D3.6 | Report on economic factors impacting collective/company energy choices

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The project in brief

The Energy Union strategy builds further on the 2030 Framework for Climate and Energy and the European Energy Security Strategy. In October 2014, the European Council agreed on a new 2030 Framework for climate and energy, including EU-wide targets and policy objectives for the period between 2020 and 2030. These targets aim to help the EU achieve a more competitive, secure and sustainable energy system and to meet its long-term 2050 greenhouse gas reductions target. In May of the same year, the European Commission released its Energy Security Strategy, which proposes to increasing energy efficiency and reaching the proposed 2030 energy and climate goals. Priorities in this area focus on buildings and industry, which use 40% and 25% of total energy respectively in the EU.

The ENABLE.EU project attempts to technological and economic factors influencing individual and collective energy choices regarding heating & cooling, energy-efficiency investments, transport and electricity. Under this broader goal is an objective to determine how energy costs and prices affect energy choices and energy-efficiency investments of companies in the region. For this purpose, ENABLE.EU employed cutting-edge micro econometric evidence on the drivers of firm-level and industry-wide innovation and technology adoption on the manufacturing sector. Using high-quality firm-level data from statistical agencies in France and Germany, the project assessed the impact of energy prices and structural changes on energy use, emission and on investments in energy efficiency technologies made to reduce them.

The final aim of this project is to contribute to more enlightened, evidence-based policy decisions, to make it easier to find the right incentives to reach the twin goals of successful implementation of the Energy Union and Europe's transition towards a decarbonised energy system. To reach this final aim, ENABLE.EU will seek to provide an excellent understanding of the social and economic drivers of individual and collective energy choices with a focus on understanding changes in energy choice patterns. Results will be disseminated to relevant national and EU-level actors as well as to the research community and a wider public.

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1. Executive Summary

The European Union's 2020 strategy, which constitutes a set of binding legislation, aims to cut greenhouse gas (GHG) emissions by 20% by 2020 compared to 1990 levels. Many governments have also adopted some energy and environmental policies to reduce energy consumption. In France, for example, "an ambitious and integrated energy and climate policy framework for the energy transition towards 2030" has been developed and adopted, including carbon budget/pricing instruments, tax incentives and considerable public funding towards implementing it (International Energy Agency, 2017). In Germany, firms are encouraged to optimize their energy behavior, adopt new technology or utilize fuel-switching possibilities through the German national action plan for energy efficiency under the slogan "Efficiency first" (Federal Ministry for Economic Affairs and Energy, 2014). Despite their immense policy implications, it is quite surprising that very few studies have been done to look at how firms behave in the event of an energy-related shock, such as an energy price change or an environmental policy that affects energy use, or structural change in the sector that may alter firm-level energy choice (e.g., firm entry and exit).

The project ENABLE.EU aims to address the above gap by providing empirical evidence on the drivers of firm-level and industry-wide energy use, emission and investment to reduce them. It uses findings from two independent but highly related studies that utilize firm-level micro data to analyse how firms and the industry as a whole respond to shocks that influence their energy use and emission levels. Our empirical evidence is seen to assist policymakers in designing and/or improving current policies geared towards attaining the Energy Union and Europe's transition towards a decarbonised energy system in a least-cost manner.

This report is divided into two parts. The first part (Chapter 2) reports the results of subtask 3.2.2 under Work Package 3, which was undertaken by GRI-LSE. The second part (Chapter 3) relates to subtask 3.2.1 of Work Package 3 undertaken by WWU.

The first part investigates the link between energy price changes and industrial firms' environmental and economic performance using a unique dataset containing firm-level data from the French manufacturing sector. The study performed two analyses. First, the study estimates a firm-level econometric model using exogenous energy price variation

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and finds that a 10% increase in energy price reduces CO_2 emission by 8%. The same increase in the energy price reduces employment by 3% in large firms but has no effect on employment in small and medium size enterprises. The policy implications of this paper are further illustrated with a simulation of the effect of the French carbon tax on CO_2 emissions and employment. Second, the study performs an industry-level analysis that incorporates not only within-firm adjustments to energy price variation but also between-firms adjustments. The study finds that (i) aggregate energy intensity of the French manufacturing sector has decreased by 33% between 2001 and 2013 and (ii) the changes in manufacturing-wide energy intensity is driven by firm-level reduction (and not market share reallocation towards energy efficient firms); and (iii) these changes are associated with an upward trend in the energy price.

The second part investigates emissions pathways in the German manufacturing sector using disaggregated data. In particular, the study decomposes the changes of industrial CO_2 emissions from energy usage in Germany between 2006 and 2014. It applies the Logarithmic Mean Divisia Index to production census data on the firm level, which allows a highly detailed separation of firm-level energy efficiency improvements from structural changes in the economy. The analysis shows that both effects are responsible for an overall decline in emissions, but differ in importance across industries. The contribution of structural change to emissions reductions is especially large in rather energy-intensive and export-oriented industries. Contrary to the previous study, the average price of energy as well as the share of energy costs do not show a significant influence. Panel regressions further highlight the importance of new firms, which are significantly more energy efficient than incumbents, as well as that of small and medium enterprises, where untapped potential for energy efficiency policies is presumably large. At last, firms with larger energy prices clearly improve their energy and CO_2 intensity, irrespective of the cost share of energy.

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2. The Joint Effects of Energy Prices and Carbon Taxes on Environmental and Economic Performance: Evidence from the French Manufacturing Sector

2.1. Introduction

According to the 2016 International Energy Agency (IEA), industrial players in 2014 consumed 79.8% of the world's coal consumption, 64.5% of oil, 38.6% of natural gas, and 42.5% of electricity. Despite being the largest consumers of energy, rarely are the impacts of energy policy – and thus energy price shocks, on these players discussed or assessed in a systematic way. Several hurdles are identified. First, it is very difficult to obtain detailed information on the use of energy inputs at the firm- or plant-level, thus hindering us in obtaining regularities in terms of how companies alter their energy use and production processes in the event of an energy price change. There are also limitations in terms of the number of actual impact assessments conducted to draw meaningful policy implications.

Meanwhile, the importance of analysing the impact of the impacts of energy policy – and thus energy price shocks, cannot be overstated. Many governments around the world have adopted some form of energy policies to reduce energy consumption (Jacobsen, 2015). The EU, for example, has set itself a 32.5% energy efficiency target by 2030 and proposed policies to ensure that the target is met. France has "developed an ambitious and integrated energy and climate policy framework for the energy transition towards 2030 and has adopted significant new policies, including carbon budget/pricing instruments, tax incentives and considerable public funding towards implementing it" (International Energy Agency, 2017).

Analysing business responses to policies and energy price changes is very complex. When faced with sudden price increases, some firms may be able to pass on the cost of price increases to consumers or firms in other sectors. Other firms may have to mitigate the energy cost impacts by reducing their energy consumption and, consequently, output. Some firms may end up altering production processes through adoption of energy-saving technology (a rise in price increases incentives for making energy savings and making investments into technology) or lowering other costs, such as wages (both the nominal wage and by reducing working hours/laying off workers). Alternatively, firms can substitute one form of energy for another, depending on which energy becomes relatively more expensive because of the shock (e.g., relying more on diesel power

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generation rather than on power from the grid or vice-versa). They can also substitute labour for capital in some instances.

The way in which businesses respond to changes in energy prices has important policy implications. For example, the economic losses among affected businesses may be small or even negative if the price change prompts companies to invest in unexploited high return energy efficient technologies. In contrast, the economic losses may be significantly greater if they respond by reducing their consumption of energy services and eventually output and employment. Evidence on firm-level responses to increased cost of energy can enhance our understanding of the ultimate economic consequences of these climate change policies.

This paper contributes to the literature by performing two analyses utilizing a unique dataset that combines firm-level information from a number of databases managed by the French Statistical Office (Insee). These data sets include the energy consumption and expenditure from the EACEI survey (Enquête sur les consommations d'énergie dans l'industrie), financial data from FARES (Fichier complet unifé de SUSE) and FICUS (Fichier approché des résultats Ésane), patent data from PATSTAT, and pollution abatement investment data from the Antipol survey.

Our first analysis is at the macro-level. We examine the drivers of the energy intensity of the entire French manufacturing sector. Following (Brucal et al., 2018), we decompose the manufacturing-wide energy intensity into two components: (i) a firm-level component reflecting firm adjustment and (ii) a between-firm component reflecting output reallocation of production between firms. This allows us to measure the relative importance of the two channels of aggregate changes in the industry-wide energy intensity. Then, we estimate the effect of energy price changes on the manufacturing-wide energy intensity and its two components. This provides some indication on the contribution of the energy price to the change in the aggregate energy intensity. We find that (i) aggregate energy intensity of the French manufacturing sector has decreased by 33% between 2001 and 2013 and (ii) the changes in manufacturing-wide energy intensity is driven by firm-level reduction (and not market share reallocation towards energy efficient firms); and (iii) these changes are associated with an upward trend in the energy price.

Our second analysis is at the micro-level. We estimate the responses of French manufacturing firms to exogenous changes in energy prices at the micro-level. Our identification relies on the use of the fixed-weight energy price index as an instrumental variable for average energy cost, following (Linn, 2008) and (Sato et al., 2015). We argue that assessing energy use using average energy cost directly would result in biased estimates due to potential endogeneity issues associated with factors that can affect energy demand and prices simultaneously. The index uses industry-wide average prices

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of different fuels and electricity and, by construction, does not include the effects of technological change, substitution or industry-specific shocks on output demand (Linn, 2008), thus providing a relevant instrument for observed energy costs.

Our micro-level results suggest that increases in energy prices result in a decline in energy use, with an own-price elasticity equivalent to 0.5. This figure is higher than estimates from previous studies looking at short-run responses of industrial energy users to energy price changes (see Labandeira et al., 2017 for a comprehensive review). We also find that, for large firms only, employment declines as energy price increases, which suggests that environmental goals have negative economic consequences. However, the employment elasticity (0.15) is far smaller than that of own-price elasticity, suggesting that affected firms manage to partly reduce their energy intensity other than through reductions in the size of the workforce. We find that small and medium-sized enterprises (SMEs) decrease their energy intensity more than large firms in response to short-run energy price increases. In contrast to large firms, SMEs (which represent 99% of French manufacturing firms and 56% of the workforce) do not reduce employment when the energy price increases. Large firms react by filing more patents while SMEs clean-up by substituting energy for capital. A part of the capital expenditure takes the form of investment in end of pipe technologies for the abatement of air, water, and waste pollution presumably because firms replace their existing energy efficient abatement.

Surprisingly, we find that output and investment increase because of higher energy prices in SMEs but not in large firms. We offer two interpretations for this result. The first is that SMEs may compensate the higher energy cost by increasing the scale of their production in order to decrease average production costs. Large firms do not do that because they have already exploited economies of scale.

Our study is related to the literature that looks at the relationship between energy prices and energy use. As a general finding, the empirical literature has identified non-negligible fuel and electricity price-elasticities, especially in the long run (Houthakker, 1951; Taylor, 1975; Bohi and Zimmerman, 1984; Al-Sahlawi, 1989; Espey, 1996; Brons et al., 2008; Havranek et al., 2012; Labandeira et al., 2017). Nonetheless, none of these studies have gone to further characterizing how firms reduce their energy consumption.

In addition, this paper relates to studies looking at the effect of the energy price on the discrete adoption of energy efficient technologies by manufacturing firms (Pizer et al., 2001; Anderson and Newell, 2004). We contribute to this literature by estimating the effect of the energy price on the number of successful patent applications and on pollution abatement capital expenditure.

More generally, the study is related to the growing literature evaluating environmental policies on firm-level environmental performance (Greenstone et al., 2012; Walker, 2013; Martin et al., 2014; Wagner et al., 2014; Flues and Lutz, 2015; Gerster, 2015; Pertrick and

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Wagner, 2018). In general, firms respond to environmental policies by cutting down on the regulated energy inputs and CO_2 emissions. However, the results in terms of the trade-off between environmental goals and economic outcomes remain highly mixed.

This paper is similar to Marin and Vona (2017) who analyze the impact of energy prices on employment and environmental performance of French manufacturing plants. Nonetheless, this study also deviates from Marin and Vona (2017) in several respects. First, while they focus on surviving plants' response to energy price variation, we start by examining the evolution and the components of the manufacturing-wide energy intensity and stress the importance of output reallocation. Second, we take firms as our unit of observation instead of plants. This allows analysing the effect of the price on real output, investment, employment, and patenting and explore the heterogeneity between SMEs and large firms.[1] Third, in addition to measuring energy use and employment elasticities, we characterize the manner by which firms reduce energy use per unit of output by examining fuel choice, input substitution as well as the investment in pollution abatement technologies. Fourth, we test for heterogeneous effects of the energy price on several dimensions: energy intensity and firm size. Finally, we simulate the effects of a planned increased of the French carbon tax on the employment and CO_2 emissions of 19 sectors using sector specific econometric estimates.[2] We believe this paper will inform policymakers further in designing appropriate environmental measures with the least potential economic losses.

