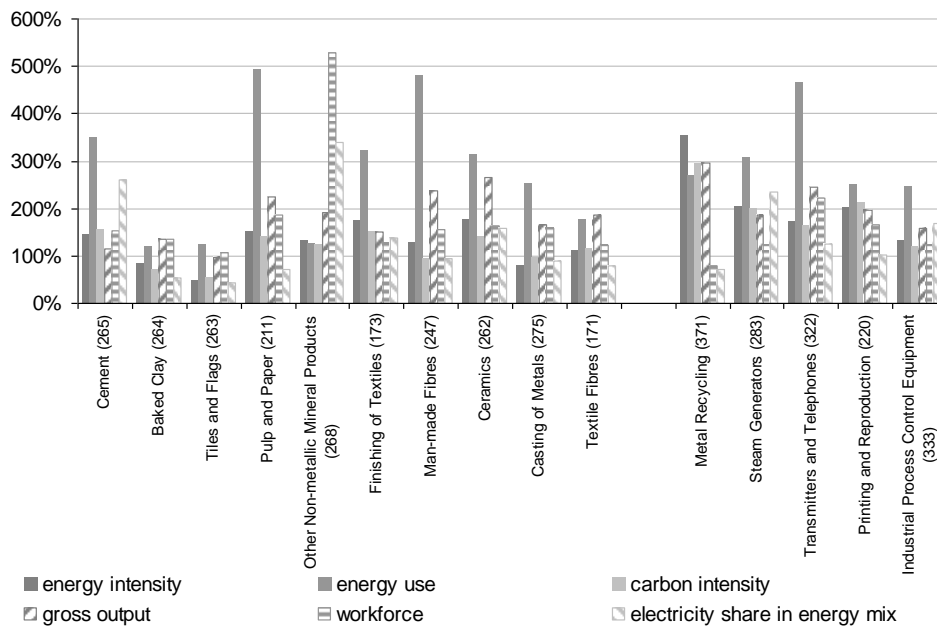
Own calculations. Note that for “Tiles and Flags” (263) the values for p10 and p90 are not shown to ensure confidentiality of data. For more information regarding gross output, workforce and payroll see Table A 4 in the appendix. For more information on energy intensity for the median of all sectors see Table A 5 in the appendix.

Figure 5: Coefficients of correlation between median energy intensity and different energy and production variables in 2006 (across sectors) .



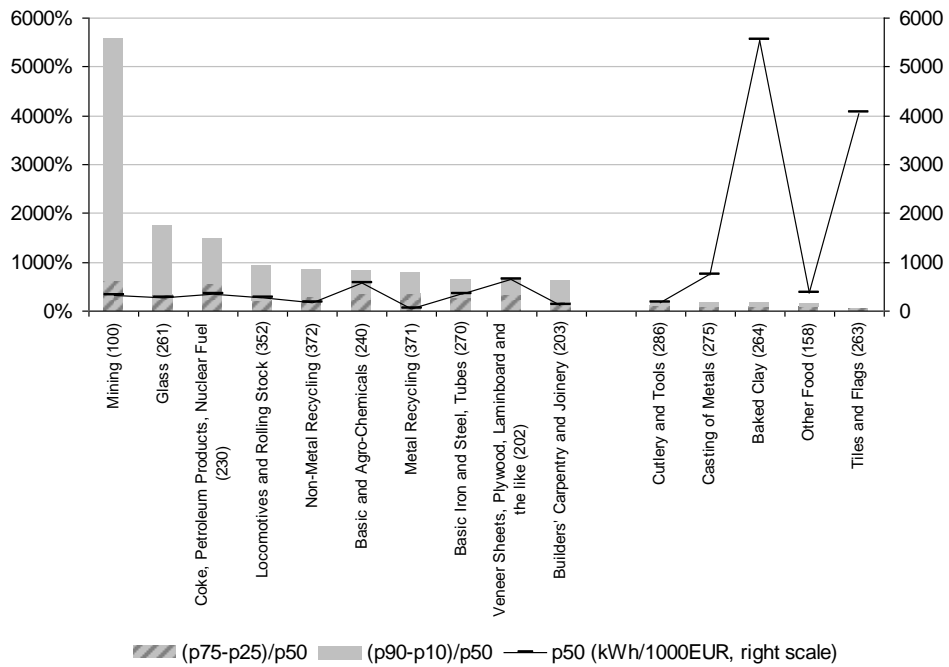
Own calculations. Several correlation coefficients can be found in Table A 6 in the appendix.

Figure 6: Variation (interquartile range-median-ratio) of several key variables for the ten most and five least energy intensive sectors (relative to median) in 2006.



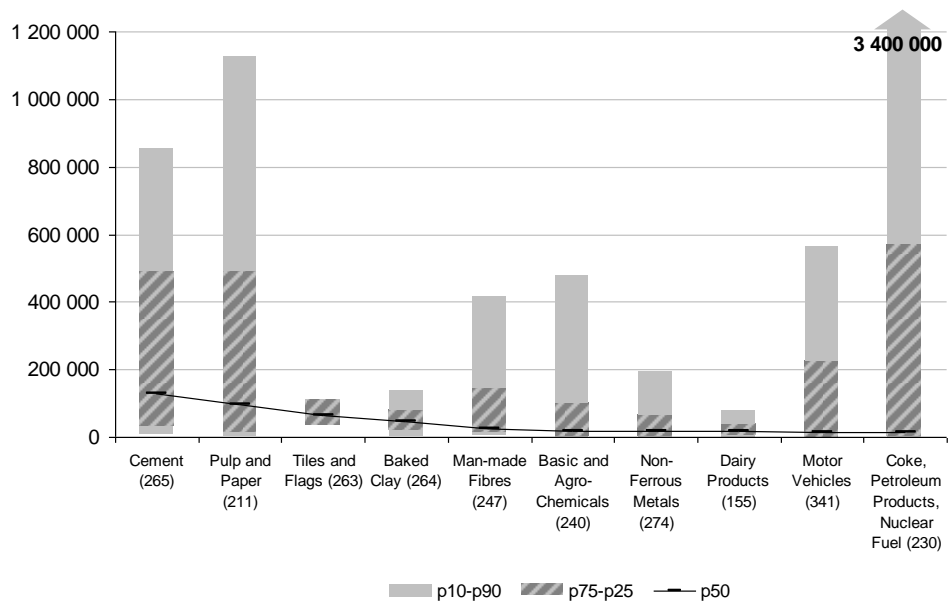
Own calculations.

Figure 7: Variation of energy intensity relative to the median (left) and median of energy intensity (right) for the top ten and bottom five sectors with respect to variation in energy intensity (2006 data).



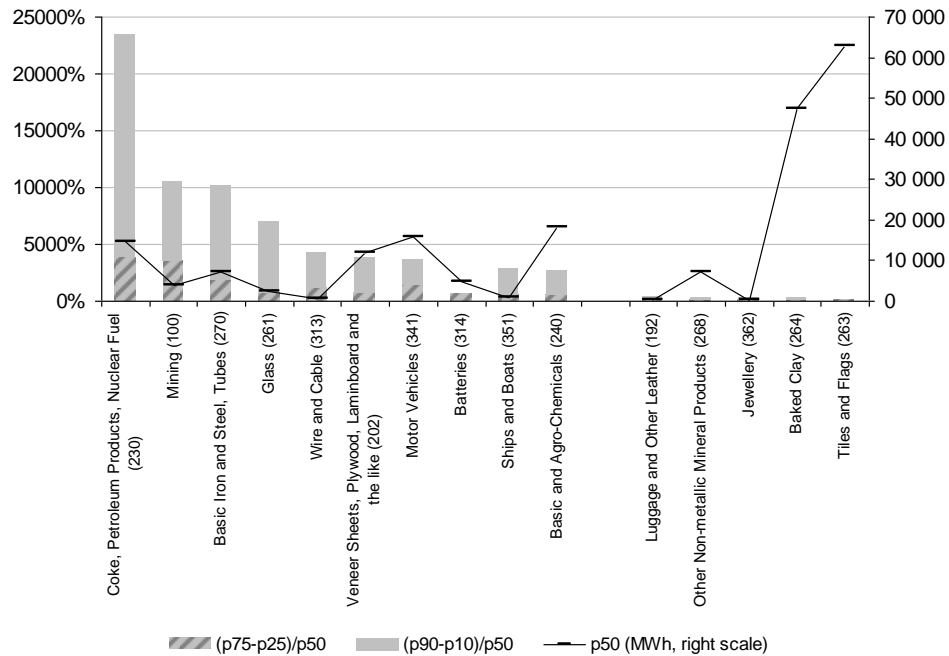
Own calculations. Sectors ranked according to (p90-p10)/p50. For a comparison of median relative Variation for different energy variables see Figure A 2.

Figure 8: The ten sectors with the highest median energy use in 2006 (in MWh).



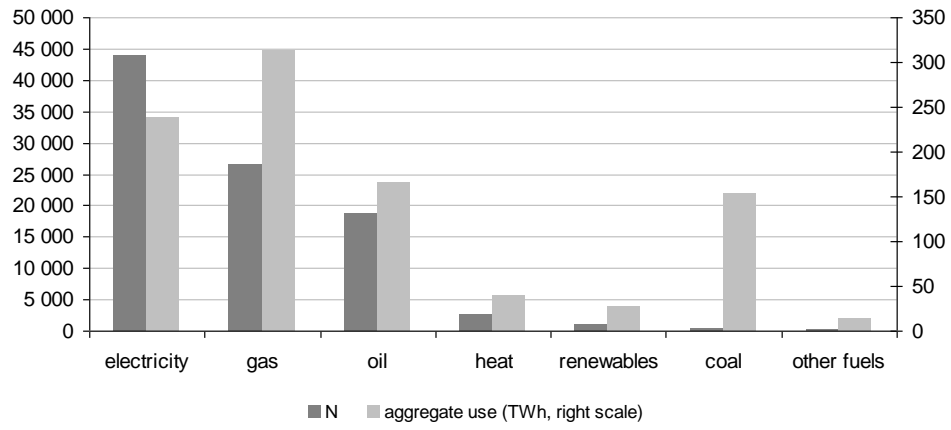
Own calculations. Note that for “Tiles and Flags” (263) the values for p10 and p90 are not available to ensure confidentiality of data. For more information regarding gross output, workforce and payroll see Table A 4 in the appendix. For more information on energy use for the median of all sectors see Table A 5 in the appendix.

Figure 9: Variation of energy use relative to the median (left) and median of energy use (right) for the top ten and bottom five sectors w.r.t. variation in energy use (2006 data).



Own calculations. Sectors ranked according to (p90-p10)/p50. Note that for “Batteries” (314) and “Tiles and Flags” (263) the values for p10 and p90 are not available to ensure confidentiality of data. In these cases, sectors were ranked according to (p75-p25)/p50. For a comparison of median relative Variation for different energy variables see Figure A 2.

Figure 10: Users and consumption of different fuels in all sectors in 2006.



Own calculations.

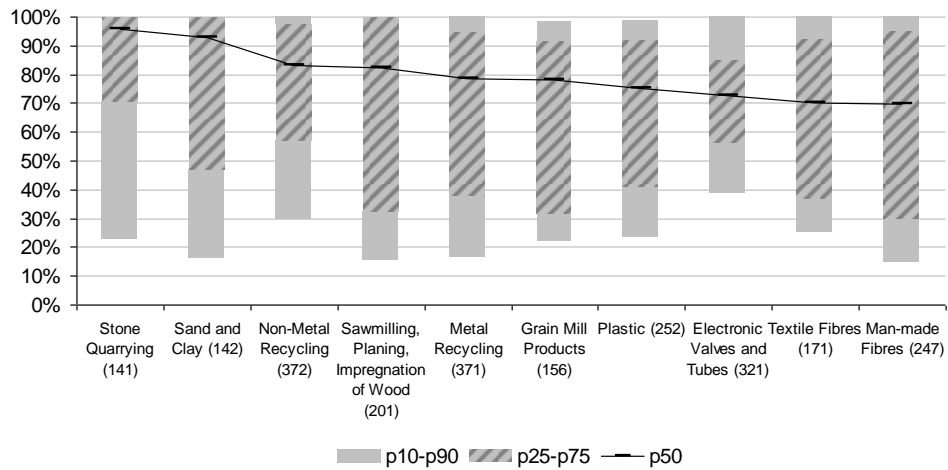
Table 1: The ten sectors with the highest and the five sectors with the lowest respective fuel share in the 2006 energy mix.

	Electricity	Gas	Oil	Heat	Renewables	Coal	Other fuels						
Top ten													
Electronic Valves and Tubes (321)	69.1%	Tiles and Flags (263)	86.7%	Cement Articles (266)	89.7%	Industrial Process Control Equipment (333)	68.6%	Wooden Containers (204)	74.3%	Musical Instruments (363)	86.1%	Textile Fibres (171)	19.8%
Wire and Cable (313)	66.1%	Ceramics (262)	77.3%	Coke, Petroleum Products, Nuclear Fuel (230)	74.2%	Man-made Fibres (247)	37.8%	Builders' Carpentry and Joinery (203)	72.7%	Basic Iron and Steel, Tubes (270)	60.3%	Cement (265)	18.1%
Optical Instruments (334)	64.2%	Baked Clay (264)	71.8%	Luggage and Other Leather (192)	31.6%	Locomotives and Rolling Stock (352)	21.8%	Sawmilling, Planing, Impregnation of Wood (201)	64.4%	Cement (265)	43.0%	Mining (100)	5.5%
Plastic (252)	62.7%	Glass (261)	68.5%	Leather (191)	26.8%	Pharmaceuticals (244)	18.6%	Veneer Sheets, Plywood, Laminboard and the like (202)	43.5%	Mining (100)	34.7%	Basic and Agro-Chemicals (240)	2.3%
Cutlery and Tools (286)	60.8%	Fruit, Oils and Fats (150)	68.0%	Knitted and Crocheted Articles (177)	23.1%	Motor Vehicles (341)	16.3%	Furniture (361)	26.2%	Casting of Metals (275)	24.9%	Pulp and Paper (211)	2.0%
Batteries (314)	60.1%	Finishing of Textiles (173)	66.9%	Footwear (193)	22.6%	Electronic Valves and Tubes (321)	14.3%	Non-Metal Recycling (372)	21.2%	Other Non-metallic Mineral Products (268)	23.6%	Pulp and Paper Articles (212)	1.8%
Non-Metal Recycling (372)	59.9%	Grain Mill Products (156)	64.5%	Machine Tools (294)	21.0%	Transmitters and Telephones (322)	12.3%	Other Wood (205)	20.0%	Stone Quarrying (141)	20.8%	Rubber (251)	1.4%
Transmitters and	59.5%	Other Special Purpose	62.4%	Jewellery (362)	20.4%	Aircraft and Spacecraft (353)	12.3%	Baked Clay (264)	13.8%	Finishing of Textiles	12.7%	Other Food (158)	1.4%

Telephones (322)		Machinery (295)								(173)			
Stone Cutting (267)	58.9%	Treatment of Metals (285)	60.8%	Other apparel (182)	19.6%	Basic and Agro- Chemicals (240)	12.1%	Pulp and Paper (211)	13.0%	Other Food (158)	11.0%	Baked Clay (264)	1.4%
Vehicle Parts and Accessories (343)	57.7%	Soap (245)	60.3%	Stone Quarrying (141)	19.3%	Jewellery (362)	11.6%	Pulp and Paper Articles (212)	9.0%	Beverages and Tobacco (160)	10.6%	Other Chemical (246)	1.1%
Bottom five (if non-zero)													
Finishing of Textiles (173)	12.5%	Cement Articles (266)	7.5%	Pulp and Paper (211)	1.7%								
Baked Clay (264)	8.6%	Wooden Containers (204)	6.0%	Ceramics (262)	1.3%								
Coke, Petroleum Products, Nuclear Fuel (230)	8.4%	Sawmilling, Planing, Impregnation of Wood (201)	5.7%	Motor Vehicles (341)	1.1%								
Musical Instruments (363)	5.2%	Musical Instruments (363)	4.1%	Mining (100)	0.3%								
Cement Articles (266)	2.5%	Builders' Carpentry and Joinery (203)	1.5%	Tiles and Flags (263)	0.2%								

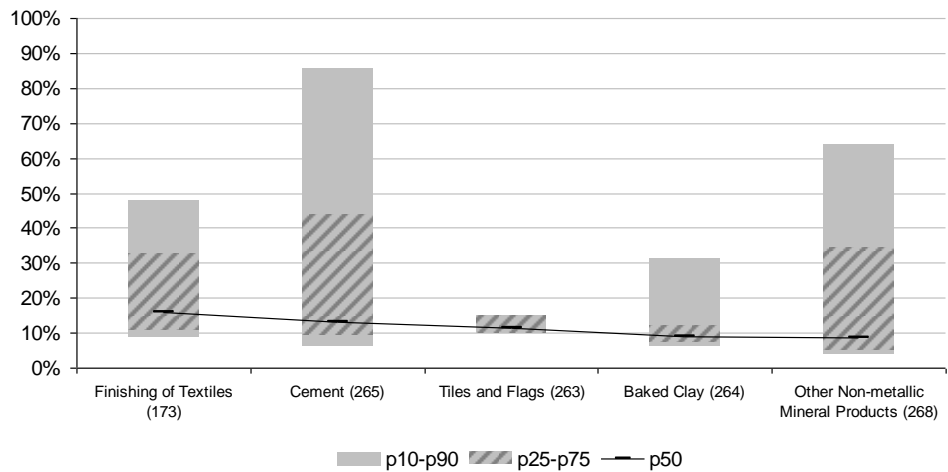
Own calculations. All shares are sector aggregates, including plants with zero fuel use.

Figure 11: The ten sectors with the highest median electricity share in their 2006 energy mix.



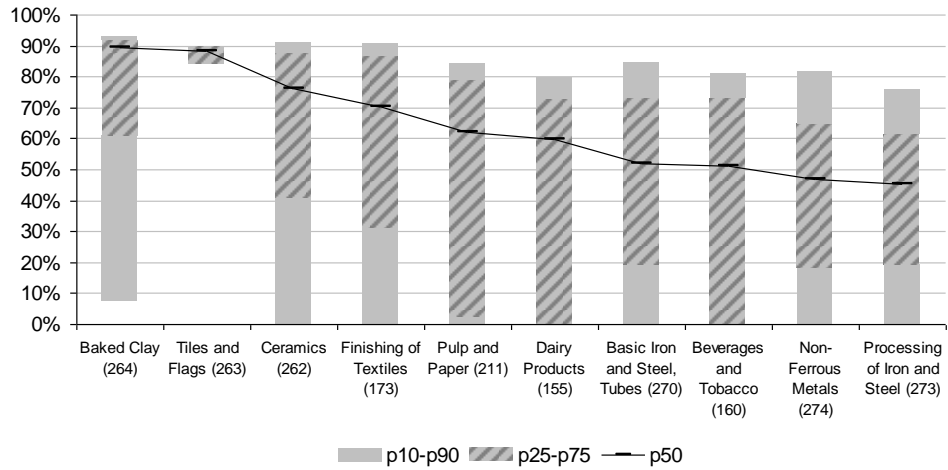
Own calculations. For more information regarding gross output, workforce and payroll see Table A 4 in the appendix. For more information on the median electricity share of all sectors see Table A 5 in the appendix.

Figure 12: The five sectors with the lowest median electricity share in their 2006 energy mix.



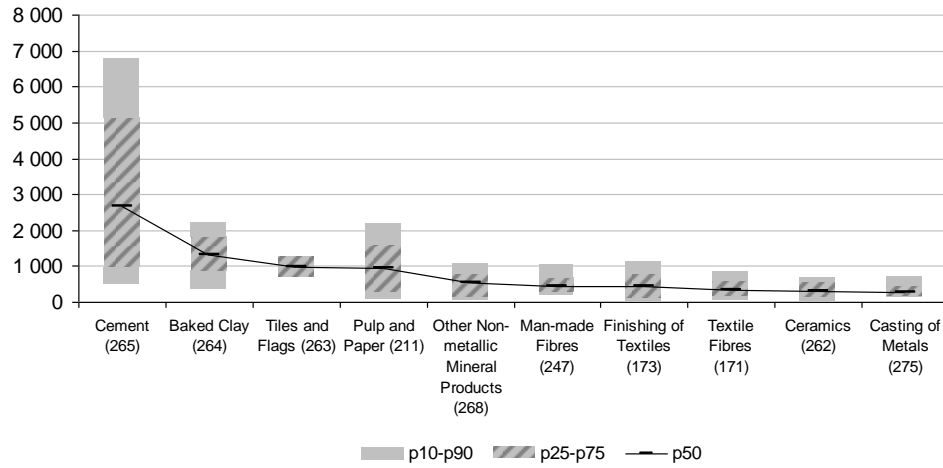
Own calculations. Note that for “Tiles and Flags” (263) the values for p10 and p90 are not available to protect confidentiality of data. For more information regarding gross output, workforce and payroll see Table A 4 in the appendix. For more information on the median electricity share of all sectors see Table A 5 in the appendix.

Figure 13: The ten sectors with the highest median natural gas share in their 2006 energy mix.



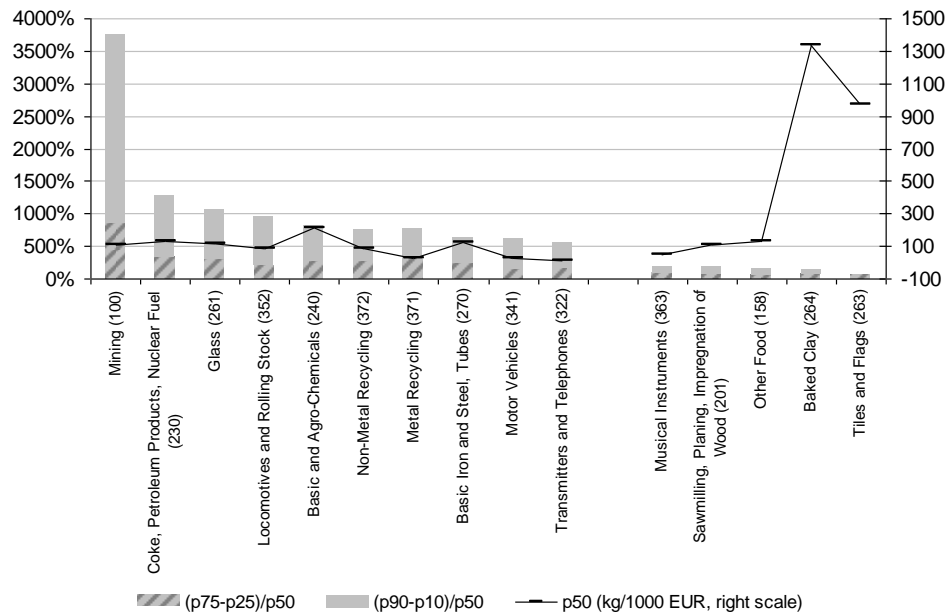
Own calculations. Note that for “Tiles and Flags” (263) the values for p10 and p90 are not available to protect confidentiality of data. For more information regarding gross output, workforce and payroll see Table A 4 in the appendix. For more information on the median natural gas share of all sectors see Table A 5 in the appendix.

Figure 14: The ten sectors with the highest median carbon intensity in 2006 (in kg/1000 EUR).



Own calculations. Note that for “Tiles and Flags” (263) the values for p10 and p90 are not available to ensure confidentiality of data. For more information regarding gross output, workforce and payroll see Table A 4 in the appendix. For more information on carbon intensity for the median of all sectors see Table A 5 in the appendix.

Figure 15: Variation of carbon intensity relative to the median (left) and median of carbon intensity (right) for the top ten and bottom five sectors w.r.t. variation in carbon intensity (2006 data).



Own calculations. Sectors ranked according to (p90-p10)/p50. Note that for “Tiles and Flags” (263) the values for p10 and p90 are not available to ensure confidentiality of data. In these cases, sectors were ranked according to (p75-p25)/p50. For a comparison of median relative variation for different energy variables see Figure A 2.

Appendix

Table A 1: Available information in the energy use module.

	Until 2002	From 2003
Electricity purchased from domestic sources:		
- from utilities		X
- from municipal utilities	X	
- from other companies	X	X
- from foreign countries		X
- total	calculated	X
Own electricity generation:		
- from hydropower	X	X
- from thermal power	merged	X
- from other sources		X
- total	calculated	X
Electricity supply:		
- to utilities		X
- to municipal utilities	X	
- to other users		X
- to other companies	X	
- to foreign countries		X
- total	calculated	X
Total electricity use	calculated	X
District heating (purchases, use, supply)		X
Natural gas/associated gas (purchases, use, non-energetic use, supply, stock)	only use and stock	X
LPG (purchases, use, non-energetic use, supply, stock)		X
Other gases (purchases, use, non-energetic use, supply, stock)		X
Total use of natural gas (incl. LPG)	calculated	calculated (excl. non-energetic use)
Light fuel oil (purchases, use, non-energetic use, supply, stock)	only use and stock	X
Heavy fuel oil (purchases, use, non-energetic use, supply, stock)	only use and stock	X
Other oil products (purchases, use, non-energetic use, supply, stock)		X
Total use of oil products	calculated	calculated (excl. non-energetic use)
Hard coal (purchases, use, non-energetic use, supply, stock)	only use and stock	X
Coke (purchases, use, non-energetic use, supply, stock)	only use and stock	X
Lignite (purchases, use, non-energetic use, supply, stock)	only use and stock	X
Lignite briquet (purchases, use, non-energetic use, supply, stock)	only use and stock	X
Other coal products (purchases, use, non-energetic use, supply, stock)		X
Total use of coal products	calculated	calculated

Renewables (purchases, use , non-energetic use , supply, stock)		X
Waste and other fuels (purchases, use , non-energetic use , supply, stock)		X
Total energy use	calculated	calculated

Source: FDZ (2010e). Variables used in this paper are **bold**.

Table A 2: CO₂ content of individual fuels (in g CO₂/kWh).

	All years	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Electricity ^a		694.0	671.0	647.0	646.0	625.0	627.0	641.0	635.0	631.0	626.0	616.0	584.8
District heat ^b		198.0	197.4	196.8	196.1	195.5	194.9	194.3	193.7	193.0	192.4	191.8	191.2
Natural gas/associated gas ^c	201.6												
LPG ^d	230.4												
Other gases ^e	188.6												
Light fuel oil ^f	266.4												
Heavy fuel oil ^g	280.8												
Other oil products ^h	270.1												
Hard coal ⁱ		336.1	335.4	336.7	336.9	336.9	337.2	337.8	338.0	338.3	338.6	338.7	339.1
Coke ^j	378.0												
Lignite ^k		401.4	401.9	402.7	403.7	405.0	407.2	407.0	406.8	406.6	407.2	406.8	406.2
Lignite briquets ^l		361.0	360.8	360.6	360.3	359.8	359.2	359.3	359.3	359.5	358.9	358.8	358.9
Other coal products ^m		353.3	353.3	353.4	353.5	353.5	353.6	353.6	353.6	353.6	353.6	353.5	353.6
Renewables	0												
Waste and other fuels ⁿ	255.9												

a) Total direct CO₂ emissions from the combustion of fossil fuels for electricity production divided by total final electricity use in Germany for each year. Imports, exports and indirect emissions from transportation and supply of fuels are not included. Source: Umweltbundesamt (2010) (1995-2003), own calculations (2006). b) Changes depending on the share of cogeneration plants and fuel mix. Source: Fritsche/Rausch (2007) (2000 and 2005), linear interpolation and extrapolation (all other years). c) Source: Umweltbundesamt (2010). d) Source: Umweltbundesamt (2010). e) Source: Umweltbundesamt (2010), weights of different gases from FDZ (2010f). f) Source: Umweltbundesamt (2010). g) Source: Umweltbundesamt (2010). h) Source: Umweltbundesamt (2010), weights of different oil products from FDZ (2010e). i) Changes depending on import share and import composition. Weighted average emission factor for domestic production and imports. Exports of hard coal neglected. Own calculations based on Statistik der Kohlenwirtschaft (2010a, 2010b) and Umweltbundesamt (2010). j) Source: Umweltbundesamt (2010). k) Changes depending on shares of mining districts. Own calculations depending on Statistik der Kohlenwirtschaft (2010c) and Umweltbundesamt (2010). l) Changes depending on shares of mining districts. Own calculations depending on Statistik der Kohlenwirtschaft (2010c) and Umweltbundesamt (2010). m) Includes only pulverized lignite and fluidized bed coal due to lack of emission data. Changes depending on shares of mining districts. Own calculations depending on Statistik der Kohlenwirtschaft (2010c) and Umweltbundesamt (2010). n) Emission factor for industrial wastes. Source: Umweltbundesamt (2010).

Table A 3: WZ 2003 industry codes and according descriptions.

WZ 2003 code	
100*	Mining and quarrying of energy producing materials and ores (includes 101 - 132)
141	Quarrying of stone
142	Quarrying of sand and clay
140*	Mining of chemical and fertilizer minerals, salt and other mining and quarrying n.e.c. (includes 143 - 145)
151	Production, processing and preserving of meat and meat products
152	Processing and preserving of fish and fish products
150*	Manufacture, processing and preserving of fruit, vegetables, animal oils and fats (includes 153 - 154)
155	Manufacture of dairy products
156	Manufacture of grain mill products, starches and starch products
157	Manufacture of prepared animal feeds
158	Manufacture of other food products
160*	Manufacture of beverages and tobacco products (includes 159 & 160)
171	Preparation and spinning of textile fibres
172	Textile weaving
173	Finishing of textiles
174	Manufacture of made-up textile articles, except apparel
175	Manufacture of other textiles
176	Manufacture of knitted and crocheted fabrics
177	Manufacture of knitted and crocheted articles
180*	Manufacture of leather clothes and articles of fur (includes 181 & 183)
182	Manufacture of other wearing apparel and accessories
191	Tanning and dressing of leather
192	Manufacture of luggage, handbags and the like, saddlery and harness
193	Manufacture of footwear
201	Sawmilling and planing of wood; impregnation of wood
202	Manufacture of veneer sheets; manufacture of plywood, laminboard, particle board, fibre board and other panels and boards
203	Manufacture of builders' carpentry and joinery
204	Manufacture of wooden containers
205	Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials
211	Manufacture of pulp, paper and paperboard
212	Manufacture of articles of paper and paperboard
221	Publishing
220*	Printing and service activities related to printing; reproduction of recorded media (includes 222 - 223)
230*	Manufacture of coke, refined petroleum products and nuclear fuel (includes 231 - 233)
240*	Manufacture of basic chemicals, pesticides and other agro-chemical products (includes 241 - 242)
243	Manufacture of paints, varnishes and similar coatings, printing ink and mastics

- 244 Manufacture of pharmaceuticals, medicinal chemicals and botanical products
- 245 Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations
- 246 Manufacture of other chemical products
- 247 Manufacture of man-made fibres
- 251 Manufacture of rubber products
- 252 Manufacture of plastic products
- 261 Manufacture of glass and glass products
- 262 Manufacture of non-refractory ceramic goods other than for construction purposes; manufacture of refractory ceramic products
- 263 Manufacture of ceramic tiles and flags
- 264 Manufacture of bricks, tiles and construction products, in baked clay
- 265 Manufacture of cement, lime and plaster
- 266 Manufacture of articles of concrete, plaster and cement
- 267 Cutting, shaping and finishing of ornamental and building stone
- 268 Manufacture of other non-metallic mineral products
- 270* Manufacture of basic iron and steel and of ferro-alloys, manufacture of tubes (includes 271 - 272)
- 273 Other first processing of iron and steel
- 274 Manufacture of basic precious and non-ferrous metals
- 275 Casting of metals
- 281 Manufacture of structural metal products
- 282 Manufacture of tanks, reservoirs and containers of metal; manufacture of central heating radiators and boilers
- 283 Manufacture of steam generators, except central heating hot water boilers
- 284 Forging, pressing, stamping and roll forming of metal; powder metallurgy
- 285 Treatment and coating of metals; general mechanical engineering
- 286 Manufacture of cutlery, tools and general hardware
- 287 Manufacture of other fabricated metal products
- 291 Manufacture of machinery for the production and use of mechanical power, except aircraft, vehicle and cycle engines
- 292 Manufacture of other general purpose machinery
- 293 Manufacture of agricultural and forestry machinery
- 294 Manufacture of machine tools
- 295 Manufacture of other special purpose machinery
- 296 Manufacture of weapons and ammunition
- 297 Manufacture of domestic appliances n.e.c.
- 300 Manufacture of office machinery and computers
- 311 Manufacture of electric motors, generators and transformers
- 312 Manufacture of electricity distribution and control apparatus
- 313 Manufacture of insulated wire and cable
- 314 Manufacture of accumulators, primary cells and primary batteries
- 315 Manufacture of lighting equipment and electric lamps
- 316 Manufacture of electrical equipment n.e.c.
- 321 Manufacture of electronic valves and tubes and other electronic components

322	Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy
323	Manufacture of television and radio receivers, sound or video recording or reproducing apparatus and associated goods
331	Manufacture of medical and surgical equipment and orthopaedic appliances
332	Manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes, except industrial process control equipment
333	Manufacture of industrial process control equipment
334	Manufacture of optical instruments and photographic equipment
335	Manufacture of watches and clocks
341	Manufacture of motor vehicles
342	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers
343	Manufacture of parts and accessories for motor vehicles and their engines
351	Building and repairing of ships and boats
352	Manufacture of railway and tramway locomotives and rolling stock
353	Manufacture of aircraft and spacecraft
350*	Manufacture of motorcycles and bicycles and other transport equipment n.e.c. (includes 354 -355)
361	Manufacture of furniture
362	Manufacture of jewellery and related articles
363	Manufacture of musical instruments
360*	Manufacture of sports goods, games and toys (includes 364 - 365)
366	Miscellaneous manufacturing n.e.c.
371	Recycling of metal waste and scrap
372	Recycling of non-metal waste and scrap

Source: Eurostat 2010, Statistisches Bundesamt (2003). To ensure confidentiality of the data, several sectors have been merged together as noted in the table. They are marked with an *. The total number of sectors has thus been reduced from originally 116 sectors to 98 sectors.

Table A 4: Medians of energy and production variables for WZ2003-three-digit-sectors in 2006.