The paper is organized as follows. Section 2 briefly discusses our empirical strategy, which includes employing a unique dataset and a novel identification strategy. Section 3 presents the results of the study, starting with an analysis of the manufacturing-wide energy intensity, followed by the empirical analysis of the effects of energy price on surviving firms' environmental performance, economic performance, input substitution, and energy saving technology adoption. Section 4 concludes the study.

2.2. Empirical Strategy

2.2.1. Data Source and Definition

Our main dataset consists of an unbalanced panel of 6,000 French firms observed yearly from 2001 to 2013 covering the entire manufacturing sector except for the industries of

[1] We also measure investment response and use more recent data than (Marin and Vona, 2017) who cover 1997-2010.

[2] (Marin and Vona, 2017) perform a simulation of a 56 € / t carbon tax but do not provide the magnitude by industry.

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tobacco, arms, and ammunition. We obtain this dataset by merging 2 datasets: an energy use dataset and a fiscal dataset described below.

Fuel consumption and expenditure data come from the EACEI survey conducted by Insee. The EACEI survey provides information on consumption of electricity, natural gas, coal, oil, and other fuels at the plant level. We combine CO_2 emission factors from the French Environment and Energy Management Agency (ADEME) with fuel use to compute CO_2 emissions from fuel combustion. These energy data are available at the plant level. However, our level of analysis is the firm since data on economic outcomes are available at the firm level and not at the plant level. Therefore, we aggregate the energy data from the plant level to the firm level. This aggregation is straightforward for single-plant firms. For multi-plants firms, we would need data for all plants. To verify whether this is the case, we proceed as follows. First, we compute the sum of employees for the plants for which the energy data is available using the list of manufacturing establishments provided by Insee. Second, we compare the sum of the plants to the total number of employees of the firms. If we cover at least 85% of the firm's total number of employees, we consider that the sum of energy expenditure and use of its plants is a measure of the firm's total energy expenditure and use. The 85% threshold represents a trade-off between (i) minimizing the error in measuring the firms' total energy use and (ii) maximizing the number of observations in order to have a representative sample. Increasing the threshold decreases the error in measuring the firms' total energy use but also lead to the loss of the firms in our sample. For instance, we have 19% less firms with a 90%. Using a very high ratio presents the risk to drop firms that have establishments such as holding or other office work that do not consume large quantities of energy and would never be sampled in the EACEI.[3]

Data on turnover, number of employees, and total investment come from the census provided by the French Ministry of Finance at the firm level. We deflate output using 3-digits industry producer price indices provided by Insee. Data on patent filings come from the PATSTAT database. We match patent filings with firms using Bureau van Dijk's Orbis-PATSTAT dataset.

In order to analyse the effect of the energy price on investment in pollution abatement technologies, we use plant-level data from the Antipol survey maintained by Insee. Every year, Antipol asks plants how much they invest in pollution abatement technologies. For the latest years, the survey is mandatory for plants with more than 250 workers. Plants between 20 and 249 workers are randomly sampled over economic activity and number of employees. The investments are broken down by destination, including air, water,

[3] In Table and Table we respectively use a 90% threshold and a 80% threshold and show that our results are not sensitive to the 85% threshold.

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waste, and soil. The survey also makes the distinction between end of pipe and integrated technologies. As the amount of data for integrated technologies is much lower than for end of pipe technologies, we focus only on the latter in this paper.

Note that the dataset used to test the effect of energy price on investment in pollution abatement is different from our main dataset. First, it is at the plant level and not at the firm level to preserve the number of observations. Second, the data availability for investment measures is lower than the availability of the energy use data. Therefore, our investment dataset is smaller than our main firm-level dataset. Summary statistics are found in the tables below.

Table 1: Summary statistics for the firm-level sample

Variable	Obs.	Mean	Std. Dev.	Min	Max
Family patent stock	9,536	-0.04	1.95	-6.49	7.00
Energy use	34,439	5.69	1.96	-2.17	13.73
Electricity use	34,434	5.05	1.89	-2.38	11.58
Fossil fuel use	30,797	4.82	2.15	-4.26	13.66
CO_2 emissions	34,439	12.91	2.12	4.48	21.60
Workers	34,439	4.75	1.03	1.95	10.18
Real output	34,439	9.90	1.28	5.99	15.41
Investment	28,068	6.04	1.75	-0.38	12.94
Real energy intensity	34,439	-4.21	1.33	-11.22	1.63
Energy use per worker	34,439	0.94	1.44	-6.21	7.55
Energy use per material	34,439	-3.11	1.55	-10.53	8.71
Energy use per capital	34,439	-3.08	1.33	-10.10	4.10
Electricity / fossil	30,792	0.35	1.38	-5.19	9.02
Average energy cost	34,439	-0.46	0.34	-5.96	5.84
Firm age in years	34,439	2.54	2.67	0.00	11.40

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ETS (0/1)	34,439	0.02	0.13	0.00	1.00
Energy price index	34,439	-0.45	0.29	-1.53	0.34
SME (0/1)	34,439	0.80	0.40	0.00	1.00
Year	34,439	2,008.49	4.05	2,001.00	2,015.00

The unit of observation is the firm. All variables are logged except plant age and the ETS dummy.

Table 2: Summary statistics for the plant-level sample

Variable	Obs.	Mean	Std. Dev.	Min	Max
Investment to reduce all kind of pollution	18,167	3.57	1.71	-2.34	10.28
Investment to reduce water pollution	18,167	2.47	1.90	-4.30	9.83
Investment to reduce air pollution	14,524	2.50	1.99	-4.43	9.38
Investment to reduce waste pollution	16,986	1.95	1.68	-5.23	9.33
Investment to reduce soil pollution	15,223	1.94	1.95	-4.70	9.54
CO_2 emissions	12,947	14.21	1.89	5.89	21.28
FEPI	18,167	-0.59	0.30	-1.73	0.25
Plant age in years	18,167	30.38	35.85	0	114
ETS (0/1)	18,167	0.05	0.21	0	1

The unit of observation is the plant. All variables are logged except plant age and the ETS dummy.

2.2.2. Identification Strategy

Assessing energy use using average energy cost directly would result in biased estimates due to potential endogeneity issues associated with factors that can affect energy demand and prices simultaneously. This is particularly concerning when the sample is composed of large firms in which energy demand can be subjected to quantity

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discounts. In order to resolve this endogeneity problem, we rely on the use of the fixed-weight energy price index as an instrumental variable for average energy cost, following (Linn, 2008) and (Sato et al., 2015). The index uses industry-wide average prices of different fuels and electricity and, by construction, does not include the effects of technological change, substitution or industry-specific shocks on output demand (Linn, 2008), thus providing a relevant instrument for observed energy costs.

In particular, we use an exogenous measure of energy price variation. More specifically, we follow (Sato et al., 2015) to compute the following fixed-weight energy price index:

$$FEPI_{it} = \sum_j w_{i0}^j \ln(p_{kt}^j)$$

where w_{i0}^j is the share of fuel f in total energy use of firm i at the pre-sample year 0 and p_{kt}^j is the median price of fuel f for the 3-digit industry k in which firm i operates at year t.[4]

The advantage of pre-sample weights is twofold. First, it is a way to aggregate the different industry-level fuel prices into a firm-level energy price index and ensuring between-firms variation. Second, firm i's decisions in the sample period are not correlated with the weights because they are fixed using data on years before the sample period. The within-firm variation thus come from the industry-level fuel prices. In comparison to fuel prices actually paid by firm i, the industry-level median fuel prices p_{kt}^j can be assumed to be exogenous to firm i and vary across time. The validity of FEPI as instrumental variable depends on this assumption. Note that the FEPI can also be computed at the industry level.

Our methodology differs from (Marin and Vona, 2017) in several aspects. First, we sum the log of the fuel prices to ensure linearity in the fuel prices while they log the sum of the fuel prices. Second, we use median fuel price at the industry level while they use nationwide fuel prices. Using nationwide fuel prices instead of industry-level prices could lead to a weak instrument problem as fuel prices differs significantly between industries. Third, they use the 12 fuels while we use the 4 main fuels. We do this because only a limited number of firms use the other 8 fuels.[5] Because these fuels are not used by most firms, there are very few observations available to compute exogenous fuel price at the industry level. The instrumental variable is valid only if firms cannot influence the average of median price. In other words, one needs a large amount of firms with positive fuel consumption in order to measure exogenous price. Firms using the other 9 fuels represent are not representative of the French manufacturing sector and, consequently, average price

4 (Linn, 2008) uses a fixed-weight energy price index where the fuel weights are computed at the level of a US state. Here total energy use is simply the sum of use of electricity, natural gas, butane propane, and heating oil.

5 The other 9 fuels include coal – agglomerates, lignite poor coal, coal coke, petroleum coke, steam, heavy fuel oil, black liquor, wood and wood by-product.

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calculation at the industry level will be largely influenced by a few firms. This inevitably increases the risk of measurement errors.

We then estimate the short-run effect of the energy price on surviving firms' environmental and economic performance, and energy saving technology adoption using the following model:

$$y_{it} = \beta_0 + \beta_1 Cost_{it-1} + \beta_2 X_{it-1} + \mu_i + \gamma_t + \varepsilon_{it}$$

where y is an outcome variable for firm i at time t, such as energy use, the number of workers, real output, etc. $Cost$ is the log of average energy cost measured by the ratio between expenditure in electricity, natural gas, heating oil, and butane propane in thousand euros and the purchased quantity of these two fuels in toe. X is a vector of firm-level controls that includes a dummy equal to 1 when the firm is included in the European Union Emission Trading Scheme starting in 2005 and the average age of the firm's plants, μ_i are firm fixed effects, γ_t are year dummies, and ε_{it} is the error term. We estimate equation (9) with a fixed-effects estimator that allows us to control for time invariant and firm specific characteristics μ_i that are correlated with the energy price index as well as with the outcome variables. This captures differences across firms operating in industries that vary substantially in terms of energy intensity. For example, large firms operating in the chemical industry obviously employ more workers, consume more energy, and face different fuel prices than small firms operating in the wearing apparel industry. μ_i also controls for historical fuel mix, used in the computation of the energy price index, that is likely correlated with future energy consumption and competitiveness.[6]

The year dummies γ_t control for consumer demand and fuel price fluctuations at the level of France affecting all French firms' outcome as well as the fuel prices used to compute the energy price index. We also include ETS status as a control variable because firms subject to EU-ETS are CO_2 intensive and are eligible to fuel tax discounts.

Note that in the above equation, y_{it} and $Cost_{it}$ are simultaneously determined. Firms can influence the fuel prices they face by changing their fuel use as well as their output level or their technologies. Therefore, regressing energy use or other firm-level outcomes on average energy cost using OLS yields a biased estimate of the fuel prices even if a fixed-effects estimator is employed. We expect the OLS estimator to be biased upward as unobserved firm efficiency or management capacity are negatively correlated with energy use and $Cost_{it}$. To address this simultaneity bias, we instrument the energy cost variable with an exogenous energy price index that was previously described. We expect FEPI to be positively correlated with the average energy cost. We test for under-identification to check the strength of our instrument. All regressors are lagged by one

[6] When the dependent variable is the energy saving innovation dummy, we cannot employ a fixed-effects estimator. Instead, we include 3-digits industry dummy in the model that we estimate using a Probit estimator.

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year. This reflects the time firms need to react to new average fuel prices. We compute robust standard errors clustered at the firm level.

It is possible that firms react to energy price increases differently depending on their size and on the industry in which they operate. Does the effect of energy price differ between Small and Medium Enterprises (SMEs) and bigger firms? Considering that 90% of firms in the French industry are SMEs, any difference with bigger firms has important policy implications.[7] In theory there are reasons to believe that the energy price impacts small and big firms differently. Our data shows that SMEs consume 36% less energy per output than large firms and that their energy cost is 12% higher.[8] Therefore, we can expect that the same increase in energy price has larger impact on big firms. On the contrary, we could also expect large firms to have more capacities, financial or managerial, to deal with price variation than SMEs. The net effect of this two opposing forces is an empirical question. Similarly, firms that are energy intensive could experience a greater decline in output or employment.

To test for heterogeneous effects of the energy price, we augment our model with two interaction terms: (i) an interaction between the average energy cost and a dummy variable SME_{i0} equal to 1 if the firms has less than 250 employees in the first year it is observed and (ii) an interaction between the average energy cost and a continuous variable Int_{i0} equal to the log ratio between energy use and the number of employees of the firm in the first year it is observed. The augmented model can be written as follows:

$$y_{it} = \alpha_0 + \alpha_1 Cost_{it-1} + \alpha_2 Cost_{it-1} \times SME_{i0} + \alpha_3 Cost_{it-1} \times Int_{i0} + \alpha_4 X_{it-1} + \mu_i + \gamma_t + u_{it} \quad (1)$$

We argue that it is important to include both interaction terms in the same model in order to not confound the effects of energy intensity and firm size, which can be correlated with each other. Our approach differs from Marin and Vona (2017) who estimate their model on separate samples. In contrast, we do not introduce some sort of sample selection by estimating the model on a unique sample.[9]

We observe significant variation in the average energy cost over time in

[7] In our sample, 80% of the firms are SMEs. The EU commission and the French administration define SMEs as firms having a staff head-count lower than 250.