	Energy intensity (kWh/ 1000 EUR)	Total energy use (kWh)	Carbon intensity (g CO ₂ /1000 EUR)	CO ₂ emissions (g CO ₂)	Electricity share in energy mix	Gross output (1000 EUR)	Payroll (1000 EUR)	Workforce
Mining (100)	325.8	3 855 634	109 572.6	1 809	50.0%	11 887	3 021	68
Other Mining (140)	532.4	3 634 911	251 224.4	1 542	64.6%	5 188	766	37
Stone Quarrying (141)	477.4	1 101 232	263 790.6	641	95.7%	2 507	445	15
Sand and Clay (142)	471.2	856 511	248 491.7	446	93.0%	1 964	377	13
Fruit, Oils and Fats (150)	464.9	4 421 916	134 833.2	1 518	20.7%	8 820	1 205	55
Meat (151)	234.0	1 079 847	95 202.8	415	48.7%	4 425	800	46
Fish (152)	186.2	1 079 444	69 855.8	440	46.9%	6 790	787	42
Dairy Products (155)	344.7	16 694 488	118 252.3	5 809	30.2%	52 091	2 704	90
Grain Mill Products (156)	404.2	8 910 902	208 067.3	4 385	78.3%	27 183	1 981	61
Animal feed (157)	302.2	4 510 495	121 671.4	1 591	51.4%	13 919	869	33
Other Food (158)	360.9	759 716	131 963.8	269	34.8%	2 233	640	42
Beverages and Tobacco (160)	483.3	4 564 453	162 553.7	1 512	24.9%	9 706	1 509	50
Textile Fibres (171)	710.6	6 661 731	339 437.2	2 964	70.3%	10 862	1 918	83
Textile Weaving (172)	511.3	5 252 251	179 176.7	2 107	45.0%	12 828	2 441	81
Finishing of Textiles (173)	1 518.9	6 088 899	443 509.7	1 860	16.0%	5 549	1 282	53
Made-up Textiles (174)	104.7	499 726	36 400.3	154	30.6%	4 714	874	43
Other Textiles (175)	268.5	2 052 009	119 987.9	859	39.1%	7 328	1 530	60
Knitted and Crocheted Fabrics (176)	242.6	1 959 973	111 223.7	870	56.0%	9 053	1 488	58
Knitted and Crocheted Articles (177)	235.8	783 478	88 452.3	292	41.0%	3 810	1 079	50
Leather Clothes and Fur (180)	61.3	180 587	21 175.8	64	34.3%	3 031	875	43
Other apparel (182)	66.9	530 988	23 154.8	175	29.8%	7 873	1 235	54
Leather (191)	577.0	8 400 734	176 009.6	2 815	25.4%	12 600	1 662	92
Luggage and Other Leather (192)	91.5	299 423	30 848.5	108	30.9%	3 823	891	38
Footwear (193)	90.6	690 957	32 009.1	261	39.5%	7 699	1 635	69
Sawmilling, Planing,	248.7	1 044 139	108 209.7	377	82.4%	3 276	494	20

Impregnation of Wood (201)								
Veneer Sheets, Plywood, Laminboard and the like (202)	649.8	11 948 169	172 018.9	3 905	42.4%	24 182	3 370	115
Builders' Carpentry and Joinery (203)	116.0	573 157	40 772.9	192	49.8%	4 573	1 019	39
Wooden Containers (204)	122.8	584 863	38 633.2	190	46.9%	5 140	935	36
Other Wood (205)	187.0	573 340	83 641.3	246	52.8%	3 310	877	40
Pulp and Paper (211)	2 950.5	96 582 472	934 499.3	30 063	24.0%	42 443	4 717	133
Pulp and Paper Articles (212)	177.6	1 856 939	76 008.8	776	47.4%	10 969	2 003	76
Printing and Reproduction (220)	156.0	648 561	70 547.5	294	64.8%	4 479	1 261	42
Publishing (221)	32.6	270 716	11 139.1	95	46.6%	8 801	1 903	55
Coke, Petroleum Products, Nuclear Fuel (230)	352.9	14 707 476	127 302.5	4 977	19.4%	72 641	7 730	146
Basic and Agro-Chemicals (240)	578.4	18 139 202	214 359.4	6 625	40.1%	33 787	3 543	88
Paints (243)	118.9	1 894 295	43 168.9	727	34.9%	18 130	2 771	72
Pharmaceuticals (244)	144.7	2 782 115	52 886.0	1 076	40.4%	20 716	4 135	118
Soap (245)	111.6	1 320 089	38 425.0	463	32.3%	13 755	2 070	71
Other Chemical (246)	166.8	3 055 878	57 996.9	1 174	33.4%	16 585	2 171	60
Man-made Fibres (247)	986.8	26 315 398	446 887.3	12 172	69.5%	37 139	5 035	182
Rubber (251)	274.1	2 467 391	118 547.5	1 085	50.6%	8 836	1 907	67
Plastic (252)	269.0	1 972 144	130 297.7	944	75.3%	7 980	1 556	57
Glass (261)	263.2	2 277 345	114 324.9	992	47.4%	9 710	1 795	71
Ceramics (262)	967.7	8 878 801	293 660.4	2 558	19.0%	8 061	2 107	79
Tiles and Flags (263)	4 066.9	62 756 276	971 899.2	16 546	11.5%	20 012	4 109	133
Baked Clay (264)	5 555.4	47 500 824	1 332 871.1	11 296	9.0%	7 659	1 336	44
Cement (265)	9 053.9	130 600 000	2 672 667.3	46 727	13.2%	23 900	3 188	78
Cement Articles (266)	144.4	455 149	60 290.5	192	52.9%	3 335	541	19
Stone Cutting (267)	230.1	629 305	102 485.7	295	56.4%	3 058	806	30
Other Non-metallic	1 738.1	7 137 535	528 800.4	2 113	8.7%	4 682	378	11

Mineral Products (268)								
Basic Iron and Steel, Tubes (270)	352.7	7 038 551	123 850.4	2 587	37.8%	23 667	3 555	98
Processing of Iron and Steel (273)	263.4	6 197 749	110 412.1	2 344	49.9%	23 129	2 523	67
Non-Ferrous Metals (274)	328.4	17 717 803	128 843.1	6 954	47.8%	48 791	4 653	118
Casting of Metals (275)	746.9	8 889 901	280 395.5	3 526	48.2%	12 750	2 859	90
Structural Metal Products (281)	90.7	427 275	31 474.0	144	33.8%	4 623	1 043	39
Tanks (282)	138.9	916 576	47 362.1	338	36.8%	7 618	1 539	51
Steam Generators (283)	36.0	203 090	12 583.4	67	32.7%	5 698	1 614	50
Forming of Metal (284)	175.1	1 557 700	79 989.7	704	61.4%	9 123	1 944	62
Treatment of Metals (285)	268.2	1 172 706	127 220.5	537	63.7%	3 839	1 097	40
Cutlery and Tools (286)	173.1	1 045 469	77 063.7	456	59.1%	6 221	1 735	54
Other Metal Products (287)	178.8	1 311 262	75 141.6	558	48.5%	8 281	1 653	55
Machinery for the Use of Mechanical Power (291)	115.1	1 433 390	46 466.1	586	49.8%	12 714	2 806	80
Other General Purpose Machinery (292)	70.6	507 419	25 123.0	177	37.0%	7 567	1 795	52
Agricultural Machinery (293)	100.8	765 922	35 921.9	286	30.1%	7 685	1 281	47
Machine Tools (294)	99.5	891 818	37 441.7	330	43.8%	8 322	2 155	60
Other Special Purpose Machinery (295)	106.4	621 963	38 975.7	241	41.7%	6 114	1 669	50
Weapons (296)	125.8	4 010 478	48 295.1	1 407	40.8%	34 364	6 998	211
Other Domestic Appliances (297)	94.4	1 343 108	37 149.3	553	41.9%	14 501	2 539	87
Office Machinery, Computers (300)	48.0	456 667	17 896.2	173	49.7%	8 509	2 012	60
Electric Motors (311)	84.3	657 665	33 062.0	234	42.4%	7 932	1 872	60
Electricity Distribution Apparatus (312)	58.4	521 972	22 515.4	185	46.6%	9 082	2 021	65
Wire and Cable (313)	85.4	604 660	37 372.0	236	51.9%	8 274	1 468	59
Batteries (314)	251.3	4 793 988	111 579.0	2 344	59.1%	24 671	4 894	129

Lighting (315)	126.7	790 868	43 151.5	274	32.8%	6 112	1 453	55
Other Electrical Equipment (316)	54.1	432 146	21 450.9	159	50.5%	9 408	1 996	62
Electronic Valves and Tubes (321)	141.6	1 485 230	66 441.8	696	72.7%	9 963	2 249	76
Transmitters and Telephones (322)	34.0	335 288	13 263.8	123	55.3%	9 791	2 531	70
TV and Radios (323)	50.8	517 397	18 851.8	198	47.0%	11 430	2 391	80
Medical Equipment (331)	72.7	159 375	28 080.9	58	47.3%	1 951	777	33
Measuring and Checking Apparatus (332)	56.2	458 462	21 086.8	168	46.0%	8 212	2 118	57
Industrial Process Control Equipment (333)	24.7	125 445	9 456.1	54	43.0%	4 777	1 461	40
Optical Instruments (334)	108.0	976 571	48 552.2	425	67.3%	9 416	2 680	79
Watches and Clocks (335)	89.1	414 000	31 050.2	108	42.6%	5 946	1 133	47
Motor Vehicles (341)	80.0	15 691 710	26 367.8	4 899	35.3%	239 041	28 137	630
Bodies for Motor Vehicles (342)	117.0	822 211	42 255.1	286	30.2%	7 398	1 512	56
Vehicle Parts and Accessories (343)	190.6	4 079 106	87 841.6	1 870	62.2%	25 815	4 508	143
Other Vehicles (350)	125.5	1 310 647	48 957.8	473	36.0%	9 646	2 101	71
Ships and Boats (351)	146.5	974 794	55 043.1	346	40.9%	5 242	1 421	45
Locomotives and Rolling Stock (352)	275.3	3 300 000	84 492.7	1 064	27.1%	10 219	3 192	106
Aircraft and Spacecraft (353)	126.5	3 341 751	44 205.8	1 553	44.4%	22 555	6 250	150
Sports goods, Games and Toys (360)	117.8	589 397	44 266.9	215	36.0%	5 656	1 255	57
Furniture (361)	146.6	1 106 388	53 060.0	371	42.5%	6 764	1 525	58
Jewellery (362)	73.9	369 556	26 679.5	144	43.0%	4 998	1 114	42
Musical Instruments (363)	145.3	505 057	52 198.6	181	29.7%	2 890	923	41
Miscellaneous Manufacturing (366)	137.4	732 250	55 601.5	266	40.4%	5 545	1 181	49
Metal Recycling (371)	47.1	1 086 347	26 159.8	493	78.6%	16 958	1 191	37

Non-Metal Recycling

(372)	162.8	1 043 098	84 034.3	482	83.0%	5 423	865	33
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Own calculations. Top ten sectors of each category are **bold**, bottom five sectors of each category are *bold and italic*.

Table A 5: Percentiles and relative variation of selected energy variables (median of all sectors, 2006).

	p10	p25	p50	p75	p90	(p90-p10)/p50	(p75-p25)/p50
Energy intensity (kWh/1000 EUR)	38.6	81.8	162.8	301.6	546.2	873.3%	269.7%
Total energy use (kWh)	218 491	444 403	1 106 388	4 111 569	13 137 878	873.3%	269.7%
Carbon intensity (g/1000 EUR)	15 206.9	176.5	69 855.8	1 606.1	5 046.6	871.0%	263.6%
Electricity share in energy mix	17.6%	28.1%	43.0%	64.4%	87.9%	154.1%	77.8%
Natural gas share in energy mix	0.0%	0.0%	20.4%	57.3%	73.7%	303.8%	230.6%

Own calculations.

Table A 6: Correlation of sector medians and sector heterogeneity between selected variables (2006).

	Energy intensity	Total energy use	Carbon Intensity	Gross output	Payroll	Workforce
Correlation of medians						
Total energy use	0.90					
Carbon intensity	0.99	0.92				
Gross output	0.05	0.23	0.06			
Payroll	0.04	0.20	0.04	0.96		
Workforce	0.04	0.21	0.04	0.94	0.98	
Electricity share in energy mix	-0.37	-0.34	-0.30	-0.11	-0.12	-0.13
Correlation of heterogeneity (p90-p10)/p50						
Total energy use	0.56					
Carbon intensity	0.98	0.59				
Gross output	0.28	0.79	0.35			
Payroll	0.49	0.32	0.52	0.55		
Workforce	0.58	0.34	0.61	0.51	0.97	
Electricity share in energy mix	0.05	0.24	0.07	0.17	0.09	0.12

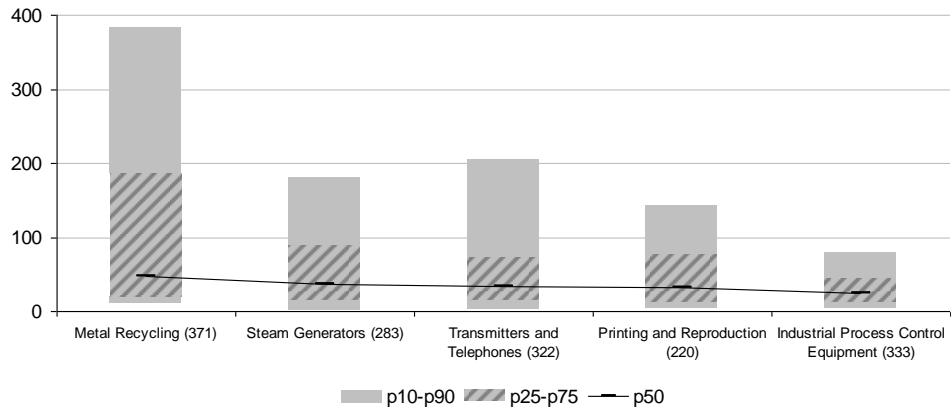
Own calculations.

Table A 7: Users and aggregate use of different fuels in 2006.

	N	Aggregate use (TWh)
Electricity	44 080	238.0
Natural gas (incl. LPG)	26 728	313.4
Petroleum products	18 786	166.2
Heat	2 648	39.0
Renewables	973	26.9
Coal	378	154.3
Other fuels	141	13.2

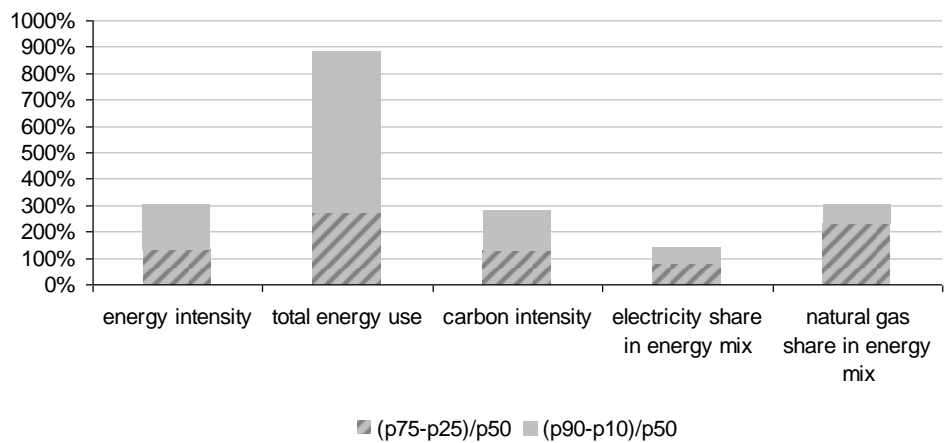
Own calculations.

Figure A 1: The five sectors with the lowest median energy intensity in 2006 (in kWh/1000 EUR).



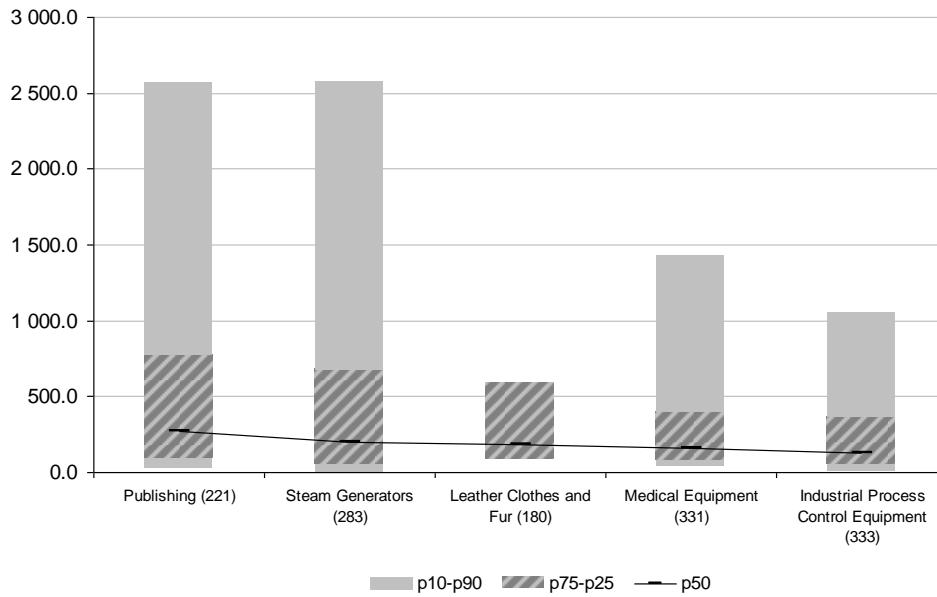
Own calculations. For more information regarding gross output, workforce and payroll see Table A 4 in the appendix. For more information on energy intensity for the median of all sectors see Table A 5 in the appendix.

Figure A 2: Variation relative to the median of selected energy variables (median of all sectors, 2006 data).



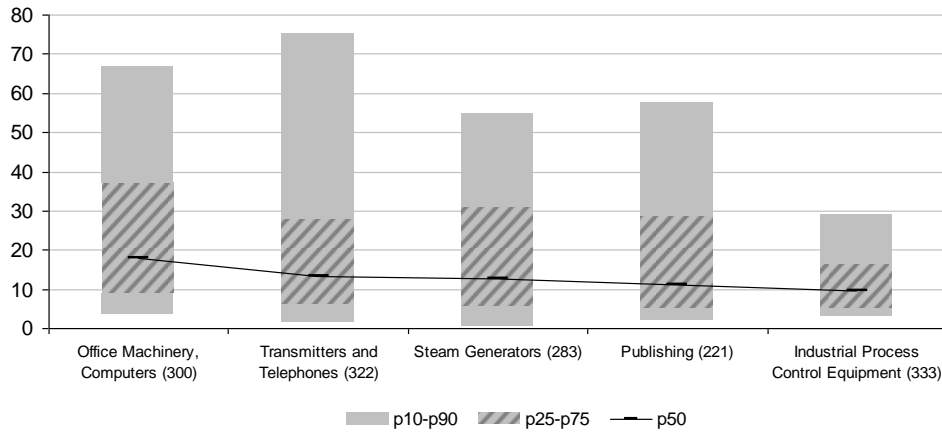
Own calculations.

Figure A 3: The five sectors with the lowest median energy use in 2006 (in MWh).



Own calculations. Note that for some sectors the values for p10 and p90 are not available to protect confidentiality of data. For more information regarding gross output, workforce and payroll see Table A 4 in the appendix. For more information on energy use for the median of all sectors see Table A 5 in the appendix.

Figure A 4: The five sectors with the lowest median carbon intensity in 2006 (in kg/1000 EUR).



Own calculations. For more information regarding gross output, workforce and payroll see Table A 4 in the appendix. For more information on carbon intensity for the median of all sectors see Table A 5 in the appendix.

Carbon Efficiency, Technology, and the Role of Innovation Patterns: Evidence from German Plant-Level Microdata^{*}

Sebastian Petrick, Kiel[†]

Abstract

We describe the determinants of energy intensity, carbon intensity, and CO₂ emissions in the German manufacturing sector between 1995 and 2007, applying the LMDI index decomposition technique to micro data. We decompose changes in total CO₂ emissions from manufacturing to changes in activity level, structural change between sectors, shifting market shares within sectors, energy intensity at the firm level, fuel mix, and emission factors. Our results show that competition between firms within one sector, although so far widely ignored as a driver of emissions and energy use, is energy- and emission-saving. Contrary to wide-spread beliefs, energy intensity improvements at the firm level do not play a significant role in reducing emissions. We use sector-level results on the relative importance of improvements in firm-level energy intensity and intra-sectoral structural change to distinguish two different innovation channels: innovation by technology and by entrants. We show that incumbent firms in a number of sectors, including some of the most energy intensive, do not significantly improve their energy efficiency. Innovation takes place via new entrants instead, rendering policies targeted at incumbents' firm-level energy efficiency ineffective.

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1 Introduction

Reducing energy use and emissions is at the top of political agendas throughout the developed world. In the pursuit of de-carbonizing the economy and reducing overall energy intensity, regulators have a number of options to regulate manufacturing firms. The regulatory toolbox comes with the means to encourage firms' investments in energy efficiency (e.g., in the form of subsidies for building insulation), fuel switching (e.g., via feed-in tariffs for renewables), or programs for "greening" the electricity mix upstream of end use (e.g., via cap-and-trade systems in the electricity sector). However, most of these measures are targeted at established firms in the market. New entrants or rising stars that challenge and compete with established incumbents are usually not the target group of regulation. If these new or rising competitors are actually driving the transformation towards a less carbon intensive economy, regulation targeted at established incumbents would be ineffective.

In this paper, we analyze and quantify the role of intra-sectoral competition in driving industrial energy and carbon efficiency improvements. Controlling for changes in activity, sectoral composition, fuel-mix, and upstream emission coefficients, we calculate the relative importance of firm-level energy efficiency and intra-sectoral competition for emission savings in the German manufacturing sector using a standard index decomposition methodology.

Contrary to existing decomposition analyses, we can explicitly include the effect of shifting market shares, or competition, within sectors on efficiency gains by using a detailed panel data set covering all manufacturing plants in Germany (except very small plants). In previous decomposition exercises, and dictated by the nature of aggregate data, efficiency gains from shifting market shares within sectors have been included in the effect of sector-level intensity change and have thus been interpreted as technological improvements (we will provide examples towards the end of this section). We, on the other hand, calculate the effect of energy intensity changes on carbon emissions purged of intra-sector changes in market share. To our

knowledge, no previous decomposition exercise using firm-level data has yet been published.

As an outlook on our results, we find that intra-sectoral competition has been a major driver of industrial energy and carbon efficiency improvements. Energy efficiency improvements on the firm-level, on the other hand, did not contribute significantly to emissions reductions, contrary to widespread beliefs. Other important drivers of emission reductions are structural change, changes in the mix of end-use fuels, and carbon efficiency improvements in the power plant fleet. Based on our findings on the role of technological progress at the firm level, we distinguish between different patterns of sector-level energy efficiency innovation across sectors. While firm-level energy efficiency innovations play a role in some sectors, other sectors innovate mostly via competition. We conclude that policies targeted at firm-level efficiency improvements, such as innovation subsidies, may be ineffective in the sectors innovating via entrants.

We focus on Germany for three reasons. First, Germany's high share of industrial value added in overall economic activity, together with the relatively high level of diversification between different industrial activities, ensures the representativeness of our results and a certain level of external validity. Second, Germany's energy system has changed significantly over our sample period, ensuring a level of inter-temporal variation in energy characteristics that allows us to identify various drivers of energy use that are sufficiently pronounced. We will elaborate on these changes in the following paragraphs. Third, our analysis is demanding in terms of data availability, and German official statistics provide a micro-panel that is suitable for our analysis. We are unaware of any other dataset on plant-level energy and carbon intensities that would be comparable to our data in terms of scale and scope. The data thus provide us with a unique opportunity to study the determinants of energy intensity, carbon intensity, and CO₂ emissions at the micro level. We will describe the datasets we use in detail in Section 3.

Over the last couple of years, energy intensity in Germany has decreased considerably, as it has in most industrialized countries (EIA 2010). Energy

use per gross value added decreased by over 20 % for the whole economy and by an even steeper 24 % for manufacturing (see Figure 1). Carbon intensity decreased even more (by 37 %), and also total carbon emissions were reduced, although not by a similar amount due to a large expansion of economic activity. Disparities in energy intensity between the sectors within manufacturing are, however, high: in 2007, the average energy intensity of four especially energy intensive sectors – metal manufacturing, paper and pulp, chemicals and glass, cement and mineral products – was more than three times the average energy intensity of all other sectors in manufacturing.¹

~ Figure 1 about here ~

At the same time, there has been significant structural change in manufacturing. While some sectors, such as the especially energy intensive sectors of mining or glass, cement and mineral products, have decreased their share in total manufacturing activity, other sectors, such as car manufacturers, have increased their share. This structural change between sectors with different sectoral energy intensities has led to changes in overall energy intensity that are not due to technological or behavioral change but rather to changes in the sectoral composition of manufacturing.

To decompose changes in overall intensity into these structural changes and “real” energy intensity changes, energy economists have applied index decomposition techniques, not least with the aim to inform policy makers about the effects of energy-saving policies on actual efficiency gains as opposed to overlying structural change. This “real” intensity effect reflects changes in individual sectors’ energy intensity. It is often perceived as an indicator of how technological progress drives overall energy intensity, implicitly assuming a homogeneous structure within the sector. Nevertheless, this assumption ignores – and usually has to because of data restrictions – a second dimension of the structural change argument. Apart from structural change between sectors, there might, of course, also be structural change between heterogeneous firms in a sector, which influences

¹ All numbers are our own calculations based on Statistisches Bundesamt (2012).

the energy intensity of a sector and, in turn, the overall energy intensity. The structural change effect within a sector could be identified as a change in the companies' share in the sector's total output (we call this the effect of shifting market shares, or competition, within the sectors). The sectors' aggregate energy intensities would decrease if relatively energy-efficient companies gain market share while relatively less-energy-efficient companies lose market share. The "true" intensity effect – i.e., changes in the firms' energy intensities – can be identified after controlling for shifting market shares of the firms. We will calculate both the effect of shifting market shares within sectors and the effect of firm-level energy efficiency improvements in the course of this paper.

For the debate on climate change, the relevant indicator is not necessarily energy intensity, but rather carbon intensity, i.e., the ratio between a sector's or firm's CO₂ emissions and the corresponding output. While energy intensity is, of course, a decisive determinant of carbon intensity, the indicators usually do not evolve in parallel, as shown in Figure 1. The difference between the two curves results from changes in the final (or end-use) energy mix and emission savings upstream of final energy provision.² Energy policies target these two variables as well. As an example, the German feed-in tariff scheme promotes fuel switching towards decentralized on-site generation of renewables through exemptions from the renewable energy surcharge for own consumption (EEG 2012). Increased use of renewables in the power sector is promoted through relatively high feed-in tariffs for wind or solar PV generation. Additionally, the EU emission trading scheme incentivizes not only industrial energy efficiency improvements but also fuel switching, both in manufacturing and in upstream energy sectors (European Commission 2009).

² Although the emission coefficients, i.e., the amount of CO₂ that is emitted by using one unit of the respective fuel, are constant for most fuels, they may change over time for some fuels because of changes in the conversion from primary to final energy. This is especially important in the case of electricity, where we observe a shift in the composition of the power plant fleet, but it can also be observed for hard coal, where the calorific value and import shares of different countries of origin vary.

In addition to energy and carbon intensity, we will add the level of activity, i.e., the overall output level, to our analysis in order to move to total CO₂ emissions, as one of the most important indicators of the sustainability of manufacturing. Consequently, we identify six drivers, or effects, that impact changes of total CO₂ emissions: (1) economic activity, (2) structural change between sectors, (3) shifting market shares of firms within sectors, (4) firm-specific energy intensity, (5) firm-specific fuel mix and (6) the effect of a changing emission factor of the individual fuels. We elaborate on the underlying identity and the derivation of the six effects in Section 2.

Existing decomposition exercises usually cover a subset of these effects. The first applications of index decomposition techniques in the field of energy economics date before the early eighties. Among the first publications are contributions from Hankinson and Rhys (1983) on the decomposition of energy use in the UK into an activity, intensity, and structural change effect, or from Jenne and Cattel (1983) on the decomposition of energy intensity into a technology and a structural change effect. While early research relied mainly on the Laspeyres index, other approximations to the more general Divisia Index, in particular the Tornqvist index, became widely accepted following the work of Boyd et al. (1988). An early and still useful systematization can be found in Liu et al. (1992). All of these methods have the disadvantage that, after re-aggregating the different components, an unexplained residuum remains in comparison with the initial total effect. This problem was addressed by Sun (1998), who simply distributed the remaining residuum equally among the components. Similar concepts to Sun's index have been developed by Diezenbacher and Los (1998) and Albrecht et al. (2002).

A different approach towards the residual problem has been taken by Ang et al. (1998) on the basis of a logarithmic mean of the weights of the two periods. Ang and Liu (2001) refined and simplified this method, calling the revised index the *Logarithmic Mean Divisia Index* (LMDI). We use their LMDI in the analysis below, (see Section 2 or the practical guide by Ang 2005). The first articles using index decomposition methods usually focused on energy intensity or energy use and distinguished between a structural and an intensity effect. Today a growing number of studies also include fuel mix

and emission factors and decompose emission intensity or emissions as opposed to energy intensity or energy use, like we do (cf., for example, Schipper et al. 2001, Diakoulaki/Mandaraka 2007 or Hatzigeorgiou et al. 2009). Liu and Ang (2007) as well as Su and Ang (2012) provide a fairly comprehensive review of studies using index decomposition techniques.

In terms of results, the existing literature reports an emission or energy saving effect of energy intensity changes in the majority of cases. In their review of 20 decomposition exercises that include results for Germany, Liu and Ang (2007) list only one case where an emissions-increasing intensity effect was found. Because the reported results are always multi-year decompositions covering between five and 15 years, so that expansive intensity effects of one year may be compensated by other years with contractive effects, this result does not mean that the other 19 studies would not have found a single year with an expansive intensity effect. Nevertheless, we believe it is a hint that expansive intensity effects are a rare exception from the rule of contractive intensity effects. For all studies covered by Liu and Ang (2007), the ratio of expansive vs. contractive intensity effects is 48 vs. 274 studies. We show below for the example of Germany that the reason for this emission- or energy-saving intensity effect is most likely not actual intensity improvements on the firm level but intra-sectoral competition among firms with different energy efficiencies. Another effect that is reported to be emission- or energy-saving in most cases is structural change. Seventeen out of 20 studies for Germany and 98 out of 322 studies report an energy-saving structural change effect. We confirm the majority's result below.

In the following Section 2, we briefly explain index decomposition methods, including an overview of the relevant literature. We present our micro-dataset in Section 3. Our results are presented in Section 4. In the last section, we conclude.

2 Index decomposition methodology

To identify the described effects and better understand what is driving the observed trends in energy and carbon intensity, we apply an index

decomposition technique. Index decomposition techniques have been widely used to disentangle structural and technological components of trends in energy intensity, carbon intensity, and emissions at the sector level (see Section 1 for references). They make use of the fact that manufacturing-wide CO₂ emissions can be regarded as a weighted average of the described six effects at the sector level, with the emission shares of the sectors as the weights. This study takes the decomposition method from the sector to the firm level. This has the advantage that we can account for changes in the output shares of firms within a sector that would otherwise be attributed to the sectoral technology effect. In so doing, we provide a more differentiated assessment of technology-driven changes in energy and carbon intensity that explicitly accounts for heterogeneity across firms within a sector, as explained in Section 1.

The following identity summarizes how the six components described in Section 1 add up to the aggregate CO₂ emissions in manufacturing:

$$CO_2 = \sum_s \sum_{i \in s} \sum_f Y \cdot \underbrace{\frac{Y_s}{Y}}_{(1) \text{ activity component}} \cdot \underbrace{\frac{Y_i}{Y_s}}_{(2) \text{ structural change between sectors component}} \cdot \underbrace{\frac{kWh_i}{Y_i}}_{(3) \text{ shifting market shares within sectors component}} \cdot \underbrace{\frac{kWh_{if}}{kWh_i}}_{(4) \text{ intensity component}} \cdot \underbrace{\frac{CO_{2if}}{kWh_{if}}}_{(5) \text{ fuel mix component}} \cdot \underbrace{\frac{CO_{2if}}{kWh_{if}}}_{(6) \text{ emission factor component}} \quad (1)$$

where s indexes sectors within manufacturing, i indexes individual companies and f indexes different fuels. CO_2 denotes CO₂ emissions, Y denotes output, and kWh denotes final energy use. Depending on the subscript, the variables are either defined for fuel-firm combinations (subscript if), the firm level (f), aggregated to the sector level (s) or aggregated to the whole manufacturing level. Variables on the whole manufacturing aggregate are not subscripted. Using formula (1), changes in

CO₂ can be traced back to changes in each of the six components described above, which correspond to the six factors of the product after the summation signs. These ceteris paribus effects then deliver the hypothetical change in total CO₂ emissions given that only one of the components had changed. These effects are calculated by aggregating the change in that respective component from the fuel per plant level to the total level, calculating the weighted average change over all fuels, companies and sectors. The respective weights for the fuel-firm combinations are delivered by the *Logarithmic Mean Divisia Index* (LMDI) procedure (Ang and Liu 2001) and are determined by the share of the fuel-firm combinations in total CO₂ emissions in all manufacturing sectors. Details on this procedure can be found in Ang and Liu (2001) or Ang (2005).

The six effects are defined for the change in overall CO₂ emissions from period 0 to period T as follows:

- 1) The activity effect (the ceteris paribus change in total CO₂ emissions if only industrial activity had changed):

$$D_{activity} = \exp\left(\sum_s \sum_{i \in s} \sum_f w_{sif} \ln \frac{Y_T}{Y_0}\right) \quad (2)$$

- 2) The effect of structural change between sectors (the ceteris paribus change in total CO₂ emissions if only the shares of sectors in total manufacturing output had changed):

$$D_{structure \text{ between sectors}} = \exp\left(\sum_s \sum_{i \in s} \sum_f w_{sif} \ln \frac{\left(\frac{Y_s}{Y}\right)_T}{\left(\frac{Y_s}{Y}\right)_0}\right) \quad (3)$$

- 3) The effect of shifting market shares within sectors (the ceteris paribus change in total CO₂ emissions if only the relative market shares of firms in sectoral output had changed):

$$D_{market \text{ shares within sectors}} = \exp\left(\sum_s \sum_{i \in s} \sum_f w_{sif} \ln \frac{\left(\frac{Y_i}{Y_s}\right)_T}{\left(\frac{Y_i}{Y_s}\right)_0}\right) \quad (4)$$

4) The effect of changes in firm-level energy intensity (the ceteris paribus change in total CO₂ emissions if only firm-level energy intensities had changed):

$$D_{\text{intensity}} = \exp \left(\sum_s \sum_{i \in s} \sum_f w_{sif} \ln \frac{\left(\frac{\text{kWh}_i}{Y_i} \right)_T}{\left(\frac{\text{kWh}_i}{Y_i} \right)_0} \right) \quad (5)$$

5) The effect of changes in firm-level fuel mix (the ceteris paribus change in total CO₂ emissions if only firm-level end-use fuel mix had changed):

$$D_{\text{fuel mix}} = \exp \left(\sum_s \sum_{i \in s} \sum_f w_{sif} \ln \frac{\left(\frac{\text{kWh}_{if}}{\text{kWh}_i} \right)_T}{\left(\frac{\text{kWh}_{if}}{\text{kWh}_i} \right)_0} \right) \quad (6)$$

6) The effect of changes in fuel-level emission factors (the ceteris paribus change in total CO₂ emissions if only the emission factors of fuels had changed):

$$D_{\text{emission factor}} = \exp \left(\sum_s \sum_{i \in s} \sum_f w_{sif} \ln \frac{\left(\frac{\text{CO}_{2if}}{\text{kWh}_{if}} \right)_T}{\left(\frac{\text{CO}_{2if}}{\text{kWh}_{if}} \right)_0} \right) \quad (7)$$

The weights of each fuel-firm combination, w_{sif} , are the ratio of the logarithmic means of firm-and-fuel-level emissions in the two periods relative to the logarithmic means of the overall manufacturing emissions in the two periods:³

$$w_{sif} = \frac{\frac{(\text{CO}_{2if})_t - (\text{CO}_{2if})_{t-1}}{\ln \frac{(\text{CO}_{2if})_t}{(\text{CO}_{2if})_{t-1}}}}{\frac{(\text{CO}_2)_t - (\text{CO}_2)_{t-1}}{\ln \frac{(\text{CO}_2)_t}{(\text{CO}_2)_{t-1}}}} \quad (8)$$

Equations (4) and (5), in particular, constitute our contribution to the existing literature, as announced in Section 1. We can only calculate equation (4), the effect of shifting market shares within sectors, because we

³ The logarithmic mean is defined as $L(a, b) = \frac{a-b}{\ln a - \ln b}$.

use firm-level data in the first place and the definition of our intensity effect (equation 5) goes beyond the intensity effect in sector-level studies because it is a more accurate representation of technology and behavior at the firm level. The product of the six effects yields the overall change in emissions:

$$\begin{aligned}
 D_{\text{total}} = \frac{\text{CO}_{2\text{T}}}{\text{CO}_{2_0}} = & D_{\text{activity}} \cdot D_{\text{structure between sectors}} \\
 & \cdot D_{\text{market shares within sectors}} \cdot D_{\text{intensity}} \cdot D_{\text{fuel mix}} \\
 & \cdot D_{\text{emission factor}}
 \end{aligned}
 \tag{9}$$

From a methodological viewpoint, the discussions about “zero values” and about correct deflators are of interest for our work. Although LMDI has a number of desirable properties, it cannot handle zero values in its most basic form. The creators of LMDI originally recommend substituting zeros by very small values and calculating LMDI according to the original formula (Ang et al. 1998, Ang 2005). Wood and Lenzen (2006) criticize this approach and show that significant errors can occur even with small values of the recommended size (approximately 10^{-10} to 10^{-20}), especially if the original data set contains a large number of zeros. They show that errors become particularly large if the disaggregated effects (i.e., the explanatory factors) change sufficiently often from a positive number to zero or vice versa. As a solution, they suggest replacing the LMDI-weights by their limits at the effect equal to zero if the weight is undefined, as is the case for any zero-value change. Because we do not decompose sector-level or macroeconomic aggregates but firm-level data, zero values occur frequently in our dataset because firms enter or leave the market or start or terminate consumption of a specific fuel. We therefore follow Wood and Lenzen (2006) in replacing undefined LMDI-weights by their limits at the effect equal to zero.

In a recent decomposition study, Ma (2010) notes that the choice of deflator may be crucial for the result of a decomposition study. The results may be biased if differences in price changes between sectors are not properly accounted for. As a reaction to Ma’s critique, we use sector-level price indices instead of one manufacturing-wide price index.

3 Data

Our analysis uses of a number of official German statistics,⁴ namely the “AFiD-Betriebspanel”, augmented with an energy data module that has recently been made available to approved researchers at the Research Data Centres of the German Federal Statistical Office and the statistical offices of the German Länder. We use annual data from 1995 to 2007 on all German manufacturing plants with more than 20 employees (approximately 50,000 plants per year).⁵ Originally designed as a data set for plant-level productivity analysis, it includes detailed data on energy consumption by fuel type. During the first half of the panel (1995-2002), only the main traditional fuel types are covered in detail (e.g., different types of coal, gas, electricity, and oil). From 2003 onwards, questions on energy use were asked in a separate survey on energy consumption, which now covers usage and stocks of more than 30 different fuel types. This survey has been matched to the AFiD panel by the Research Data Centres. We exploit this information to conduct precise calculations of the energy and carbon intensities of production at the firm level. While the data are originally at the plant level, we aggregate our plant-specific data to the firm level to avoid bias in the valuation of plant-specific output due to arbitrary, firm-specific internal accounting rules.