[8] This observation is consistent with quantity discounts.

[9] They also estimate heterogeneity between firms exposed to carbon leakage and firms not exposed to carbon leakage. We also perform this test but in the appendix since we argue that size and energy intensity matters more than trade exposure.

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Figure 1 and significant variation of the energy cost across industries in

Figure 2. However, for identification we need within-firm level variation in both the average energy cost and the energy price index over time. To verify whether this is the case, we scale the two variables by subtracting their within firm average. We then compute the standard variation of the two mean-reduced variables. We find that the standard variation equals 17% for the average energy cost and 15% for the energy price index. Therefore, we should have sufficient within-firm level variation to estimate our models.

Figure 1: Evolution of the average energy cost

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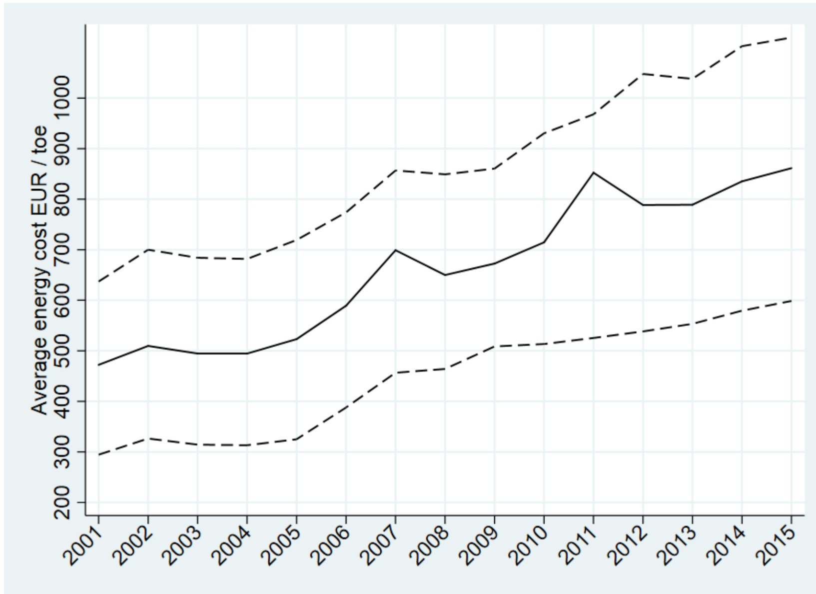

Dotted lines represent the 10th and the 90th percentiles. Source: Authors' calculation.

Figure 2: Energy intensity by industry

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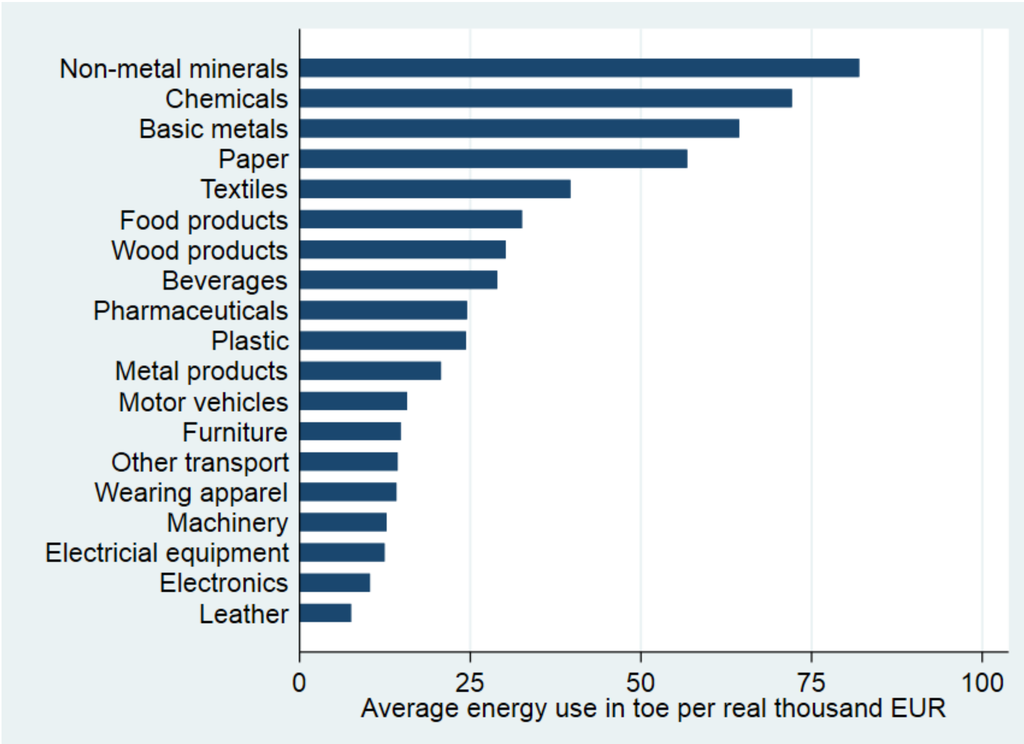

Average computed over 2003-2015. Source: Authors' calculation.

2.3. Results

2.3.1. Industry-wide Analysis

This subsection explores the link between energy prices and aggregate energy intensity (measured as energy use/output) for the French manufacturing sector during our sample period. We can decompose this aggregate energy intensity into two components: the unweighted average energy intensity and covariance of energy intensity, and observe how changes in aggregate energy intensity and the two components are associated with movements in energy prices. To do this, we follow (Brucal et al., 2018) and compile the aggregate energy intensity measure W_t, which is the average of the firms' individual energy intensities weighted by the firm's share in total manufacturing output s_{it}. We calculate $W_t$for all firms in the sample for each year t. Then we decompose the aggregate energy intensity into the unweighted aggregate energy intensity and the

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covariance between firms' shares of the entire industry's output and its energy intensity:

$$\underbrace{W_t = \sum_i s_{it}\ lnEI_{it}}_{\substack{\text{Aggregate} \\ \text{energyintensity}}} = \underbrace{\overline{lnEI_t}}_{\substack{\text{Unweightedaverage} \\ \text{energyintensity}}} + \underbrace{\sum_i (s_{it} - \overline{s}_t)(lnEI_{it} - \overline{lnEI_t})}_{Covariance} \quad (2)$$

where s_{it} is the share of firm i's output to total industry's output at time t, $\overline{s}_t$ is the average share over all firms in the industry, $lnEI_{it}$ is firm i's log(energy expenditure/real output), $\overline{lnEI_t}$ is the average log(energy expenditure/real output) over all plants in the manufacturing sector.

Changes in the first term (unweighted average energy intensity) reflect firm-level changes in energy intensity. Changes in the second term (covariance), if positive, indicate that more output is produced by more energy intensive producers. Thus, changes in the second term capture the effects of reallocation of market shares across firms with different energy intensity levels.

Figure 3 shows the annual changes in the weighted average energy intensity and its two components. First, we observe that these annual changes are mainly negative. This reflects that the French manufacturing sector is cleaning up. Second, the changes in weighted average energy intensity seems to be mainly driven by firm-level reductions between 2001 and 2009 while it is mainly driven by reallocation of outputs towards energy efficient firms after 2009.[10] This potentially reflects a structural shift generated by the financial crisis.

Figure 4 shows the evolution of the weighted average energy intensity and the energy price index. Results are expressed as changes relative to 2001, the initial year in our sample. Our calculations show that the energy intensity of firms in our sample has decreased by 43% between 2001 and 2015. During the same period, energy prices rose by 91% on average. The figure suggests a negative correlation between energy intensity and price.

Figure 3: Aggregate energy intensity and its components in the French manufacturing industry

10 Change in unweighted energy intensity represents 69% of the variation in weighted energy intensity between 2001 and 2009 and 36% after 2009.

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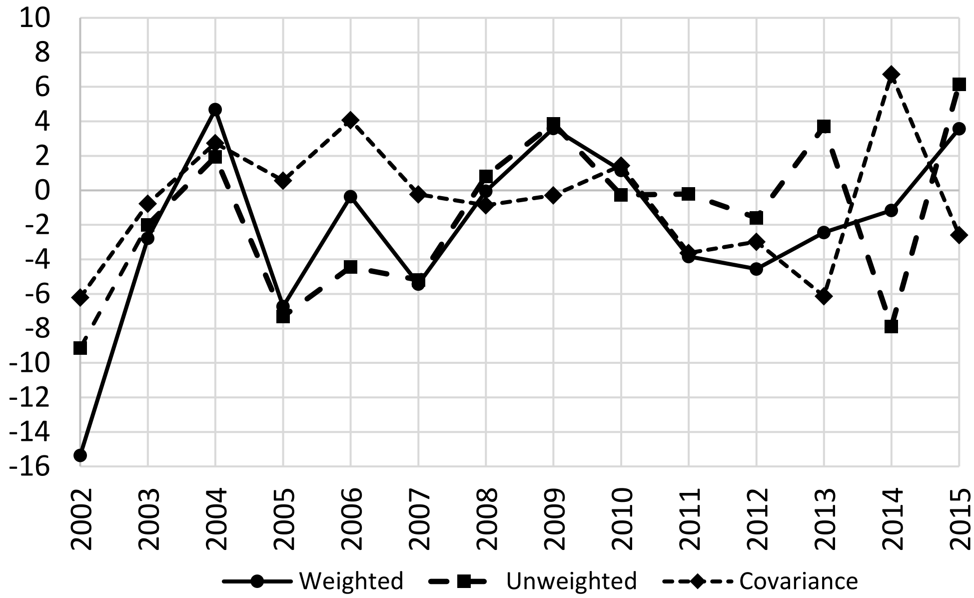

Note: Year to year change in manufacturing wide energy intensity and its components as defined in equation (2).

Figure 4: Aggregate energy intensity and average price index (FEPI)

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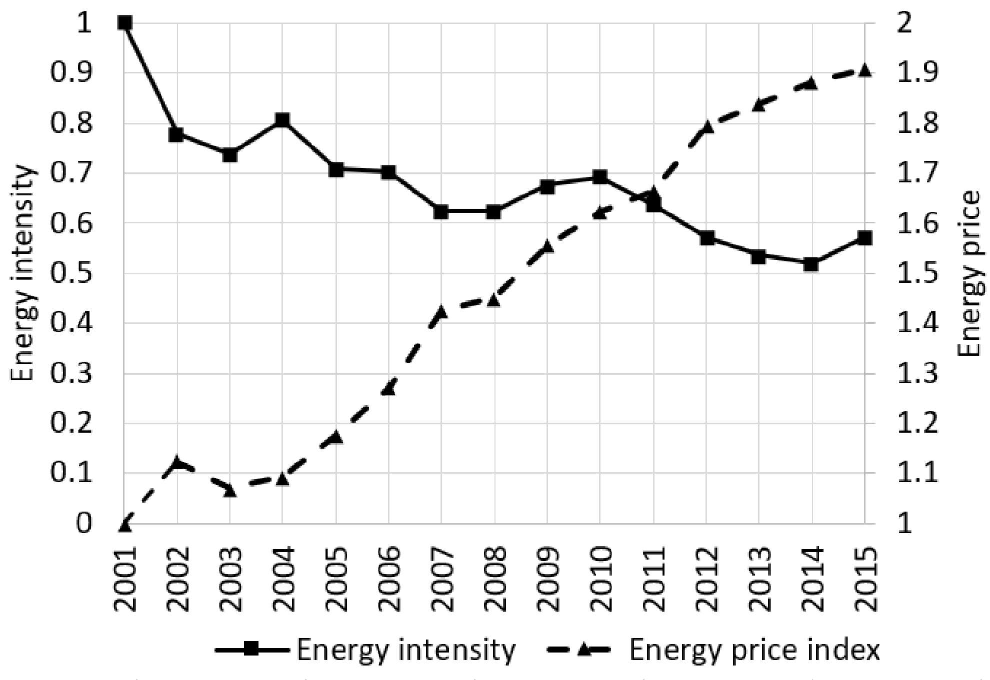

Note: Figures are relatives to 2001 levels. Energy intensity is weighted by output share.