The structural change, shifts in market shares, and intensity effects may in principle depend on the choice of output variable. The central output variable we are using is gross output, which is available for the complete sample of firms. Because gross output does not take into account different levels of inputs, we run an auxiliary analysis using value added in addition to using gross output as the output variable.⁶ While the sample using gross

⁴ Sources: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, as well as Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industrieunternehmen, 1995-2007.

⁵ For some sectors, mainly the food producing sectors, the cut-off threshold is 10 employees.

⁶ Gross output-based intensities are just as meaningful as intensities based on any other activity variable, but counting all intermediate goods repeatedly in the producing plant and in all plants downstream the product chain.

output utilizes all German manufacturing firms,⁷ any analysis based on value added is restricted to the subset of firms with more than 500 employees.⁸ Note that the subset of these large firms is much smaller than the whole sample (up to 1 205 instead of 51 845 firms).⁹ We report the results only for the structural change and intensity effects because the different output variable has no effect on the fuel mix effect and the emission factor effect. Differences in the activity level are negligible for our purpose. We show below that the choice of activity variable does not change the quality of our central results on the three effects named above.

To account for price changes in as differentiated a manner as possible and as a response to Ma's (2010) critique (cf. Section 2), we construct sector-specific deflators from product-level producer price indices. We form sectoral averages from product-level producer price indices and match them to our data at the sector level. The original price data and the weighting scheme were provided by the German Federal Statistical Office (Statistisches Bundesamt 2009).

In terms of sectoral aggregation, we go down to the three-digit sector level, which means we distinguish 110 different manufacturing sectors (cf. Statistisches Bundesamt 2006). We include all manufacturing sectors, apart from energy production sectors (e.g., coal mining, oil and gas production).

4 Results

The total CO₂ emissions for the whole manufacturing sector did not change much between 1995 and 2007. Considerable reductions in some years, such

⁷ By "all", we mean all firms in our sample, i.e., those with less than 20 employees are not included; see above (the cutoff is indeed based on plants, not firms). We also discard firms reporting implausible data, e.g., firms with a yearly turnover of less than 10 000 EUR, a value added of less than 5 000 EUR or zero electricity use.

⁸ Firms are excluded from the subsample if their employee count drops below 500 at least once.

⁹ Because we do not apply statistical inference on random variables, the smaller number of observations does not affect the credibility of our results.

as 1996 and 2005, were offset by increases in total emissions in other years, such as 2000, 2004, and 2006 (Figure 2).¹⁰

~ Figure 2 about here ~

Because the effects of intra-sector competition and firm-level intensity are the center of our analysis, we begin the description of results with these two effects (effects 3 and 4 in equation 1) instead of presenting our results in the order displayed in equations 1 and 9. After this, we continue with the effects of activity changes (effect 1), sectoral composition (effect 2), fuel mix (effect 5), and emission factors (effect 6).

4.1. Intra-sector competition, firm-level energy intensity, and the effect of aggregation level

4.1.1. The effect of intra-sector competition and firm-level intensity improvements on emissions

Our main goal in this paper is to quantify the effect of intra-sectoral competition on total manufacturing CO₂ emissions vis-à-vis the effect of firm-level technological progress. We thus begin the discussion of the drivers of CO₂ emissions with the effects of shifting market shares within sectors and firm-level intensity reductions on industrial CO₂ emissions. Our firm-level data allow us to differentiate these two effects as opposed to sector-level studies that, by construction, have to merge the effect of shifting market shares into the (sector-level) intensity effect.

As Figure 3 shows, changes in firms' market shares within their industries led to a marked *ceteris paribus* decrease of industrial CO₂ emissions. Without reallocation of production within sectors to less carbon-intensive firms, CO₂ emissions would have increased by 7.5 % between 1995 and

¹⁰ Any changes based on energy use information between 2002 and 2003 should be interpreted with caution due to a break in the energy statistics (see Section 3). It seems that the broader variety of fuels covered after 2002 led to a more comprehensive picture, especially for energy from renewable sources.

2007 instead of decreasing by 2.2 %. For nearly every year, intra-sectoral competition led, on average, to relatively energy-efficient companies taking market share from more inefficient companies in the same sector, with annual reductions in CO₂ emissions of up to 2.2 %.

~ *Figure 3 about here* ~

Also when firms' output is measured in terms of value added instead of gross output, the effect of shifting market shares is mostly contractive.¹¹ Emissions of the firms with more than 500 employees would have increased even more by 55.4 % instead of 27.9 % between 1995 and 2007, mainly due to large shifts in market shares in 2006 and 2007 (Figure 4) that we do not observe if we use gross output in the large sample. Naturally, the effect sizes, and in a few individual years, even the effect signs, differ between results based on gross output versus results based on value added because the sample of firms is structurally different. Value added is only available for relatively large firms, also affecting the relative importance of different sectors. Nevertheless, the general trend of an energy- and emission-saving market share effect remains the same. In order to be able to distinguish between the effects of the different sample and the use of value added instead of gross output, we perform the decomposition exercise again using gross output but disregarding all firms with less than 500 employees (Figure 5). We find a year-by-year pattern that resembles the results for gross output using all firms. Especially the relatively large expansions in the value added-based time series for the years 1996, 2000 and 2002 are not due to the sample restriction but to the use of value added instead of gross output. The same is true for the decisive contractions towards the end of the sample period that make up most of the difference between the value added and gross output-based series. In general, both the use of value added as well as the choice of a smaller sample, lead to more extreme amplitudes in both directions. The overall result of an emission-reducing intra-sectoral competition effect remains unchanged irrespective of the sample and the

¹¹ By contractive (expansive), we mean that the emission level of a component is lower (higher) in a period compared to the previous period. In other words, the rate of change of the component is negative (positive).

output measure. We therefore conclude that intra-sectoral competition is an important driver of CO₂ emissions in industry. In fact, it is the most important contractive effect among the six drivers studied here. It plays a pivotal role in counteracting the large expansion of emissions due to increasing production.

~ *Figure 4 and Figure 5 about here* ~

With regard to the intensity effect, i.e., the change in the companies' energy use per output ratio, the existing literature at the sectoral level usually finds contractive intensity effects.¹² We utilize the finer aggregation level of our micro-dataset to compute the intensity effect at the firm level, where we cannot unequivocally confirm this finding.

We find that changes in energy intensity only have a small and volatile effect on CO₂ emissions. If we calculate energy intensity relative to gross output and for all firms in the panel, we cannot confirm the clear-cut emission-saving influence of changes in energy intensity that some previous studies have postulated (cf. Footnote 12). Although the overall intensity effect is slightly negative over all firms (-2.6 % in 2007 compared to 1995), its impact is negligible compared to the other effects. In some periods, the intensity effect is even expansive. The difference from the sector-level findings is even more pronounced if we use value added as the activity variable, which means we have to restrict our sample to firms with more than 500 employees. Here, changes in firm-level energy intensity (measured in terms of value added) have an expansive effect in 7 of the 12 years. As Figure 4 shows, the effect of changes in energy use per value added increased emissions both before 1998 and after 2003. Over the whole

¹² In their review of 20 decomposition studies that include results for Germany, Liu/Ang (2007) list only one case where an expansive intensity effect was found. Because the reported results are always multi-year decompositions covering between five and 15 years so that expansive intensity effects of one year may be compensated by other years with contractive effects, this result does not mean that the other 19 studies would not have found a single year with an expansive intensity effect. Nevertheless, we believe it is a hint that expansive intensity effects are a rare exception from the rule of contractive intensity effects. For all studies covered by Liu/Ang (2007), the ratio of expansive vs. contractive intensity effects is 48 over 274 studies.

observation period, energy use per value added increased by nearly 30 %. As we show for the restricted sample using gross output, the increase in the contribution of intensity changes to overall emissions for value added-based numbers in comparison to gross output-based numbers is due to the choice of output variable (Figure 5). The effect using gross output for the restricted sample is even more contractive over the whole sample than for the unrestricted sample, while it is expansive if we use value added. In fact, the small-sample results based on gross output is the only case where we do find a significant emission-reducing effect of firm-level energy intensity changes. This effect vanishes if we take inputs into account by using value added. Also year-by-year changes are larger and more often positive if gross output is used. We conclude that our energy intensity numbers based on gross output might even be overly optimistic about the emission saving potential of firm-level energy intensity improvements.

The intensity effect is often regarded as a measure of technological progress. A contractive (expansive) intensity effect, in other words, a smaller (higher) energy intensity, means a firm is able to produce the same amount of output with less (more) energy. It is striking that the intensity effects are especially low at the end of boom periods, such as until 2000 or after 2004, and are especially high at the end of recession periods, such as from 2001 to 2003.¹³ We see this as an indication that the intensity effect is not exclusively driven by technological changes but also to a significant extent by rigidities in the adaptation of energy use to changes in production. In other words, some fixed amount of energy is used independent of the level of production. We concede, however, that these indications can only be generalized to a limited extent because our sample covers only a small number of complete business cycles.

¹³ See Figure 9 and Figure 10 on the activity effect. These figures depict changes in industrial output and provide information on the industrial business cycle.

4.1.2. The impact of aggregation level on the analysis of the intensity effect

The firm-level nature of our data allows us to introduce and analyze a new factor compared to sector level analyses, namely, the effect of intra-sectoral changes in firms' market shares. To illustrate the difference to the analysis using sector-level data and to highlight the relevance of our results for the interpretation of the intensity effect in sector-level analyses, we show how our results would have differed if we had conducted our analysis with the aggregated (i.e., sector-level) data instead. In this case, shifts in market shares within sectors would have been included in the intensity effect. The intensity effect would have looked pronouncedly different, as seen in Figure 6 based on gross output and Figure 7 based on value added as the activity variable. In the interest of completeness, we add Figure 8 to show the impact of sample and variable choice on the difference between Figure 6 and Figure 7. As the Figures show, the difference between the two curves for the intensity effect at the firm and sector levels remains substantial if the analysis is conducted on the smaller subset using gross output, even though the cumulative effect from 1995-2007 decreases slightly. Also the direction of the cumulative effects is similar, as the intensity effect is contractive both on the firm and on the sectoral level. This is contrary to the effect using value added, as described in Section 4.1.1. As the number of firms is smaller in Figure 8 compared to Figure 6, the volatility of the curves, i.e. the year-to-year movements, is larger and similar to Figure 7. Since the market share effect is almost entirely emission-saving, the intensity effect at the sector level, aggregated from our firm-level intensity effect and the effect of shifting market shares within sectors, is downward biased compared to the intensity effect at the firm level. Expansive intensity effects are less frequent and less pronounced. In some years, the intensity effect at the sector level even has a different sign than the intensity effect that is purged of intra-sectoral shifts in market share. A considerable share of energy efficiency improvements that appear on the sector level is not caused by technological or managerial improvements within a firm but by the "dirty" firms losing market shares or even closing down entirely, while "clean" firms gain market shares. This context is not only relevant for the interpretation of

sector-level results, it also has implications for policy making as well. The common misinterpretation of the immense effect of contractive intensity effects from sector-level studies as representing technological progress has underpinned the targeting of energy efficiency policies at well-established incumbents rather than at innovative new entrants. The latter, however, drive technological progress.

~ Figure 6, Figure 7 and Figure 8 about here ~

4.2. The effect of changes in activity, sectoral composition, fuel mix, and emission factors

Apart from the effects of shifting market shares and firm-level intensity, we also calculate the impact of the remaining four effects from equation 9. Over the whole period, the most important driver of CO₂ emissions in terms of cumulative change of emissions is the effect of expanding overall activity in the manufacturing sector. Figure 9 shows that, over the whole period, a nearly monotonic increase in industrial production had a strongly expansive impact on CO₂ emissions. Annual activity effects, of course, resemble the German business cycle, with recessions in approximately 1996 and 2001/2002 as well as boom periods between 1996 and 2000 and between 2005 and 2007. *Ceteris paribus*, annual increases of up to 8 % add up to a hypothetical increase in CO₂ emissions of approximately 40 % from 1995 to 2007 due to economic activity, highlighting the need for the decoupling of production and emissions.

~ Figure 9 about here ~

One important driver of decoupling at the national level is the effect of structural change between sectors, i.e., a shift from energy-intensive sectors to less-energy-intensive sectors. With the exception of 1997, we observe only contractive (or negligibly expansive) structural change effects (Figure 9). We can confirm this result for structural change measured in terms of value added instead of gross output structural changes for large firms: structural changes between sectors are nearly continuously contractive after 1998 (Figure 10). As the comparison with small-sample values based on

gross output shows, correcting for the use of inputs by using value added as the activity measure leads to a moderation of otherwise even larger effects among larger firms (Figure 11). While the overall effect of structural change for the period from 1995 to 2007 is still negative, the last years of our sample exhibit emission-increasing structural change if measured by gross output, as opposed to emission-decreasing structural change if measured by value added. Apart from distinguishing between the impacts of using different output measures and small samples, Figure 11 also shows that the structural change effect is to some degree sensitive to the choice of sample. Overall, we confirm the results from previous studies using more aggregate data, namely, that structural change leads to a significant reduction in CO₂ emissions in highly industrialized countries. Naturally, it is also an indicator for the relocation of “dirty”, i.e., emission-intensive, industries to other parts of the world with potentially less strict environmental regulation.

~ Figure 10 and Figure 11 about here ~

The two remaining effects are the impact of a change of the end-use fuel mix and changing emission factors (Figure 12). Quite surprisingly, the composition of the fuel mix had virtually no effect on total CO₂ emissions of the whole sample between 1995 and 2002. This changes slightly after 2002, most likely because the newly established energy statistic better covers renewable energies such as biomass (cf. Section 3). Changes in the (upstream) emission factors were usually contractive, which led to a steady ceteris paribus decrease of CO₂ emissions, caused mainly by changes in the electricity mix towards cleaner power plants.¹⁴

~ Figure 12 about here ~

4.3. Sector-specific energy innovation patterns

In the previous section, we presented the aggregated results of our decomposition analysis and refrained from making detailed statements

¹⁴ The choice of activity measure, whether gross output or value added, does not impact the calculation of the fuel mix or emission factor effect, which is why we refrain from showing the results for value added.

about specific sectors. In this section, we study the nature of the innovation process towards more efficient energy use in different sectors by analyzing the sector-level contributions to the various effects. The sector-level contributions are the summands of equations (2) to (7) before summing up across all sectors, but after summing up fuels across each firm and firms across each sector. As before, a positive contribution of a sector to one of the effects increases emissions, while a negative contribution decreases emissions. Specifically, we contrast the energy saving effect of intra-sectoral competition, or shifting market shares, with the contribution of firm-level energy efficiency improvements at the sector level.¹⁵

We distinguish four types of sectors: (1) Sectors with energy innovation through entrants are sectors whose firms mostly increase their energy intensity and which, at the same time, show energy-saving intra-sectoral competition. (2) Sectors with innovation through technological progress are sectors whose firms by the majority decrease their energy intensity (i.e., improve energy efficiency), while intra-sectoral competition is not energy-saving. (3) A minority of sectors saves energy both through entrants and technology improvements, which means the median contribution over all firms is energy-saving, both for the intra-sectoral competition effect and for the intensity effect. (4) The remaining sectors increase their energy use via both effects. We do not analyze them in detail.

From this classification of sectors, we draw conclusions about the potential for firm-level improvements in energy intensity in the future. While analysts and policy makers pin their hopes on energy efficiency improvements in industrial firms,¹⁶ we have shown in the previous section that firm-level energy efficiency improvements have not contributed much to curbing CO₂ emissions during our sample period. One reason for this is the considerable number of firms in sectors that innovate via entrants only. Contrary to new entrants, incumbents in these sectors are relatively unlikely to innovate

¹⁵ For the sake of representativeness and brevity, we concentrate on energy intensity with respect to gross output only, and we disregard our auxiliary analysis based on value added in this section.

¹⁶ Cf., e.g., the McKinsey marginal abatement cost curve, as in, e.g., Enkvist et al. (2010).

themselves. We can only speculate about the potential reasons. Technological lock-in because of prohibitive switching costs could be one reason, especially because less-energy-intensive production is generally possible in these sectors, as shown by the efficiency level of new entrants. In any case, political measures targeted at firm-level energy efficiency improvements will usually be ineffective for this type of sector.

If, however, a sector innovates via technological progress, firms are able to adjust their energy productivity. In these sectors, we can assume untapped potential through innovation at the firm level. This potential might be activated by future energy price shocks, or even future political interventions. In this case, the high hopes placed on energy efficiency improvements might still be fulfilled.

As Figure 13 shows, the classification of the sectors into the different groups varies over the years due to year-specific effects. To identify the long-term affiliation of a sector, we assign a sector to a group if that sector is in this group for more than half the years (see the last column of Figure 13), similarly to a smoothing effort. Accordingly, the overall number of sectors that fall into the first three classes in the long run is lower than for the annual classification. The number of undetermined sectors increases, mostly because both their median effects become zero.

~ Figure 13 about here ~

We presume that firms in especially energy intensive sectors, where low energy costs are a decisive competitive advantage, are more likely to reap the benefits from energy efficiency improvements than their counterparts in less energy intensive sectors. We argue that firms in these especially energy-intensive sectors will be especially active in enhancing their energy productivity, resulting in larger energy intensity changes. We therefore pay

special attention to our findings for the 10 % of the most energy intensive sectors, which are twelve in total (see solid bars in Figure 13).¹⁷

Among the dozen most energy-intensive sectors, we can identify some that follow relatively pronounced patterns in their attempt to cut down on energy use: A number of sectors, such as Pulp and Paper (211), Basic Iron and Steel (271) or Casting of Metals (275), belong to group 2 and innovate via technology. We can identify a consistent pattern of negative median growth rates of energy intensity at the firm level, while changes in market shares within a sector do not play a significant role. The same is true for one of Germany's most prominent (but not exceptionally energy intensive) sectors, the car manufacturers (Motor Vehicles, 341). In these industries, the median growth rate of energy intensity was negative throughout nearly the whole observation period. Firms in these sectors seem to be able to innovate and compete within their sectors by investing in less-energy-intensive technologies. We take this as an indication of a successful tapping of energy efficiency potentials.

In other especially energy-intensive sectors, such as Tiles and Flags (263) or Baked Clay (265), consistent progress towards more efficient production has been made, not in the form of firm-level improvements in energy intensity, but in the form of competition within the sector (group 1). In these sectors, more efficient firms gained market shares at the cost of their less-efficient counterparts in many years, while energy intensities at the firm level did not change much. We argue that firm-level innovations in energy efficiency are less probable and that the effectiveness of policy measures targeted at firm-level energy intensity, such as subsidies for energy efficiency improvements, is questionable.

¹⁷ Defined by median energy intensity of the firms in the respective sector over the whole period of observation. This includes (three-digit sector codes in parenthesis) Mining of Hard Coal (101), Other Mining (145), Finishing of Textiles (173), Pulp and Paper (211), Man-made Fibres (247), Ceramics (262), Tiles and Flags (263), Baked Clay (264), Cement (265), Basic Iron and Steel (271) and Casting of Metals (275). We have to exclude Salt Extraction (144) because of data confidentiality requirements due to the small size of the sector.

5 Summary and Conclusions

Based on a detailed firm data set on the German manufacturing sector, we perform a decomposition analysis of industrial CO₂ emissions. Due to the degree of detail in our micro dataset, we can identify the effects of intra-sectoral competition and energy efficiency improvements on the firm level, in addition to the effects of changes in economic activity, sectoral structure, fuel mix, and emission factors.

We show that, despite a large increase in economic activity, CO₂ emissions in the German manufacturing sector did not change much between 1995 and 2007. Structural change between sectors, shifting market shares within sectors, and a cleaner electricity generation mix prevented an upsurge of CO₂ emissions. We see the large contractive effect of structural change as evidence supporting the pollution haven hypothesis: the production of carbon intensive goods may have moved away from Germany towards countries with weaker environmental regulations.

Changes in energy intensity at the plant level played only a negligible role in reducing overall emissions and actually increased emissions for the subset of large firms. In any case, we cannot confirm that energy intensity improvements in the manufacturing sector led to any significant improvement in CO₂ emissions when measured at the micro level. Adding the effect of shifting market shares, or competition, within sectors to the analysis reveals that a contractive energy intensity effect at the sector level, as often found in comparable sector-level studies, is at least in our case mainly due to shifting market shares within the sectors rather than to progress in efficiency at the firm level. We find that, over time, comparably inefficient firms in a sector lose market shares in favor of energy-efficient firms.

From the prevalence of firm-level energy efficiency improvements and intra-sectoral competition, we identify different innovation patterns at the sector level. In some cases, technological or behavioral innovations that improve CO₂ or energy intensity penetrate the market through new entrants instead of by being adopted by the incumbents. We can only speculate about

the reasons for the incumbents' lack of enthusiasm in improving energy efficiency, although technological lock-in may be one of them. We posit that in this case, policy measures targeted at improving firm-specific energy intensity, such as innovation subsidies, do not bear much potential for future improvements of overall energy efficiency. Hopes on these measures are more justified in sectors that innovate mostly via technology instead of competition through entrants. Among the most energy intensive sectors, we find examples for both innovation patterns.

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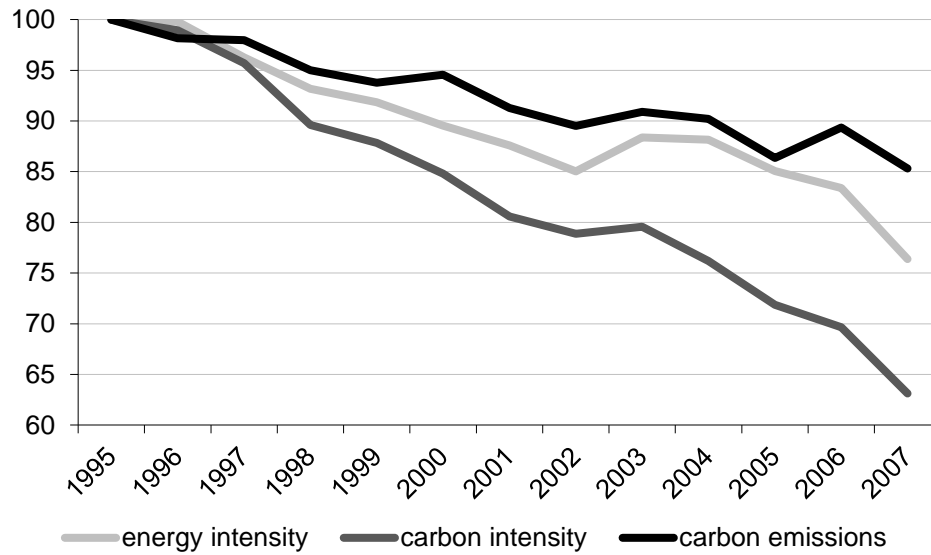
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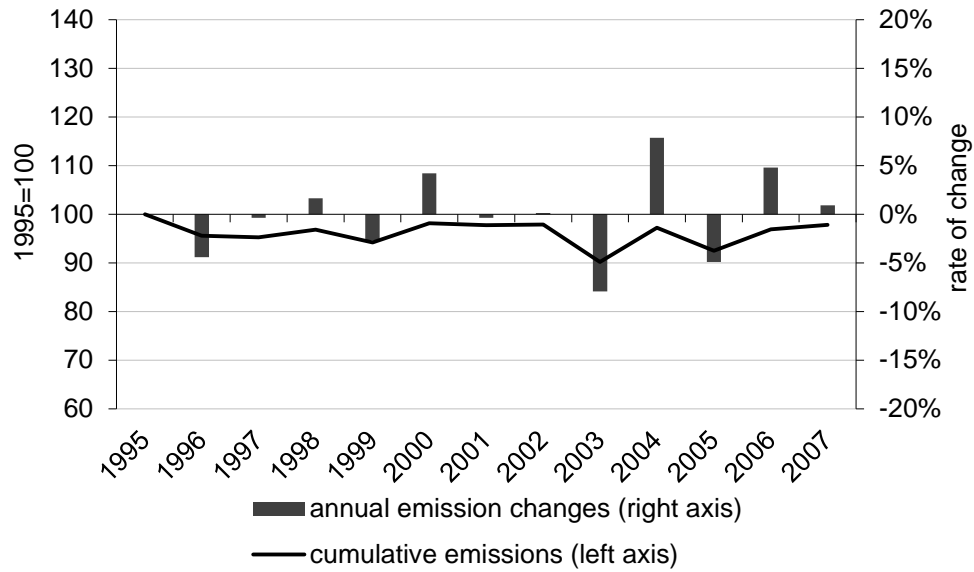
Figures

Figure 1: Energy and carbon intensities in manufacturing (1995=100)



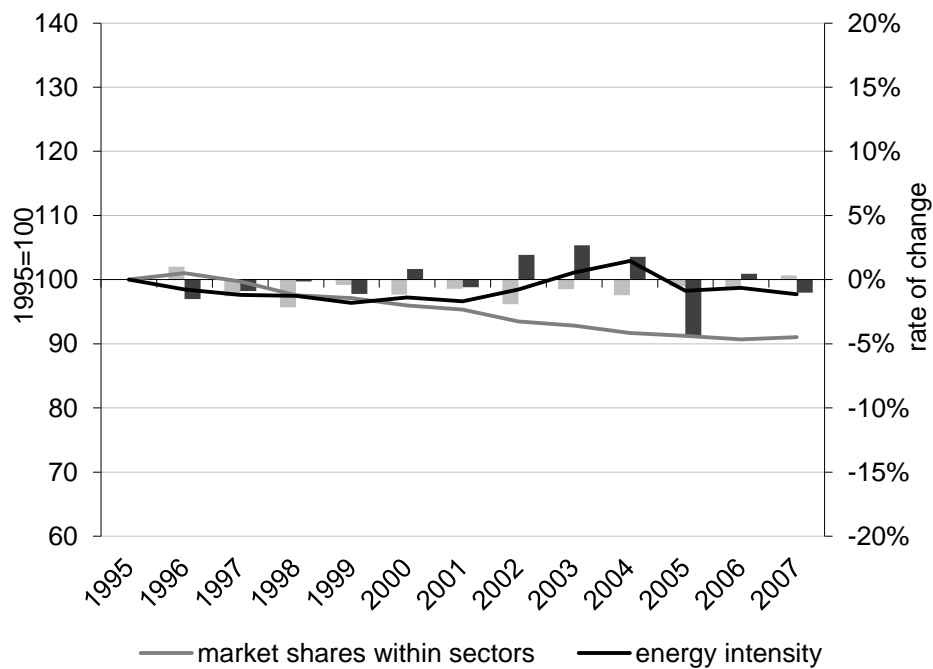
Source: Statistisches Bundesamt.

Figure 2: Total CO₂ emissions (based on gross output)



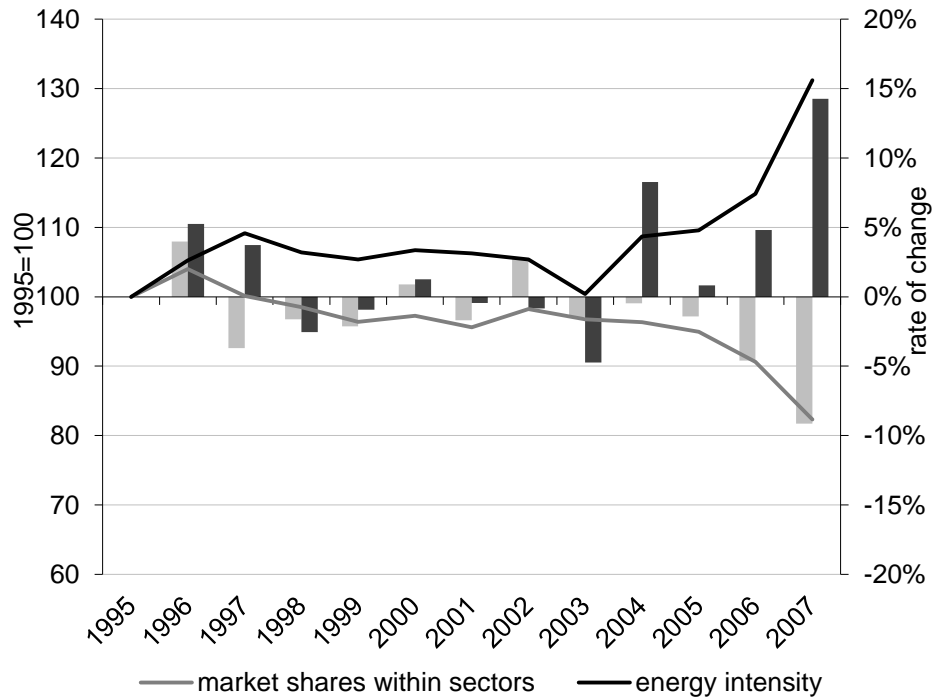
Cumulative emissions as line (left axis), annual changes as bars (right axis). Observations from up to 51 845 firms per year. Note that the change from 2002 to 2003 is affected by a break in the energy statistics and should be interpreted cautiously. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, own calculations.

Figure 3: Effects of shifting market shares within sectors and energy intensity effect (based on gross output)



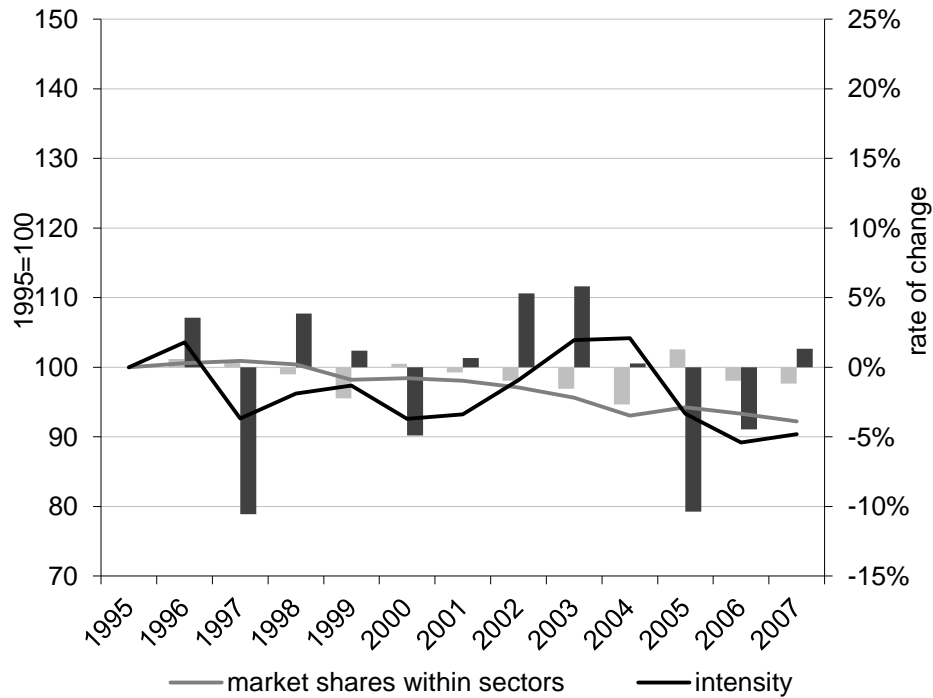
Cumulative effect on emissions as line (left axis), annual changes as bars (right axis). The “market shares within sectors” effect shows the ceteris paribus change in total CO₂ emissions if only the relative market shares of firms in sectoral output had changed. The “energy intensity” effect shows the ceteris paribus change in total CO₂ emissions if only firm-level energy intensities had changed. Observations from up to 51 845 firms per year. Note that the change from 2002 to 2003 is affected by a break in the energy statistics and should be interpreted cautiously. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, own calculations.

Figure 4: Effects of shifting market shares within sectors and energy intensity effect (based on value added)



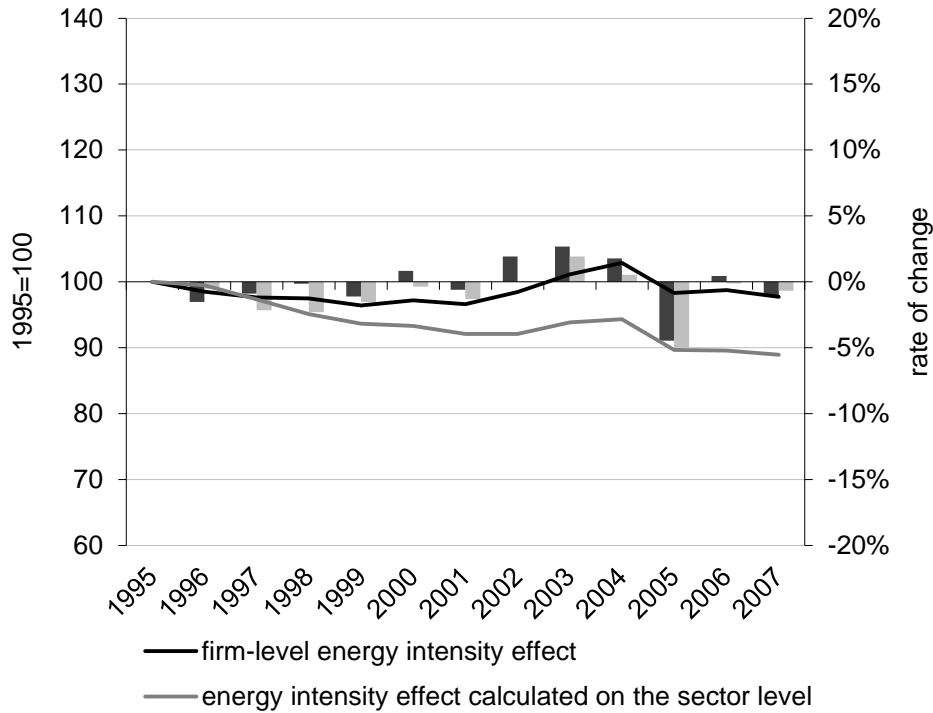
Cumulative effect on emissions as line (left axis), annual changes as bars (right axis). Only firms with more than 500 employees due to data restrictions. The “market shares within sectors” effect shows the ceteris paribus change in total CO₂ emissions if only the relative market shares of firms in sectoral output had changed. The “energy intensity” effect shows the ceteris paribus change in total CO₂ emissions if only firm-level energy intensities had changed. Observations from up to 1 205 firms per year. Note that the change from 2002 to 2003 is affected by a break in the energy statistics and should be interpreted cautiously. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, own calculations.

Figure 5: Effects of shifting market shares within sectors and energy intensity effect (based on gross output, only firms with >500 employees)



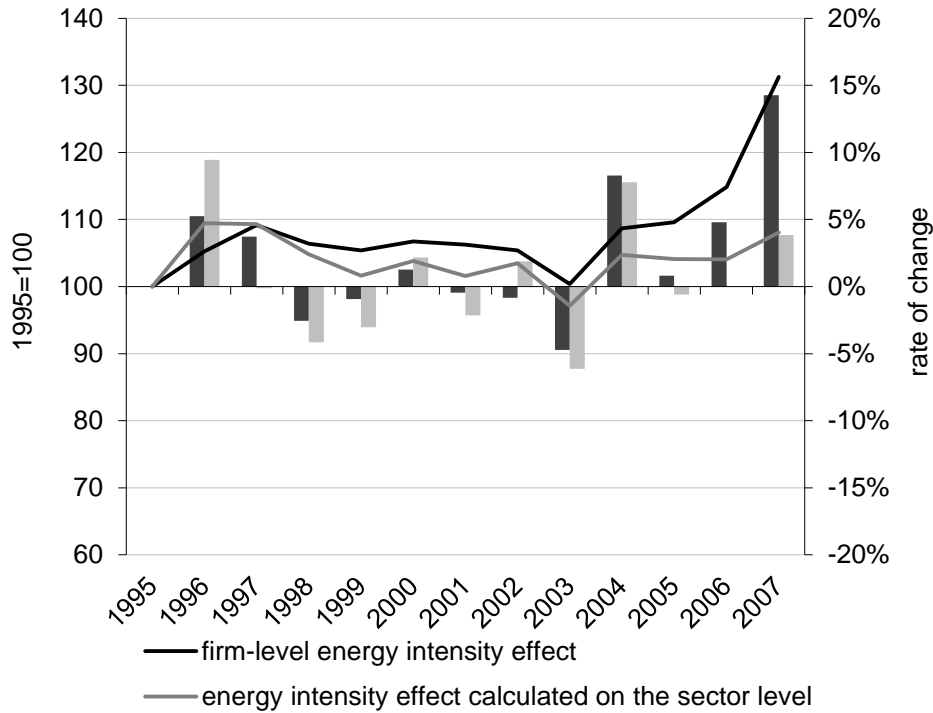
Cumulative effect on emissions as line (left axis), annual changes as bars (right axis). Only firms with more than 500 employees. The “market shares within sectors” effect shows the ceteris paribus change in total CO₂ emissions if only the relative market shares of firms in sectoral output had changed. The “energy intensity” effect shows the ceteris paribus change in total CO₂ emissions if only firm-level energy intensities had changed. Observations from up to 1 375 firms per year. Note that the change from 2002 to 2003 is affected by a break in the energy statistics and should be interpreted cautiously. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, own calculations.

Figure 6: Intensity effects calculated at the firm and sector level (based on gross output)



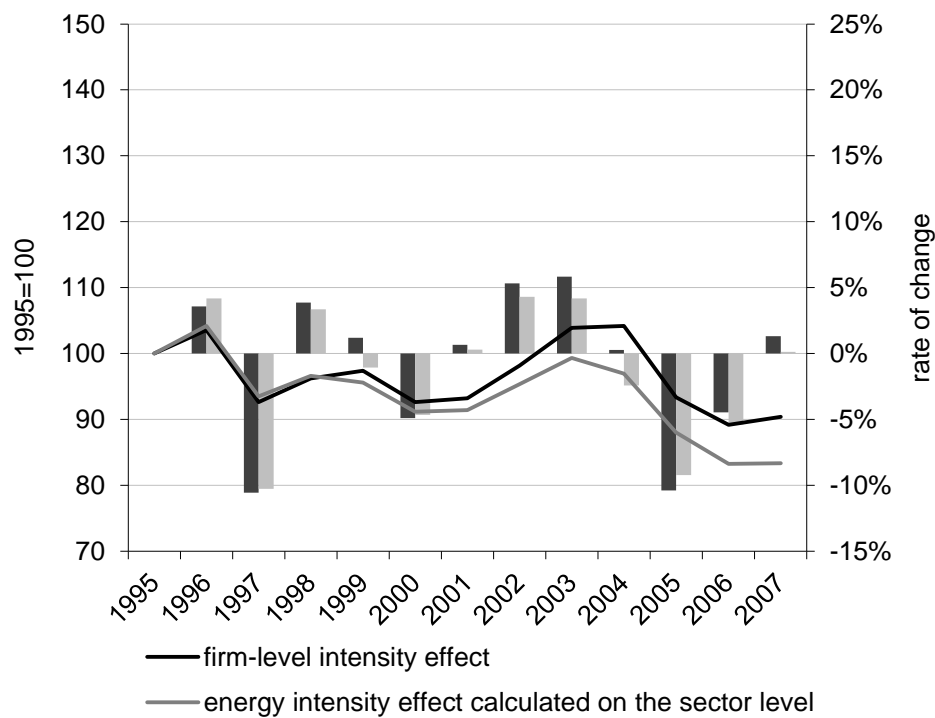
Firm-level intensity effect as in Figure 3. Intensity effect on the sector level calculated by aggregating firm-level intensity effect and the effect of shifting market shares within sectors. Cumulative effect on emissions as line (left axis), annual changes as bars (right axis). Observations from up to 51 845 firms per year. Note that the change from 2002 to 2003 is affected by a break in the energy statistics and should be interpreted cautiously. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, own calculations.

Figure 7. Intensity effects calculated at the firm and sector level (based on value added)



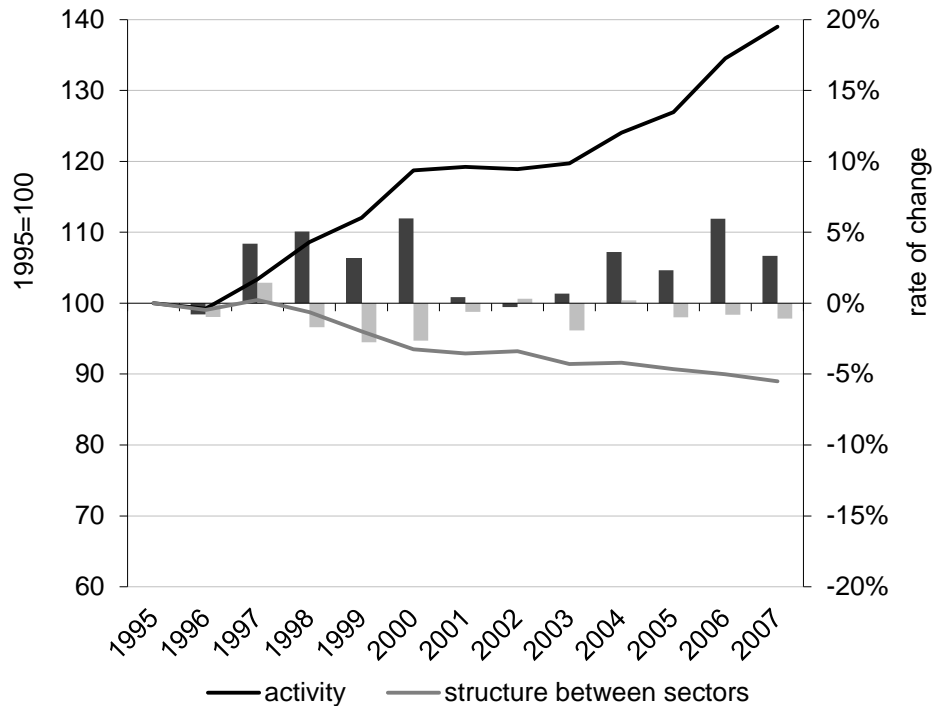
Firm-level intensity effect as in Figure 4. Intensity effect on the sector level calculated by aggregating firm-level intensity effect and the effect of shifting market shares within sectors. Cumulative effect on emissions as line (left axis), annual changes as bars (right axis). Only firms with more than 500 employees due to data restrictions. Observations from up to 1 205 firms per year. Note that the change from 2002 to 2003 is affected by a break in the energy statistics and should be interpreted cautiously. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, own calculations.

Figure 8. Intensity effects calculated at the firm and sector level (based on gross output, only firms with >500 employees)



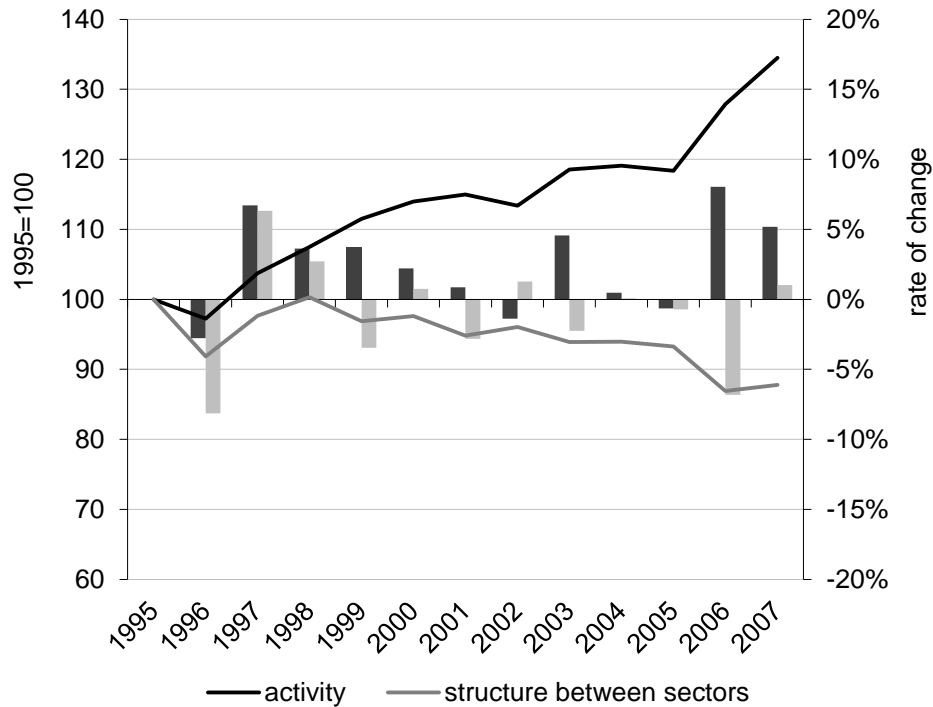
Firm-level intensity effect as in Figure 4. Intensity effect on the sector level calculated by aggregating firm-level intensity effect and the effect of shifting market shares within sectors. Cumulative effect on emissions as line (left axis), annual changes as bars (right axis). Only firms with more than 500 employees. Observations from up to 1 375 firms per year. Note that the change from 2002 to 2003 is affected by a break in the energy statistics and should be interpreted cautiously. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, own calculations.

Figure 9: Emissions due to the activity and structural change effects (based on gross output)



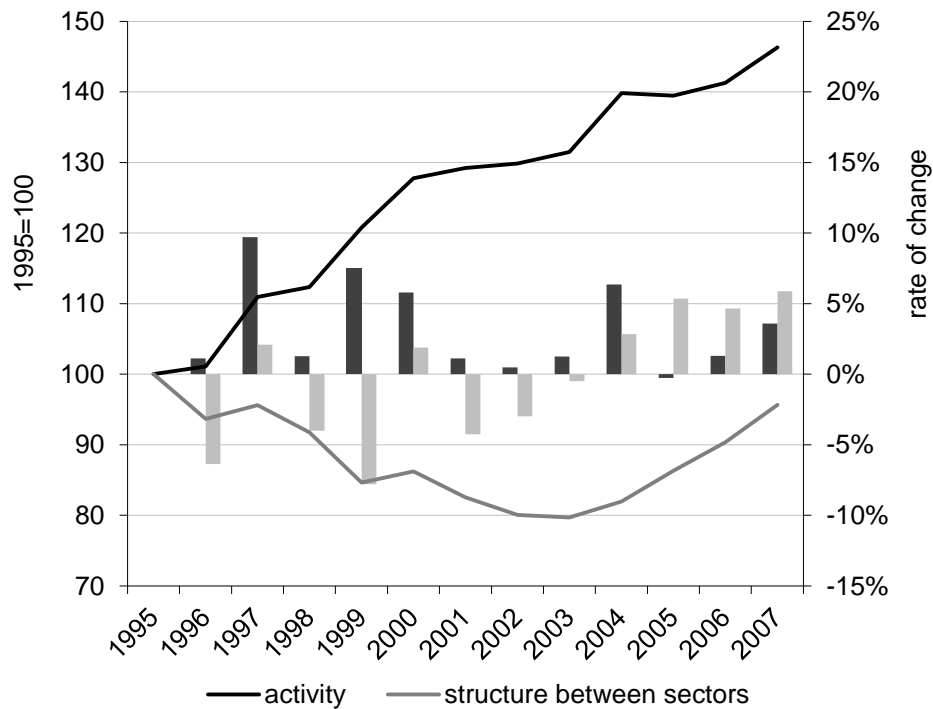
Cumulative effect on emissions as line (left axis), annual changes as bars (right axis). The “activity” effect shows the ceteris paribus change in total CO₂ emissions if only total manufacturing activity had changed. The “structure between sectors” effect shows the ceteris paribus change in total CO₂ emissions if only the shares of sectors in total manufacturing output had changed. Observations from up to 51 845 firms per year. Note that the change from 2002 to 2003 is affected by a break in the energy statistics and should be interpreted cautiously. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, own calculations.

Figure 10: Emissions due to the activity and structural change effects (based on value added)



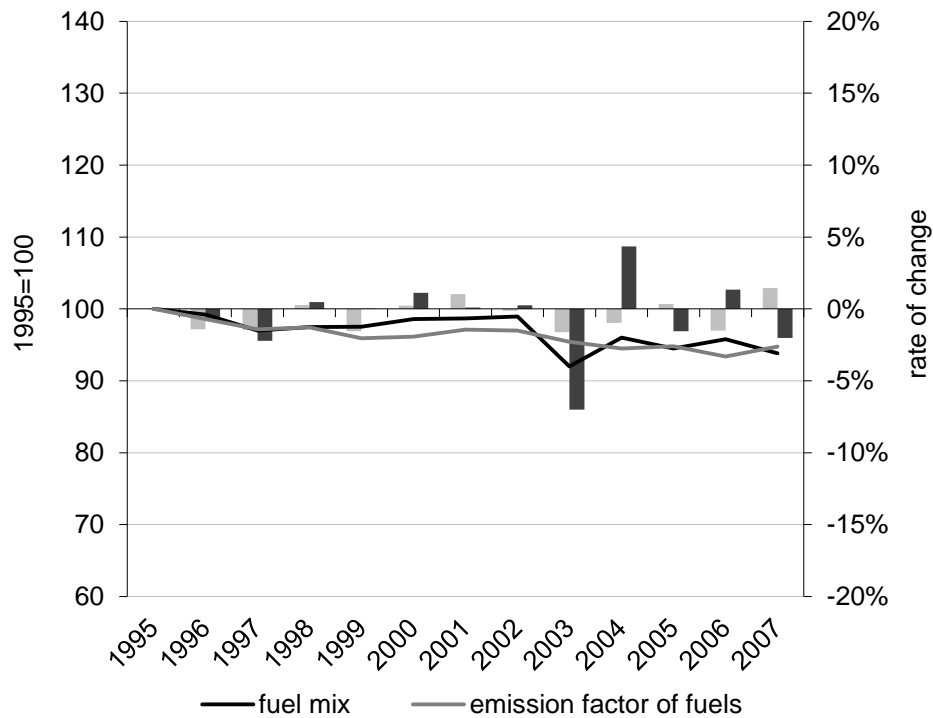
Cumulative effect on emissions as line (left axis), annual changes as bars (right axis). Only firms with more than 500 employees due to data restrictions. The “activity” effect shows the ceteris paribus change in total CO₂ emissions if only total manufacturing activity had changed. The “structure between sectors” effect shows the ceteris paribus change in total CO₂ emissions if only the shares of sectors in total manufacturing output had changed. Observations from up to 1 205 firms per year. Note that the change from 2002 to 2003 is affected by a break in the energy statistics and should be interpreted cautiously. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, own calculations.

Figure 11: Emissions due to the activity and structural change effects (based on gross output, only firms with >500 employees)



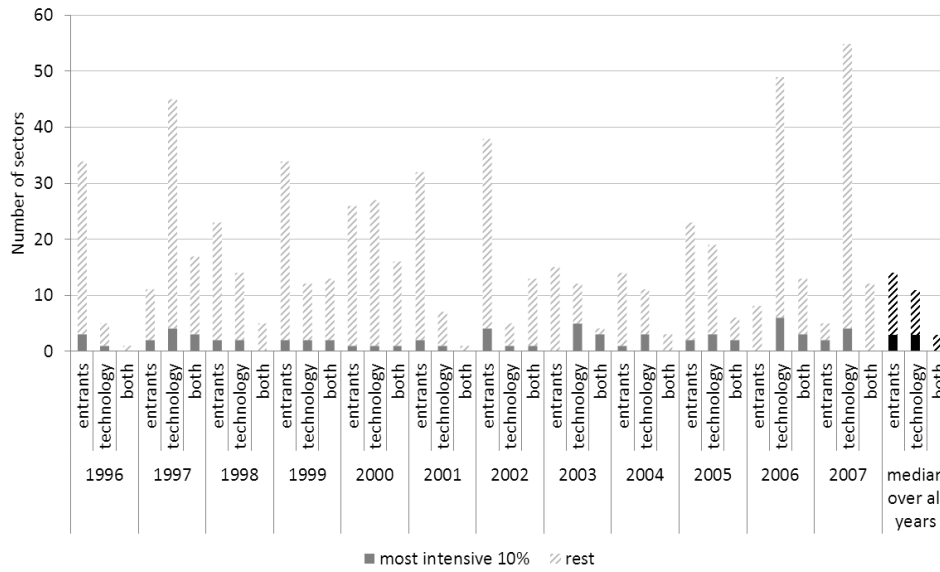
Cumulative effect on emissions as line (left axis), annual changes as bars (right axis). Only firms with more than 500 employees. The “activity” effect shows the ceteris paribus change in total CO₂ emissions if only total manufacturing activity had changed. The “structure between sectors” effect shows the ceteris paribus change in total CO₂ emissions if only the shares of sectors in total manufacturing output had changed. Observations from up to 1 375 firms per year. Note that the change from 2002 to 2003 is affected by a break in the energy statistics and should be interpreted cautiously. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, own calculations.

Figure 12: Emissions due to the fuel mix and emission factor effects (based on gross output)



Cumulative effect on emissions as line (left axis), annual changes as bars (right axis). The “fuel mix” effect shows the ceteris paribus change in total CO₂ emissions if only end-use firm-level fuel-mix had changed. The “emission factor of fuels” effect shows the ceteris paribus change in total CO₂ emissions if only the emission factors of fuels had changed. Observations from up to 51 845 firms per year. Note that the change from 2002 to 2003 is affected by a break in the energy statistics and should be interpreted cautiously. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, own calculations.

Figure 13: Sectors' energy innovation patterns of sectors



Innovation through entrants: median intensity effect over all firms of a sector is non-negative, median effect of structural change within the sector is negative. Innovation through technology: median intensity effect over all firms of a sector is negative, median effect of structural change within the sector is not negative. Innovation through both: median intensity effect and median effect of structural change are negative. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1995-2007, own calculations.

The Impact of Carbon Trading on Industry: Evidence from German Manufacturing Firms*

Sebastian Petrick[†] Ulrich J. Wagner[‡]

Abstract

We estimate the causal impact of the EU Emissions Trading Scheme on manufacturing firms using comprehensive panel data from the German production census. Semiparametric matching estimators yield robust evidence that the policy caused treated firms to abate one-fifth of their CO₂ emissions between 2007 and 2010 relative to non-treated firms. This reduction was achieved predominantly by improving energy efficiency and by curbing the consumption of natural gas and petroleum products, but not electricity use. We find no evidence that emission trading lowered employment, gross output or exports of treated firms.

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1 Introduction

In many classical areas of market failure, there has been a paradigm shift away from heavy-handed regulation toward policies that decentralize the decision of how to comply with a given regulatory objective. Preeminent examples are the privatization of state-owned natural monopolies and the liberalization of formerly monopolistic markets. Similarly, market-based instruments have gained momentum in the regulation of external effects. In pollution control, for example, the traditional quota-based approach has been increasingly replaced by markets where polluters can trade the right to pollute among each other. This approach, known as ‘cap-and-trade’ or ‘emissions trading’, is cost effective because market forces equalize marginal abatement costs across polluters.

Within the span of just two decades, emissions trading has evolved from an idea contemplated in academic circles to a widely implemented policy instrument.¹ Since the 1980s, emissions trading systems for conventional pollutants have been implemented on an ever growing scale. The culmination of this remarkable development was reached in 2005 when the European Union (EU) launched the first mandatory carbon trading scheme in history.² The EU Emissions Trading Scheme (EU ETS) covers more than 2 billion tons of CO₂ in 31 countries, making it the most significant market-based instrument of climate policy implemented to date, the first trans-boundary cap-and-trade system, and the world’s largest carbon pricing experiment per se. Although the EU ETS is a prime candidate for evaluating the effectiveness and economic consequences of cap-and-trade in the real world, a recent literature survey concludes that causal evidence on these issues is still very scant, owing to the recency of the policy and a lack of suitable emissions data (Martin et al., 2013c).³

This paper seeks to fill this gap. Using administrative panel data for the

¹The idea behind emissions trading has also been applied successfully to renewable resource management, establishing individually transferable quotas (ITQs) for fisheries.

²The 1997 Kyoto Protocol to the UN Framework Convention on Climate Change stipulated worldwide trading of carbon emissions between governments, which came into force in 2008.

³Much of the early academic research on the EU ETS is concerned with ex-ante impact assessments and based on CGE modeling or “theory with numbers” (e.g. Demailly and Quirion, 2008, 2006). Interim empirical assessments are based on surveys or interviews (e.g. McKinsey and Ecofys, 2006a,b; Kenber et al., 2009).

universe of German manufacturing plants with at least 20 employees (approximately 50,000 per year), we estimate the causal impact of the EU ETS by combining a differences-in-differences approach with semiparametric matching techniques. The dataset is highly representative and covers a wide range of plant characteristics that we use as outcome variables and for matching. Its particular strength, for the purposes of this analysis, is the extraordinarily detailed information on energy consumption, which allows for very precise calculations of carbon emissions. The window of our analysis covers phase I of the EU ETS, which ran from 2005 until 2007 and the first three years of phase II up until 2010.

Our study focuses on Germany, Europe's largest economy and also its largest emitter. More than 1,900 of all EU ETS installations are based in Germany, accounting for approximately one fifth of total regulated CO₂ emissions. The strong orientation of the German manufacturing sector toward export markets makes Germany a particularly interesting case for investigating the validity of widespread concerns that unilateral regulation of European firms leads to a loss of competitiveness in international product markets.

Our results indicate that the EU ETS did not reduce emissions in significant ways during its first phase, but it caused participating firms to substantially reduce their carbon emissions relative to untreated firms during phase II. This abatement was achieved through a reduction in the carbon intensity rather than through a reduced scale of production. While phase I saw some substitution of low-carbon for high-carbon fuels at treated firms, in phase II treated firms drastically reduced their use of all primary energy while maintaining constant their level of electricity consumption. We attribute this outcome to firms curbing onsite generation of heat as the pre-dominant way of reducing compliance costs. Qualitative evidence from telephone interviews with managers suggests that regulated firms optimized their use of process heat. In contrast, we find no evidence of major technological upgrades that would explain the reduction of carbon intensity.

We examine the competitiveness issue by estimating the impact of the EU ETS on employment, gross output, and exports of participating firms. Based on these estimates, we can reject the hypothesis that the EU ETS reduced gross output or exports. The impact on employment is insignificant

in statistical and economic terms.

Our study is timely and contributes to the literature in several ways. The principal contribution is to provide robust evidence concerning the causal impact of world's largest emissions trading scheme on the manufacturing sector. This evidence not only is relevant for the policy debate in Europe but also informs policymakers in other parts of the world who are considering the adoption of regulatory instruments to curb carbon emissions. For instance, the EU ETS has served as a blueprint for similar policies in Australia, California, New Zealand, South Korea and other places where initiatives to establish carbon trading can be found at different stages of planning and implementation. From a broader perspective, the drive for more efficient regulation of market failures mentioned at the outset has made the need for empirical evaluation of regulatory instruments very salient. In this vein, our study adds to a broader literature on market-based regulation and, in particular, to a nascent empirical literature on cap-and-trade. While the bulk of this literature focuses on emissions trading among electricity producers (e.g. Ellerman et al., 2000), researchers have only just started to study cap-and-trade programs in the manufacturing sector (e.g. Fowlie et al., 2012; Fowlie and Perloff, 2013).

The remainder of the paper is structured as follows. The next section describes the institutional details of the EU ETS, to the extent that they are relevant for the subsequent analysis, and reviews the related literature. Section 3 explains our research design and Section 4 describes the principle dataset. Section 5 presents our main results along with numerous robustness checks. Section 6 explores several channels of emission reductions. Section 7 concludes.

2 Institutional background: The EU ETS

2.1 Scope

The EU ETS is implemented as a classical cap-and-trade system for CO₂ emissions. Participating firms receive emission permits – called EU Allowance Units (EUA) – that are fully tradable across firms in all participating countries. The EU ETS has been implemented in three phases.

Phase I ran from 2005 to 2007 and served mainly as a trial phase to test the functioning of the system. Phase II coincided with the first commitment period of the Kyoto Protocol – 2008 to 2012 – which stipulated an 8% reduction in GHG emissions compared to 1990 as the EU’s Kyoto commitment under the burden sharing agreement. The current third phase of the EU-ETS will run until 2020. Independently of international efforts to curb greenhouse gas emissions beyond the EU, the ETS is the centerpiece of the EU’s unilateral climate policy, which stipulates a 20% reduction of GHG emissions in 2020 relative to 1990. A comprehensive review of the history and structure of the EU ETS can be found in Ellerman et al. (2014).

According to the Emissions Trading Directive,⁴ participation in the EU ETS is mandatory for all combustion installations with a rated thermal input of 20 MW or more. This concerns mostly heat and power generation, regardless of the industry. In addition, industrial plants are regulated under the EU ETS if they specialize in certain industrial activities and exceed specific capacity thresholds. The activities defined in the Emissions Trading Directive correspond to four industry codes, namely “manufacture of paper and paper products” (WZ classification code 17), “manufacture of coke and refined petroleum products” (WZ19), “manufacture of other non-metallic mineral products” (WZ23, including i.a. manufacture of glass, ceramics, and cement), and “manufacture of basic metals” (WZ24).⁵ Henceforth, we shall refer to these industries as the “process regulated sectors”. Beginning in 2012, emissions from other industries, such as aviation, have been included in the EU ETS as well.

2.2 Related literature

In spite of the geographic, environmental, and financial scope of the EU ETS, little is known so far about the causal impacts of this policy (Martin

⁴Directive 2009/29/EC of the European Parliament and of the Council amending Directive 2003/87/EC so as to improve and extend the greenhouse gas emission allowance trading scheme of the Community (2009) OJ L 140, 5.6.2009, p. 63–87 (Emissions Trading Directive).

⁵Note that the WZ classification system used in German Statistics corresponds to the ISIC codes (Rev. 4). From 2008 onwards, some activities have been added, e.g. from the chemical industry. The interested reader is referred to Appendix A.1 for more details.

et al., 2013c). On the one hand, this lack of knowledge is due to the recency of this regulation; on the other hand, it results from the difficulty of obtaining representative firm-level data, especially for CO₂ emissions. Early assessments by Ellerman and Buchner (2007, 2008); Ellerman et al. (2010); Anderson and Di Maria (2011) thus rely on more aggregate emissions data available at the sector level, and estimate counterfactual baseline emissions by extrapolating trends in these series. These studies find that emissions across all regulated sectors – energy and industry – declined by approximately 3% in Phase I and during the first two years of Phase II, relative to estimated business-as-usual emissions. The contribution of the industrial sector to this aggregate figure is not always clear. Using data for Germany, Ellerman and Feilhauer (2008) estimate that emissions by EU ETS participants fell by 5 percent, due to a 6.3 percent in industrial emissions and 4.1 percent emissions abatement in the power sector. A limitation of these studies is that the use of aggregate data does not support a causal attribution of the calculated emission reductions to the EU ETS.

Unlike emissions data, balance-sheet data on economic outcomes is readily available at the firm-level in databases such as AMADEUS (Bureau van Dijk, 2008), including for pre-treatment years. These data have been used in conjunction with differences-in-differences estimators to evaluate the impact of the EU ETS on economic performance and competitiveness (Anger and Oberndorfer, 2008; Commins et al., 2011; Chan et al., 2013). While there is a fair amount of heterogeneity across studies and outcomes, they do not support the view that the EU ETS had strong detrimental effects on the economic performance of regulated firms. In a large-scale survey of manufacturing firms in the EU, Martin et al. (2013a) find that regulated firms report a higher propensity to downsize their operations in response to future carbon pricing than non-ETS firms, but the effect is not large. Veith et al. (2009) and Bushnell et al. (2013) present evidence that stock owners of large EU ETS firms expected them to actually profit from higher permit prices as they could pass these on to product markets.⁶

Recent research resorts to matching estimators as a way of credibly establishing identification of the causal impact of emissions trading on

⁶In contrast, an event study of the NO_x Budget Trading Program by Linn (2010) shows that cap-and-trade reduced profits of power generators in the US.

firm behavior. Fowlie et al. (2012) combine matching and differences-in-differences to evaluate the impact of the RECLAIM program on NO_x emissions of industrial emitters in Southern California. For the EU ETS, Abrell et al. (2011) apply nearest-neighbor matching to a large sample of European firms and find that the policy caused a small but significant decrease in employment of 0.9 percent between 2004 and 2008. Using data on patent applications filed at the European Patent Office, Calel and Dechezleprêtre (2012) estimate that the EU ETS is responsible for an additional 188 low-carbon patents, which corresponds to an increase of approximately 8.1% for ETS firms. Unpublished work by Wagner et al. (2013) uses plant-level data from the French manufacturing sector to construct matching estimators of the impact of the EU ETS. These authors find that the EU ETS had no impact in phase I but reduced both emissions and employment during the first half of the second trading phase.

3 Research Design

It is useful to distinguish between the direct and indirect effects of the EU ETS on manufacturing firms. As a rule, conventional power generation in Europe is subject to cap-and-trade. As the power sector passes the opportunity cost of emission permits to consumers in the form of higher prices (Sijm et al., 2006; Zachmann and Von Hirschhausen, 2008; Fabra and Reguant, 2014), there is an indirect impact on manufacturing through higher electricity prices. In addition, by establishing a uniform carbon price, the ETS has a direct impact on those firms participating in it. The parameter we seek to identify and estimate is the average effect of the EU ETS on participating firms, over and above any indirect effect the EU ETS may have had on the entire manufacturing sector. Similar to Fowlie et al. (2012), we resort to a matching approach that exploits both the longitudinal structure of our dataset and the rich information on firm characteristics to recover a consistent estimate of the treatment effect.⁷

⁷In principle, the threshold-based eligibility rules of the EU ETS could be exploited in a regression discontinuity design (RDD). As shown in Appendix A.1, thresholds are tied to technical characteristics such as the production capacity of a particular product in process-regulated industries, and the rated thermal input of combustion facilities. German law requires firms to submit this information to the regulator when applying

3.1 Difference-in-difference matching estimator

In line with the potential outcome framework, denote by $Y_i(1)$ the outcome at firm i when subject to the ETS and by $Y_i(0)$ the outcome when the plant is not subject to the ETS. Let D_i denote the treatment indicator, and subscripts t' and t denote pre- and post-treatment periods, respectively. X is a set of observable covariates. We are interested in the average treatment effect on the treated (ATT)

$$\alpha_{ATT} = E(Y_{it}(1) - Y_{it}(0)|X, D = 1). \quad (1)$$

The fundamental evaluation problem arises because $Y_{it}(0)$ is unobserved for the treated. The matching approach to solving this problem consists of imputing $Y_{it}(0)$ using outcomes for untreated firms that are observationally equivalent to the treated firm. The ATT can then be estimated from the sample equivalent of the expression $E(Y_{it}(1)|X, D = 1) - E(Y(0)|X, D = 0)$, assuming conditional independence between outcomes and treatment status, $(y_{it'}(0), y_{it'}(1)) \perp D|X$. In view of the participation thresholds for the EU ETS, this unconfoundedness assumption appears too demanding in the policy context considered here. However, the ATT can be identified under a weaker such assumption by bringing in longitudinal information and focusing on differences-in-differences (DD) of outcomes. In particular, Heckman et al. (1997) suggest to estimate the ATT from the sample analogues of the population moments

$$D_{t,t'}(X) = E(Y_{it}(1) - Y_{it'}(0)|X, D = 1) - E(Y_{it}(0) - Y_{it'}(0)|X, D = 0). \quad (2)$$

To implement this, they propose a semiparametric conditional DD matching estimator

$$\hat{\alpha} = \frac{1}{N_1} \sum_{i \in I_1} \left\{ (Y_{it}(1) - Y_{i0}(0)) - \sum_{k \in I_0} W_{N_0, N_1}(i, k) \cdot (Y_{kt}(0) - Y_{k0}(0)) \right\} \quad (3)$$

for an operating permit, but only large facilities have to make it public. For instance, while the participation threshold for combustion installations is 20 MW rated thermal input, the application procedure is public only for combustion installations with at least 50 MW. In process-regulated sectors, the participation threshold often coincides with the one for publication. Therefore, RDD is not feasible.

where I_1 is the set of N_1 ETS participants and I_0 is the set of N_0 non-participants. The weight $W_{N_0, N_1}(i, k)$ with $\sum_{k \in I_0} W_{N_0, N_1}(i, k) = 1$ determines how strongly the counterfactual observation k contributes to the estimated treatment effect. A control plant is weighted more strongly the more similar – in covariate space – it is to the treated facility. The specific weighting function is determined by the matching algorithm.⁸

To pair treated and control firms, we specify weights $W_{N_0, N_1}(i, k)$ that combine nearest neighbor (NN) matching algorithms and propensity score matching (cf. Rosenbaum and Rubin, 1983). The propensity score, denoted p_i , predicts a firm’s probability of participating in the EU ETS, $P(X) \equiv \Pr(D = 1|X)$, for given observable characteristics X . We estimate the propensity score in a probit regression of a firm’s treatment status on a vector of firm characteristics \mathbf{x} . Under one-to-one NN matching, the outcome of a treated firm is compared to the outcome of the non-treated firm whose propensity score is closest to that of the treated firm. Under one-to-many NN matching, the counterfactual outcome is a simple average of the outcomes at all neighboring non-treated firms.

Below we also report the results from an alternative approach to estimating the ATT, based on a combination of weighting and regression. Specifically, we perform OLS on the weighted DD equation

$$\Delta y_{it} = \text{constant} + \alpha_{ATT}^R D_i + x'_{it} \beta + \epsilon_{it} \quad (4)$$

where the propensity score is used to reweight the distribution of treated and non-treated firms. Contrary to NN matching, weighted outcomes of *all* untreated firms are used to construct the counterfactual. While treated firms enter the regression with a weight of one, the weights for the untreated firms $\frac{p_k}{1-p_k}$ are based on the estimated propensity score and ensure that the distribution of the control variables is approximately equal for both groups. Including the covariates x used for estimating the propensity score in (4) is redundant if the propensity score is estimated consistently. Hence, the

⁸To be precise, we will estimate an averaged version of this parameter

$$M(S) = \frac{\int_S E(Y_1 - Y_0|X, D = 1) dF(X|D = 1)}{\int_S dF(X|D = 1)}$$

where S is a subset of the support of X given $D = 1$ (Heckman et al., 1997).

reweighting estimator is double-robust in the sense that it is consistent if either the propensity score model is correctly specified or the outcome is linear in the explanatory variables (Hirano and Imbens, 2001; Imbens, 2004; Lunceford and Davidian, 2004; Busso et al., 2013).

3.2 Identifying assumptions

The matching estimators in (3) and (4) identify the ATT under the assumption (Heckman et al., 1998)

$$E(Y_{it}(0) - Y_{it'}(0)|P(X), D = 1) = E(Y_{it}(0) - Y_{it'}(0)|P(X), D = 0) \quad (5)$$

This is considerably weaker than conditional independence.⁹ In the given application, it means that counterfactual trends in outcomes in ETS firms must not be systematically different from those in the group of matched control firms. A further identifying assumption is that matching is performed on a common support $X \in S(P(X)|D = 1)$ where the distributions of covariates in the treatment and control groups overlap. Finally, we must rule out the possibility that the treatment effect spills over from the treated to the untreated. In the program evaluation literature, this assumption is referred to as the Stable Unit Treatment Value Assumption (SUTVA). An immediate concern in this regard is with spillovers between treated and untreated plants within the firm. To circumvent this problem, we conduct the analysis at the firm level, thereby internalizing such spillovers.¹⁰ If firms used to construct the counterfactual are affected by the treatment, their post-treatment outcomes, and thus also the estimated treatment effect, will be biased.

While the common support assumption is directly testable, unconfoundedness and SUTVA are not. We will evaluate the plausibility of these assumptions in Section (5.2) below.

⁹Using experimental data on a job training program for comparison, Heckman et al. (1997) test different variants of the unconfoundedness assumptions. While assumption (5) cannot be rejected, stronger assumptions are indeed rejected by the data.

¹⁰Aggregating plants to the firm level also circumvents the problem that prices in intra-firm trade might differ from market prices.

4 Data

4.1 Data sources

Our principal dataset is the “AFiD-Betriebspanel” from Germany, which is available to approved researchers at the Research Data Centres maintained by the German Federal Statistical Office and the statistical offices of the German Länder. The AFiD panel currently comprises annual data from 1995 until 2010 on the universe of German manufacturing plants with more than 20 employees.¹¹ The dataset covers approximately 50,000 plants per year and contains information on a wide range of economic variables such as employment, gross output, investment, and exports. These data are collected as part of the monthly production surveys administered by the German statistical office.

Energy use is a central aspect of this study. For the first half of the panel (1995-2002), this information is available for the main fuel types, i.e., coal, gas, electricity and oil. From 2003 onwards, the information comes from a separate but also mandatory survey covering energy consumption for more than 15 different fuel types, electricity generation on site and electricity trading (see Petrick et al., 2011, for details). This information allows us to calculate plant-level carbon emissions and carbon intensity of production with unprecedented accuracy.

The list of treated plants is available from the CITL, the official registry of the EU ETS. We use a combination of trade registry numbers, VAT numbers and Bureau von Dijk identifiers to match information on EU ETS participation to firm identifiers in the AFiD panel.¹² Starting with a complete list of German trading account holders, we first drop hospitals, universities, and other accounts that are clearly not part of the manufacturing sector. Of the remaining 1,879 facilities, 1,658 (88%) were successfully matched to AFiD firms. The other 221 account holders could not be matched to any entry in the official firm register at the Statistical Offices. Most likely, this

¹¹Smaller plants are included as well if they belong to a firm with at least 20 employees. From 2007 onwards, the cutoff is 50 employees. The earliest period used in this paper is 1998.

¹²The matching could not be done at the plant level as there is no concordance table between AFiD plant identifiers and the available identifiers in the CITL. Confidentiality rules prevented us from matching on installation names.

is because small plants are not sampled in the AFiD panel, or because the account holder is not a manufacturing firm. Given these circumstances, the effective matching rate is likely to be considerably higher than 88%.

4.2 Descriptive statistics

Because we are interested in the firm-level impact of the EU ETS, we aggregate all plant-level variables on economic performance and energy mix up to the firm level. Table 1 summarizes the firm characteristics that are central to our analysis, using observations for the year 2003. Panel A reports summary statistics for the full sample after cutting off the top and bottom one percent of the outcome distribution.¹³ Approximately one percent of the remaining 41,000 firms participate in the EU ETS. Panel B summarizes the characteristics of these firms.¹⁴ Upon comparing panels A and B, we see that ETS participants are considerably larger, more prone to export, and paying higher wages than firms in the full sample. This highlights the extent of selection on observable firm characteristics.