We then formally assess how changes in the energy prices are associated with industry-wide aggregate energy intensity by regressing the aggregate energy intensity and each of its components on our measure of energy prices, $FEPI_{it}$, at the 3-digit industry-year level. We estimate the following equation:

$$lnEI_{kt} = \beta FEPI_{kt} + \gamma_k + \delta_t + \varepsilon_{kt} \tag{3}$$

where $lnEI_{kt}$ is the logged aggregate energy intensity and its components relevant to industry k operating at year t and $FEPI_{kt}$ is the fixed-weight energy price index in the 3-digit industry. γ_k and δ_t are 3-digit industry and year fixed effects, respectively. Standard errors are clustered at the sector level. We then estimate an alternative model where we allow β to be different before and after 2007 to test for differences in the effect between two periods of identical length. This can capture a potential structural change after the 2008 financial crisis.[11]

Results are summarized in Table 3. Our estimation shows that increased energy prices are

11 Note that it is not possible to include the square value of FEPI as additional regressor in (3) to capture potential nonlinear effects because the correlation between FEPI and its square value equal -0.96. If we add the square value of FEPI in our model, we will suffer from a high degree of collinearity and obtain a biased estimate.

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not associated with change in aggregate energy intensity on average. We also find that increased energy prices are negatively associated with aggregate energy intensity but only in the 2007-2015 period. A 10% increase in the energy price is associated with a 6% decrease in energy intensity. This heterogenous effect could come from industry specific demand shocks that are correlated with $FEPI_{kt}$. However, we do not know what causes the different effect between the two periods.

Table 3: Energy price index and energy intensity at the 3-digits level

	Weighted energy intensity	Unweighted energy intensity	Covariance	Weighted energy intensity	Unweighted energy intensity	Covariance
FEPI	-0.262	-0.220	-0.007	-0.385	-0.419	-0.009
	(0.273)	(0.289)	(0.027)	(0.267)	(0.283)	(0.026)
FEPI x after 2007 (0/1)				-0.604***	-0.975***	-0.012
				(0.222)	(0.301)	(0.016)
Industry FE	X	X	X	X	X	X
Year dummies	X	X	X	X	X	X
Observations	587	587	587	587	587	587
Number of sectors	59	59	59	59	59	59
Adjusted R-squared	0.19	0.34	0.04	0.22	0.39	0.05

Robust standard errors clustered at the industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are logged. All columns represent separate regressions estimated via OLS.

This suggests that increased prices may be facilitating improvements in overall energy intensity in the French manufacturing industry in the recent years. We also find an indication showing that price-induced reduction in energy intensity is channelled through within-firm reduction in energy per unit of output rather than a reallocation of market shares towards less energy intensive firms. The price effect is larger on unweighted energy intensity than on weighted energy intensity. This is because the energy price is only one factor of output reallocation that depends on firms' total cost.

2.3.2. Micro-level analysis

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a) Impact of energy price changes in environmental and economic performance

Table 4 shows the estimated effects of the energy price index on firm energy performance and economic performance.[12] We find that an increase in the energy price index is associated with a statistically significant reduction in the energy use. In particular, a 10% increase in the energy price leads to a decrease of 4.7% of the energy use. The reduction of fossil fuel amounting to 4.6% is larger than for electricity, which is lower than 1% and statistically insignificant. Consistently, the reduction in CO_2 emissions, equal to 8.2%, is larger than the energy use reduction because the combustion of fossil fuel generates more CO_2 than electricity use.[13] This difference in magnitude might be due to the evolution of relative fuel prices. Real electricity prices have increased by 44% over the sample period but this figure equals 70% for butane/propane, 85% for natural gas, and 156% for domestic heating oil.[14] The further decrease in fossil fuel might also be due to electricity being less substitutable.

We also find evidence that changes in energy prices affect some dimensions of firms' economic performance but not all. Table shows that an increase of 10% in the energy price lowers employment by 1.5%. This elasticity is much lower to the estimated elasticity for energy use and CO_2 emissions.[15] Moreover, the effect of energy price on real output and investment is not statistically different from 0. To pursue our understanding on firms' adjustments, we investigate in the next section whether changes in the energy price lead to input substitution, fuel substitution, and change in energy intensity.

TABLE 4. ENERGY PRICE EFFECT ON ENVIRONMENTAL PERFORMANCE AND ECONOMIC PERFORMANCE

	Environmental performance				Economic performance		
	Energy use	Electricity use	Fossil fuel use	CO_2 emissions	Workers	Real output	Investment
ln(avg. energy cost)	-0.469***	-0.063	-0.456**	-0.819***	-0.153**	-0.017	-0.183

[12] See appendix for the test on the strength of the instrumental variables used.

[13] The emission factor is 2,750 kg CO_2/toe for natural gas, 3,700 kg CO_2/toe for domestic heating oil, 3,170 kg CO_2/toe for butane/propane, and 582 kg CO_2/toe for electricity.

[14] See Table .

[15] Our results for energy use and carbon emissions are similar to (Marin and Vona, 2017)'s. However, they find a much larger impact on employment equal to 2.6%.

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	(0.146)	(0.139)	(0.218)	(0.178)	(0.062)	(0.082)	(0.298)
Firm age in years	-0.024***	-0.034***	-0.015	-0.018**	-0.030***	-0.033***	0.000
	(0.007)	(0.007)	(0.010)	(0.008)	(0.004)	(0.005)	(0.015)
ETS (0/1)	0.056	-0.019	0.122*	0.111**	0.073***	0.097***	0.017
	(0.039)	(0.035)	(0.069)	(0.048)	(0.021)	(0.029)	(0.091)
Firm FE	X	X	X	X	X	X	X
Industry x Year dummies	X	X	X	X	X	X	X
Observations	32,132	32,125	28,724	32,132	32,132	32,132	25,595
Number of firms	6,346	6,344	5,617	6,346	6,346	6,346	5,600
KP LM statistic	311	310	272	311	311	311	235

Robust standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are logged. All columns are estimated with the 2-state least square estimator. Average energy cost equals the log of the ratio between energy expenditure and energy use. The instrumental variable for average energy cost is the Fixed Weight energy price Index. The first-stage regressions are reported in Table . Regressors are lagged one period. Energy use is the sum of electricity, natural gas, heating oil, and butane propane consumption. CO_2 emissions are emissions from energy consumption.

b) Impact of energy price changes on input substitution

In the previous section, we find that a change in the energy cost has a significant effect on energy use, CO_2 emissions and employment. In this section, we test whether the energy cost has an impact on energy intensity. Then, we explore through which channels the changes in energy intensity occur. Do firms reduce their energy intensity through input or fuel substitution or through the adoption of cleaner technologies?

Table shows the effect of the average energy cost on energy intensity, energy use per worker, energy use per material, energy use per capital, and the ratio between electricity use and fossil fuel use. The effect of energy cost on energy intensity is equal to -4.5% and

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is statistically significant.[16] We find some evidence that labor, material, and capital decrease significantly less than energy use when the energy price increases. A 10% rise in the energy cost reduces energy use per worker by 3.2%, energy use per material by 4.4% and energy use per capital by 4%. In addition, we find that the same increase in the energy price increases relative electricity use by 3.8%. Our results suggest that firms reduce their energy intensity by decreasing energy use more than the other inputs as well as their CO_2 intensity by increasing electricity use relative to fossil fuel use.

Table 5: Energy price on energy intensity and input substitution

	Real energy intensity	Energy use per worker	Energy use per material	Energy use per capital	Electricity / fossil fuel
ln(avg. energy cost)	-0.452***	-0.316**	-0.436**	-0.403**	0.381*
	(0.147)	(0.140)	(0.180)	(0.159)	(0.199)
Firm age in years	0.008	0.006	0.006	0.005	-0.013
	(0.007)	(0.006)	(0.008)	(0.008)	(0.009)
ETS (0/1)	-0.041	-0.016	-0.001	-0.011	-0.136**
	(0.043)	(0.039)	(0.084)	(0.051)	(0.062)
Firm FE	X	X	X	X	X
Industry x Year dummies	X	X	X	X	X
Observations	32,132	32,132	32,132	32,132	28,717
Number of firms	6,346	6,346	6,346	6,346	5,615
KP LM statistic	311	311	311	311	271

Robust standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are logged. All columns are estimated with the 2-stage least squares estimator. Average energy cost equals the log of the ratio between energy expenditure and energy use. The instrumental variable for average energy cost is the Fixed Weight energy price Index. The first-stage regressions are reported in Table . Regressors are lagged one period. Energy use is the sum of electricity, natural gas, heating oil, and butane propane consumption. CO_2 emissions are emissions from energy consumption.

[16] For an increase of 10% in the energy cost.

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c) Impact of energy price changes on investment on pollution abatement

A more convenient way of measuring innovation is with patent filings and applications. However, patents do not capture all kind of changes in the firms' technology. First, patents do not capture all kind of innovation as firms patent only part of their knowledge leaving the rest in secrecy. Second, patents do not measure technology adoption but rather technology creation. In this section, we look at firms' investment in pollution control technologies (although we will go back to patents in the succeeding section). This is interesting given that these technologies require large quantity of energy to function. The efficiency of pollution abatement of an equipment is often positively related to its energy consumption.[17]

Table shows the estimation of model when the outcome variable is investment in pollution abatement and the main independent variable is the FEPI.[18] We find evidence that change in the energy price is positively associated with investment in air, water, and waste pollution control investment at the plant level.[19] Where the energy price increases by 10%, investments in air and waste pollution abatement increase by 7% and investments in water pollution abatement increase by 6%. In addition, we find that the same increase leads CO_2 emissions to fall by 3% providing some evidence that aggregating data at the firm level does not affect our results.

Table 6: Energy price and pollution abatement investment

	End of pipe investment					CO_2
	All	Water	Air	Waste	Soil	Emissions
FEPI	0.554**	0.573**	0.669**	0.726**	-0.004	-0.288***
	(0.245)	(0.274)	(0.314)	(0.305)	(0.317)	(0.108)

[17] For instance, (Mussatti and Hemmer, 2002) explain that high energy venturi scrubbers provides increased collection efficiency for fine and submicron Particulate Matters (PM) but that their capital costs and electrical power requirements are much higher than a conventional venturi. Another example is the incineration of volatile organic compounds (VOCs) which often requires addition of auxiliary fuel such as natural gas to raise the waste gas temperature at the appropriate level (Vatatuk et al., 2000). Similarly, the reduction of Nitrous Oxide by Selective Noncatalytic Reduction is more efficient at higher temperature (Mussatti et al., 2000). (Englehardt, 1993) highlights the energy cost of different waste abatement technologies.

[18] We prefer estimating a reduced form equation here because the number of observations are limited. Using energy cost would decrease the number of observations available. This is because FEPI only requires pre-sample fuel consumption weights in order to be computed while the energy cost requires fuel consumption data each year.

[19] As explained in section 2, pollution abatement investment data are available at the plant level. However, it is not feasible to aggregate these data at the firm level because there are too many missing plants.

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Firm age in years	-0.010*	-0.007	-0.012	0.013	-0.026***	-0.001
	(0.006)	(0.007)	(0.008)	(0.011)	(0.006)	(0.002)
ETS (0/1)	0.140	0.026	0.237*	0.055	0.127	-0.084**
	(0.101)	(0.121)	(0.123)	(0.128)	(0.148)	(0.039)
Firm FE	X	X	X	X	X	X
Industry x Year dummies	X	X	X	X	X	X
Observations	14,838	14,838	11,346	13,298	12,111	10,580
Number of firms	3,886	3,886	3,064	3,860	3,345	2,834

Robust standard errors clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The stock of patents is logged. The model is estimated via OLS. FEPI is the fixed weight energy price index. All outcome variables are logged. Investment to prevent pollution in air, water, and waste are end of pipe investment.

Our results suggest that increased energy price not only leads firms to reduce their energy use and therefore their CO_2 emissions, but also conducts firms to invest more in the abatement of emissions of other pollutants. Why would a firm invest in clean water investment when it has to reduce its energy use? Because the production of clean water from polluted water requires energy (Barakat, 2011, Gude, 2012). Therefore, other things equal, to maintain a given amount of water pollution, the firm has to compensate lower energy use by investing in machines that are more energy efficient in cleaning polluted water.

Our results highlight the trade-off between using cheaper energy intensive abatement systems and using more capital-intensive energy efficient abatement systems. If energy becomes more expensive, then firms have more incentive to invest in more energy efficient abatement equipment to keep a given amount of pollution.

d) Differing effects of energy price changes

In this section, we dig deeper into the analysis to look at different effects of energy price movements on firms with different characteristics and its effect on different sectors. Here we ask the following questions: Are the elasticities the same for all French firms or do they depend on firm size and energy intensity? Do bigger firms innovate more in the event of a price increase relative to smaller firms? Is the effect of a change in energy price similar across sectors/subsectors? The following subsections examine these questions in detail.

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1. **By firms' initial size and energy intensity**

Sector-specific impacts

So far, we have assumed that the parameter of model (9) are the same for all sectors. There are reasons to believe that the parameters of the model are actually different because sectors vary on many dimensions: market demand, the elasticity of substitution between energy and other inputs, number of firms operating the sector. Therefore, we estimate model (9) for each NACE 2 digits sector separately. Note that we use an OLS estimator in that case and not a TSLS estimator because the instrumental variable exploits between industries variation in the fuel price. Therefore, we acknowledge that the sector level coefficient is probably a lower bound of what the true effect is.