To construct a meaningful control group for the ETS participants from the large set of untreated firms, we resort to semi-parametric matching techniques discussed in Section 4.3 below. Panel C of Table 1 summarizes the characteristics of the control firms selected by a one-to-one NN matching algorithm.¹⁴ While matching likens the distribution of firm characteristics to the distribution among treated firms, a test of equality of means still rejects at the 5-percent significance level for a number of outcome variables (see panel A of Table 2). Thus, assuming conditional independence between outcomes and treatment status seems too restrictive in the given policy context. The identifying assumption (5) adopted here posits conditional independence between *changes* in the outcome variables and treatment status. While untestable, this assumption is more plausible if outcome trends are parallel in the years leading up to the policy intervention. A visual inspection of these trends – graphed in Figure C.1 of the Appendix – confirms this. Moreover, panel B of Table 2 reports the results

¹³This is meant to minimize the influence of outliers in the subsequent estimations.

¹⁴Confidentiality restrictions imposed by the data provider prevent us from reporting arithmetic means by treatment status, but we report *t*-statistics from a test of equality in Panel A of Table 2.

Table 1: Summary statistics for outcome variables and covariates in 2003

Variable	(1) Mean	(2) Std. Dev.	(3) p10	(4) p50	(5) p90	(6) N
<i>A. Full sample (mid-98%)</i>						
CO ₂ emissions from energy (t)	1,912	5,618	35	314	4,098	40,834
CO ₂ intensity (g/€ 1000)	108,581	143,612	8,250	62,793	248,907	40,709
Employees	104	158	22	49	233	40,325
Gross output (€ 1000)	17,597	38,223	1,435	5,299	40,580	40,204
Exports (€ 1000)	4,978	15,776	0	198	11,542	40,947
Export share of output	0.16	0.22	0.00	0.04	0.53	40,931
Average wage rate (€)	28,649	9,681	15,998	28,458	41,213	40,409
<i>B. ETS participants</i>						
CO ₂ emissions from energy (t)	.	795,888	6,146	51,716	457,851	408
CO ₂ intensity (g/€ 1000)	.	1,449,921	84,392	670,420	2,604,891	413
Employees	.	11,370	52	388	4,103	433
Gross output (€ 1000)	.	4,191,998	6,748	95,703	1,125,042	430
Exports (€ 1000)	.	2,853,722	324	28,064	647,477	369
Export share of output	.	0.27	0.00	0.29	0.70	408
Average wage rate (€)	.	9,393	26,729	37,214	48,408	408
<i>C. Non-ETS participants (matched sample)</i>						
CO ₂ emissions from energy (t)	.	372,759	510	12,047	891,534	278
CO ₂ intensity (g/€ 1000)	.	1,786,216	37,991	155,349	1,769,886	283
Employees	.	1,994	42	208	4,384	296
Gross output (€ 1000)	.	759,593	5,728	64,809	825,606	293
Exports (€ 1000)	.	323,759	936	21,537	802,049	248
Export share of output	.	0.25	0.00	0.28	0.64	278
Average wage rate (€)	.	9,283	25,767	39,210	49,010	278

Notes: CO₂ intensity in terms of gross output (g/€ 1000). Means for matched sample cannot be obtained for reasons of data privacy.

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 2005-2010, own calculations.

Table 2: Pre-treatment outcomes in the matched sample

Variable	Null hypothesis: Equality of pre-treatment outcomes					
	A. Levels			B. Trends		
	<i>p</i> -value	Number of		<i>p</i> -value	Number of	
		treated	controls		treated	controls
CO ₂ emissions	0.0911	408	278	0.0505	405	.
CO ₂ intensity	0.0197	413	283	0.2025	409	.
Gross output	0.0054	430	293	0.3141	428	.
Employees	0.0051	433	296	0.6177	431	.
Exports	0.0073	369	248	0.1047	336	.
Export share	0.1634	408	278	0.2483	406	.
Average wage rate	0.0086	408	278	0.0603	285	.

Notes: Number of control firms for matched sample are not reported for confidentiality reasons. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 2005-2010, own calculations.

of a *t*-test of equal pre-treatment trends in the treatment and control group, based on logged differences in outcome variables between 2002 and 2003. We cannot reject the Null hypothesis at the 5-percent significance level for any of the outcome variables. Because the test statistics for emissions and the average wage rate are statistically significant at the 10-percent significance level, we dedicate ample space in Section 5.2 below to exploring the robustness of our estimation results to alternative conditioning strategies. Among other things, we shall show that the estimated treatment effects are robust to matching directly on pre-treatment growth rather than the level of the outcome variable.

4.3 Matching

We use propensity score matching techniques to construct counterfactuals for each treated firm. We estimate the propensity score using a probit regression of treatment status on a rich set of observable pre-treatment characteristics, including CO₂ emissions, gross output, export share of output, number of employees, and the average wage rate, as well as the squares of all of these variables. We also include dummies that control for the two-digit industry (WZ classification) and for the state (Bundesland) wherein the firm is located. The results are reported in Table C.1 in the Appendix.

As mentioned above, participation rules under the EU ETS follow two

basic principles. On the one hand, certain industrial processes are regulated directly, with process-specific capacity thresholds determining participation.¹⁵ On the other hand, combustion installations with a rated thermal input of 20 MW or more are subject to emissions trading, regardless of the industry. On account of the difference in treatment assignment between these two groups, we partition the sample in process-regulated industries vs. all other industries, and require sharp overlay of NN matches with respect to these strata.¹⁶ While treated firms are more abundant in process regulated industries than in all other industries (260 compared to 188), the total number of firms is considerably larger in the other stratum (24,947 compared to 2,486).

To find suitable matches for the treated firms among the untreated firms, we perform NN matching based on the predicted propensity scores.¹⁷ Our preferred estimates are based on one-to-one NN matching, i.e. we match to each treated firm the untreated firm with the minimal distance in the propensity scores. For robustness, we also present estimates based on one-to-twenty NN matching where a synthetic counterfactual for each treated firm is constructed as the mean outcome calculated among the twenty untreated firms with the most similar propensity score. Oversampling control firms is known to reduce the variance of the estimate, though potentially at the cost of a higher bias. The reweighted OLS estimator described in (4) uses the complete set of non-treated firms with a weighting scheme that is based on the same covariates as the propensity score.

In Section 5.2 below, we demonstrate that our main results are robust to a series of alternative choices for the set of conditioning variables, the base year for matching, the level of stratification, and the matching algorithm.

¹⁵For more information on process regulated industries, see Section 2 above and Section A.1 of the appendix.

¹⁶For example, this means that a steel-producing firm (process regulated) cannot be matched to a firm in the chemical industry, but it can be matched either to an untreated steel-producing firm or to a paper mill (also process regulated). Because the propensity score includes sector dummies, matching across 2-digit sectors is not likely to occur, however. In one of the robustness checks, we rule out such matches altogether and find that this has very little impact on our qualitative findings.

¹⁷We use NN matching with replacement, i.e. each firm in the control group can be used more than once as a match.

5 Results

5.1 Main Results

The principal objective of the EU ETS is to reduce carbon dioxide emissions in Europe. Estimating the average treatment effect of the EU ETS on emissions of treated firms tells us how successful the policy has been at curbing CO₂ emissions in the German manufacturing sector. Table 3 displays the ATT estimates for CO₂ emissions. Columns (1) and (2) report coefficients estimated with one-to-one and one-to-twenty nearest-neighbor matching, respectively. Column (3) reports the coefficient estimated using the reweighted OLS estimator from (4). Columns (4) and (5) report numbers of treated and control observations for nearest neighbor matching.¹⁸ Panel A reports the log change in CO₂ emissions that can be causally attributed to participation in the EU ETS, whereas panel B reports the causal effect in terms of the log change in the carbon intensity of output. The estimates are reported separately for phase I (2005-2007) and the first half of phase II (2008-2010).

A clear pattern emerges from panel A. The point estimates for the first trading phase are positive, very close to zero and lack statistical significance. We thus cannot reject the Null hypothesis that treated firms conducted no abatement in the first phase. In contrast, we see strong evidence that phase II of the EU ETS caused treated firms to reduce their emissions by a substantial margin, in the order of 25 to 28 percentage points more than non-treated firms. This finding is statistically significant at the 5% level and robust across specifications.

The impact on carbon intensity, reported in Panel B, closely mimics the overall effect on emissions. Carbon intensity remains almost unchanged throughout phase I, although the point estimates are somewhat larger than for emissions and the reweighting estimator actually yields an increase by 5 percentage points at the 10 percent significance level. However, in phase II, carbon intensity fell between 18 and 30 percentage points faster at EU ETS firms than at the control firms, and again this effect is statistically significant at the 5 percent level. This result suggests that firms responded to

¹⁸Note that the double-robust reweighting estimator (OLS w/R) covers more firms because control firms outside the region of common support are included as well.

Table 3: Impact on CO₂ emissions

	(1)	(2)	(3)	(4)	(5)
	Estimation Algorithm			Number of	
	NN (1:1)	NN (1:20)	OLS w/R	Treated	Controls
A. CO ₂ emissions: $\Delta \ln(CO_2)$					
Phase I	0.00 (0.03)	0.02 (0.02)	0.03 (0.03)	452	27,710
Phase II	-0.28** (0.05)	-0.25** (0.03)	-0.26** (0.03)	408	23,908
B. CO ₂ intensity of gross output: $\Delta \ln(\frac{CO_2}{GO})$					
Phase I	0.04 (0.05)	0.03 (0.03)	0.05* (0.03)	451	27,637
Phase II	-0.18** (0.05)	-0.20** (0.04)	-0.30** (0.03)	412	23,742

Notes: NN(1:1) and NN(1:20) denote nearest neighbor matching with one and 20 neighbors, respectively. OLS w/R denotes the reweighted OLS estimator. Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

the introduction of the EU ETS mainly by adjusting intensity, not scale.¹⁹

We investigate this further by examining changes in output and employment. Panel A of Table 4 reports the average treatment effects of the EU ETS on employment. The point estimates for employment range from -0.02 to 0.01 log points. None of the coefficient estimates is statistically significant at the 5% level.²⁰ Hence our results do not support fears that putting a price on carbon comes at the expense of domestic job destruction.

The estimated impact of the EU ETS on gross output, reported in Panel B of Table 4, is small and insignificant in phase I. In phase II, however, we estimate that the EU ETS increased gross output at regulated firms by a statistically significant amount of between 4 and 7 percent. We thus reject the hypothesis that the EU ETS caused firms to reduce the scale of production. The positive effect on gross output is consistent with both firms producing more and charging higher prices. Unfortunately, we cannot

¹⁹Further results reported in Table C.5 in the appendix show that both process-regulated and all other EU ETS firms reduced their carbon emissions. The response is slightly stronger in the former.

²⁰The phase-I coefficients for employment in columns 2 and 3 are -0.166 and -0.019 with standard errors 0.013 and 0.013, respectively.

Table 4: Impact on employment, gross output and exports

	(1)	(2)	(3)	(4)	(5)
	Estimation Algorithm			Number of	
	NN (1:1)	NN (1:20)	OLS w/R	Treated	Controls
A. Employees ($\Delta \ln L$)					
Phase I	0.00 (0.02)	-0.02 (0.01)	-0.02 (0.01)	454	28,396
Phase II	0.03 (0.02)	0.01 (0.01)	0.01 (0.01)	433	24,237
B. Gross output ($\Delta \ln GO$)					
Phase I	0.01 (0.03)	0.01 (0.02)	0.01 (0.02)	449	28,465
Phase II	0.07*** (0.03)	0.05*** (0.02)	0.04** (0.02)	430	24,240
C. Exports: $\Delta \ln(X)$					
Phase I	0.06 (0.06)	0.10** (0.04)	0.11*** (0.04)	371	17,864
Phase II	0.18*** (0.06)	0.09** (0.04)	0.07* (0.04)	348	15,463

Notes: NN(1:1) and NN(1:20) denote nearest neighbor matching with one and 20 neighbors, respectively. OLS w/R denotes the reweighted OLS estimator. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

distinguish further between these two responses for lack of a measure of physical output.

If firms did in fact increase prices to recoup the costs of carbon trading, this means that their competitiveness is not jeopardized at least in the domestic product market. The concern with unilateral regulations is, however, that regulated firms lose competitiveness in international markets where they compete with unregulated firms from overseas. To shed light on this, we estimate the ATT of the EU ETS on total exports, reported in panel C of Table 4. The point estimates range from 0.06 to 0.11 for phase I and from 0.07 to 0.18 for phase II. The precision of these estimates varies across specifications, with only four out of six being statistically significant at the 5 percent level or better. In these cases, we can reject the hypothesis that the EU ETS caused regulated firms to reduce their overall exports. Again, it is not clear whether the increase in exports reflects an increase in the volume of shipments or a price increase, or both.²¹

5.2 Robustness checks

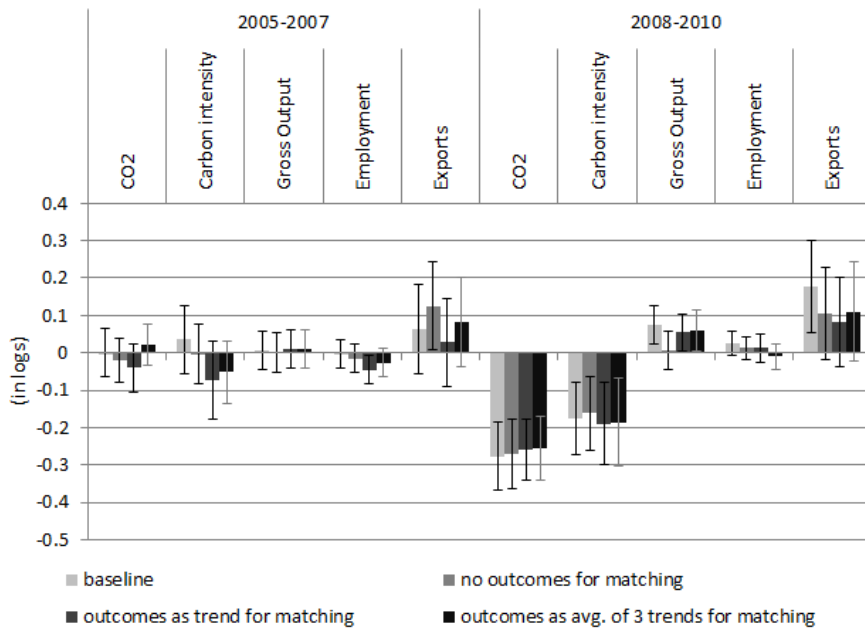
The results reported above show that the point estimates are quite robust to increasing the number of control firms in NN matching algorithms from one to twenty, as well as to using a linear regression approach with reweighting. Nonetheless, consistent estimation of the ATTs above is predicated on a number of identifying assumptions. This section provides further evidence that our results are robust to a number of challenges to the identifying assumptions.

Unconfoundedness

Unconfoundedness – i.e., the assumption in (5) that the counterfactual trend in the outcome variable is not systematically different between treatment and control groups – is not directly testable, so we assess its credibility from a number of different angles. We start by examining the pre-treatment

²¹Table C.7 in the appendix reports the ATT estimates for the share of exports in gross output. The point estimates in panel A range from 0.03 to 0.07 and the Null hypothesis of no impact on the export share is rejected only once. Robustness checks reported in panel B and C yield similar findings.

Figure 1: NN (1:1) estimates when matching on pre-treatment trends

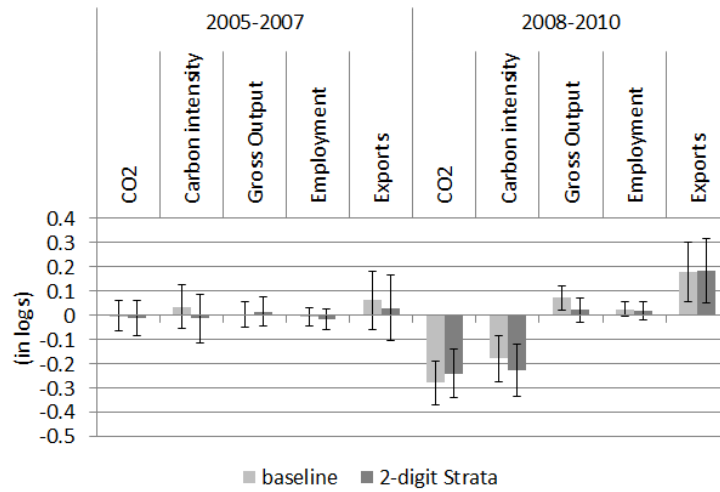


Notes: Error bars represent the 95 % confidence interval. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

trends across treatment groups. Because unconfoundedness assumes parallel trends in the counterfactual scenario, it is more credible if these trends are parallel already in the years prior to the intervention. Figure C.1 in the appendix plots the trends for the outcome variables by treatment status, showing in fact parallel trends prior to treatment. Moreover, panel B of Table 2 shows that a formal test of equality of pre-treatment trends does not reject at the 5 percent level.

Next, we investigate how robust the estimated ATTs are to directly controlling for pre-treatment trends. To this end, we re-estimate the ATTs after matching treated and control firms based on pre-treatment changes (not levels) in the respective outcome variable. Figure 1 shows three sets of alternative ATTs – obtained in the preferred NN(1:1) specification – next to the baseline specification which matches on the outcome variables in levels. The first alternative specification does not match on lagged outcome variables at all, the second one matches on the 2002-2003 change in the outcome variable, and the last one matches on the average change in the

Figure 2: NN (1:1) estimates with exact matching on 2-digit industry code

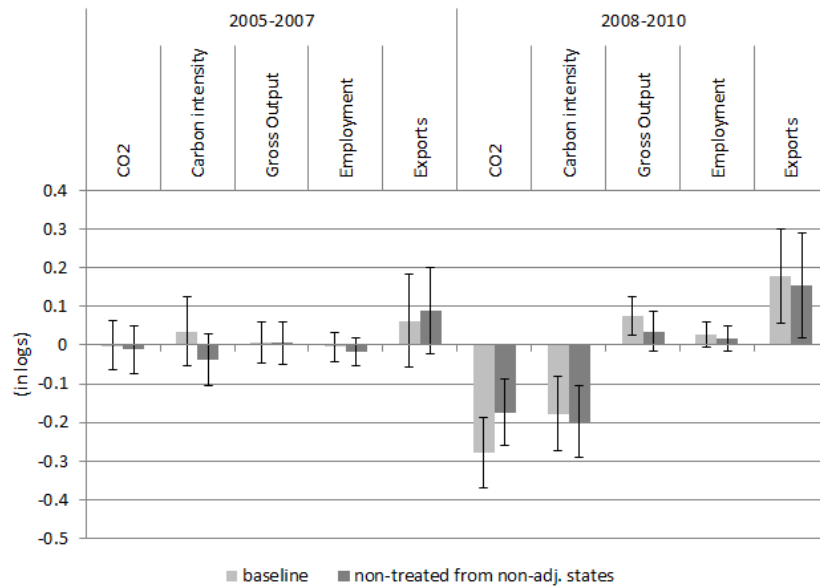


Notes: Error bars represent the 95 % confidence interval. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

outcome variable between the years 2000 and 2003. The resulting point estimates and confidence bands for carbon emissions and intensity are very close to those obtained in the baseline specification. The point estimates of the impact on exports in phase II remain positive, but are no longer statistically significant under the alternative matching strategies. The impact on gross output remains positive and statistically significant except for the case where no pre-treatment output variable is included in the matching algorithm.

As a further check of unconfoundedness, we re-estimate all ATTs after imposing exact matching on firms' two-digit sector. This addresses the worry that differential post-treatment shocks across sectors could be confounding the treatment estimates. As shown in Figure 2, the results are very similar to the baseline specification, the only qualitative difference being that the estimate for gross output, though still positive, is not statistically significant in phase II. Recall that the baseline specification imposes exact matching only within two strata (process-regulated sectors vs. all other sectors) and includes two-digit sector dummies in the propensity score estimation. Defining strata at the two-digit sector level rules out matching of, e.g., a treated steel plant with an untreated paper mill, even

Figure 3: NN (1:1) estimates with matching in non-contiguous states



Notes: Error bars represent the 95 % confidence interval. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

if both are alike in terms of emissions, gross output, number of employees and the average wage. Instead, the control firm is taken from within the iron and steel sector, even though its characteristics – size, in particular – might differ more than those of the control firm. The robustness of the results to these choices suggests that the trade-off is small.²²

Stable Unit Treatment Value Assumption (SUTVA)

As we have noted above, the EU ETS likely affects the entire economy indirectly through rising electricity prices. We seek to identify the effect the policy had on firms over and above this indirect effect. Doing so requires us to rule out the possibility that the direct treatment impact “spills over” from treated to untreated firms. In the program evaluation literature, this assumption is referred to as the Stable Unit Treatment Value Assumption

²²Fowlie et al. (2012) combine stratification by industry with nearest-neighbor matching on a single covariate. We explore this using 2-digit sector and carbon emissions per employee as the matching covariates, as in Wagner et al. (2013). The results, reported in Table C.4 of the appendix, are qualitatively similar to the baseline specification, although the coefficient estimates are somewhat larger in magnitude.

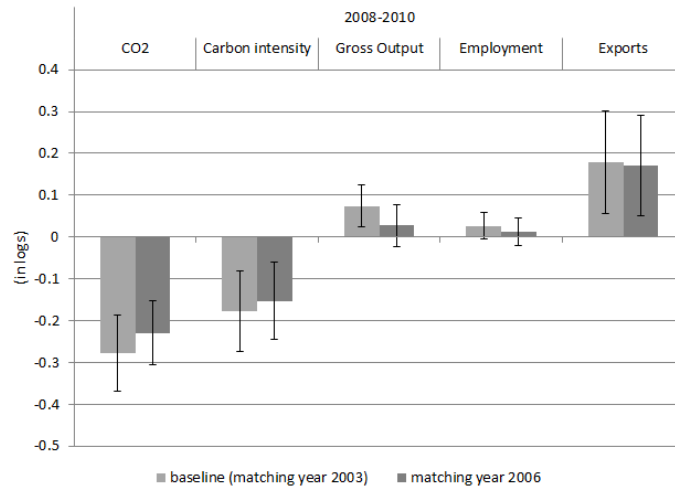
(SUTVA). An immediate concern in this regard arises with spillovers between treated and untreated plants within the firm. We circumvent this problem by conducting the analysis at the firm level, which internalizes such spillovers.²³ Nonetheless, if firms used to construct the counterfactual are affected by the treatment, their post-treatment outcomes, and thus the estimated treatment effect as well, will be biased. While the SUTVA is untestable, Fowlie et al. (2012) propose to generate testable hypotheses of how violations of SUTVA would manifest. For example, one such hypothesis would be that the EU ETS caused emissions to shift from treated firms to nearby untreated firms. If this was the case then we would obtain larger treatment effects than when using only untreated firms not affected by those spillovers to construct the counterfactual outcomes. Under the assumption that spillovers are local, we can test this by excluding all control firms that are in the same state as the treated firm or in one adjacent to it. Figure 3 shows that this leads to small – and mostly insignificant – changes in point estimates. The point estimate for CO₂ emissions drops in magnitude but remains statistically significant, whereas the treatment effect for gross output becomes statistically insignificant.

Stable covariates

To avoid matching on endogenous covariates, we estimate the propensity score using covariates from 2003, the year in which the EU Trading Directive was passed. Hence, five years lie between the matching year and the beginning of phase II. It is possible that the relevant counterfactual for the treated firms change in this relatively long time period, making the control group unrepresentative when phase II starts. We investigate this by re-estimating the ATTs for the second period after matching the treated and control firms on propensity scores estimated on data from 2006. While 2006 covariates are not exogenous, the bias should be small given that we do not find large, let alone significant, effects of the treatment in phase I. At the same time, the sensitivity of the ATTs toward change between the two matching years gives us an intuition about whether the counterfactual has changed over time. Figure 4 compares the two sets of treatment ef-

²³That is, we focus on the outcome that results after treated firms re-optimize production decisions across plants.

Figure 4: NN (1:1) estimates with matching in different periods



Notes: Error bars represent the 95 % confidence interval. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

fects. Similarly to previous robustness checks, the ATT for gross output becomes insignificant, casting another shred of doubt on the robustness of the positive ATT estimated for gross output. The other results remain qualitatively unchanged. Quantitatively, the point estimate on the emissions reduction drops by one standard deviation, from -0.28 to -0.23, and the one on carbon intensity from -0.18 to -0.15 (three fifths of a standard deviation).

Pre-treatment dynamics

The EU ETS directive was finalized and announced in October 2003. If the announcement of emissions trading affected firm behavior even before its implementation in 2005, then 2004 would not be the appropriate base year for before-and-after comparisons. In fact, the ATT estimates reported above would not capture the full treatment effect, and the consistency of the matching approach would be impaired as firm characteristics in the year 2003 were no longer exogenous to treatment status. These possible concerns motivate taking a closer look at pre-treatment dynamics.

One can think of two potential causes for a pre-treatment impact – or “announcement effect” – of the EU ETS. On the one hand, firms may have

Table 5: Pre-treatment Effects for the 2000-2004 period

	(1)	(2)	(3)	(4)	(5)
	Estimation Algorithm			Number of	
	NN (1:1)	NN (1:20)	OLS w/R	Treated	Controls
CO ₂ emissions: $\Delta \ln(CO_2)$					
	-0.08 (0.07)	-0.09** (0.03)	-0.09** (0.03)	356	12,778
CO ₂ intensity: $\Delta \ln(CO_2/GO)$					
	-0.17* (0.1)	-0.10** (0.03)	-0.09** (0.03)	357	12,784

Notes: NN(1:1) and NN(1:20) denote nearest neighbor matching with one and 20 neighbors, respectively. OLS w/R denotes the reweighted OLS estimator. Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

had an incentive to strategically adjust their pre-treatment emissions. That is, they could have switched technologies to steer clear of the thresholds that govern participation, or they could have spurred emissions in order to receive more grandfathered permits in future trading phases.²⁴ On the other hand, firms may have taken early action, e.g., by investing in projects that became profitable once the expected payoff from excess emission allowances was taken into account.

We estimate the announcement effect using a placebo treatment for the pre-treatment difference in outcomes between 2000 and 2004, after matching treated and control firms using covariates from 1999. While we find no statistically significant treatment effect on employment, gross output and exports, the point estimates for carbon emissions and carbon intensity are negative and statistically significant at the 5 percent level in some specifications, see Table 5.²⁵ If we interpret this to mean that the announcement of the EU ETS decreased emissions, then matching on 2003 emissions in the main specification compares treated firms with controls that are too clean, and would bias the estimated impact on emissions towards zero. However,

²⁴The base period for the allocation of free permits for phase I was 2000 to 2002 for existing installations. Free permit allocation in phase II was based on emissions during the period 2000-2005.

²⁵The results for gross output and employment are reported in Appendix Table C.2.

when we estimate the ATT after matching on 1999 covariates, the impact estimate for carbon emissions hardly changes (the results are reported in Table C.3 in the appendix). If anything, the point estimates are smaller in magnitude, not larger. While there are some differences in magnitude and significance levels for the other outcome variables, there is no logical connection to an announcement effect. These differences are more likely due to the different conditioning strategy and the smaller sample.

The great recession

Trading phase II coincides with the onset of the deepest economic downturn in recent history, triggered by the financial crisis in September 2008. While the recession struck more mildly in Germany than in most other EU countries, its effects and subsequent recovery are clearly appreciable in the trajectory of real gross output, plotted in panel (d) of Figure C.1 in the appendix. Clearly, this event poses an additional challenge to our identification strategy because, even if counterfactual trends are parallel in “normal” economic conditions, they might not be in a major economic slump. Again, this issue cannot be tested, so we try to assess it in more indirect ways.

A visual inspection of the trends by treatment status suggests that gross output evolved in a parallel fashion even during the recession. To assess this more rigorously, we use ATT estimates to test for differences in real gross output growth between 2007 (pre-crisis) and 2010. Matching firms based on characteristics for the year 2006 ensures that a possible confounding impact of the EU ETS is limited to later years. This exercise yields small and statistically insignificant point estimates for gross output and employment, as shown in Figure 4.²⁶ For there to be a differential effect of the recession, it must be the case that the impacts of the recession and of the EU ETS cancel out.

Finally, we look at macroeconomic fluctuations that occurred when treatment was imminent, such as the economic fallout of the 9/11 terrorist attacks and the dotcom recession, for evidence of a differential effect of recessions on the treatment group. We implement this by estimating placebo

²⁶The point estimates are 0.03 for gross output and 0.01 for employment. None of them is statistically significant at the 5 percent level in any of the three specifications.

ATTs for employment and gross output separately for the treatment periods 2001-2002 and 2001-2004, after matching on 1999 covariates. The results are reported in Table C.2 of the appendix and show no statistically significant differences across treatment groups. While this is reassuring, it is evident that the magnitude of these downturns was much smaller than the 2008/09 recession.

Overall, we conclude that our findings for CO₂ emissions, carbon intensity and employment are robust to a host changes to the specification and in the identifying assumptions. While the statistical significance of the positive impact for gross output and exports is not robust to these changes, in no case did they give rise to a negative and significant impact estimate.

6 How did treated firms reduce carbon emissions?

A robust finding established in the previous section is that the EU ETS caused firms to substantially cut back on CO₂ emissions in phase II. Further, this cutback was achieved through a reduction in the carbon intensity rather than the scale of production. In this section we draw on additional data from various sources to shed more light on how treated firms reduced the carbon footprint of production. From a conceptual point of view, firms can achieve this by reducing the carbon intensity for a given level of energy consumption – for example by switching from high-carbon fuels to low-carbon fuels – or by using energy more efficiently for a given energy mix.

6.1 Fuel switching

We look for evidence of fuel switching by estimating the causal impact of the EU ETS separately for the consumption of electricity, primary energy as well as for the most common non-electricity fuels, natural gas and petroleum products. We start by looking at the absolute response, summarized in Table 6. Panel A shows that ATT estimates for electricity consumption are between -0.03 and -0.04 in phase II, but only the OLS

reweighting estimate is also statistically significant. In contrast, the estimated ATTs for non-electricity fuels, reported in Panel B, are highly statistically significant, with an increase of between 0.11 and 0.16 log points in phase I and a subsequent decrease by 0.81 to 0.87 log points in phase II. As Panels C and D show, this decrease is explained by the strong reductions in both natural gas and oil consumption, with point estimates between -0.21 to -0.33 for the former and between -0.45 and -0.56 for the latter. Moreover, the number of firms consuming natural gas and petroleum products falls by a larger proportion among treated than among untreated firms, as is evident from the last two columns. The point estimates for phase I suggest that some firms engaged in substitution of natural gas for oil, but this effect is not statistically significant in our preferred specification, and – as we already know – did not result in a significant reduction of overall carbon emissions.

Table 7 summarizes the impact of the EU ETS on the fuel shares in overall energy consumption. These results confirm the relative increase of electricity in the fuel mix by 0.26 to 0.28 in phase II, due to the drastic reduction of non-electricity fuels. Panels C and D lend additional support to the conjecture that EU ETS firms substituted to low-carbon fuels like natural gas in phase I, as suggested by the increased share of natural gas and the reduced petroleum share. The mostly insignificant point estimates for these fuel shares in phase II corroborate the previous finding that the strong reductions in non-electricity fuels are not counterveiled by increases in electricity use.

Overall, these findings suggest that treated firms pursued different strategies to cope with carbon pricing in the two trading phases. While treated firms first switched from high- to low-carbon content among non-electricity fuels, they drastically reduced their use of fossil fuels in phase II. It appears that carbon pricing in phase II increased the cost of generating heat or electricity on site beyond economically viable levels for the average treated firm. Less heat generation on site could mean that treated firms were making more efficient use of process heat, or that they shut down or throttled their on-site power plants. Given that we find no significant impact on electricity consumption, firms that reduced electricity generation on site did so in favor of additional procurement from the grid, thereby transferring the

Table 6: Impact on fuel use

	(1)	(2)	(3)	(4)	(5)
	Estimation Algorithm			Number of	
	NN (1:1)	NN (1:20)	OLS w/R	Treated	Controls
A. Electricity consumption: $\Delta \ln(ELEC)$					
Phase I	0.01 (0.03)	0.03 (0.02)	0.02 (0.03)	453	27,699
Phase II	-0.04 (0.03)	-0.03 (0.02)	-0.04** (0.02)	428	23,867
B. Consumption of all non-electricity fuels: $\Delta \ln(EPRIMARY)$					
Phase I	0.16*** (0.05)	0.13*** (0.04)	0.11*** (0.03)	435	24,601
Phase II	-0.81** (0.15)	-0.83** (0.11)	-0.87** (0.1)	376	21,331
C. Consumption of natural gas: $\Delta \ln(GAS)$					
Phase I	0.01 (0.07)	0.10** (0.04)	0.11** (0.04)	412	16,817
Phase II	-0.21** (0.11)	-0.32** (0.08)	-0.33** (0.07)	217	10,506
D. Consumption of petroleum products: $\Delta \ln(OIL)$					
Phase I	-0.05 (0.12)	-0.02 (0.08)	-0.15** (0.07)	232	8,857
Phase II	-0.56** (0.17)	-0.45** (0.11)	-0.48** (0.13)	163	7,815

Notes: NN(1:1) and NN(1:20) denote nearest neighbor matching with one and 20 neighbors, respectively. OLS w/R denotes the reweighted OLS estimator. Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

obligation to surrender emission certificates to the electricity provider.²⁷

6.2 Technology upgrades and other emissions reducing measures

To the extent that the substantial reduction in carbon emissions during phase II of the EU ETS cannot be attributed to the substitution toward fuels with a lower emissions intensity, it is likely the result of increased energy conservation efforts. For instance, the adoption of more efficient technologies tends to reduce energy use. We test for this possibility by estimating the impact of the EU ETS on investment and gross investment. The results, which are reported in Table C.6 in the appendix, show that the EU ETS had no statistically significant impact on investment in either of the two trading phases.

While this exhausts the range of abatement options we can test for using AFiD data, it is far from exhausting firms' options to abate CO₂ emissions. To shed light on other ways of reducing CO₂ emissions, we resort to qualitative data from a broad-based survey of managers at medium-sized European manufacturing firms. The data were collected by Martin et al. (2013a) using a bias-reducing, "double-blind" telephone interview method developed by Bloom and van Reenen (2007). Participating firms were drawn at random from all mid-sized firms contained in a large commercial database (Bureau van Dijk, 2008). We use data on 138 German firms that were interviewed between late August and October 2009. Due to oversampling of EU ETS firms, 95 of the firms participate in the EU ETS. Appendix B describes aspects of the data collection in more detail.

We focus on interview responses pertaining to measures that were implemented at the production site in order to reduce carbon dioxide emissions.²⁸ Table 8 summarizes these measures. The mean adoption rates reported in column 1 highlight the role of optimization processes that affect the use of machinery or heating and cooling for emissions abatement. Improving

²⁷Remember that we only estimate the direct effect of the EU ETS on firms, over and above any indirect effect induced via the electricity sector.

²⁸Managers were asked "Can you tell me what measures you have adopted in order to reduce GHG emissions (or energy consumption) on this site? Have you bought any new equipment, or have you changed the way you produce?"

Table 7: Impact on fuel shares in total energy use

	(1)	(2)	(3)	(4)	(5)
	Estimation Algorithm			Number of	
	NN (1:1)	NN (1:20)	OLS w/R	Treated	Controls
A. Electricity share: $\Delta \ln(ELEC/ENERGY)$					
Phase I	-0.01 (0.03)	-0.02 (0.02)	-0.04* (0.02)	441	27,716
Phase II	0.26*** (0.06)	0.27*** (0.04)	0.28*** (0.03)	378	23,863
B. Share of non-electricity fuels: $\Delta \ln(EPRIMARY/ENERGY)$					
Phase I	0.07** (0.03)	0.08*** (0.02)	0.08*** (0.02)	443	24,586
Phase II	-0.40** (0.10)	-0.42** (0.08)	-0.47** (0.07)	380	21,320
C. Share of natural gas: $\Delta \ln(GAS/ENERGY)$					
Phase I	0.13*** (0.05)	0.12*** (0.03)	0.11*** (0.04)	414	16,810
Phase II	0.02 (0.09)	-0.14** (0.06)	-0.19** (0.05)	220	10,509
D. Share of petroleum products: $\Delta \ln(OIL/ENERGY)$					
Phase I	-0.18* (0.10)	-0.08 (0.08)	-0.21** (0.07)	230	9,156
Phase II	0.06 (0.16)	0.18 (0.12)	0.12 (0.15)	167	7,842

Note: NN(1:1) and NN(1:20) denote nearest neighbor matching with one and 20 neighbors, respectively. OLS w/R denotes the reweighted OLS estimator. Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFid-Panel Industriebetriebe, 1998-2010, own calculations.

Table 8: Adoption of emissions reducing measures

	(1) All measures adopted	(2)	(3) Most significant measure	(4)
	Share of adopters (%)	Effect of ETS	Share of adopters (%)	Effect of ETS
I. Heating and cooling				
1. Optimized use of process heat	37.7*** (4.1)	1.02*** (0.31)	20.5*** (3.8)	1.01*** (0.34)
2. Modernization of cooling / refrigeration system	9.4*** (2.5)	-0.22 (0.30)	0.9 (0.9)	
3. Optimization of air conditioning system	4.4** (1.7)	0.15 (0.42)	0.9 (0.9)	
4. Optimization of exhaust air system / district heating system	27.5*** (3.8)	0.01 (0.23)	9.8*** (2.8)	-0.64* (0.34)
II. More climate-friendly energy generation on site				
1. Installation of CHP plant	13.0*** (2.9)	0.17 (0.28)	6.3*** (2.3)	0.05 (0.34)
2. Biogas feed-in into local CHP plant or domestic gas grid	2.9** (1.4)	0.20 (0.46)	5.4** (2.1)	
3. Switching to natural gas	2.9** (1.4)	-0.38 (0.44)	0.9 (0.9)	
4. Exploitation of renewable energy source	13.8*** (2.9)	-0.17 (0.34)	9.8*** (2.8)	0.08 (0.50)
III. Machinery				
1. Modernization of compressed air system	14.5*** (3.0)	0.07 (0.25)	5.4** (2.1)	-0.29 (0.43)
2. Other industry-specific production process optimization/machine upgrade	63.0*** (4.1)	0.41** (0.20)	23.2*** (4.0)	0.29 (0.27)
3. Production process innovation	8.0*** (2.3)	0.13 (0.37)	1.8 (1.3)	
IV. Energy management				
1. Introduction of energy management system	8.0*** (2.3)	-0.14 (0.30)	1.8 (1.3)	
2. Submetering / upgrade of existing energy management system	7.3*** (2.2)	0.56 (0.42)	0.9 (0.9)	
3. (External) energy audit	7.3*** (2.2)	-0.14 (0.30)	-	
4. Installation of timers attached to machinery	4.4** (1.7)	-0.89** (0.35)	-	
5. Installation of heating systems	2.2* (1.3)	-0.59 (0.51)	2.7* (1.5)	-0.52 (0.52)
V. Other measures on production site				
1. Modernization of lighting system	12.3*** (2.8)	-0.68** (0.32)	1.8 (1.3)	
2. Energy-efficient site extension/ improved insulation/building management	18.1*** (3.3)	-0.87*** (0.23)	5.4** (2.1)	-0.76 (0.46)
3. Employee awareness campaigns and staff trainings	12.3*** (2.8)	-0.29 (0.28)	-	
4. Non-technical reorganization of the production process	2.2* (1.3)	-0.13 (0.41)	0.9 (0.9)	
5. Installation of energy efficient IT system	6.5*** (2.1)	0.10 (0.40)	-	
6. Improved waste management / recycling	5.1 *** (1.9)	0.54 (0.45)	0.9 (0.9)	

Notes: Based on telephone interviews with managers of 138 German manufacturing firms, 95 of which were EU ETS participants in 2009. Columns (1) and (3) report the mean and standard deviation (in parentheses) of the adoption rate for a given measure. Columns (2) and (4) report the coefficient on EU ETS participation in a probit regression of adoption, controlling for employment size, interviewer fixed effects, and respondent characteristics. Standard errors in parentheses are clustered at the 3-digit sector level.

the production process or upgrading machinery is the most common such measure, with an adoption rate of 63 percent, followed by optimized use of process heat (38 percent) and optimization of the exhaust air system or district heating system (28 percent). A second tier of measures reduces the carbon content of generation on site via combined heat and power (CHP) generation (13 percent) or exploitation of renewable energy sources (14 percent). In addition, numerous measures target the reduction of energy use through efficiency improvements, e.g., of buildings (18 percent), the compressed air system (15 percent) or lighting (12 percent), through the introduction or upgrading of an energy management system (15 percent), via staff training (12 percent) and external energy audits (8 percent). Only 8 percent of respondents conduct process innovation that leads to emissions reductions.

We investigate how these measures are associated with participation in the EU ETS. Column 2 reports the coefficient obtained in probit regressions of adoption on the treatment dummy, conditional on employment size and controls for interview noise. This reveals that ETS firms are significantly more likely to make better use of process heat and to optimize processes specific to their industry. In contrast, ETS participation is negatively associated with modernizing the lighting system and energy efficient site extension/insulation/building management.

Furthermore, column 3 summarizes the adoption rates for the one measure that achieved the largest reduction in carbon emissions.²⁹ This confirms once again the importance of optimizing industry-specific processes and use of process heat for reducing carbon emissions. In fact, the latter is the only measure for which we obtain a positive association with ETS participation that is significant at the 5 percent level (reported in column 4).

Needless to say, these correlations do not necessarily represent causal relationships. Together with the causal impact estimates from the previous subsection, however, they provide a consistent answer to the question posed in the title of this section. To abate CO₂ emissions, treated firms reduced heat rather than electricity consumption through the optimized

²⁹Managers were asked: “Which one of these measures achieved the largest carbon saving?”, referring to the measures named in response to the previous question.

use of process heat, particularly improved recovery of waste heat.

7 Conclusion

In this paper we have presented new econometric evidence on the causal impact for the EU ETS on CO₂ emissions and on economic performance in the manufacturing sector. Drawing on high-quality microdata for German manufacturing firms, our analysis yields two principal findings.

First, we establish that the EU ETS caused treated firms to reduce their CO₂ emissions by one-fifth relative to non-treated firms, and we go to considerable lengths to explain how firms managed to abate their carbon emissions. While it is not difficult to think of reasons why the abatement occurred entirely in the second trading phase, we leave it as a task for future research to disentangle competing explanations.³⁰

Our second main result is that we do not find a negative effect of the EU ETS on gross output, employment or exports over the sample period. This contrasts with claims by industry associations that a regional carbon trading scheme leads to drastic job losses. It also casts doubt on the legitimacy of the generous compensation that European manufacturing industries receive from the EU Commission for presumably adverse competitiveness effects of the EU ETS (Martin et al., 2013a,b). As most of German exports go to other EU countries where industry is also subject to the EU ETS, an analysis of exports to non-EU countries should provide more direct evidence on the issue of international competitiveness. Because the AFiD dataset does not provide the precise destination of exports, this is left as a topic for future research.

Our study has focused on Germany, the largest economy in the EU ETS, its largest emitter, and a leading exporter of manufactured goods in the world. All of these aspects make Germany a natural starting place for a comprehensive policy evaluation of the causal impact of the EU ETS,

³⁰For example, the marginal incentive to curb emissions was very low during the second half of phase I because the overall cap was revealed to be not binding, and because banking of permits for use in later trading phases was prohibited. The marked knock-on effect of abatement in phase II is consistent with this explanation, inasmuch as overall emissions target in phase II was tighter and unlimited banking of permits for future use provided stronger intertemporal abatement incentives.

but future research will not stop here. Collecting and analyzing suitable microdata across a large set of member states is necessary to obtain a complete picture of the effects of this landmark policy.

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Appendix

A Policy Background

A.1 Activities and thresholds for ETS eligibility

European Commission (2009) covers the following activities (cf. Annex I):³¹

- Energy activities
 - Combustion installations with a rated thermal input exceeding 20 MW (except hazardous or municipal waste installations)
 - Mineral oil refineries
 - Coke ovens
- Production and processing of ferrous metals
 - Metal ore (including sulfide ore) roasting or sintering installations
 - Installations for the production of pig iron or steel (primary or secondary fusion) including continuous casting, with a capacity exceeding 2.5 tons per hour
- Mineral industry
 - Installations for the production of cement clinker in rotary kilns with a production capacity exceeding 500 tons per day or lime in rotary kilns with a production capacity exceeding 50 tons per day or in other furnaces with a production capacity exceeding 50 tons per day
 - Installations for the manufacture of glass including glass fiber with a melting capacity exceeding 20 tons per day
 - Installations for the manufacture of ceramic products by firing, in particular roofing tiles, bricks, refractory bricks, tiles, stoneware or porcelain, with a production capacity exceeding 75 tons per day, and/or with a kiln capacity exceeding 4 m³ and with a setting density per kiln exceeding 300 kg/m³
- Other activities

³¹Note that the directive covers more activities, we list those relevant for our period of observation.

- Industrial plants for the production of (a) pulp from timber or other fibrous materials
- Industrial plants for the production of (b) paper and board with a production capacity exceeding 20 tons per day

B Background on manager interviews

Interviews were carried out by graduate and postgraduate students after they had been trained. The interviewers were paid according to the number of interviews conducted, encouraging them to conduct more interviews and discouraging any firm background research, thus preserving the double-blind nature of the survey. Interviewers made “cold calls” to production facilities (not head offices), gave their name and affiliation and then asked to be put through to the production or environmental manager. In the case of EU ETS firms, interviewers requested to speak to the person responsible for the EU ETS. At this stage, the terms “survey” and “research” were avoided as both are associated with commercial market research and some switchboard operators have instructions to reject such calls. Instead, the interviewers told them that they were doing “a piece of work” on climate change policies and their impact on competitiveness in the business sector and that they would like to have a conversation with the manager best informed.

Once the manager was on the phone, the interviewer asked whether s/he would be willing to have a conversation of approximately 40-45 minutes about these issues. Depending on the manager’s willingness and availability to do so, an interview was scheduled. If the manager refused, s/he was asked to provide the interviewer with another knowledgeable contact at the firm who might be willing to comment. Managers who agreed to give an interview were sent an email with a letter in PDF format to confirm the date and time of the interview and to provide background information and assure them of confidentiality. A similar letter was sent to managers who requested additional information before scheduling an interview.

All interviewers worked on computers with an internet connection and used VOIP software to conduct the interviews. They accessed a central interview database via a custom-built, secure web interface which included a scheduling tool and the interview application which displayed the questions along with the scoring grid. The interview screen contained hyperlinks to a manual with background information on each question. Interviewers scored answers during the interview. For all interviews, the scheduling history as well as the exact time and date, duration, identity of interviewer, etc. were recorded. All interviews were conducted in the language of the interviewee’s residence.

The interview format follows the design pioneered by Bloom and van Reenen (2007). This approach seeks to minimize cognitive bias by asking open-ended questions and by delegating the task of scoring the answers to the interviewer. In addition, a large sample size and interviewer rotation is exploited to control for possible bias on the part of the interviewers by including interviewer fixed effects in regression analyses. For further

Table B.1: Interview response rates by country

Variable	Germany	All countries
Number of firms interviewed	138	761
- of which in EU ETS	95	429
- of which not in EU ETS	43	332
Number of firms contacted	337	1451
Number of firms refused	199	691
Response rate	41%	52%

Table B.2: Firm characteristics by ETS participation status

	ETS Firms			non ETS Firms		
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
Firm						
Age (years)	47	48	89	49	80	42
Turnover (EUR million)	1,028.15	2,319.12	74	505.81	2,226.71	32
Number of employees	1,749	4,404	85	609	1,477	38
EBIT (EUR million)	35.96	139.97	65	1.82	17.06	18
Number of shareholders	3	6	95	2	1	43
Number of subsidiaries	11	62	95	2	5	43
Firm's Global Ultimate Owner						
Turnover (USD million)	13,844	17,470	25	11,996	20,955	9
Number of employees	24,083	32,157	25	49,104	73,834	8

Notes: Based on 2007 data. None of the respective means for ETS and non ETS firms are significantly different at the 10% level or better. Source: ORBIS database (Bureau van Dijk), own elaboration.

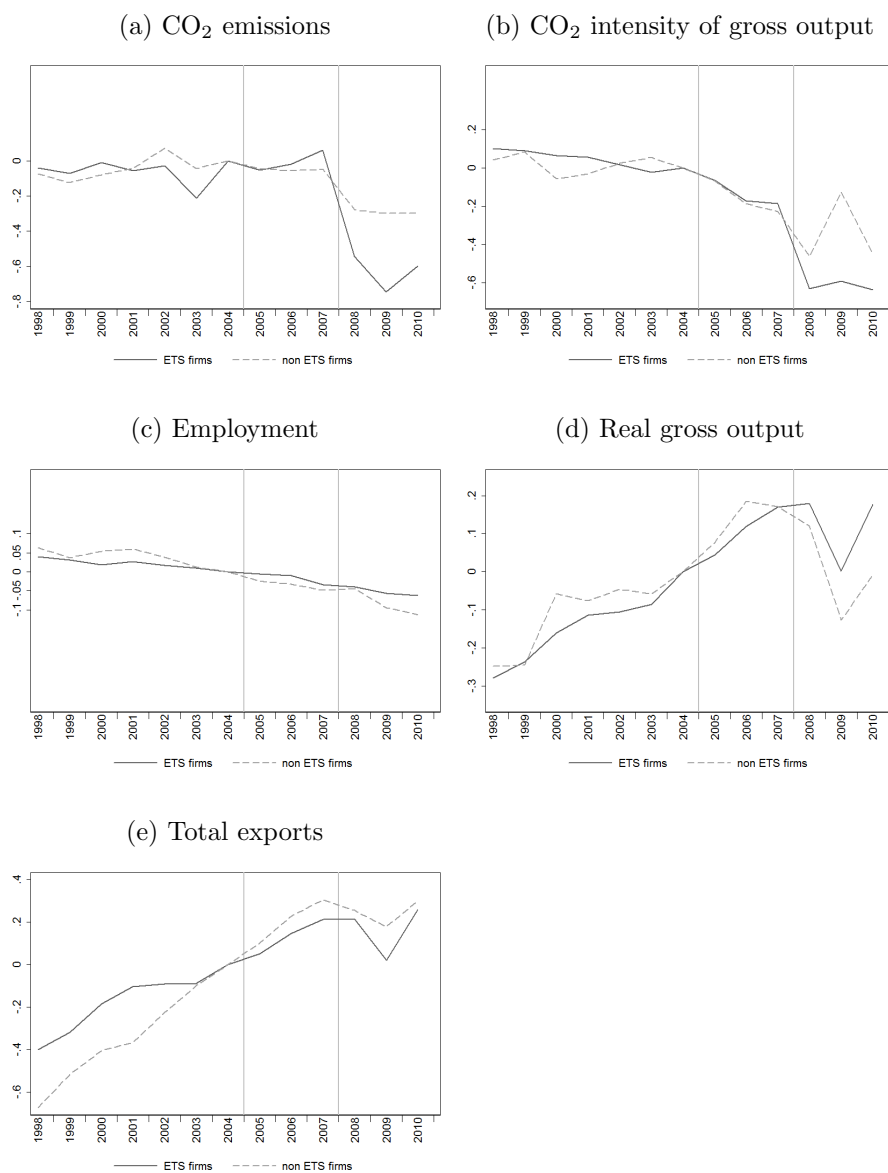
details, see Bloom and van Reenen (2010).

Table B.1 provides an overview of the number of interviews and the response rates broken down by country and by EU ETS participation status.³² The last line reports the response rate as the fraction of firms that were contacted and with whom an interview took place. Table B.2 reports the further descriptive statistics of the firms surveyed in Germany, taken from the ORBIS data base.

C Additional Tables and Figures

³²All analysts would first conduct interviews in the UK and only then go on to conduct interviews in another country allowing a common reference, hence the larger number of interviews for this country. This allows us to control for interviewer bias as discussed below and also for UK responses to be used as a benchmark.

Figure C.1: Outcome Trends By Treatment Status



Notes: The figure plots the trends in log outcome variables for treated and non-treated plants. Both series are normalized to with respect to their 2004 values. The sample consists of treated and control firms in our NN(1:1) specification which remain in the sample in all years. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

Table C.1: Propensity score estimation by stratum

	(1)	(2)	(3)	(4)
	Phase I		Phase II	
	Process-regulated sectors	Other sectors	Process-regulated sectors	Other sectors
CO ₂ emissions	43*** (5)	45*** (6)	56*** (6)	48*** (7)
Employees	699 (1731)	4567*** (891)	3058*** (1372)	3922*** (559)
Gross output	7.0 (7.0)	-2.0 (4.0)	-6.0** (3.0)	0.3 (2.0)
Average wage rate	1045*** (221)	1170*** (216)	903*** (249)	1110*** (230)
Export share of output	1.94*** (0.52)	1.03** (0.48)	2.15*** (0.57)	1.31** (0.52)
(CO ₂ emissions) ²	-0.004*** (0.001)	-0.020*** (0.003)	-0.006*** (0.001)	-0.010*** (0.002)
(Employees) ²	-266*** (84)	-72* (37)	-314*** (84)	-45*** (9)
(Gross output) ²	-0.0004 -0.0003	0.0005 -0.0006	0.0001 -0.0001	0.0001 -0.0001
(Average wage rate) ²	-9*** (3)	-10*** (3)	-7** (3)	-9*** (3)
(Export share of output) ²	-1.39* (0.72)	-0.92 (0.58)	-1.61** (0.8)	-1.01 (0.62)
Sector fixed effects	yes	yes	yes	yes
Region fixed effects	yes	yes	yes	yes
N	2,893	25,269	2,499	21,817

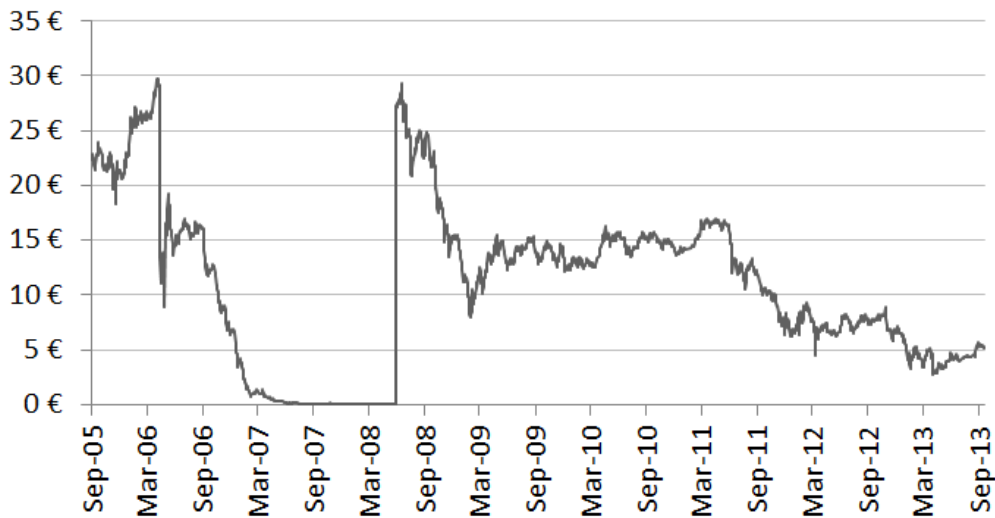
Note: All covariates in 2003 logs. Parameters for CO₂ emissions, employees, gross output, and the average wage rate are in 10 million, parameters for the corresponding squared terms are in 10 billion. Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

Table C.2: Differential impact of pre-treatment fluctuations

	(1)	(2)	(3)	(4)	(5)
	Estimation Algorithm			Number of	
	NN (1:1)	NN (1:20)	OLS w/R	Treated	Controls
A. Gross output: $\Delta \ln(GO)$					
2001-2002	-0.03 (0.04)	-0.01 (0.01)	0.00 (0.01)	371	15,362
2001-2004	0.03 (0.06)	0.03 (0.02)	0.02 (0.02)	352	13,126
B. Employment: $\Delta \ln(L)$					
2001-2002	-0.01 (0.03)	0.00 (0.01)	0.00 (0.01)	372	15,367
2001-2004	0.01 (0.04)	-0.01 (0.01)	-0.01 (0.01)	352	13,129

Notes: Matching covariates are from 1999. Number of firms is for nearest neighbor matching. Double-robust reweighting covers more firms because control firms outside the region of common support are included as well. Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1999-2010, own calculations.

Figure C.2: Allowance price over time



Notes: The figure plots historic spot market prices of EU Allowances (EUAs). Source: Point Carbon (2014), own representation.

Table C.3: Baseline specification with matching on 1999 covariates

	(1)	(2)	(3)	(4)	(5)
	Estimation Algorithm			Number of	
	NN (1:1)	NN (1:20)	OLS w/R	Treated	Controls
A. CO ₂ emissions: $\Delta \ln(CO_2)$					
Phase I	0.00 (0.04)	0.01 (0.02)	0.08*** (0.03)	379	21,418
Phase II	-0.21** (0.05)	-0.22** (0.04)	-0.27** (0.04)	351	19,071
B. CO ₂ intensity of gross output: $\Delta \ln(CO_2/GO)$					
Phase I	-0.03 (0.04)	-0.01 (0.03)	0.06* (0.04)	379	21,436
Phase II	-0.30** (0.05)	-0.26** (0.04)	-0.33** (0.04)	354	19,088
C. Employment: $\Delta \ln(L)$					
Phase I	0.02 (0.02)	0.00 (0.01)	0.03** (0.01)	381	22,173
Phase II	0.02 (0.02)	0.02 (0.01)	0.01 (0.01)	371	19,368
D. Gross output: $\Delta \ln(GO)$					
Phase I	0.06** (0.03)	0.04* (0.02)	0.07*** (0.02)	376	22,163
Phase II	0.07** (0.03)	0.05** (0.02)	0.05*** (0.02)	369	19,328
E. Exports: $\Delta \ln(X)$					
Phase I	0.20*** (0.07)	0.15*** (0.05)	0.20*** (0.05)	320	14,654
Phase II	0.11* (0.07)	0.11** (0.05)	0.06* (0.04)	319	13,675

Notes: Matching covariates are from 1999. NN(1:1) and NN(1:20) denote nearest neighbor matching with one and 20 neighbors, respectively. OLS w/R denotes the reweighted OLS estimator. Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

Table C.4: Coarse matching on $\frac{CO_2}{L}$ and 2-digit sector. Base year 2003

	(1)	(2)	(3)	(4)	(5)
	Estimation Algorithm			Number of	
	NN (1:1)	NN (1:20)	OLS w/R	Treated	Controls
A. CO ₂ emissions: $\Delta \ln(CO_2)$					
Phase I	0.00 (0.03)	-0.01 (0.02)	0.01 (0.02)	444	16,144
Phase II	-0.23** (0.04)	-0.22** (0.03)	-0.33** (0.03)	405	13,978
B. CO ₂ intensity of gross output: $\Delta \ln(CO_2/GO)$					
Phase I	0.03 (0.04)	0.03 (0.03)	0.03 (0.02)	444	16,166
Phase II	-0.23** (0.05)	-0.25** (0.03)	-0.35** (0.03)	410	14,133
C. Employment: $\Delta \ln(L)$					
Phase I	-0.02 (0.02)	-0.03** (0.01)	-0.05** (0.01)	450	16,271
Phase II	0.00 (0.02)	0.00 (0.01)	-0.01 (0.01)	430	14,393
D. Gross output: $\Delta \ln(GO)$					
Phase I	-0.03 (0.03)	-0.02 (0.02)	-0.01 (0.01)	446	16,300
Phase II	0.04* (0.02)	0.03* (0.02)	0.03** (0.01)	427	14,413
E. Exports: $\Delta \ln(X)$					
Phase I	0.09 (0.07)	0.06 (0.05)	0.05 (0.04)	x	x
Phase II	0.23*** (0.07)	0.14*** (0.05)	0.08** (0.04)	365	9,914
F. Export share in gross output: $\Delta \ln(X/GO)$					
Phase I	0.01 (0.06)	0.05 (0.04)	0.02 (0.03)	x	x
Phase II	0.12* (0.06)	0.07* (0.04)	0.05 (0.03)	367	9,924

Notes: Matching covariates are from 2003. NN(1:1) and NN(1:20) denote nearest neighbor matching with one and 20 neighbors, respectively. OLS w/R denotes the reweighted OLS estimator. x: Number not cleared for reasons of privacy protection. NN matching for 2005-2007 for outcome variable carbon intensity: 10 treated off common support. NN matching for 2008-2010 for outcome variable exports: 1 treated off common support. Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

Table C.5: Impact on CO₂ emissions: Process-regulated sectors and other sectors

	(1)	(2)	(3)	(4)	(5)
	Estimation Algorithm			Number of	
	NN (1:1)	NN (1:20)	OLS w/R	Treated	Controls
A. CO ₂ emissions from process-regulated sectors: $\Delta \ln(CO_2)$					
Phase I	0.08*	0.05	0.07**	264	2,629
	(0.04)	(0.03)	(0.03)		
Phase II	-0.33**	-0.27**	-0.28**	237	2,262
	(0.06)	(0.05)	(0.04)		
B. CO ₂ emissions from other sectors: $\Delta \ln(CO_2)$					
Phase I	-0.10*	0.00	-0.08**	188	25,081
	(0.05)	(0.03)	(0.04)		
Phase II	-0.22**	-0.21**	-0.20**	171	21,646
	(0.07)	(0.04)	(0.04)		
C. CO ₂ intensity of output from process-regulated sectors: $\ln(CO_2/GO)$					
Phase I	0.04	0.03	0.03	265	2,627
	(0.04)	(0.03)	(0.02)		
Phase II	-0.36**	-0.34**	-0.34**	242	2,265
	(0.06)	(0.05)	(0.04)		
D. CO ₂ intensity of output from other sectors: $\ln(CO_2/GO)$					
Phase I	-0.04	0.00	0.03	187	25,105
	(0.06)	(0.04)	(0.04)		
Phase II	-0.23**	-0.21**	-0.25**	171	21,642
	(0.07)	(0.05)	(0.06)		

Notes: NN(1:1) and NN(1:20) denote nearest neighbor matching with one and 20 neighbors, respectively. OLS w/R denotes the reweighted OLS estimator. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

Table C.6: Impact on Investment

	(1)	(2)	(3)	(4)	(5)
	Estimation Algorithm			Number of	
	NN (1:1)	NN (1:20)	OLS w/R	Treated	Controls
A. Investment: $\Delta \ln(I)$					
Phase I	-0.09 (0.12)	-0.08 (0.09)	-0.05 (0.07)	420	21,723
Phase II	0.03 (0.12)	0.05 (0.09)	0.04 (0.08)	397	18,850
B. Gross Investment: $\Delta \ln(GI)$					
Phase I	-0.06 (0.12)	-0.07 (0.08)	-0.03 (0.07)	426	22,799
Phase II	-0.17 (0.12)	0.00 (0.09)	0.00 (0.08)	407	19,764

Notes: NN(1:1) and NN(1:20) denote nearest neighbor matching with one and 20 neighbors, respectively. OLS w/R denotes the reweighted OLS estimator. Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

Table C.7: Impact on export share in gross output $\Delta \ln(X/GO)$

	(1)	(2)	(3)	(4)	(5)
	Estimation Algorithm			Number of	
	NN (1:1)	NN (1:20)	OLS w/R	Treated	Controls
A. Matching based on covariates in 2003 (baseline specification)					
Phase I	0.05 (0.05)	0.06 (0.04)	0.07** (0.03)	378	18,184
Phase II	0.05 (0.06)	0.06 (0.04)	0.03 (0.04)	371	16,635
B. Matching based on covariates in 1999					
Phase I	0.10* (0.06)	0.07 (0.04)	0.11*** (0.04)	321	14,652
Phase II	0.03 (0.07)	0.05 (0.04)	0.01 (0.03)	321	13,670
C. Coarse matching on CO_2/L in 2003					
Phase I	0.01 (0.06)	0.05 (0.04)	0.02 (0.03)	x	x
Phase II	0.12* (0.06)	0.07* (0.04)	0.05 (0.03)	367	9,924

Notes: NN(1:1) and NN(1:20) denote nearest neighbor matching with one and 20 neighbors, respectively. OLS w/R denotes the reweighted OLS estimator. Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Länder (2012): AFiD-Panel Industriebetriebe, 1998-2010, own calculations.

The Impact of Temperature Changes on Residential Energy Consumption^{*}

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Abstract:

In order to explore the impact of climate change on energy use, we estimate an energy demand model that is driven by temperature, prices and income. The estimation is based on an unbalanced panel of 62 countries over three decades. We limit the analysis to the residential sector and distinguish four different fuel types (coal, electricity, natural gas and oil). Compared to previous papers, we have a better geographical coverage and consider both a heating and cooling threshold as well as further non-linearities in the impact of temperature on energy demand and temperature-income interactions. We find that oil, gas and electricity use are driven by a non-linear heating effect: Energy use decreases with rising temperatures due to a reduced demand for energy for heating purposes, but the speed of that decrease declines with rising temperature levels. We cannot find a significant impact of temperature on the demand for cooling energy.

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1 Introduction

During the last century, the global average temperature rose by about one degree Celsius, and may easily rise by another 1.8 to 4.0 degrees over the current century, depending on the emission scenario (IPCC 2007). Among the various economic consequences of a global temperature rise, the impact on energy consumption is of particular importance and frequently discussed as one of a number of important economic consequences of climate change (Tol 2009, Roson and van der Mensbrugge 2012). Furthermore, greenhouse gases emitted by the energy sector are themselves a main driver of climate change and responsible for a good quarter of global greenhouse gas emissions (IPCC 2007). Energy consumption thus affects and is affected by both climate change and climate policy. This paper aims to disentangle the impact of temperature changes on energy consumption and to calculate the temperature sensitivity of energy demand for selected fuels.

By now a number of studies (see below) analyse the driving forces behind the temperature sensitivity of energy under specific conditions. Usually based on micro level data, these analyses tend to take into account as many socio-economically and geographically relevant determinants as possible. For assessing particular policy measures targeted at region specific problems (e.g. number of energy poor households, distributional effects of different policies etc.) or for analysing the energy demand reaction to temperature changes in a specific country or region, this micro-perspective is advantageous. The aim of our paper is to go beyond the single country analysis. Data from multiple countries exhibit a wider range of energy uses, technologies, economic circumstances, and climates. The estimated relationships are therefore better suited for extrapolation to future climate and economic conditions. Information about the temperature sensitivity of energy demand is essential for a thorough understanding of the

consequences of climate change – e.g. as a basis for calibrating general equilibrium or integrated assessment models.

We concentrate on *residential* energy demand, because previous studies showed that energy use in the services and manufacturing sectors reacts only minimally to temperature variations; see Bigano et al. (2006) for a discussion on that point.

We add to the existing literature (see Agrawala et al., 2011, for an overview) by combining many of the conceptual achievements of previous studies as well as by introducing new features. Most previous studies, both on the micro and on the macro level, focused solely on electricity use. We extend our analysis to heating oil, natural gas and solid fuels as well. We use a large sample of countries to increase confidence in the estimated relationships, not only because we have more observations, but also because we measure the effects over a wider range of income and temperature levels.

Instead of estimating the temperature effect on energy use only linearly, we allow for the temperature elasticity to depend on temperature itself by estimating non-linear specifications. We account not only for a smooth non-linear dependency, but also account for a discontinuous heating threshold by introducing heating degree months. Additionally, we consider that the temperature elasticity of energy use may also depend on other variables, namely income.

In the following section, we give a brief overview of the existing literature. In Section 3, we describe how we model the determinants of energy use, including the concept of heating degree months. We describe our data in Section 4. In Section 5, we present our results on the heating effect and the cooling effect as well as some supplementary and sensitivity analysis. Section 6 discusses the results and concludes.

2 Existing Work

As mentioned above, most contributions so far addressed the topic either on a micro-level (e.g. Quayle and Diaz 1980; Rosenthal and Gruenspecht 1995; Henley and Peirson 1997, 1998; Florides et al. 2000; Vaage 2000, Zarnikau 2003; Larsen and Nesbakken 2004; Mansur et al. 2005; Mansur et al. 2007) or using country or regional time series data (e.g. Al-Zayer and Al-Ibrahim 1996; Hunt et al. 2003; Mirasgedis et al. 2004; Amato et al. 2005; Pezzulli et al. 2006). Naturally, these studies concentrate on specific countries without aiming at large-scale representativeness. Often, the impact of temperature is not the central focus. Methodologies vary greatly, as do the results. We present an overview of results of selected macro-level studies on residential energy use in the appendix (Table A 2).

Studies using multi-country panel data are less common. Bigano et al. (2006) study the impact of temperature changes on several fuels in OECD countries from 1978 to 2000. Even though they include “a few” non-OECD countries, their focus is on the developed world. They find a significant negative impact of average annual temperature on electricity, natural gas and oil consumption in the residential sector. Elasticities vary between -0.57 for electricity and -3.05 for oil. The authors find a positive effect of temperature changes on coal consumption, with an elasticity of 2.85.

Asadoorian et al. (2008) study the impact of temperature changes on electricity demand in urban versus rural Chinese provinces from 1995 to 2000, thus including several climate zones and some variation in development levels. They find that the temperature elasticity of electricity

demand varies between 0.59 and 0.76. Neither Bigano et al. (2006) nor Asadoorian et al. (2008) report semi-elasticities or marginal effects.¹

Bessec and Fouquau (2008) study the impact of temperature changes on electricity consumption in 15 member states of the European Union for the period 1985 to 2000. Since they use a panel threshold model, they can in detail model a smooth, non-linear transition from a heating regime with negative temperature elasticities to a cooling regime with positive temperature elasticities. They conclude that both non-linearity and a cooling effect are not very pronounced in cold countries, as opposed to southern EU member states. They also report an increasing impact of warmer summers on electricity demand for cooling.

Lescaroux (2011) focuses on the impact of income on energy demand, but includes temperature as a control variable. His estimation results report a temperature semi-elasticity of total residential energy consumption between -0.03% (in the short run) and -0.08% (in the long run) per degree centigrade. Based on a comprehensive panel of 101 countries and three aggregates over the period 1960 to 2006, the results are representative for a large number of development levels and climate zones. However, only country average temperature levels are considered. Since he utilizes an autoregressive specification, he can distinguish short-run and long-run effects. He does not include non-linearities in the reaction of electricity use on temperature changes.

¹ By “semi-elasticities”, we mean the percentage change in energy use (or any other dependent variable) per one-degree temperature change (or a change in any other explanatory variable by one unit) instead of percentage change in the explanatory variable. The use of semi-elasticities instead of real elasticities is advisable in the case of temperature, since temperature in degrees centigrade (as well as Fahrenheit) is measured on an interval scale but not on a ratio scale and thus has no non-arbitrary absolute zero value as a reference point. The problem does not arise if degree days are used instead of (average) temperature levels.

De Cian et al. (2013) study residential energy use in 26 OECD and five non-OECD countries for the period 1978-2000, covering a wider variety of development levels and climate zones than many previous macro-panel studies. They conclude that demand for heating and cooling and its response to changes in temperature depend on region, season and fuel type. They account for non-linearities in the reaction to temperature changes by clustering their sample into three groups, cold, mild and hot, depending on the baseline temperature level of countries. They also distinguish seasonal impact by utilizing four seasonal average temperature levels per year and country. Long-run and short-run temperature elasticities are estimated as constants within climate clusters using an error correction specification. For the different groups and seasons, they estimate long-run temperature elasticities between -3.33 and 5.42 for electricity, -2.6 for natural gas and between -3.45 and 3.36 for oil products. Short-run temperature elasticities are smaller, spanning from -0.39 to 0.92 for electricity, from -0.95 to -0.18 for gas and from -0.7 to -0.02 for oil products.

3 Modeling determinants of residential energy consumption and empirical strategy

In our model, households adapt their use of energy to income, fuel prices and temperature. Microeconomic theory suggests that energy fuels are normal goods with positive income elasticities, negative price elasticities and zero or positive cross price elasticities towards other energy fuels. We show below, however, that not all fuels are necessarily normal or ordinary goods, e.g. due to substitution effects from low-quality fuels such as coal towards high-quality fuels such as natural gas. We assume that households (and thus also countries) need a lag of one year to adapt to changes in prices. This addresses common adaptation lags due to information lags, habit

persistence, stock holding or contractual obligations. We cannot implement shorter lags due to the yearly frequency of our data.

We account for differences in temperature as well. With rising temperatures, households need less heating, whereas the demand for cooling is likely to rise. With rising temperatures the heating effect, therefore, reduces energy consumption, while the cooling effect increases it.

A vital question is the nature of the interdependence between temperature changes and adjustments in the consumption of energy. Assuming a linear relationship seems rather counterintuitive.² One would expect that the impact of temperature changes differs depending on the historical temperature level. Presumably, if temperature rises, the reduced heating demand would be smaller for warmer countries than for colder ones; while increased cooling demand would be larger.³ To address this issue, firstly, we use heating degree months instead of untransformed temperature values to cover the impact of heating and cooling thresholds (see below for more details on the concept of degree months). Secondly, we estimate a non-linear relationship between degree months and energy. For each fuel type we estimate three functional forms, linear, quadratic and logarithmic, and compare with a baseline specification without any temperature impact (see equations (3) to (6) for details on the specifications). Furthermore, we interact temperature and (per-capita) income. Richer households might have a higher ability to adapt to climate change, e.g. by investing in insulation,

² See for example Bigano et al. (2006), who identify the use of a linear model as a major drawback of their analysis.

³ Since the specific process of the adaptation of energy use in the course of changes in temperature depends on local conditions like insulation, heating and cooling equipment, local conventions etc., the link between temperature and energy use may of course be linear on a small scale, e.g. for a country that is located in only one climate zone. In this case, variation in annual average temperature levels in that country is limited. On a global scale however, where annual average temperature varies more, a non-linear relationship is much more likely. The question concerning the interpretation of the results of the global analysis is of course whether patterns derived from comparisons between countries also hold within a country, given that temperatures rise significantly in the future.

heating appliances, air conditioning etc. At the same time, poorer households might be less responsive to changing temperature levels since they are constrained in their adaptation options. The same rationale applies to rich and poor countries – if temperature rises, the decrease in energy consumption may be steeper if a country is richer. In this case, the level of income has an effect on the temperature elasticity of energy demand – the elasticity will increase (in absolute value) with rising income.