The results on CO_2 emissions are displayed in Figure and the results on the number of workers are displayed in Figure 6. We find that there are large differences between industries. More specifically, 58% of the sectors experience a reduction in CO_2, 25% reduce employment, 38% reduce CO_2 but not employment, and 0% reduce employment but not CO_2 emissions in response to higher energy price. The largest reduction in CO_2 emissions occurs in beverages, wearing apparel, and furniture with respectively 11.7%, 6.2% and 5.9%. The largest reduction in employment occurs in basic metals, wood products, and textiles with respectively 0.76%, 0.74% and 0.59%. These magnitudes are in line with our main results when using the OLS estimator as shown in Table . Table reports the detailed coefficient along with the average energy intensity in the sector. The effect on workers is more negative for firms operating in energy intensive sector.

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Table reports the interaction terms with the SME dummy and the logged ratio between energy use and workers used as a proxy for energy intensity.[20] We find that the effect of energy cost on environmental performance is not statistically different between SME and large firm. However, we find that the marginal effects of energy cost on environmental performance decrease with firms' initial energy intensity. In other words, firms that were more energy intensive at the beginning of the period reduce more their environmental impact in response to higher energy price.

The responses in terms of economic performance also greatly differ but the heterogeneity comes from the firms' size and not from their initial energy intensity. We find that a 10% increase in the energy price does not affect employment in SMEs but reduces it by 3.1% for large firms.[21] This result is consistent with the fact that it is harder for SMEs to recruit or replace workers. Therefore, SMEs have lower incentive to reduce employment when facing an increase in other inputs' price.

Surprisingly, we find that output and investment increase because of higher energy prices in SMEs but not in large firms. We offer two interpretations for this result. The first is that SMEs may compensate the higher energy cost by increasing the scale of their production in order to decrease average production costs. Large firms do not do that because they have already exploited economies of scale. This interpretation relies on the relatively strong assumption that SMEs do not minimize their production cost. It is similar to the (Porter and Van der Linde 1995)'s argument where a sufficient energy price increase triggers the reorganization of the firms' production that unveils possibilities to reduce cost. A second interpretation is that SMEs being more energy efficient than large firms gain the market shares that are lost by bigger firms. This interpretation is in line with the regressions results for a model with only one interaction term with the SME dummy that are reported in Table where large firms reduce real output and investment.[22]

Do these significant differences in economic outcome between large firms and SMEs come from differences in their substitution behavior? **Errore. L'origine riferimento non è stata trovata.** shows the input substitution results for the augmented model. We find that SMEs clean up more than large firms in response to higher energy price as they substitute energy for labor, material, and capital with greater magnitude than large firms. These effects decrease with firms' initial energy intensity. Finally, there is no statistical difference between firms in terms of fuel substitution towards electricity.

These results suggest that input substitution plays an important role in the reduction of

[20] These coefficients are obtained by the estimation of model (10).

[21] The coefficients for SMEs are obtained by the addition of the elasticity coefficient and the interaction coefficients.

[22] The advantage of the model with one interaction term over the model with two interaction terms is that it does not lose observations for which the pre-sample energy use per worker ratio is not available.

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energy intensity of SMEs.

2. Firm size and innovation

So far, we show that for large firms a rise in the energy price has a negative effect on employment while leaving real output and investment unchanged. In this subsection, we look at the effect of energy price on an additional dimension of competitiveness: innovation output as measured by the stock of patents filed by the firm.[23] In theory, an increase in the energy price can have two effects on innovation. First, there could be a negative scale effect where the firm market share decreases because higher energy price increases production cost. A smaller market share means that the gain from innovation will be lower which reduces the firm's incentives to invest in R&D. Second, there could be a positive differentiation effect where firms have more incentive to develop new products to maintain their market share. Ideally, we would also look at innovation in energy saving technologies but we do not have sufficient data on firm-level invention in energy efficient technologies.

Table summarizes our results.[24] We find that a 10% increase in the energy price leads to an increase in the discounted stock of family patents of 11% for large firms while it does not have a statistically significant impact of SMEs. Therefore, it is possible that the differentiation effect is stronger than the scale effect for large firms. SMEs do not innovate more because they have probably lower capacities to do so.[25] Potentially, SMEs use completely different strategies that may entail increasing their production scale.

3. Sector-specific impacts

So far, we have assumed that the parameter of model (9) are the same for all sectors. There are reasons to believe that the parameters of the model are actually different because sectors vary on many dimensions: market demand, the elasticity of substitution between energy and other inputs, number of firms operating the sector. Therefore, we estimate model (9) for each NACE 2 digits sector separately. Note that we

[23] More specifically, we measure the discounted stock of patents to account for knowledge depreciation over time using the usual 15% rate commonly used in most literature (Keller W., 2004). We count patent families and not patent applications so that we count the inventions only once.

[24] We estimate a reduced form equation to obtain the largest amount of observation possible. The interaction terms with energy intensity is not significant so we favor a model with only 1 interaction term.

[25] (Czarnitzki and Hottenrott, 2011) find that small or young firms may face financing constraints for their R&D projects. (Hottenrott, H., and Peters, B., 2012) shows that the size of the firm is positively associated with innovation.

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use an OLS estimator in that case and not a TSLS estimator because the instrumental variable exploits between industries variation in the fuel price. Therefore, we acknowledge that the sector level coefficient is probably a lower bound of what the true effect is.[26]

The results on CO_2 emissions are displayed in Figure and the results on the number of workers are displayed in Figure 6.[27] We find that there are large differences between industries. More specifically, 58% of the sectors experience a reduction in CO_2, 25% reduce employment, 38% reduce CO_2 but not employment, and 0% reduce employment but not CO_2 emissions in response to higher energy price. The largest reduction in CO_2 emissions occurs in beverages, wearing apparel, and furniture with respectively 11.7%, 6.2% and 5.9%.[28] The largest reduction in employment occurs in basic metals, wood products, and textiles with respectively 0.76%, 0.74% and 0.59%. These magnitudes are in line with our main results when using the OLS estimator as shown in Table . Table reports the detailed coefficient along with the average energy intensity in the sector. The effect on workers is more negative for firms operating in energy intensive sector.[29]

[26] We expect the OLS estimator to be biased upward as unobserved firm efficiency or management capacity are negatively correlated with employment and $Cost_{it}$. An efficient firm produces the same quantity of output with fewer workers and will manage to bargain better fuel prices.

[27] Detailed results are available in Table .

[28] Surprisingly, we observe an increase in CO2 emission for "Other transport" as a result of an increase in energy price. Potentially, this is because we limited our measure of energy price to select energy sources. Increases in prices for these fuels may have effects on the demand for other fuels depending on their substitutability, which then may increase demand for "other transport" that uses this fuel. We reserve the analysis of this issue to future research.

[29] However, the regression results of model (2) show that the interaction with energy intensity is not statistically significant.

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TABLE 7: HETEROGENEOUS ENERGY PRICE EFFECT ON ENVIRONMENTAL PERFORMANCE AND ECONOMIC PERFORMANCE.

	Energy use	Electricity use	Fossil fuel use	CO_2 emissions	Workers	Real output	Investment
ln(avg. energy cost)	-0.149	0.321	-0.165	-0.569**	-0.313***	0.047	0.062
	(0.217)	(0.225)	(0.309)	(0.255)	(0.100)	(0.142)	(0.472)
ln(avg. energy cost) x SME (0/1)	-0.008	0.030	0.030	-0.049	0.266***	0.210***	0.334***
	(0.061)	(0.063)	(0.080)	(0.069)	(0.039)	(0.051)	(0.115)
ln(avg. energy cost) x energy use / worker	-0.125***	-0.137***	-0.120***	-0.094**	0.012	-0.026	-0.095
	(0.034)	(0.036)	(0.045)	(0.039)	(0.017)	(0.022)	(0.063)
Firm age in years	-0.021***	-0.028***	-0.012	-0.016*	-0.026***	-0.028***	0.002
	(0.008)	(0.008)	(0.011)	(0.008)	(0.004)	(0.006)	(0.017)
ETS (0/1)	0.153***	0.090**	0.211***	0.182***	0.098***	0.137***	0.085
	(0.039)	(0.037)	(0.066)	(0.047)	(0.022)	(0.031)	(0.091)
Firm FE	X	X	X	X	X	X	X
Industry x Year dummies	X	X	X	X	X	X	X
Observations	21,018	21,015	19,696	21,018	21,018	21,018	17,292
Number of firms	3,640	3,640	3,420	3,640	3,640	3,640	3,376
KP LM statistic	181	181	161	181	181	181	133

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Robust standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are logged. All columns are estimated with the TSLS estimator. Average energy cost equals the log of the ratio between energy expenditure and energy use. The SME dummy equals 1 when the pre-sample number of workers of the firms is lower than 250. Energy use per worker is logged and corresponds to a pre-sample value to avoid endogeneity issues. The instrumental variables for the average energy cost and the interactions terms are the Fixed Weight energy price Index (FEPI), the FEPI interacted with the SME dummy, and the FEPI interacted with the energy use per worker ratio. The first-stage regressions are reported in Table . Regressors are lagged one period. Energy use is the sum of electricity, natural gas, heating oil, and butane propane consumption. CO_2 emissions are emissions from energy consumption. Table shows the summary statistics for the estimation sample.

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Table 8: Heterogeneous energy price effects on energy intensity and input substitution

	Real energy intensity	Energy use per worker	Energy use per material	Energy use per capital	Electricity / fossil fuel
ln(avg. energy cost)	-0.197	0.164	-0.012	-0.045	0.44
	(0.229)	(0.208)	(0.290)	(0.245)	(0.285)
ln(avg. energy cost) x SME (0/1)	-0.218***	-0.275***	-0.229***	-0.285***	0.011
	(0.063)	(0.054)	(0.099)	(0.070)	(0.070)
ln(avg. energy cost) x energy use / worker	-0.099***	-0.137***	-0.181***	-0.085**	-0.014
	(0.034)	(0.032)	(0.046)	(0.038)	(0.043)
Firm age in years	0.007	0.005	0.007	0.003	-0.012
	(0.008)	(0.007)	(0.010)	(0.009)	(0.010)
ETS (0/1)	0.016	0.055	0.122	0.029	-0.116*
	(0.042)	(0.038)	(0.085)	(0.051)	(0.060)
Firm FE	X	X	X	X	X
Industry x Year dummies	X	X	X	X	X
Observations	21,018	21,018	21,018	21,018	19,693
Number of firms	3,640	3,640	3,640	3,640	3,420
KP LM statistic	181	181	181	181	161

Robust standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are logged. All columns are estimated with the TSLS estimator. Average energy cost equals the log of the ratio between energy expenditure and energy use. The SME dummy equals 1 when the pre-sample number of workers of the firms is lower than 250. Energy use per worker is logged and corresponds to a pre-sample value to avoid endogeneity issues. The instrumental variables for the average energy cost and the interactions terms are the Fixed Weight energy price Index (FEPI), the FEPI interacted with the SME dummy, and the FEPI interacted with the energy use per worker ratio. The first-stage regressions are reported in Table .1. Regressors are lagged one period. Energy use is the sum of electricity, natural gas, heating oil, and butane propane consumption. CO_2 emissions are emissions from energy consumption. Table shows the summary statistics for the estimation sample.

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Table 9: Innovation output and energy price index

	Stock of patents
FEPI	1.079***
	(0.414)
FEPI x SME (0/1)	-0.760***
	(0.262)
Firm age in years	0.005
	(0.023)
ETS (0/1)	-0.169
	(0.153)
Firm FE	X
Industry x Year dummies	X
Observations	9,094
Number of firms	1,611
Marginal effect of SME	0.319
	(0.392)

Robust standard errors clustered at the firm level. * p < 0.10, ** p < 0.05, *** p < 0.01. The stock of patents is logged. The model is estimated via OLS. FEPI is the fixed weight energy price index.