Note that heating demand is insensitive to temperature changes above a certain temperature threshold, the heating threshold. The heating threshold is the temperature level at which it is warm enough so that households feel comfortable enough not to use their heating equipment. The analogue is true for cooling and temperature changes below a cooling threshold. The traditional approach to this problem is the use of heating (HDD) and cooling degree days (CDD),⁴ as for example in Al-Zayer and Al-Ibrahim (1996) or Amato et al. (2005). Since HDD and CDD are not available for a sufficiently broad range of countries, their use is not an option for our analysis.

As we investigate annual and national data, we face the problem of how to represent heterogeneous temperature levels (and changes) within countries and years in the aggregate – especially if countries and seasonal temperature variation are large. We therefore use gridded monthly data instead of annual country averages. To account for the heating and cooling thresholds, we construct regionalized heating (HDM) and cooling degree months (CDM) from the monthly, gridded temperature averages. Our regionalized HDM

⁴ Heating degree days are usually defined as the difference between the average temperature of a period and the heating threshold, multiplied with the number of days within that period if the average temperature is below the heating threshold and zero if the average temperature is above (e.g. EUROSTAT 2008). Cooling degree days are the difference between the cooling threshold and the average temperature of the period, also multiplied with the number of days if the average temperature is above the threshold and zero if it is below.

and CDM are closely linked to the concept of heating degree months used in Maddison and Rehdanz (2011). To construct HDM and CDM, we calculate deviations of the monthly mean temperature from the threshold temperature⁵ for each 0.5 degree grid cell in the grid. The deviation is set to zero if the monthly mean temperature is higher (lower for CDM) than the threshold temperature. The mean of the remaining differences is the heating/cooling degree value for that month and that country. Finally, all months of a year are summed up and form the yearly (regionalized) HDM/CDM value for the country:

$$HDM_{i,t} = \sum_{m \in t} \left(MEAN_{g \in i} \left(POS(18.3 - T_{m,g}) \right) \right) \text{ and} \quad (1)$$

$$CDM_{i,t} = \sum_{m \in t} \left(MEAN_{g \in i} \left(POS(T_{m,g} - 18.3) \right) \right), \quad (2)$$

where the function POS returns only positive deviations, $MEAN_{x_{cy}}$ returns the arithmetic mean over all x within y and $\sum_{x_{cy}}$ returns the sum over all x within y. T is the monthly mean temperature, indices m, t, g and i denote month, year, 0.5-degree grid cell and country, respectively. In Section 5.3.7 we additionally use a population density weighted mean over the grid cells in a country to account for unevenly distributed population across countries with mixed climate.

Apart from temperature, income and prices, household energy demand is determined by a multitude of factors that are unobservable by nature or for practical reasons, such as limited data availability. This is especially true on a cross-country scale. Since we employ a panel data set, we are able to address the problem of time-invariant, country-specific unobserved determinants of energy use by including fixed effects in our regression

⁵ In accordance with the literature, we use 18.3 degrees centigrade as threshold temperature. Cf. e.g. Uri (1979) or Dublin and McFadden (1984). See Section 5.3.6 for supplementary analyses using different threshold temperatures.

model. However, some unobserved characteristics, although being highly persistent, will still be time-variant and therefore unaccounted for in the standard fixed-effects model. This includes classical unobservables like habits, but also long-run changes in the prevailing and available technology, capital stock or government policies.⁶ Furthermore, transient (or so perceived) shocks of the explanatory variables will have a smaller impact on energy demand than sustained changes. To include some of the persistent but time-variant omitted explanatory power, and to differentiate between transient and sustained shocks, we include the history of a country's energy use in the form of a lagged dependent variable additional to the country-specific fixed effects.⁷ To rule out that we interpret time-invariant factors as being highly persistent and thus overestimate long-run shocks, we reject any specification with an autoregressive term that is not significantly different from one for standard significance levels.⁸ As a sensitivity test, we also estimate each specification with either fixed effects or lagged dependent variables. To summarize, we estimate the following equations:

No temperature impact:

$$\log(\text{fuel}_{i,t}) = \beta_0 + \mu_i + \lambda \log(\text{fuel}_{i,t-1}) + \beta_1 \log(y_{i,t}) + \beta_2 \log(p_{i,t}) + \beta_3 \log(\mathbf{X}_{i,t}) \quad (3)$$

⁶ Prevailing technology standards are one classical example for such time-variant unobservables in the long run. They have been discussed in the literature on rebound effects, Sorrell et al. (2009) provide an overview of the literature.

⁷ The interpretation of a lagged dependent variable as a representation of persistent shocks is based on the Koyck transformation. Koyck (1954) showed that an infinite distributed lag model of geometric structure (i.e. a model where the exogenous variables are included with infinitely many lags, the parameters of which follow a geometric distribution) can be transformed into a model with one lagged dependent variable and only contemporaneous exogenous variables.

⁸ This criterion is not relevant for the selection of our specification of choice, but only in the sensitivity analysis in Section 5.3.3, where we study the impact of sample size on our results. Some small-sample specifications that omit the price variable, mainly of the coal model, yield autoregressive parameters that are not significantly different from one (cf. Section 5.3.3.). This issue touches the concern of non-stationary series, which we address in Section 5.3.1.

Linear:

$$\log(\text{fuel}_{i,t}) = \beta_0 + \mu_i + \lambda \log(\text{fuel}_{i,t-1}) + \beta_1 \log(y_{i,t}) + \beta_2 \log(p_{i,t}) + \beta_3 \log(\mathbf{X}_{i,t}) + \beta_4 \log(DM_{i,t}) \quad (4)$$

Quadratic:

$$\log(\text{fuel}_{i,t}) = \beta_0 + \mu_i + \lambda \log(\text{fuel}_{i,t-1}) + \beta_1 \log(y_{i,t}) + \beta_2 \log(p_{i,t}) + \beta_3 \log(\mathbf{X}_{i,t}) + \beta_4 \log(DM_{i,t}) + \beta_5 \log(DM_{i,t})^2 \quad (5)$$

Logarithmic:

$$\log(\text{fuel}_{i,t}) = \beta_0 + \mu_i + \lambda \log(\text{fuel}_{i,t-1}) + \beta_1 \log(y_{i,t}) + \beta_2 \log(p_{i,t}) + \beta_3 \log(\mathbf{X}_{i,t}) + \beta_6 \log(\log(DM_{i,t})) \quad (6)$$

where DM is either CDM or HDM, fuel is coal, electricity, gas, or oil consumption per capita, y is real GDP in Purchasing Power Parities (PPP), p is fuel price, and \mathbf{X} is a vector of potential additional covariates we use for supplementary and sensitivity analyses (Section 5.3). \mathbf{X} may, for example, include income-temperature interactions or cross prices. β_3 is zero in our baseline specification.

Since we include lagged dependent variables in addition to fixed effects, the standard fixed effects least squares estimator will be biased due to endogeneity of the lagged dependent variable (Nickell 1981). The literature on dynamic panel data models contains a variety of estimators that overcome this “Nickell bias” and yield unbiased estimators by instrumenting for the endogenous lagged variable, such as the estimators by Anderson and Hsiao (1981), Arellano and Bond (1991) or Blundell and Bond (1998). However, the generalized-method-of-moments (GMM) estimators by Arellano and Bond as well as by Blundell and Bond are constructed to suit large N , small T panels, while their usefulness for macroeconomic panels (such as ours) with small N and moderate T has been

doubted based on a root-mean-square error (RMSE) criterion in favor of a corrected least squares dummy variable (LSDVC) estimator proposed by Kiviet (1995; see also Judson and Owen, 1999). Kiviet's LSDVC estimator is meant to combine the merits of the conventional, biased least squares dummy variables estimator in terms of efficiency with the consistency of the GMM approaches. It was extended by Bruno (2005a) to suit also unbalanced panels. Since our panel is a macroeconomic panel similar to the one used in the Monte Carlo study by Judson and Owen (1999), we choose Bruno's (2005a) LSDVC estimator as our estimator of choice. The GMM-based estimator of Arellano and Bond (1991) with Windmeijer's (2005) variance correction for small samples is used to test for sensitivity with regards to the estimator (see Section 5.3).

Unlike many existing studies, we study not only electricity, where data availability is good. We include four fuels that represent the vast majority of fuels used for heating and cooling worldwide: Coal and solid biomass⁹ as well as electricity, natural gas and fuel oil. Demands for the four fuels are estimated individually, not as a system. However, we estimate cross price elasticities as a sensitivity analysis.

4 Data

Data on energy consumption, prices and real GDP are retrieved from ENERDATA (2005) for up to 176 countries and the period 1970 to 2002.¹⁰ Data availability differs considerably between the four fuels, coal, electricity, natural gas and oil types; both regarding use and price data (see Table 1 for details). Data on the use of gas and coal are available for about

⁹ We cannot differentiate between coal and solid biomass due data restrictions. Coal and biomass are represented in one aggregate variable, which we will call coal in the further course of the paper.

¹⁰ Enerdata is a research & consulting firm that compiles and publishes global energy use data. The database is compiled from various international organizations as well as national statistical offices and other national institutions, for details see ENERDATA (2012).

70 countries; for oil and electricity there are time series for almost every country in the world. In comparison, data on prices are scarce. Reliable price data are available mostly for developed countries and only from 1978 onwards (for information about the geographical coverage of the data, cf. Figures A1-A4 in the appendix, for information about temporal coverage, cf. Table A 1 in the appendix). This limits the estimation sample to 25 years at most if price data are included. Regarding geographic coverage, coal is again the fuel type with the lowest coverage: the price of coal for residential consumption is available for only 22 countries. Even though the share of coal in residential energy demand is usually of minor (and diminishing) importance, both from a global and from national perspectives, this constitutes a shortcoming of the analysis. It was however impossible to impute the price of residential coal by other prices, e.g. coal prices from other sectors. Data availability is better for the prices of other fuel types. For natural gas and light fuel oil, more than 30 countries are covered. Electricity prices are available for 63 countries. Nonetheless, also for those energy types, limited availability of price data imposes a drawback of the analysis in terms of representativeness, reliability and quality of the estimation results. We solve this drawback by testing the robustness through regressions without prices on the same sample. As a proxy for household income we use per-capita GDP in purchasing power parities (converted to 1995 international dollars). Compared to information on energy prices and consumption, data availability is good.

We use monthly average temperature values taken from the High Resolution Gridded Dataset of the Climatic Research Unit of the University of East Anglia (CRU 2008, Mitchell and Jones 2005) available at a 0.5 degree grid. We transform the gridded, monthly temperature averages to annual HDM and CDM on the country level according to the procedure described in Section 3. Temperature data are available for most countries and all years of

interest. All temperature variables are in degrees centigrade. For additional analysis using population weighted DM, we use population data from the HYDE database (before 1990, Klein Goldewijk 1995) and the GPWv3 database (from 1990 onwards, CIESIN and CIAT 2005), interpolating missing years (see Section 5.3.7).

~ Table 1 about here ~

5 Results

To identify the best (in terms of explanatory power) and most robust specification for each fuel type, we compare three functional forms of temperature impact on energy use, namely linear, quadratic and logarithmic, and one specification without temperature impact. For each functional form, we compare specifications with and without fuel prices. The impact of cross prices and temperature-income interactions is studied as a sensitivity analysis in Section 5.3. In the following, we discuss the specifications with the best score on the Akaike Information Criterion (AIC). The results of all specifications, however, can be found in the appendix (Table A 3).

5.1 Heating Effect

For all fuels we find a significant heating effect (cf. Table 2). We find that the quadratic specification is superior to the others in terms of parameter significance and AIC for all fuels (for an overview of all relevant specifications, cf. Table A 3).¹¹ This confirms our hypothesis that the response in energy use to temperature changes is non-linear, even beyond the discontinuity imposed by the heating threshold. While in warmer countries less energy is used for heating than in colder countries, the

¹¹ Logarithmic specifications do either not yield significant results or copy the quadratic specification closely. Since fit is usually better for the quadratic specifications, we do not present the logarithmic models here.

marginal impact of temperature changes on fuel use decreases in absolute tons of oil equivalents with increasing temperature (see Figure 1). At the same time, the relative impact, i.e. the elasticity, increases with rising temperature levels (see Figure 2).

~ Table 2 about here ~

~ Figure 1 about here ~

~ Figure 2 about here ~

The size of the non-linear effect is different among the four fuels. As Figure 1 shows, electricity demand is almost constant, even for very cold countries, and the squared parameter is small compared to coal, gas and oil. This is reasonable since electricity has a multitude of other uses apart from space heating that accordingly reduce temperature dependence of the fuel. Non-linearities play a much larger role for the other three fuels. For temperatures below 90 HDM, where 75 % of the observations are located, predicted coal, gas and oil consumption is particularly curved, leading to a decelerating rise in the temperature elasticity of fuel use. For example, we estimate that a country with only around 10 HDM (e.g. Saudi Arabia, India or Namibia), although 15 times hotter than a country with around 150 HDM (e.g. China, the USA or North Korea), has a short-run temperature elasticity of oil that is only 10 times smaller (0.32 versus 3.12) – all other explanatory variables equal. Non-linearities aside, coal is the most temperature-elastic fuel in the short run, followed by gas, oil and electricity.¹² Interestingly, this order is changed in the long run due to the relatively low persistence of shocks of coal use. Short-run and long-run elasticities are compared in Figure 2. Persistence of shocks is similar for electricity, gas and oil products.

¹² Note that the representativeness of our coal model is limited, since it uses only 270 observations from 20 countries. For an overview of the regional coverage of our data for the different fuels, see Figure A 3 to Figure A 6.

Because of the differences in methodology, data and especially due to the use of degree months, our results are not easily comparable to the results of previous studies (cf. Section 2). For average HDM levels, our estimated elasticities are about the same order of magnitude as those in Bigano et al. (2006) for electricity and natural gas, while our elasticity is larger for coal and smaller for oil. Compared to the results of De Cian et al. (2013), our elasticities are within the range of their estimates for electricity and oil, but larger for natural gas. De Cian et al. (2013) do not estimate coal use. See Table A 2 in the appendix for an overview of selected results of macro-level studies on residential energy use.

Although not at the core of our analysis, the estimated price and income elasticities of the four fuels show interesting differences (for a detailed picture, see Figure A 2 in the appendix). Electricity, gas and oil are normal goods. This is not true for coal. Coal use reacts negatively to changes in income and positively to changes in coal price. Coal is an inferior good. The income effect more than offsets the substitution effect in the price reaction, leading to an overall positive price elasticity. Thus, coal is a Giffen good according to our estimation. As mentioned before, our coal model relies on a relatively small sample and is not as representative as in the cases of the other fuels (cf. Footnote 12). In all countries except China, residential coal use has remained constant or declined over the last decades, both per capita and in absolute terms. Nowadays coal plays a substantial role for residential space heating only in a limited number of countries, namely in the countries of the Commonwealth of Independent States (CIS) and China. In the rest of the world, it competes on a very low level with oil and gas on the one hand and with firewood on the other.

The price elasticity of oil has a positive sign, too. The parameter is, however, not significantly different from zero. If found significant, a

potential reason for a small and positive price elasticity of oil could be competition from the superior natural gas option, the latter reacting most strongly to changes both in income and price. Another reason may be that the oil price picks up some variation in cross prices as well, since the correlation of each fuel price with the oil price is usually highest compared to the correlation with other fuel prices (see also Section 5.3.2).

Not surprisingly and supposedly due to the broad use of electricity for a large variety of applications with few substitution possibilities, income and price elasticities of electricity use are lowest. Since persistence of shocks is similar for electricity, gas and oil, the responsiveness ranking between those three does not change in the long run.

5.2 Cooling Effect

An increase in cooling demand is one of the predicted effects of climate change. Although quantifying the cooling effect was one of our declared goals, we are unable to find a significant cooling effect on energy use, irrespective of the functional form and irrespective of whether we estimated the cooling effect jointly with the heating effect or separately. This does not necessarily mean that there is no cooling effect. The geographical scope of our data set is broad, it includes developed as well as many developing countries. So far on the macro scale, the cooling effect has been derived mainly for developed countries (De Cian et al., 2013, for example cover the OECD countries and in addition South Africa, India, Thailand and Venezuela; Bessec and Fouquau 2008 cover the EU-15 countries). However, households in developing countries will most probably respond differently to temperature changes. Although most developing countries are located in warm climates, the endowment with air conditioning and other cooling devices is supposedly below average, since the households' incomes are so low. Also, including only per-capita GDP might not be sufficient for

capturing these structural differences. Furthermore our sample covers a rather long time period, starting in the 1970s. Since cooling is a relatively new phenomenon in the household sector outside the USA, the cooling effect might be obscured by the long time span.

Then again, estimations restricted to all OECD countries, to all warm OECD countries, and to the European Mediterranean did not yield a significant cooling effect either, even if we restrict the sample to the 10 most recent years. However, the estimation of a single-country time series model based only on data for the US suggested a significant cooling effect.¹³ We conclude that within our observation period cooling is still only a regional issue, if not an US-issue – although this finding is likely to change in the future.¹⁴

While Bigano et al. (2006) do not test for a cooling effect, De Cian et al. (2013) find a significant positive influence of summer temperature on electricity demand for a subsample of mild and hot countries. Asadoorian et al. (2008) find a cooling effect for the residential sector in China. We cannot confirm their result with our data.

5.3 Supplementary and sensitivity analyses

5.3.1 Testing for unit roots

Since we are using a macroeconomic panel with relatively large T and, compared to microeconomic panels, small N , one potential source of error is non-stationarity. Non-stationarity would invalidate inference, leading to

¹³ For the USA, the cooling effect turned out to be linear, with a short-run elasticity of 0.13 and a long-run elasticity of 0.26. The cooling effect is significant on the 1% level, but it has to be kept in mind that this single-country estimation is based on 24 observations only.

¹⁴ Note that our observation period ends already 2002 and therefore excludes most recent developments, namely in the number of air conditioning installations e.g. in Asia and the Pacific Region. As an example, Akpınar-Ferrand and Singh (2010) report an increase in sales for air conditioning units in India from just above 600,000 in 2002 to around 2,000,000 in 2008. Before 2002, they report a much slower increase in sales.

erroneous conclusions based on spurious significance testing. For this reason we test for the presence of unit roots (which imply non-stationarity) in the variables that form our model. Since in a panel context convergence can run both via the time dimension and over cross sections (countries in our case), we have to consider the nature of the panel when choosing the appropriate unit root test. The test's assumptions on asymptotics over T and N need to be realistic given the nature of the panel. Since we analyze country-level data, which implies a finite number of cross sections, we assume that N is finite or that at least T grows faster than N . We opt for the commonly used Levin-Lin-Chu (LLC, Levin et al. 2002) and Fisher-type tests (Choi 2001). Fisher-type tests combine the p values from separate time series ADF unit root tests of the individual country series.¹⁵ LLC assume $\frac{N}{T} \rightarrow 0$, the Fisher tests we use assume $T \rightarrow 0$ and N finite (Hlouskova and Wagner 2006). Both tests use the null hypothesis that all country series have a unit root.

Unfortunately, both tests are only implemented for balanced panels, which is why we trim our panel to a balanced panel before testing. We report test statistics for a long and narrow panel (1976-2002)¹⁶ that maximizes observations as well as for a short and broad panel (1992-2002), which includes a larger number of countries. We assume that shorter country series or country series with gaps that had to be dropped are sufficiently represented by the remaining sample. As Table 3 shows, we cannot reject the null hypothesis of a unit root only for very few isolated LLC tests of coal use per capita, coal price, and gas price. The large majority of tests, however, rejects the presence of a unit root and confirm stationarity. We, therefore, conclude that our inference is based on stationary series and valid, even though further doubt is cast on the coal model.

¹⁵ See Baltagi (2008, chapter 12) for an overview of the LLC and Fisher tests.

¹⁶ 1978-2002 in the case of price variables.

~ Table 3 about here ~

5.3.2 The price of oil

To capture the impact of substitutes or complements, we include oil prices into the various specifications. Since the oil price and the prices of the other three fuels are highly correlated and due to the role of the oil price as lead or reference price on international and national energy markets, we refrain from including more than one cross price to avoid multi-collinearity.¹⁷ Generally, the oil price does not have a significant impact on the demand for any of the fuels, for most of the functional forms and especially for our specifications of choice.¹⁸ A notable exception is natural gas. Gas and oil prices are either both significant or both insignificant. We therefore exclude oil prices from the final natural gas specification, not least for consistency reasons. The impact of prices on gas use is to a considerable extent governed by a small group of outliers, as we describe below.

5.3.3 Sample size

As mentioned in Section 4, data availability is low for residential energy prices. We therefore repeat the analysis without prices to determine the impact of sample size. See Figure A 3 to Figure A 6 in the appendix on the impact of variable choice for spatial coverage. To differentiate between the effect of increased sample size and the effect of including prices, we estimate all specifications excluding prices, both for the largest available sample and restricted to the sample for which price data is available. The latter sample is equivalent to that of our reference specification. In the case of coal, we find that the income effect is lower in the large sample, which is not surprising as the difference in samples includes many developing and

¹⁷ Correlation coefficients (p-values) with oil prices are -0.4 (0.0) for coal prices, 0.3 (0.0) for gas prices and -0.1 (0.03) for electricity prices.

¹⁸ The same remains true if all three cross prices are included in the estimation.

emerging countries. The temperature effect has about the same size, but the quadratic term becomes insignificant (the linear term remains significant). The persistence parameter is considerably higher, but still significantly different from one. The parameter changes for the lagged dependent variable, income and temperature squared are also present in the small sample and thus attributed to the omitted price variable.

For electricity, income and persistence parameters are stable across sample sizes, but the temperature effect is considerably smaller for the large sample. The linear and quadratic temperature parameters are insignificant individually, but jointly significant. The temperature parameter is also insignificant for the small sample if prices are excluded.

In the case of natural gas, the income and temperature effects are lower but still significant for the larger sample, including the quadratic term. The income and HDM parameters do not change as much if prices are excluded from the small sample, suggesting that the changes can indeed be attributed mostly to the larger sample.

For oil, the persistence, income and temperature parameters are lower and become insignificant for the large sample. Contrary to the income effect, the temperature effect is also insignificant for the small sample if prices are excluded, meaning that the insignificance of the temperature effect might be caused by the exclusion of the oil price and not the larger sample.

5.3.4 Interactions

Above, we study non-linearities in temperature. Here we turn to non-linearities in income. The impact of changes in temperature on energy demand might not only depend on the level of temperature itself, but also on income. Households with higher income have more options to adapt to temperature changes than low-income households (e.g. by improving

insulation or heating systems); the same rationale holds for high and low income countries. If temperatures rise, the decrease in energy use should be steeper if a country is richer. In this case, the level of income has an effect on the temperature elasticity of energy demand – the elasticity will increase (in absolute value) with rising income. We allow for this effect by including an interaction term into the regression. Income-temperature interaction terms are insignificant for practically all specifications and fuels. We find some weak indication for income dependence of the temperature elasticity of fuel use in the case of natural gas. Although the interaction term is in some cases significant, it usually renders the temperature coefficient itself insignificant. We therefore regard the specification without interactions more credible.

5.3.5 Outliers

Natural gas is not only an interesting fuel because it shows some signs of weak impacts of cross prices and income-temperature interaction, but also because the result is driven to some extent by a small number of outliers in the original sample, in particular with respect to the impact of gas prices. For that reason, the results for natural gas presented so far are purged of those outliers. We excluded 14 observations from 7 countries.¹⁹ The outliers were identified by iteratively deleting the most influential observation until the parameter changes remained sufficiently small.²⁰ The single qualitative difference between the specifications including and excluding outliers is that the gas price parameter is significant if outliers are excluded and insignificant if they are included for all specifications.

¹⁹ This includes four observations from Chile, three from Romania, two from Bolivia and Finland as well as one from Colombia, Czech Republic and Ireland.

²⁰ The most influential observation was identified by calculating the changes in the parameter of the most sensitive variable (in this case gas price) if each observation was included or excluded using Stata's -dfbeta- post-estimation routine.

5.3.6 HDM and CDM threshold values

The choice of heating and cooling degree months comes with the necessity to define heating and cooling thresholds. In line with the existing literature (cf. Footnote 5), we use 18.3 degrees centigrade for both thresholds. The use of the same threshold both for heating and for cooling is, however, prone to provoke criticism. To demonstrate the sensitivity of our results towards the choice of the heating or cooling thresholds, we conduct our analysis again with different threshold temperatures. As an alternative heating threshold we use 15.5 degrees centigrade and as an alternative cooling threshold we use 24.0 degrees centigrade.²¹ Neither specification choice nor the qualitative results of the resulting (quadratic) specification are affected by changing the threshold temperature. We report the results of all specifications in the Appendix in Table A 4. The parameters of heating and cooling degree months mostly increase, as could be expected, because the warmer (with cooling degree months: colder) and less energy intensive temperatures drop out. Neither the signs of the linear or quadratic terms nor their general significance at conventional significance levels change. The single exception is oil use, where the quadratic term is rendered insignificant, without changing in size. Gas is another notable case, because apart from the HDM parameter also the price parameter is affected and increases by 2 percentage points. Gas is also the only fuel where the HDM parameter decreases. The CDM parameter remains insignificant irrespective of the cooling threshold.

5.3.7 Population weighted temperature variables

So far, we did not account for the fact that population density differs across countries. Not considering population density in the characterization of

²¹ We also conducted the analysis using 21.1 degrees centigrade as the cooling threshold without reporting the results here. They do not qualitatively differ from the results using the 24.0 degrees threshold.

“average” climate conditions driving residential energy use may be an issue for countries which population is spread out unevenly over areas with different temperatures, as may be suspected especially for large countries such as China, Russia, or the United States. The same is true if there are significant population movements within countries and between areas with different average temperature over time during our sample period. Because we use unweighted country averages for the temperature variables in our reference specifications, specification choice and parameters may suffer of such errors. To check whether population weighting changes our results, we conduct our analysis again using population weighted HDM and CDM. The weighting is introduced when aggregating grid-cell values to country values. Population data was retrieved from the HYDE database (before 1990, Klein Goldewijk 1995) and the GPWv3 database (from 1990 onwards, CIESIN and CIAT 2005). The population weights used are available only on a 10 year (until 1990) and 5 year (from 1990 onwards) frequency; the remaining years are linearly interpolated for each 0.5° grid cell. In general, correlation between weighted and unweighted HDM or CDM is high, 0.89 for HDM and 0.82 for CDM. The results are summarized in Table A 5 in the appendix.

Model choice is hardly affected by introducing population weighted temperature variables, although in general the statistical significance of the temperature variables is reduced. Still, electricity, the fuel with the smallest temperature elasticity of fuel use, is the only fuel for which the impact of HDM for fuel use becomes insignificant after including population weights. In line with the finding of lower significance, the temperature elasticities decrease for all fuels except natural gas (Figure 3). Since the parameter of the autoregressive term remains virtually unchanged, the ratio between long-run and short-run elasticities stays the same. As before, electricity demand is not affected by cooling degree months.

- *Figure 3 about here* ~

5.3.8 Estimator

Some authors have advocated the use of either fixed effects or lagged dependent variables in applied econometrics (cf. Angrist and Pischke 2009), since the price of including both (having to cope with the Nickell bias, cf. Section 3) is too high compared to the gains (being able to correctly map our theoretical model onto an estimation equation). We feel that by choosing the LSDVC estimator we made a viable compromise between estimation effort and validity. Still, as a sensitivity check, we estimate each of our specifications with only fixed effects as well as with only a lagged dependent variable, excluding the respective other. We used standard OLS procedures for the estimation. We found that, apart from electricity, exclusion of either fixed effects or lagged dependent variables leads to a significant, even qualitative, alteration of the results. Especially the omission of time-invariant heterogeneity, i.e. the fixed effects, renders the impact of temperature, income and fuel prices insignificant for all fuels except electricity and for most specifications. The exclusion of lagged dependent variables has a large impact as well, even though it is less consistent throughout all specifications compared to the exclusion of fixed effects. Again, electricity remains comparably stable. Temperature impact remained significant and non-linear for oil but not for coal and gas. We could not confirm a significant effect of income on oil use, while income remained significant for coal and gas. We conclude from our comparison of estimations using either fixed effects or lagged dependent variables or both that it is important to account for both time-variant as well as time-invariant heterogeneity across countries and include both lagged dependent variables as well as fixed effects.

Referring to the debate about what is the most appropriate dynamic panel estimator for small N, moderate T panels, we further compare our results with Arellano and Bond's (1991) GMM estimator (AB estimator from now on).²² Since the LSDVC estimator has been argued to be favourable based on an RMSE criterion, we expect to find larger standard errors when using the AB estimator. Since the bias will be smaller or about equal for the AB estimator compared to the LSDVC estimator, the difference between the parameter values will give some indication about the unbiasedness of our estimates. We find the differences between the two estimation procedures to be generally small for our specifications of choice, in any case qualitatively. As expected, standard errors estimated using the AB estimator are generally higher. In some cases, this affects the significance of the results. Fuel prices are generally insignificant in the AB model, as are the temperature effects for electricity and oil. The parameter values are remarkably stable. One exception is the parameters of the lagged dependent variables. The AB models estimate a considerably smaller persistence parameter, which at the same time is less significantly different from one. In general, the parameters of the two estimators differ most for the coal model. Since the sample size for coal is considerably smaller than for the other fuels, this is not surprising. Most important, the size of the HDM coefficients is generally unaffected by changing the estimator.

²² For this sensitivity analysis, we use the two-step GMM estimation procedure of Arellano and Bond's (1991) estimator with Windmeijer's (2005) robust standard errors and forward orthogonal deviations instead of first differences (Arellano and Bover 1995) to avoid loss of observations. As recent debates indicate, a large instrument collection, which easily evolves with panels with sufficiently large time dimension, overfits the model and leads to invalid estimates for the standard errors (cf. e.g. Roodman 2009 on this issue). To confine this problem, we limited the number of instruments used in our estimations by "collapsing" the instrument matrix. "Collapsing" instruments means that one instrument for each variable and lag distance is used, rather than one for each time period, variable and lag distance. See Roodman (2009) and the references given there for details. Arellano and Bond's (1991) estimator was implemented using Stata 10.1 and Roodman's (2006) -xtabond2- procedure.

6 Discussion and conclusion

In this paper, we examine the impact of temperature changes on residential energy consumption and calculate temperature elasticities of energy use. We use heating degree months as a temperature measure. The responsiveness of energy use to temperature changes depends on the temperature level itself, even beyond the threshold effect included in the heating degree months. Energy use is non-linear in temperature, but the curvature differs between fuels. Energy use decreases with rising temperatures (because of a decreased demand for heating), but above the heating threshold the marginal decrease declines with rising temperature levels.

The geographical scope of our paper is considerably larger than in most previous studies, and covers both developed and developing countries. This allows us to form conclusions of general validity. However, this generality necessarily involves a loss of provision for specific circumstances: For example, we are not able to identify a cooling demand of worldwide impact, a result that is due to the fact that cooling is not a global issue, yet – however it certainly is a regional.

What are the implications of our findings for economic impacts of climate change? Private households would benefit from the reduced spending on heating energy. Energy suppliers would be hit as their markets shrink. This effect is largest in the cold and rich North. According to our elasticity ranking, gas suppliers will suffer most from climate change, since the temperature elasticity of natural gas is highest. Gas is followed by oil and electricity. However, gas is at the same time also most responsive to income changes. Thus the contractive effect of climate change on gas consumption would be offset by economic growth. The same is true to a lesser extent for oil and electricity. Coal use will decrease due to warming, but also if incomes rise or coal prices fall, due to it being an inferior Giffen good.

The reduction in heating energy demand could be partly or even completely offset by two developments: Firstly, an increased use of cooling devices, though not important in our observation period, could in the future increase energy use. Secondly, economic growth in warm developing countries will increase energy use.

Adding energy demand in industry and services would be a natural extension of this study. Even if the residential sector is the one with the highest sensitivity towards temperature changes with respect to energy demand, other sectors may feature similar effects as well. Furthermore, broadening the analysis to include other fuel types could be a sensible extension. Especially the consideration of (traditional) biomass would lead to a more complete picture of the interrelations in developing countries, since a considerable fraction of residential energy consumption falls upon fire wood and other biomass-based fuels. Availability of data prevents progress in that respect at the moment. An empirical study of the impact of weather and climate on energy supply would be another valuable extension. All this is deferred to future research.

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Tables and Figures

Table 1: Descriptive Statistics.

Variable	Mean	Std. Dev.	Min	Max	Included Observations		
					N	n	T
Fuel use (tonnes of oil equivalent (toe) per person per year)							
Solid fuels (coal)	44.25	87.33	0.00	632.49	1 346	69	20
Electricity	56.93	98.02	0.15	692.71	4 290	176	24
Gas	90.29	140.66	0.00	806.86	1 580	72	22
Light fuel oil	65.88	127.73	0.03	1 170.27	4 351	174	25
Fuel price (PPP(95USD) per toe)							
Coal	163.53	65.03	13.38	305.23	308	22	14
Electricity	1 329.18	1 014.09	40.45	8 835.40	1 029	63	16
Gas	429.12	233.04	5.10	1 300.17	614	38	16
Light fuel oil	412.79	189.57	112.36	1 352.68	662	33	20
GDP (1000 PPP(95USD) per person per year)	6.68	6.82	0.42	43.94	4 265	162	26
Average temperature (°C, country-year-median) ^a	19.74	8.35	-9.00	31.75	6 768	183	37
Regionalized Heating Degree Months (HDM) ^b	44.26	63.84	0.00	331.11	6771	183	37
Regionalized Cooling Degree Months (CDM) ^b	55.29	39.67	0.00	132.57	6771	183	37

Note: N: Total number of observations; n: Number of countries with at least one observation; T: Average number of periods per country. ^a: Median average temperature is not used in regressions and displayed solely for the information of the reader. ^b: For the definition of Regionalized Heating and Cooling Degree Months (HDM and CDM), cf. Section 2.

Table 2: LSDVC estimation of coal, electricity, gas and oil use for heating purposes.

Dependent variable: log(fuel use per capita)	Coal	Electricity	Gas	Oil
log(fuel use per capita) _(t-1)	0.83*** (0.04)	0.94*** (0.01)	0.92*** (0.02)	0.95*** (0.01)
log(GDP per capita in PPP)	-0.82*** (0.16)	0.07*** (0.01)	0.2*** (0.06)	0.1** (0.04)
log(fuel price in PPP) _(t-1)	0.26** (0.11)	-0.01*** (0.003)	-0.08** (0.04)	0.03 (0.02)
log(HDM)	0.21 (0.21)	0.02** (0.01)	0.31*** (0.07)	0.12* (0.06)
(log(HDM)) ²	0.05** (0.02)	0.002* (0.001)	0.02*** (0.01)	0.01** (0.005)
Observations	270	884	527	597
No. of countries	20	56	36	32
AIC	727.25	518.15	1216.4	1540.8
p((b_log(fuel use per capita) _(t-1))=1)	0.00	0.00	0.00	0.00

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. p((b_log(fuel use per capita)_(t-1))=1) is the p-value for a test that the coefficient on the lagged dependent variable is equal to one. Gas: Excluding outliers. 14 observations from Bolivia (2), Chile (4), Colombia (1), Czech Republic (1), Finland (2), Ireland (1) and Romania (3) were determined using DFBETA influence statistics. HDM: Regionalized Heating Degree Months. For an overview of the panel structure, see Table A 1.

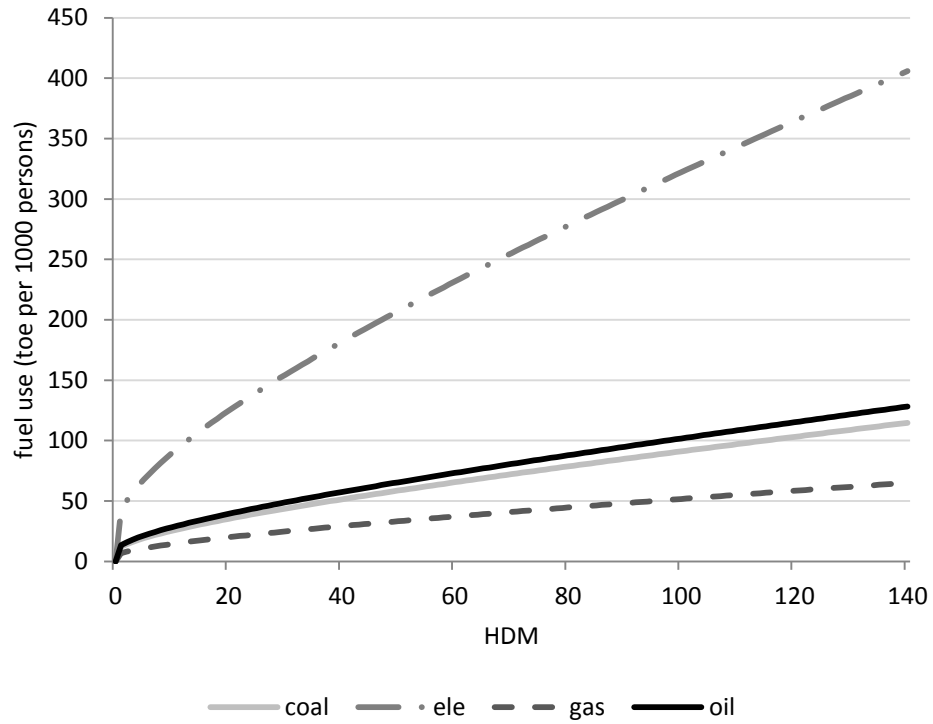
Table 3: Unit root tests.