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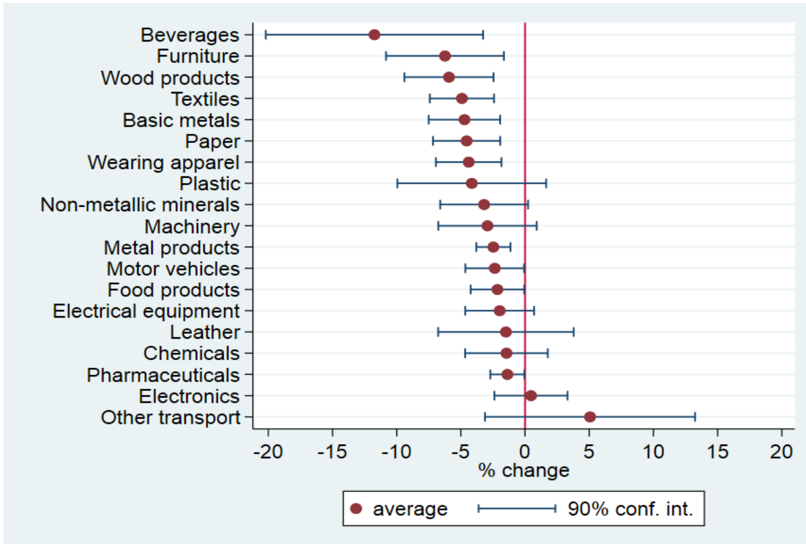
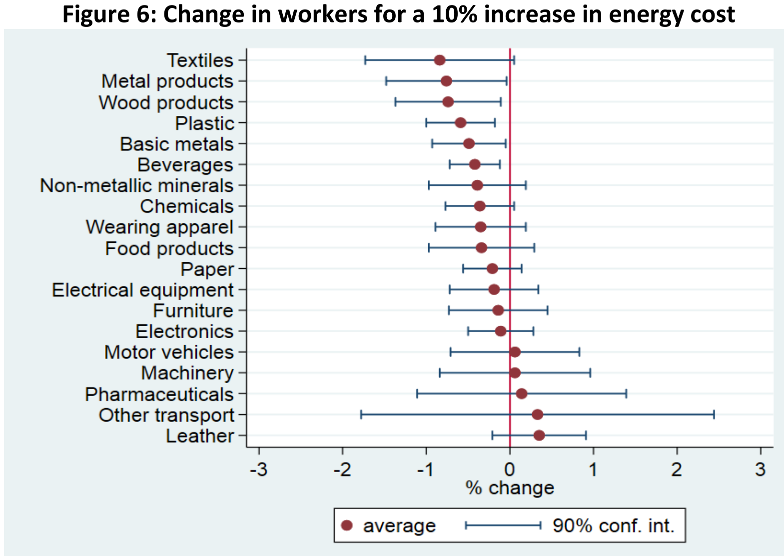
FIGURE 5: CHANGE IN CO_2 EMISSIONS FOR A 10% INCREASE IN ENERGY COST



Note: These confidence intervals are estimated via separate OLS regression.

Figure 6: Change in workers for a 10% increase in energy cost



Note: These confidence intervals are estimated via separate OLS regression.

2.3.3. Simulating the impact of increasing carbon tax

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement number 727524.

In this section, we simulate the impact of a carbon tax increase on firms CO_2 emissions and employment. The carbon tax was introduced in France in 2014 at 7 € per ton of CO_2.

Table shows the evolution of the legislation. Since its introduction, the carbon tax has dramatically increased to reach 44.6 € per ton of CO_2 in 2018. Because fuels have a different emission factor, the tax on CO_2 translates into different fuel specific carbon taxes. For instance, the 2022 carbon tax equals 208 € / toe for natural gas, 315 € / toe for domestic heating oil, and 259 € / toe for butane/propane.

Table 10: The evolution of the French carbon tax

	Carbon tax (€ / ton of CO_2)	Natural gas (€ / MWh)	Heating oil (€ / hectolitre)	Butane propane (€ / 100 kg)
2014	7	1.41		
2015	14.5	2.93		
2016	22	4.64		
2017	30.5	5.88		
2018	44.6	8.45	15.62	15.90
2019	55	10.34	18.38	19.01
2020	65.4	12.24	21.14	22.11
2021	75.8	14.13	23.89	25.22
2022	86.2	16.02	26.65	28.32

Source: the data for the years before 2018 come from article 266 quinquies B of the French customs law. The data from 2018 comes from the first part of the 2018 Finance Bill adopted by the French Parliament on October 24th 2017. There may be changes for 2019 that this paper does not account for.

We consider a scenario where the carbon tax increases from its 2018 rate of 44.6 € per ton of CO_2 to its 2022 rate of 86.2 € per ton of CO_2 as planned by the 2018 Finance Bill adopted by the French Parliament on 24th of October 2017. First, we use firm-level data of 2011-2015 to compute the change in average energy cost due to the tax increase.[30] As ETS firms are exempted from the carbon tax, we attribute them a 0% change in energy cost. Second, we map the average energy cost change into emissions reduction and employment reduction using our sector specific elasticities estimates reported in Table .

[30] We take the last year available for each firm.

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Table 1 shows the results for 19 different sectors in our estimation sample composed of 3,346 firms. Under the finance bill scenario, the average energy cost rises by 4.9% on average. Unsurprisingly, there is substantial heterogeneity across industries. The increase in energy cost is at least equal to 6% for other transport, chemicals, textiles, and wearing apparel whereas it is not above 3% for wood products, plastics, and electronics. The average firm reduces its emissions by 22 tons of CO_2 and its employment by 0.1 full time equivalent (FTE). The largest emissions declines are over 153 tons of CO_2 and take place in the basic metal sector. The largest average loss in employment per firm, 0.8 FTE, occurs in the basic metals sector. Note that these industry-specific simple averages are driven by large firms that are over-represented in our sample.[31] Consequently, the averages tend to overestimate the reduction in emissions and employment.

To solve this, we provide an order of magnitude of the effect at the manufacturing sector level. To do that, we need to assume that the small firms in our sample are representative of their industries. We use data on the number of firms and the number of employees for the universe of French firms provided by Insee. To obtain the total reduction of emissions, we multiply the sector-specific marginal effects reported in

[31] Because they are sample more regularly in the EACEI survey.

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Table 1 by the total number of firms operating in these industries.[32] For each industry, we compute the average percentage of employment loss using the energy cost increase on the 2011-2015 data and the employment elasticity of Table A.10. We multiply the industry specific percentage loss with the firm actual number of employees. These firm level losses are then summed to estimate the total loss in the 19 industries. The results are reported in Table 2.

We find that increasing the carbon tax on natural gas from 44.6 € to 86.2 € per ton reduces CO_2 emissions by 3.9 million tons and gross employment by 3,281 FTE representing respectively 5.5% of total emissions and 0.12% of the workforce of the 19 industries covered. Note that these figures are only orders of magnitude and not accurate estimates. General equilibrium effects are not modelled in this microeconometric model so we do not know whether an energy price increase is not associated with net job creation/destruction. It is also crucial to note that these figures are for surviving firms only and do not account for entry of new firms in the market due to the energy price increase.[33]

Why would a 100% increase in the carbon tax have such a small effect on total CO_2 emissions and employment? Mainly because ETS firms are exempted from the tax.

[32] The number of firms and the number of employees of all French firms are provided by Insee.

[33] Therefore, we are only able to estimate gross loss in employment and not net loss in employment.

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Table 1 shows that the sectors that consume the most fossil fuels (Chemicals, Basic chemicals, non-metallic minerals) are covered by the EU ETS. About 60-80% of the total fossil fuel consumption by these sectors are consumed by EU-ETS firms. On top of that, only 36% of the typical firm's total energy use is composed of fossil fuel.[34]

34 The remaining 60% of energy use come from power (which is mostly from nuclear power plants).

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Table 1: Carbon tax increase on emissions and employment for firms in our sample

Sector code	Sector label	Number of firms	SME (%)	ETS (%)	Fossil fuel (% of energy use)	% increase in energy cost	ETS fossil fuel use (% total sector)	Fossil fuel consumption (ktoe)	CO_2 emissions reduction		Employment	
									(t CO_2 / firm)	(%)	(fte per firm)	(%)
10	Food products	283	84	1.4	35	4.9	28.6	147	0.0	0.0	0.0	0.0
11	Beverages	39	74	5.1	33	3.9	28.6	14	86.8	4.3	0.0	0.0
13	Textiles	126	86	0.8	43	6.2	4.2	44	45.8	2.7	0.4	0.3
14	Wearing apparel	21	76	0.0	46	6.1	0.0	2	21.1	3.6	0.0	0.0
15	Leather	29	79	0.0	41	4.9	0.0	2	0.0	0.0	0.0	0.0
16	Wood products	151	97	3.3	19	2.3	71.4	46	11.8	1.1	0.2	0.2
17	Paper	248	89	9.7	39	4.6	77.2	275	37.3	1.9	0.0	0.0
20	Chemicals	256	85	2.7	46	7.2	80.0	1,074	0.0	0.0	0.0	0.0
21	Pharmaceuticals	63	67	4.8	44	5.9	58.3	90	0.0	0.0	0.0	0.0
22	Plastic	406	87	0.7	21	2.9	38.1	76	7.6	0.7	0.2	0.1
23	Non-metallic minerals	278	90	8.6	45	5.8	80.2	569	38.5	1.3	0.0	0.0
24	Basic metals	184	68	8.2	41	5.6	66.2	607	153.7	2.4	0.8	0.4
25	Metal products	616	88	0.5	36	4.9	21.4	192	9.5	0.7	0.3	0.2
26	Electronics	36	69	0.0	19	2.5	0.0	6	0.0	0.0	0.0	0.0
27	Electrical equipment	156	64	1.3	38	5.0	8.3	57	0.0	0.0	0.0	0.0
28	Machinery	207	63	1.4	46	6.4	8.2	72	15.7	1.3	0.0	0.0
29	Motor vehicles	166	58	0.6	31	4.1	2.4	56	0.0	0.0	0.0	0.0
30	Other transport	19	58	0.0	58	8.3	0.0	19	0.0	0.0	0.0	0.0

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31	Furniture	62	79	0.0	40	5.8	0.0	11	26.7	3.2	0.0	0.0
	Weighted average	3,346	82	2.9	36	4.9	39.0	256	22.0	0.9	0.1	0.1

The quantities reported in this table are estimated using the coefficients reported in Table and firms specific simulated increase in average energy cost due to the carbon tax increase. In this table, the effects for the sectors where the coefficient is not statistically are set to zero but they are available upon request. In this scenario, the carbon tax increases from 44.6 € per ton of CO_2 to its 2022 rate of 86.2 € per ton of CO_2.

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Table 2: Extrapolated effect of a carbon tax increase on CO_2 emissions and employment

Sector code	Sector label	Number of firms	Number of employees	Employment loss (1,000 FTE)	Reduction in emissions (kt CO_2)
10	Food products	58,889	580,966	1,034	1,349
11	Beverages	3,454	41,969	132	300
13	Textiles	6,273	48,589	210	288
14	Wearing apparel	16,426	53,371	137	347
15	Leather	2,833	29,199	-32	15
16	Wood products	11,667	78,516	167	138
17	Paper	1,867	63,711	27	70
20	Chemicals	3,470	151,196	213	144
21	Pharmaceuticals	471	79,130	-26	-3
22	Plastic	4,521	166,367	239	35
23	Non-metallic minerals	10,469	115,288	306	403
24	Basic metals	1,241	77,367	312	191
25	Metal products	22,758	327,799	834	217
26	Electronics	3,658	135,422	42	13
27	Electrical equipment	2,911	125,803	198	69
28	Machinery	6,388	184,060	-343	101
29	Motor vehicles	2,234	216,577	-53	50
30	Other transport	1,261	137,314	-164	-169
31	Furniture	13,936	55,713	48	372
	Total	174,727	2,668,357	3,281	3,927

The quantities reported in this table are extrapolated based on Table and the employment structure of the French manufacturing sector. Note that all quantities reported are total and not average. Sectors with coefficient that are not statistically significant are included in the calculation.

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2.4. Conclusion

This study provides new evidence on the effect of energy price changes on firm-level environmental and economic performance using a unique dataset utilizing micro-level information from French manufacturing firms. Our study relies heavily on the variation from our fixed-weight price index, which we believe appropriately deals with the endogeneity issues inherent in using average prices.

At the aggregate level, we find that energy intensity has significantly decreased between 2001 and 2013 essentially through changes at the firm-level and not market share reallocation towards energy efficient firms. The decrease in overall energy intensity is consistent with the increase in the energy price during our period of observation. Our estimation procedure reveals that in general, the changes in price has no effect on aggregate energy intensity. Nonetheless, we find that increased energy prices are negatively associated with aggregate energy intensity for the period 2007-2015 period.

In addition, our results at the micro-level highlight that while there is a trade-off between environmental and economic outcomes due to changing prices, the reduction in emission is significantly higher. Only large firms, 250 employees or more, experience a loss in employment. In contrast with large firms, SMEs do not reduce employment in responses to higher price because they substitute energy for labor with greater magnitude. We measure the size of emissions reductions and employment loss by simulating the effect of a planned increase in the French carbon tax. We find that, on average, total emissions would reduce by about 5%, which is substantially greater than the 0.12% gross employment loss. However, the impact of the carbon tax is limited given that EU-ETS firms are exempted.

Our results provide some evidence that an increase in the energy price modifies the technology produced and used by the firms. Large firms innovate more while all firms invest more in end of pipe pollution abatement technologies presumably because energy efficient abatement equipment are more expensive. However, we cannot test whether this spur in investment leads to lower air, water, and waste pollution due to missing data on these pollutants emission.

The results of the study, while informative, warrant future research to draw more meaningful policy implications. First, because there is no output data at the plant level we do not analyze the potentially important role of between plants reallocation of production in explaining within-firm variation in energy intensity. Even if the employment effect is small at the firm-level, reallocation of production and workers between firms is

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not without cost or redistributive consequences. Second, the absence of data on output quantity prevents us from analyzing the effect of the energy price on total factor productivity and output prices. Third, sufficient data on emissions of other pollutants will be necessary to understand the net effect of energy taxation on total pollution, particularly when co-benefits (or spillovers) are occurring simultaneously with changes in energy prices.

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2.6. Appendices

2.6.1. Testing for weak instruments

The consistency of the above estimations lies on the strength of our instrumental variable. The estimated Kleibergeen Paap statistic is statistically different from zero in all regressions.[35] Thus, we reject the null hypothesis that FEPI is a weak instrumental variable. Table shows the first-stage estimation results. For the first stage estimation of model (9), the coefficient of FEPI equals 0.598 and is statistically different from 0 at the 1% level. In addition, the F-statistic equals 107 which is way above 10 that is the usual threshold used. Similarly, the instrumental variables for the estimation of model (10) are strong.

TABLE A.1: FIRST-STAGE REGRESSIONS

	Model (9)	Model (10)		
	ln(avg. energy cost)	ln(avg. energy cost)	ln(avg. energy cost) x SME (0/1)	ln(avg. energy cost) x energy use / worker
$FEPI$	0.598***	0.486***	-0.322***	-0.522***
	(0.031)	(0.040)	(0.036)	(0.077)
$FEPI \times SME\ (0/1)$		-0.078***	0.907***	-0.114***
		(0.015)	(0.011)	(0.033)
$FEPI \times energy\ use\ /\ worker$		0.065***	0.050***	0.983***
		(0.008)	(0.008)	(0.024)
$Firm\ age\ in\ years$	0.001	-0.002	-0.001	-0.003
	(0.002)	(0.002)	(0.002)	(0.003)
$ETS\ (0/1)$	0.070***	0.005	-0.006	0.100**
	(0.013)	(0.014)	(0.011)	(0.049)
Firm FE	X	X	X	X
Industry x Year dummies	X	X	X	X
Observations	32,132	21,018	21,018	21,018
Number of firms	6,346	3,640	3,640	3,640
F-statistic	107	74	1,250	316

35 The Kleibergeen Paap statistic is a version of the first stage F-statistic that is robust to heteroskedasticity.

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Robust standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table shows the summary statistics for the estimation sample. $FEPI$ is the fixed-weight average energy price.

2.6.2. Supplementary Tables and Figures

Table A.2: Summary statistics for the firm-level sample

Variable	Obs.	Mean	Std. Dev.	Min	Max
Family patent stock	9,536	-0.04	1.95	-6.49	7.00
Energy use	34,439	5.69	1.96	-2.17	13.73
Electricity use	34,434	5.05	1.89	-2.38	11.58
Fossil fuel use	30,797	4.82	2.15	-4.26	13.66
CO_2 emissions	34,439	12.91	2.12	4.48	21.60
Workers	34,439	4.75	1.03	1.95	10.18
Real output	34,439	9.90	1.28	5.99	15.41
Investment	28,068	6.04	1.75	-0.38	12.94
Real energy intensity	34,439	-4.21	1.33	-11.22	1.63
Energy use per worker	34,439	0.94	1.44	-6.21	7.55
Energy use per material	34,439	-3.11	1.55	-10.53	8.71
Energy use per capital	34,439	-3.08	1.33	-10.10	4.10
Electricity / fossil	30,792	0.35	1.38	-5.19	9.02
Average energy cost	34,439	-0.46	0.34	-5.96	5.84
Firm age in years	34,439	2.54	2.67	0.00	11.40
ETS (0/1)	34,439	0.02	0.13	0.00	1.00
Energy price index	34,439	-0.45	0.29	-1.53	0.34
SME (0/1)	34,439	0.80	0.40	0.00	1.00
Year	34,439	2,008.49	4.05	2,001.00	2,015.00

The unit of observation is the firm. All variables are logged except plant age and the ETS dummy.

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Table A.3: Summary statistics for the plant-level sample

Variable	Obs.	Mean	Std. Dev.	Min	Max
Investment to reduce all kind of pollution	18,167	3.57	1.71	-2.34	10.28
Investment to reduce water pollution	18,167	2.47	1.90	-4.30	9.83
Investment to reduce air pollution	14,524	2.50	1.99	-4.43	9.38
Investment to reduce waste pollution	16,986	1.95	1.68	-5.23	9.33
Investment to reduce soil pollution	15,223	1.94	1.95	-4.70	9.54
CO_2 emissions	12,947	14.21	1.89	5.89	21.28
FEPI	18,167	-0.59	0.30	-1.73	0.25
Plant age in years	18,167	30.38	35.85	0	114
ETS (0/1)	18,167	0.05	0.21	0	1

The unit of observation is the plant. All variables are logged except plant age and the ETS dummy.

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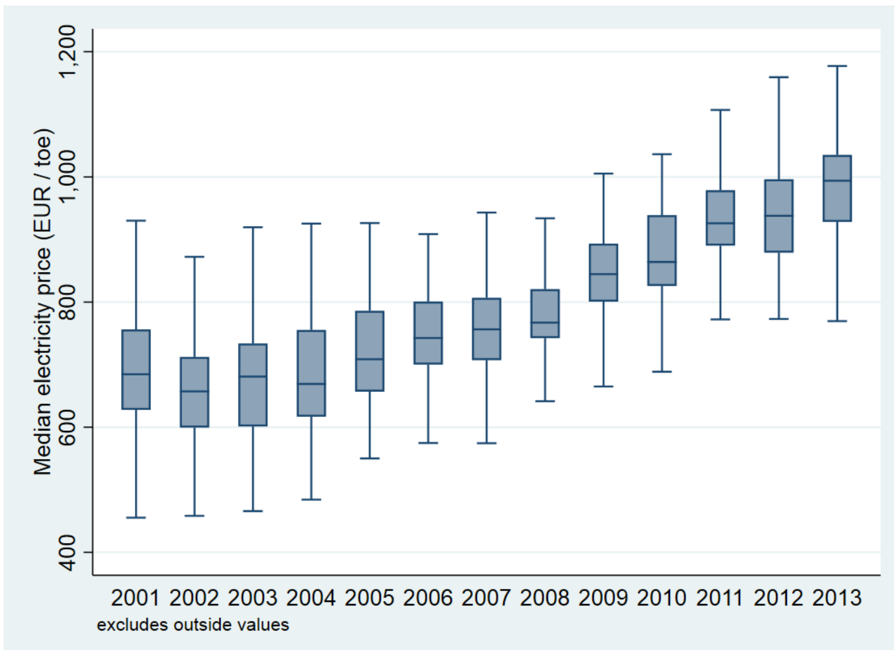
FIGURE A.1: DISTRIBUTION OF MEDIAN ELECTRICITY PRICE OVER TIME



Note: median computed for each 3-digit industry.

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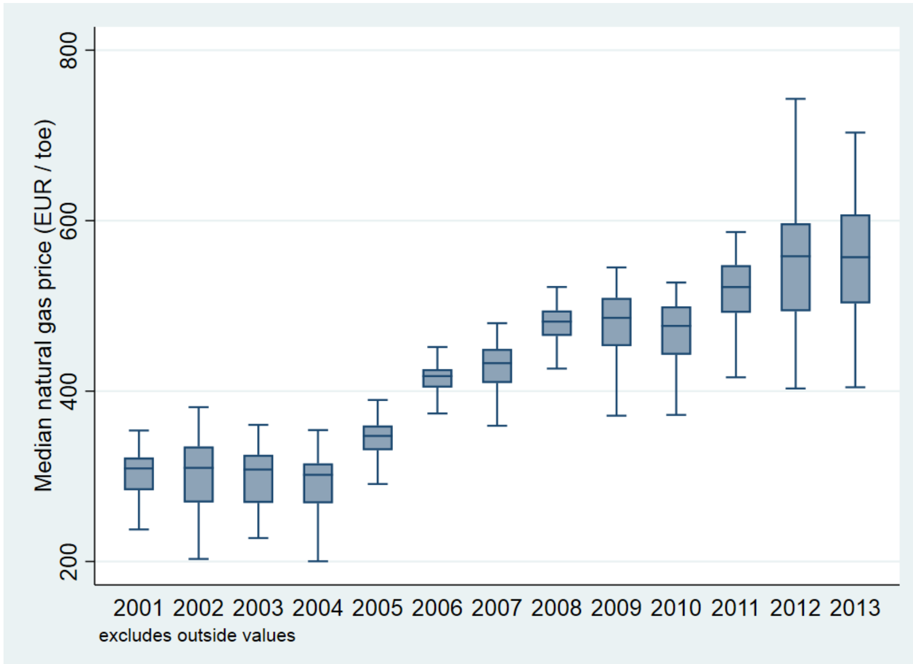
FIGURE A.2: DISTRIBUTION OF MEDIAN NATURAL GAS PRICE OVER TIME



Note: median computed for each 3-digit industry.

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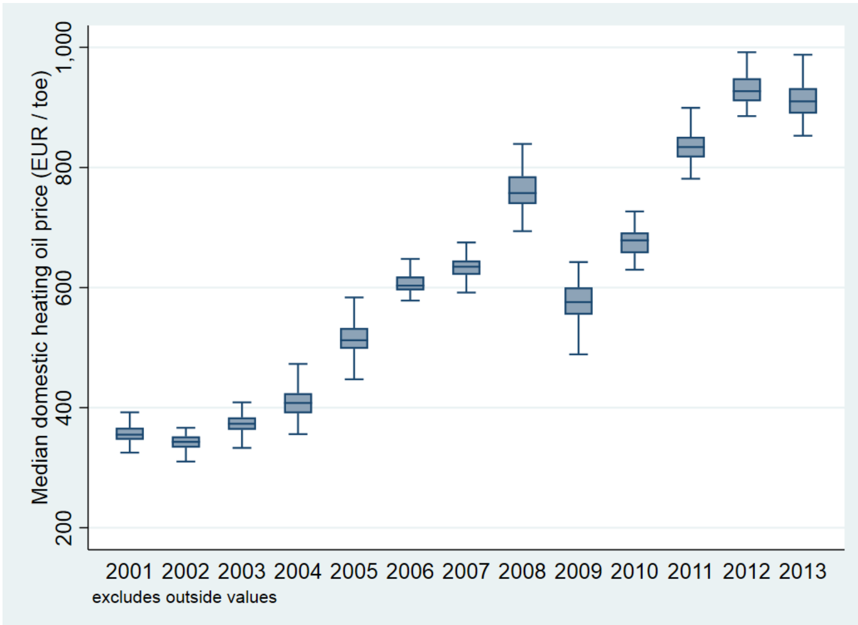
FIGURE A.3: DISTRIBUTION OF MEDIAN HEATING OIL PRICE OVER TIME



Note: median computed for each 3-digit industry.

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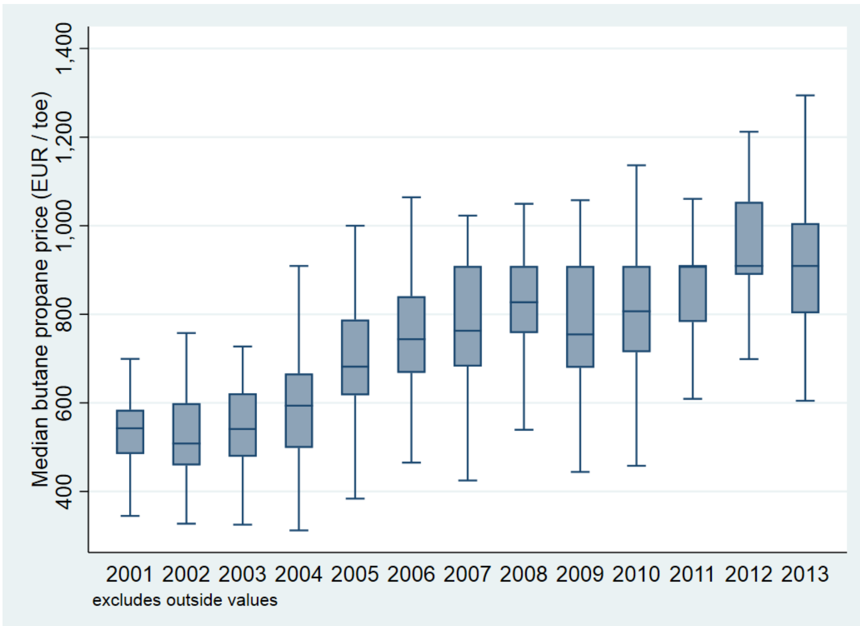
FIGURE A.4: DISTRIBUTION OF MEDIAN BUTANE PROPANE PRICE OVER TIME



Note: median computed for each 3-digit industry.