Variable	Sample	Test	t*, Z	p-value	Obs.	No. of countries
log(coal use per capita)	1976-2002	LLC t*	-0.83	0.20	850	34
		Fisher Z	-7.90	0.00	918	34
	1992-2002	LLC t*	-12.65	0.00	441	49
		Fisher Z	-9.81	0.00	539	49
log(electricity use per capita)	1976-2002	LLC t*	-6.31	0.00	3 575	143
		Fisher Z	-16.67	0.00	3 861	143
	1992-2002	LLC t*	-11.39	0.00	1 557	173
		Fisher Z	-14.84	0.00	1 903	173
log(gas use per capita)	1976-2002	LLC t*	-4.02	0.00	1 150	46
		Fisher Z	-8.59	0.00	1 242	46
	1992-2002	LLC t*	-10.09	0.00	558	62
		Fisher Z	-11.16	0.00	682	62

log(oil use per capita)	1976-2002	LLC t*	-5.10	0.00	3 600	144
		Fisher Z	-18.23	0.00	3 888	144
	1992-2002	LLC t*	-18.54	0.00	1 512	168
		Fisher Z	-17.66	0.00	1 848	168
log(GDP per capita in PPP)	1976-2002	LLC t*	-6.69	0.00	3 375	135
		Fisher Z	-16.69	0.00	3 645	135
	1992-2002	LLC t*	-10.81	0.00	1 458	162
		Fisher Z	-15.61	0.00	1 782	162
log(coal price in PPP)	1978-2002	LLC t*	-1.17	0.12	115	5
		Fisher Z	-3.04	0.00	125	5
	1992-2002	LLC t*	-2.67	0.00	72	8
		Fisher Z	-3.90	0.00	88	8
log(electricity price in PPP)	1978-2002	LLC t*	-6.10	0.00	575	25
		Fisher Z	-11.13	0.00	625	25
	1992-2002	LLC t*	-5.47	0.00	333	37
		Fisher Z	-8.07	0.00	407	37
log(gas price in PPP)	1978-2002	LLC t*	-2.73	0.00	345	15
		Fisher Z	-7.13	0.00	375	15
	1992-2002	LLC t*	-0.98	0.16	189	21
		Fisher Z	-4.50	0.00	231	21
log(oil price in PPP)	1978-2002	LLC t*	-3.59	0.00	414	18
		Fisher Z	-7.00	0.00	450	18
	1992-2002	LLC t*	-4.53	0.00	216	24
		Fisher Z	-6.52	0.00	264	24
log(HDM)	1976-2002	LLC t*	-17.54	0.00	3 100	124
		Fisher Z	-30.83	0.00	3 348	124
	1992-2002	LLC t*	-20.40	0.00	1 134	126
		Fisher Z	-22.24	0.00	1 386	126
log(CDM)	1976-2002	LLC t*	-14.76	0.00	4 025	161
		Fisher Z	-29.37	0.00	4 347	161
	1992-2002	LLC t*	-28.83	0.00	1 503	167
		Fisher Z	-27.44	0.00	1 837	167

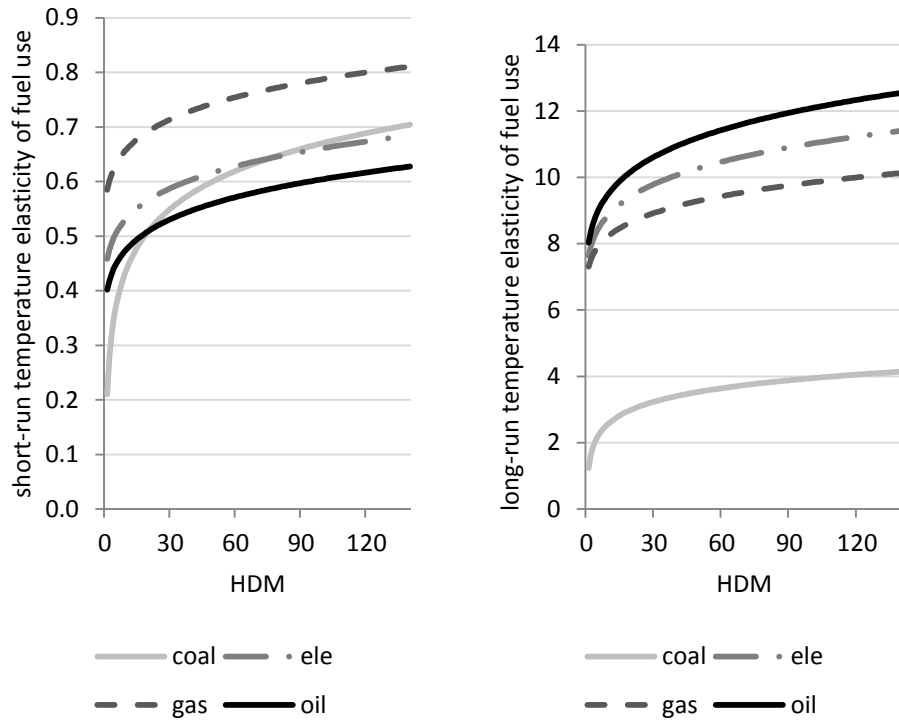
Note: Test statistics with p-values larger 0.01 are in **bold**. LLC test statistics use LLC's bias-adjusted t* statistics. Fisher-type tests use Choi's (2001) Z statistics and augmented Dickey-Fuller tests with drift. Number of observations for the Fisher-type tests are for Choi's (2001) aggregation, the underlying ADF tests lose 2 periods of each cross section by using lagged differences. All tests are robust to autocorrelation of order 1 and demeaned in order to mitigate the impact of cross-sectional dependence (Levin et al. 2002).

Figure 1: Non-linear response in energy use to temperature changes (quadratic specifications).



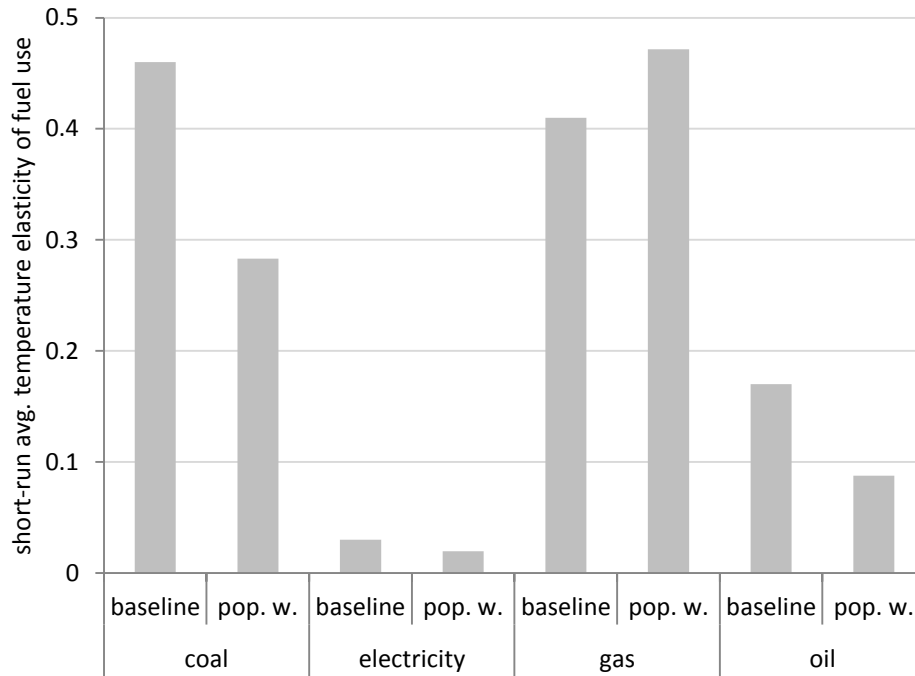
Note: Own presentation. Predicted values using average explanatory variables.

Figure 2: Short-run and long run temperature elasticity of fuel use (quadratic specifications).



Note: Own presentation. Predicted values using average explanatory variables. Note the different scales of the vertical axes.

Figure 3: Average temperature elasticities without and with population weighting.



Note: Own presentation. Predicted values using average explanatory variables. Note that the parameter of the lagged dependent variable stays virtually the same, so long-run elasticities change relatively in the same way as short-run elasticities.

Appendix

Table A 1: Structure of unbalanced panel.

No. of countries with the following pattern:		1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Coal																									
5	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
2	X	X	X	X	X	X	X	X	X
2	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
1	X	X
1	X	X	X	X	X	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X	X	.	.	.
1	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
1	.	.	.	X	X	X	X	X	X
1	.	X	X	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X

Electricity:

2																							
4	X	.	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
4	X	X	X	X	X	X	X	X
4	X	X	X	X	X	X	X	X	X	X	X
3	X	X	X	X	X	X	X	X	X
3	X	X	X	X	X	X	X	X	X	X
2	X	.	.	.	X	X	X
1	X
1	X	X	X
1	X	.	.	X	X	.	.
1	X	X	.	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	

Oil																							
1	X	.	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
7
2	X	X	X	X	X	X	X	X
1	X
1	X	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X	X
1	X	X	X	X	X	X	X	X
1	.	.	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	
1	.	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	
1	X	X	X	X	X	X	X	
1	X	X	X	X	X	X	X	X	X	X	X	
1	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	

Note: Structure of panel for the quadratic estimation including fuel prices (baseline specification). Note that the first observation of each series is used to construct the lagged dependent variable.

Table A 2: Selected results on the impact of temperature changes on residential energy demand.

Source	Regional Sample	Timespan	Temperature variable	Sector	Measure ^a	Results
Al-Zayer and Al-Ibrahim (1996)	Eastern Province, Saudi Arabia	1986-1990	monthly CDD	all sectors pooled	ME	Electricity: 1759.28 MWh/Degree Day
Amato et al. (2005)	Massachusetts, USA	1977-2001	monthly HDD and CDD	residential and commercial	SE	Electricity: 0.00047% per person and month/HDD, Electricity: 0.00038% per person and month/CDD Gas: 0.0017% per person and month/HDD Oil: 0.0013% per person and month/HDD(60°F) (all after controlling for annual HDD and CDD trends)
Asadoorian et al. (2008)	China	1995-2000	monthly, seasonal, and annual mean temperature	residential and non-residential	E	Electricity: 0.58 to 0.76
Bigano et al. (2006)	up to 29 countries	1978-2000	annual average temperature	residential, commercial, and industrial	E	Electricity: -0.57 Gas: -1.82 Oil: -3.05 Coal: 2.85
De Cian et al. (2013)	31 countries	1978-2000	seasonal average temperature	residential	E	Electricity: -3.33 to 5.42 Gas: -2.6 Oil: -3.45 to 3.36 (all are long run elasticities)
Hunt et al. (2003)	UK	1971-1997	quarterly average temperature	all sectors pooled	ME	Total final energy demand: -0.02 mtoe/°C
Lescaroux (2011)	101 countries	1960-2006	annual average temperature	residential	SE	Final energy demand: -0.03%/°C (short run) to -0.08%/°C (long run)
Mirasgedis et al. (2004)	Greece	1993-2002	monthly HDD and CDD	all sectors pooled	ME	Electricity: 1.96×10^{-4} Mwh/HDD Electricity: 3.38×10^{-4} Mwh/CDD

Note: ^a ME: marginal effect, E: elasticity, SE: semi-elasticity. Where applicable, only elasticities for residential energy use are presented.

Table A 3: LSDVC Estimation results for various functional forms.

	coal			electricity			gas			oil		
	no temp.	linear	quadr.	no temp.	linear	quadr.	no temp.	linear	quadr.	no temp.	linear	quadr.
log(fuel use per capita) _(t-1)	0.93*** (0.03)	0.83*** (0.04)	0.83*** (0.04)	0.93*** (0.01)	0.94*** (0.01)	0.94*** (0.01)	0.91*** (0.02)	0.91*** (0.02)	0.92*** (0.02)	0.95*** (0.01)	0.95*** (0.01)	0.95** (0.01) *
log(GDP per capita in PPP)	- 0.64*** (0.17)	- 0.86*** (0.17)	- 0.82*** (0.16)	0.07*** (0.02)	0.07*** (0.02)	0.07*** (0.02)	0.11* (0.06)	0.13** (0.06)	0.2*** (0.06)	0.06 (0.04)	0.07 (0.04)	0.1** (0.04)
log(fuel price in PPP) _(t-1)	0.20** (0.1)	0.25** (0.11)	0.26** (0.11)	- 0.01*** (0.004)	- 0.01*** (0.004)	- 0.01*** (0.004)	-0.07** (0.03)	-0.07* (0.04)	-0.08** (0.04)	0.02 (0.03)	0.03 (0.02)	0.03 (0.02)
log(HDM)		0.35* (0.19)	0.22 (0.21)		0.01 (0.01)	0.02** (0.01)		0.12*** (0.05)	0.31*** (0.07)		0.02 (0.05)	0.12* (0.06)
(log(HDM)) ²			0.05** (0.02)			0.002* (0.001)			0.02*** (0.01)			0.01** (0.005)
Observations	293	270	270	971	884	884	547	527	527	633	597	597
No. of countries	21	20	20	62	56	56	37	36	36	33	32	32
AIC (smaller is better)	882.2	729.7	727.3	963.5	521.6	518.2	1 304.1	1 233.6	1 216.4	1 663.2	1 547.3	1 540.8
p((b_log(fuel use) _(t-1))=1)	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Gas: Excluding outliers. HDM: Regionalized Heating Degree Months. The logarithmic model does usually not yield significant temperature impact or copies the quadratic specification closely. We therefore do not present the logarithmic model here.

Table A 4: LSDVC Estimation results using the 15.5 degrees heating threshold.

	coal			electricity			gas			oil		
	no temp.	linear	quadr.	no temp.	linear	quadr.	no temp.	linear	quadr.	no temp.	linear	quadr.
log(fuel use per capita) _(t-1)	0.93***	0.84***	0.82***	0.93***	0.94***	0.94***	0.91***	0.92***	0.92***	0.95***	0.95***	0.95***
	-0.03	(0.05)	(0.05)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
log(GDP per capita in PPP)	-	-	-	0.07***	0.06***	0.07***	0.11*	0.16***	0.21***	0.06	0.09*	0.11**
	0.64***	0.88***	0.81***	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.06)	(0.04)	(0.05)	(0.05)
	(0.17)	(0.20)	(0.21)	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.06)	(0.04)	(0.05)	(0.05)
log(fuel price in PPP) _(t-1)	0.20**	0.27**	0.26**	-	-	-0.01**	-0.08**	-	-	0.02	0.03	0.03
	(0.10)	(0.10)	(0.11)	0.01***	0.01***	(0.004)	(0.03)	0.11***	0.11***	(0.03)	(0.02)	(0.02)
log(HDM)		0.10	0.32**		0.02*	0.03***		0.17**	0.29***		0.09	0.13*
		(0.14)	(0.14)		(0.01)	(0.01)		(0.07)	(0.05)		(0.07)	(0.07)
(log(HDM)) ²			0.03*			0.003**			0.02***			0.01
			(0.01)			(0.002)			(0.01)			(0.01)
Observations	293	254	254	971	832	832	544	499	499	633	561	561
No. of countries	21	20	20	62	52	52	37	35	35	33	30	30
AIC (smaller is better)	882.2	691.9	683.4	963.5	442.3	437.4	1 297.3	1 034.9	1 025.0	1 663.2	1 443.8	1 439.5
p((b_log(fuel use) _(t-1))=1)	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

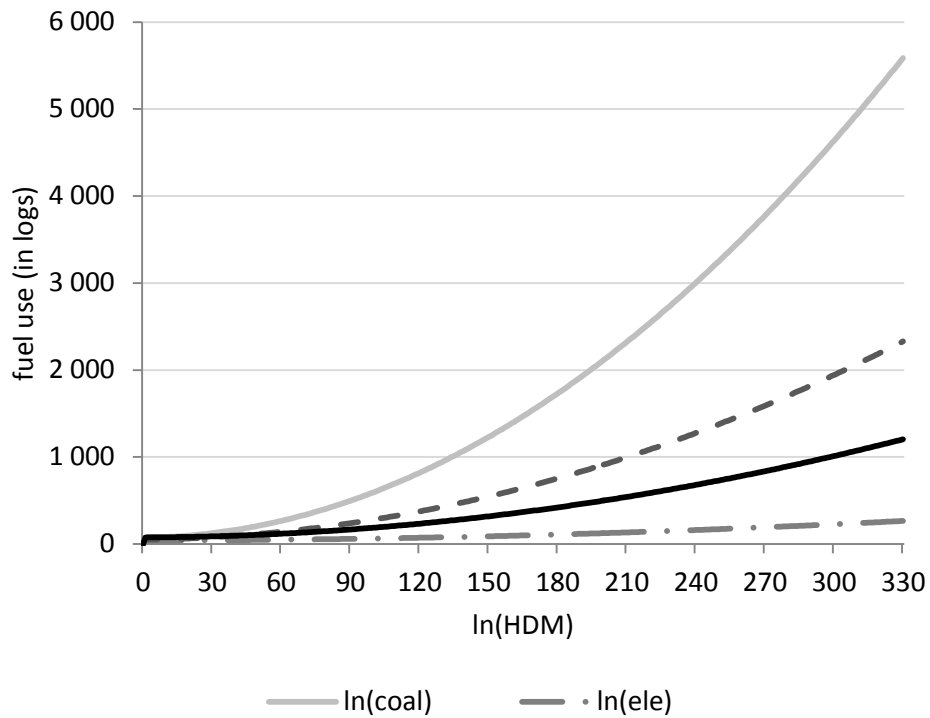
Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Gas: Excluding outliers. HDM: Regionalized Heating Degree Months. The logarithmic model does usually not yield significant temperature impact or copies the quadratic specification closely. We therefore do not present the logarithmic model here.

Table A 5: LSDVC estimation results using population weighted HDM.

	coal			electricity			gas			oil		
	no temp.	linear	quadr.	no temp.	linear	quadr.	no temp.	linear	quadr.	no temp.	linear	quadr.
log(fuel use per capita) _(t-1)	0.93*** (0.03)	0.83*** (0.04)	0.83*** (0.04)	0.93*** (0.01)	0.94*** (0.01)	0.94*** (0.01)	0.91*** (0.02)	0.93*** (0.02)	0.93*** (0.02)	0.95*** (0.01)	0.95*** (0.02)	0.95*** (0.02)
log(GDP per capita in PPP)	- 0.64*** (0.17)	- 0.89*** (0.17)	- 0.82*** (0.16)	0.07*** (0.02)	0.06*** (0.02)	0.07*** (0.02)	0.1* (0.06)	0.08 (0.06)	0.11* (0.06)	0.06 (0.04)	0.07* (0.04)	0.1** (0.04)
log(fuel price in PPP) _(t-1)	0.2** (0.1)	0.25** (0.11)	0.26** (0.11)	- 0.01*** (0.004)	- 0.01*** (0.004)	- 0.01*** (0.004)	-0.06* (0.03)	-0.07** (0.03)	- 0.08*** (0.03)	0.02 (0.03)	0.03 (0.02)	0.03 (0.02)
log(HDM)		0.12 (0.1)	-0.48* (0.25)		0.01 (0.01)	0.01 (0.01)		0.06* (0.03)	0.09** (0.04)		0.01 (0.03)	0.04 (0.04)
(log(HDM)) ²			0.08*** (0.03)			0.001 (0.0009)			0.01*** (0.003)			0.01* (0.003)
Observations	293	270	270	971	852	852	550	506	506	633	573	573
No. of countries	21	20	20	62	54	54	37	35	35	33	31	31
AIC (smaller is better)	882.2	733.8	726.7	963.5	459.7	459.6	1 366.7	1 121.3	1 116.2	1 663.2	1 475.6	1 472.5
p((b_log(fuel use per capita) _(t-1))=1)	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

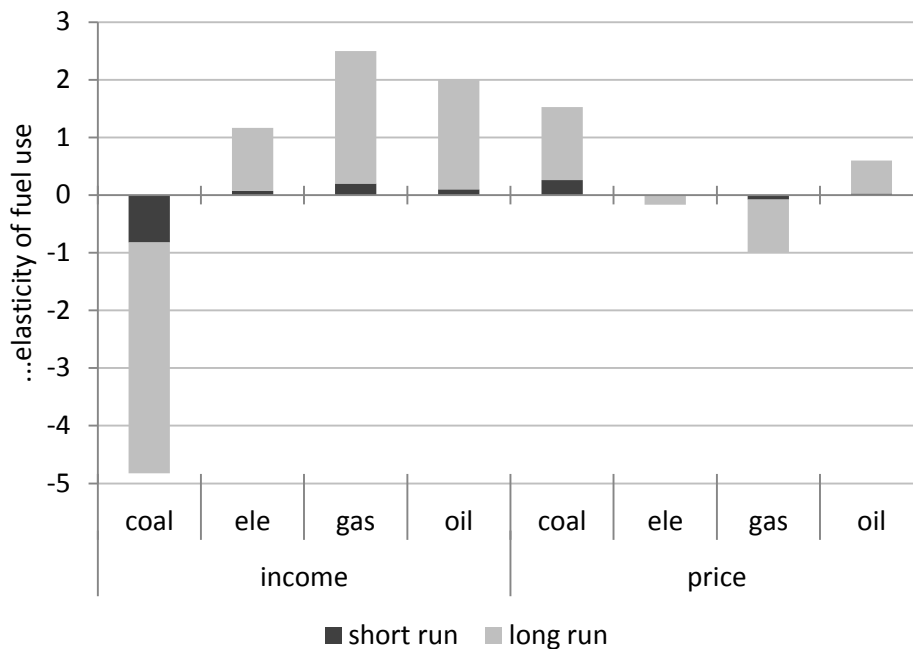
Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Gas: Excluding outliers. HDM: Regionalized Heating Degree Months. The logarithmic model does usually not yield significant temperature impact or copies the quadratic specification closely. We therefore do not present the logarithmic model here.

Figure A 1: Non-linear response in energy use to temperature changes (quadratic specification, presentation in logs).



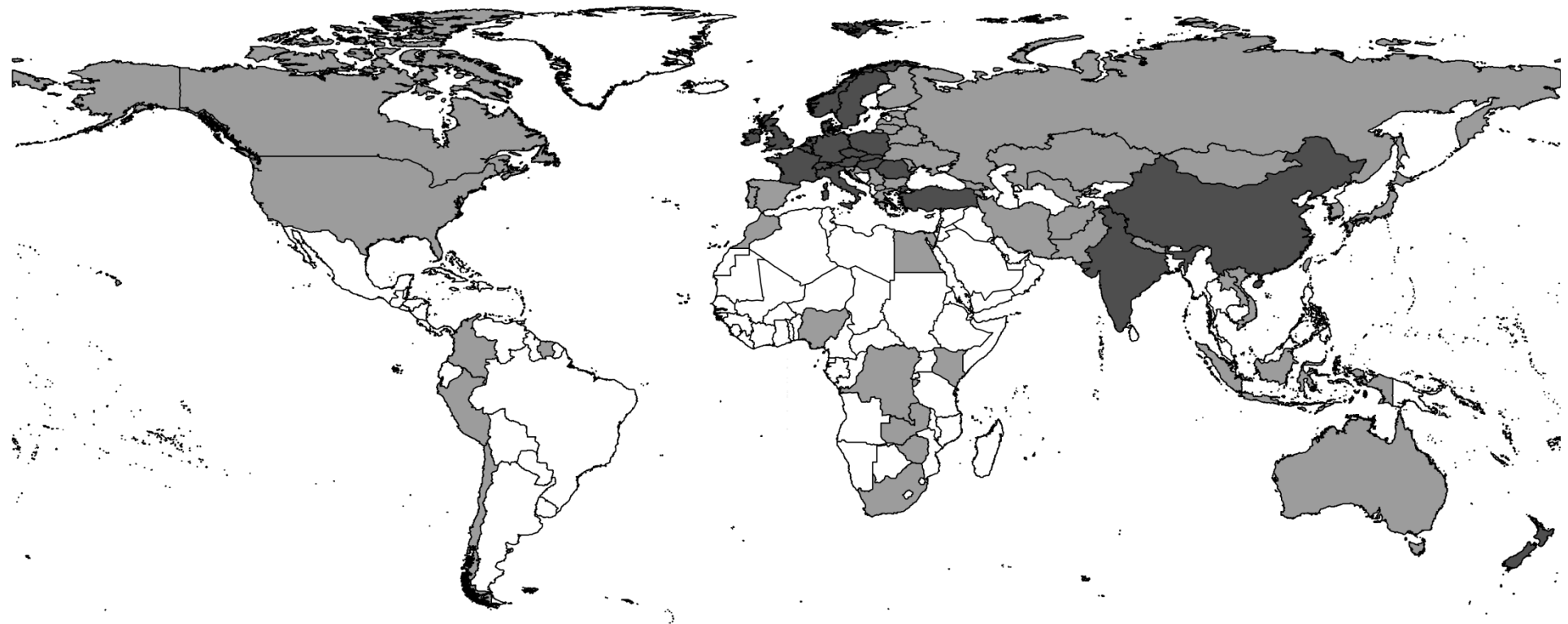
Note: Own presentation. Predicted values using average explanatory variables.

Figure A 2: Income and price elasticities of fuel use. (quadratic specification)



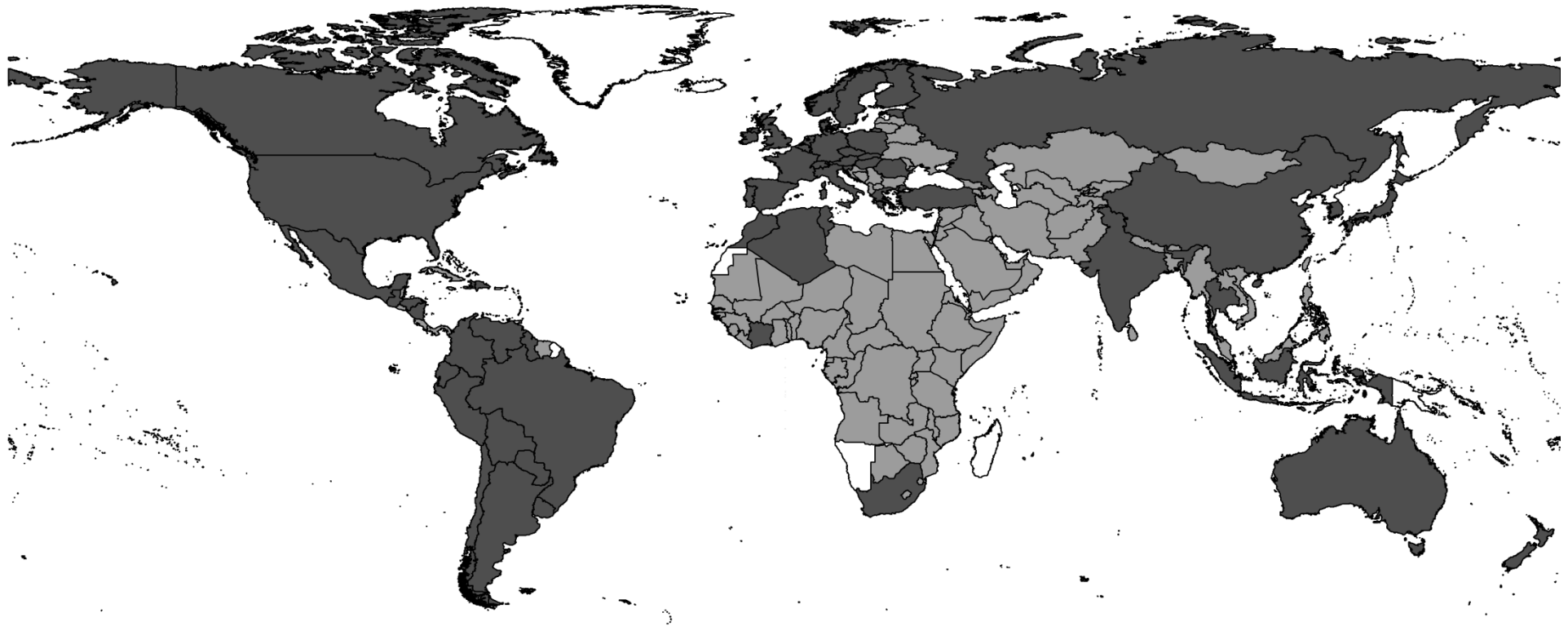
Note: Own presentation. Predicted values using average explanatory variables.

Figure A 3: Geographical coverage of coal data



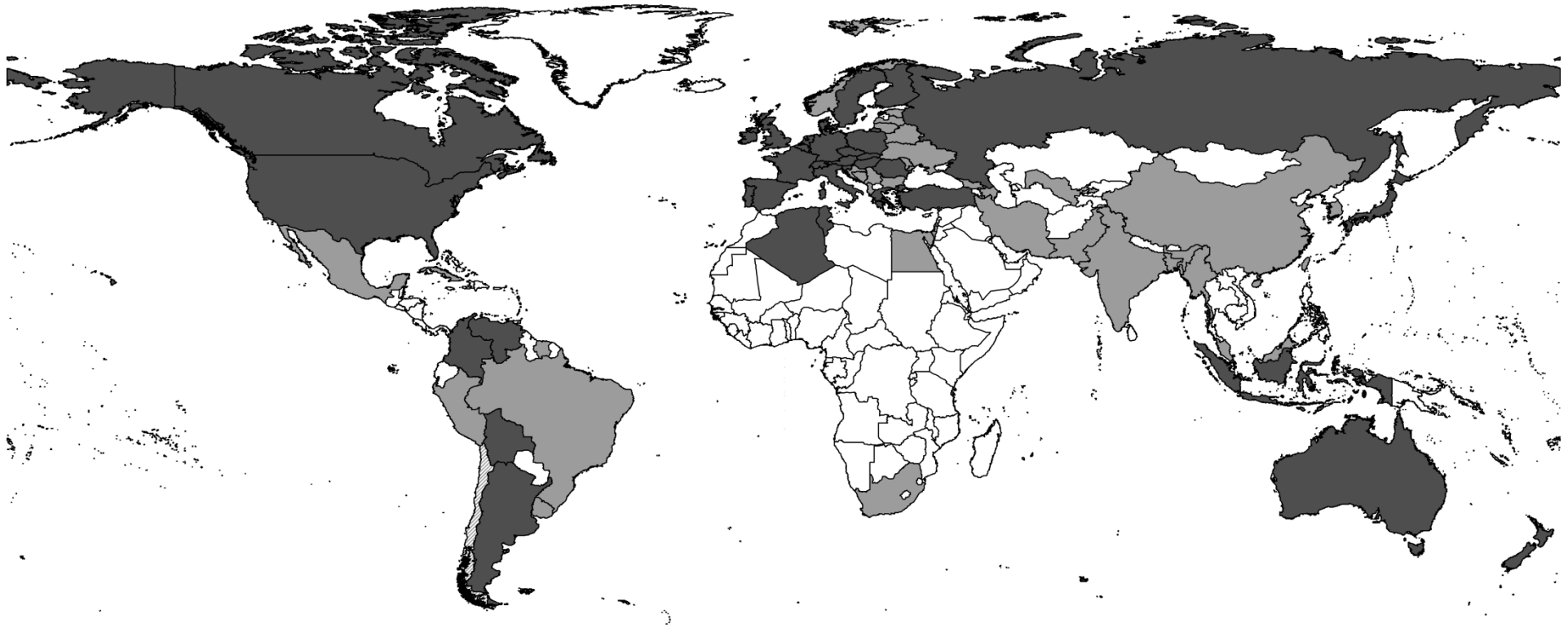
Note: Own presentation. ◆: Consumption data available; ◆: Consumption and price data available; blank: no data.

Figure A 4: Geographical coverage of electricity data



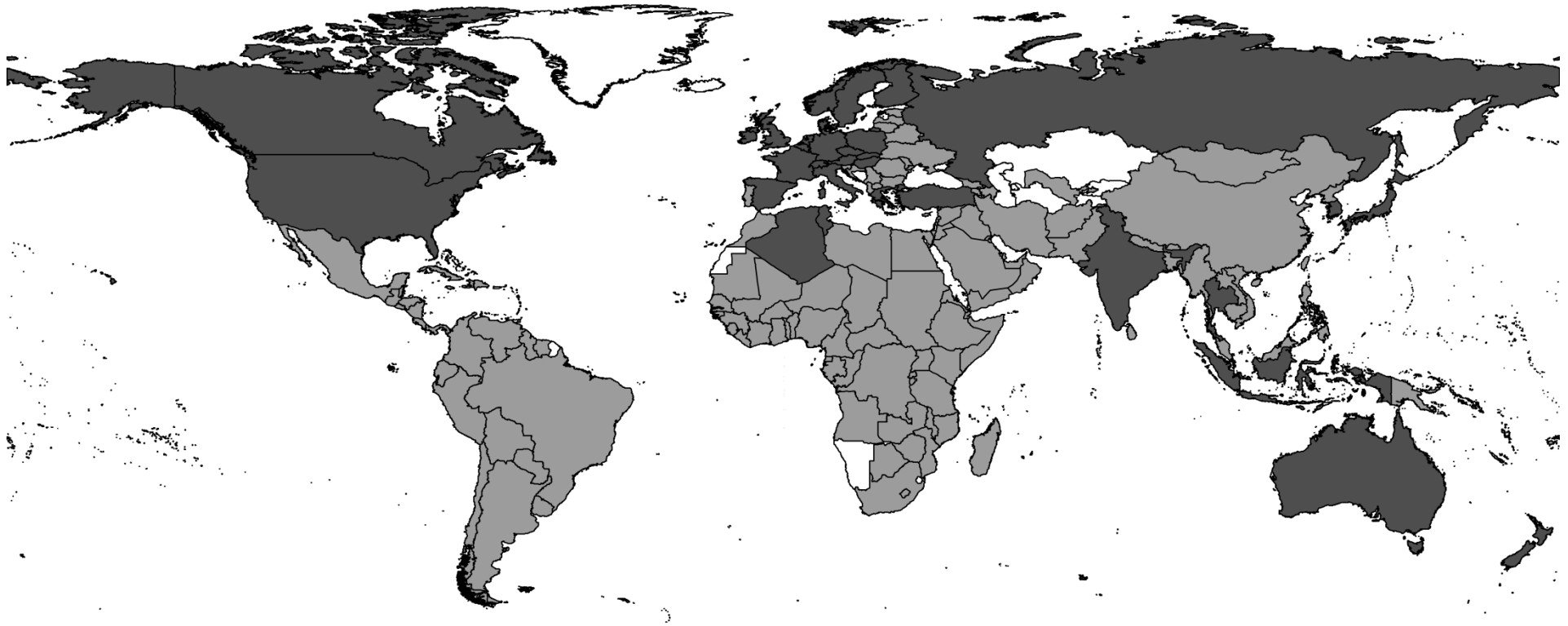
Note: Own presentation. ◊: Consumption data available; ◊: Consumption and price data available; blank: no data.

Figure A 5: Geographical coverage of natural gas data



Note: Own presentation. ◆: Consumption data available; ◆: Consumption and price data available; blank: no data.

Figure A 6: Geographical coverage of oil data



Note: Own presentation. ◊: Consumption data available; ◊: Consumption and price data available; blank: no data.

Curriculum Vitae – Sebastian Petrick

Professional and Research Experience

- since 2015 Researcher at the German Institute for Economic Research (DIW Berlin), Climate Policy Department
- 2008-2015 Researcher at the Kiel Institute for the World Economy, i.a. within the Cluster of Excellence “The Future Ocean” and under the EU-FP7 Project „Arctic Climate Change, Economy and Society (ACCESS)“
- 2011-2012 Visiting Scholar at the Department for Agricultural and Resource Economics, University of California, Berkeley (CA), USA
- 2010-2011 Assistant to the Head of the Research Area “Environment and Natural Resources” at Kiel Institute for the World Economy
- 2007-2008 Research Assistant, Institute for Empirical Economic Research, Leipzig University
- 2004-2006 Intern at German Federal Ministry of Economics and Technology, intern at Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI), intern at Leibnitz Institute of Agricultural Development in Central and Eastern Europe (IAMO)
-

Education

- 2008-2015 PhD Candidate in the International Doctoral Program “Quantitative Economics” at Kiel University
- 2007 Diplom, Volkswirtschaftslehre (Economics) at Leipzig University. Thesis: “Adjusting for Structural Factors of Energy Intensity and Determination of its Determinants”
- 2001 Abitur, Bergstadt-Gymnasium Lüdenscheid
-