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TABLE A.4: WITHIN SECTOR VARIATION IN FUEL PRICES

Sector code	Sector label	Electricity			Natural gas			Heating oil			Butane propane		
		Mean	Std. Dev.	CV (%)	Mean	Std. Dev.	CV (%)	Mean	Std. Dev.	CV (%)	Mean	Std. Dev.	CV (%)
10	Food products	999	193	19%	529	139	26%	748	266	36%	738	401	54%
11	Beverages	1,061	165	16%	558	109	20%	807	309	38%	787	316	40%
13	Textiles	1,090	290	27%	602	254	42%	744	212	28%	946	308	33%
14	Wearing apparel	1,290	648	50%	679	279	41%	843	321	38%	993	419	42%
15	Leather	1,264	245	19%	1,007	2,092	208%	714	157	22%	1,187	619	52%
16	Wood products	1,324	1,779	134%	681	300	44%	751	193	26%	961	590	61%
17	Paper	1,074	252	23%	530	157	30%	761	198	26%	1,023	512	50%
20	Chemicals	1,077	245	23%	567	405	71%	783	308	39%	925	451	49%
21	Pharmaceuticals	943	120	13%	503	93	18%	803	234	29%	1,291	513	40%
22	Plastic	1,039	198	19%	666	549	82%	787	321	41%	1,024	613	60%
23	Non-metallic minerals	1,124	286	25%	555	219	39%	753	186	25%	948	531	56%
24	Basic metals	1,031	235	23%	498	139	28%	801	203	25%	935	482	52%
25	Metal products	1,120	269	24%	589	169	29%	752	174	23%	908	408	45%
26	Electronics	1,081	221	20%	648	216	33%	753	229	30%	977	630	64%
27	Electrical equipment	1,105	206	19%	654	663	101%	788	271	34%	990	519	52%
28	Machinery	1,119	208	19%	592	177	30%	771	211	27%	1,124	539	48%
29	Motor vehicles	1,018	213	21%	564	125	22%	787	242	31%	860	380	44%
30	Other transport	1,105	267	24%	586	168	29%	811	286	35%	1,178	486	41%
31	Furniture	1,224	365	30%	697	778	112%	686	137	20%	928	455	49%

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Mean of all sectors	1,110	337	29%	616	370	53%	771	235	30%	985	483	49%

Author's calculation based on the year 2015. All values are expressed in euros per ton of oil equivalent.

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Table A.5: Distribution of the median price at the 3-digits industry level

Fuel	Obs.	Mean	Std. Dev.	p10	p90	CV (%)	Increase (%)
Electricity	856	793	142	619	985	18	44
Natural gas	856	414	106	282	554	26	85
Heating oil	856	613	222	348	917	36	156
Butane propane	856	739	211	480	930	29	70

Table A.6: First-stage regressions

	Model (9)	Model (10)		
	ln(avg. energy cost)	ln(avg. energy cost)	ln(avg. energy cost) x SME (0/1)	ln(avg. energy cost) x energy use / worker
$FEPI$	0.598***	0.486***	-0.322***	-0.522***
	(0.031)	(0.040)	(0.036)	(0.077)
$FEPI \times SME\ (0/1)$		-0.078***	0.907***	-0.114***
		(0.015)	(0.011)	(0.033)
$FEPI \times energy\ use\ /\ worker$		0.065***	0.050***	0.983***
		(0.008)	(0.008)	(0.024)
$Firm\ age\ in\ years$	0.001	-0.002	-0.001	-0.003
	(0.002)	(0.002)	(0.002)	(0.003)
$ETS\ (0/1)$	0.070***	0.005	-0.006	0.100**
	(0.013)	(0.014)	(0.011)	(0.049)
Firm FE	X	X	X	X
Industry x Year dummies	X	X	X	X
Observations	32,132	21,018	21,018	21,018
Number of firms	6,346	3,640	3,640	3,640
F-statistic	107	74	1,250	316

Robust standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table shows the summary statistics for the estimation sample. $FEPI$ is the fixed-weight average energy price.

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TABLE A.7: HETEROGENEOUS ENERGY PRICE EFFECT ON ENVIRONMENTAL PERFORMANCE AND ECONOMIC PERFORMANCE

	Energy use	Electricity use	Fossil fuel use	CO_2 emissions	Workers	Real output	Investment
ln(avg. energy cost)	-0.415***	-0.105	-0.463**	-0.645***	-0.430***	-0.430***	-0.517**
	(0.123)	(0.123)	(0.182)	(0.146)	(0.059)	(0.077)	(0.260)
ln(avg. energy cost) x SME (0/1)	0.079	0.118**	0.075	0.036	0.307***	0.249***	0.410***
	(0.056)	(0.059)	(0.076)	(0.062)	(0.035)	(0.046)	(0.106)
Firm age in years	-0.022***	-0.032***	-0.014	-0.016**	-0.033***	-0.037***	-0.001
	(0.007)	(0.007)	(0.010)	(0.008)	(0.004)	(0.005)	(0.015)
ETS (0/1)	0.056	-0.008	0.120*	0.103**	0.094***	0.128***	0.023
	(0.039)	(0.033)	(0.070)	(0.048)	(0.020)	(0.028)	(0.087)
Firm FE	X	X	X	X	X	X	X
Industry x Year dummies	X	X	X	X	X	X	X
Observations	32,138	32,131	28,730	32,138	32,138	32,138	25,600
Number of firms	6,347	6,345	5,618	6,347	6,347	6,347	5,601
KP LM statistic	372	371	321	372	372	372	292

Robust standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are logged. All columns are estimated with the TSLS estimator. Average energy cost equals the log of the ratio between energy expenditure and energy use. The SME dummy equals 1 when the pre-sample number of workers of the firms is lower than 250. The instrumental variables for the average energy cost and the interactions terms are the Fixed Weight energy price Index (FEPI) and the FEPI interacted with the SME dummy. The first-stage regressions are available upon request. Regressors are lagged one period. Energy use is the sum of electricity, natural gas, heating oil, and

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butane propane consumption. CO_2 emissions are emissions from energy consumption. Table shows the summary statistics for the estimation sample.

TABLE A.8: ENERGY PRICE EFFECT ON ENVIRONMENTAL PERFORMANCE AND ECONOMIC PERFORMANCE WHEN THE EMPLOYMENT THRESHOLD IS 90%

	Environmental performance				Economic performance		
	Energy use	Electricity use	Fossil fuel use	CO_2 emissions	Workers	Real output	Investment
ln(avg. energy cost)	-0.500***	-0.024	-0.436*	-0.884***	-0.122*	-0.141	-0.389
	(0.154)	(0.146)	(0.232)	(0.189)	(0.064)	(0.087)	(0.329)
Firm age in years	-0.025***	-0.036***	-0.023**	-0.021***	-0.029***	-0.030***	-0.001
	(0.007)	(0.007)	(0.011)	(0.008)	(0.004)	(0.005)	(0.017)
ETS (0/1)	0.047	-0.035	0.087	0.100*	0.057**	0.130***	0.058
	(0.044)	(0.040)	(0.072)	(0.054)	(0.023)	(0.032)	(0.093)
Firm FE	X	X	X	X	X	X	X
Industry x Year dummies	X	X	X	X	X	X	X
Observations	24,020	24,014	21,592	24,020	24,020	24,020	19,391
Number of firms	5,124	5,122	4,552	5,124	5,124	5,124	4,520
KP LM statistic	264	263	226	264	264	264	203

Robust standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are logged. All columns are estimated with the TSLS estimator. Average energy cost equals the log of the ratio between energy expenditure and energy use. The instrumental variable for average energy cost is the Fixed Weight energy price Index. The first-stage regressions are available upon request.

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Regressors are lagged one period. Energy use is the sum of electricity, natural gas, heating oil, and butane propane consumption. CO_2 emissions are emissions from energy consumption. Table shows the summary statistics for the estimation sample.

TABLE A.9: ENERGY PRICE EFFECT ON ENVIRONMENTAL PERFORMANCE AND ECONOMIC PERFORMANCE WHEN THE EMPLOYMENT THRESHOLD IS 80%

	Environmental performance				Economic performance		
	Energy use	Electricity use	Fossil fuel use	CO_2 emissions	Workers	Real output	Investment
ln(avg. energy cost)	-0.530***	-0.081	-0.625***	-0.897***	-0.164***	-0.01	-0.138
	(0.135)	(0.133)	(0.196)	(0.162)	(0.058)	(0.077)	(0.270)
Firm age in years	-0.025***	-0.033***	-0.018**	-0.019***	-0.031***	-0.032***	-0.01
	(0.006)	(0.007)	(0.009)	(0.007)	(0.004)	(0.004)	(0.014)
ETS (0/1)	0.058	-0.013	0.129**	0.114**	0.078***	0.102***	0.025
	-0.038	(0.035)	(0.065)	(0.046)	(0.021)	(0.028)	(0.084)
Firm FE	X	X	X	X	X	X	X
Industry x Year dummies	X	X	X	X	X	X	X
Observations	36,408	36,399	32,406	36,408	36,408	36,408	28,889
Number of firms	6,918	6,915	6,097	6,918	6,918	6,918	6,128
KP LM statistic	342	341	292	342	342	342	270

Robust standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are logged. All columns are estimated with the TSLS estimator. Average energy cost equals the log of the ratio between energy expenditure and energy use. The instrumental variable for average energy cost is the Fixed Weight energy price Index. The first-stage regressions are available upon request. Regressors are lagged one period. Energy use is the sum of electricity, natural gas, heating oil, and butane propane consumption. CO_2 emissions

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are emissions from energy consumption. Table shows the summary statistics for the estimation sample.

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TABLE A.10: CO_2 EMISSIONS AND WORKERS ELASTICITIES BY SECTOR

Sector code	Sector label	Number of firms	Energy use / worker (ktoe)	SME (%)	Energy as % of turnover	CO_2 emissions		Workers	
						Coeff.	Std. Err.	Coeff.	Std. Err.
10	Food products	843	86.5	89%	1.5%	-0.198	0.163	-0.039	0.035
11	Beverages	91	19.1	82%	1.2%	-1.173**	0.514	-0.084	0.054
13	Textiles	234	55.2	85%	2.2%	-0.472***	0.169	-0.059**	0.025
14	Wearing apparel	405	27.1	75%	0.9%	-0.624**	0.279	-0.035	0.033
15	Leather	338	16.4	78%	0.4%	-0.415	0.352	0.033	0.128
16	Wood products	283	32.4	94%	1.7%	-0.492***	0.152	-0.074*	0.038
17	Paper	456	71.2	85%	2.4%	-0.439***	0.155	-0.011	0.024
20	Chemicals	442	50.3	84%	2.9%	-0.145	0.196	-0.021	0.021
21	Pharmaceuticals	67	36.5	68%	1.8%	0.046	0.173	0.006	0.055
22	Plastic	742	54.0	83%	1.5%	-0.247***	0.081	-0.049*	0.027
23	Non-metallic minerals	459	83.0	86%	3.6%	-0.236*	0.139	-0.036	0.025
24	Basic metals	289	117.8	67%	3.1%	-0.455***	0.159	-0.076*	0.044
25	Metal products	1,108	32.9	84%	1.2%	-0.138*	0.081	-0.042**	0.018
26	Electronics	107	16.5	76%	0.7%	-0.149	0.321	-0.014	0.036
27	Electrical equipment	242	24.5	61%	0.7%	-0.293	0.233	-0.034	0.038
28	Machinery	368	20.5	63%	0.7%	-0.215*	0.127	0.035	0.034
29	Motor vehicles	235	42.6	56%	1.1%	-0.319	0.208	0.006	0.047

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30	Other transport	31	25.9	57%	0.8%	0.506	0.497	0.014	0.076
31	Furniture	145	30.5	80%	0.9%	-0.593***	0.211	-0.019	0.032

TABLE A.11: OLS ESTIMATES FOR ENVIRONMENTAL AND ECONOMIC PERFORMANCE

	Environmental performance				Economic performance		
	Energy use	Electricity use	Fossil fuel use	CO_2 emissions	Workers	Real output	Investment
ln(avg. energy cost)	-0.150***	-0.026	-0.288***	-0.269***	-0.033***	-0.042***	-0.067
	(0.041)	(0.034)	(0.065)	(0.052)	(0.008)	(0.010)	(0.043)
Firm age in years	-0.024***	-0.034***	-0.015	-0.019**	-0.030***	-0.033***	0.000
	(0.007)	(0.007)	(0.010)	(0.008)	(0.004)	(0.005)	(0.015)
ETS (0/1)	0.022	-0.023	0.106	0.051	0.060***	0.100***	0.004
	(0.038)	(0.031)	(0.068)	(0.048)	(0.021)	(0.028)	(0.085)
Firm FE	X	X	X	X	X	X	X
Industry x Year dummies	X	X	X	X	X	X	X
Observations	32,132	32,125	28,724	32,132	32,132	32,132	25,595
Number of firms	6,346	6,344	5,617	6,346	6,346	6,346	5,600

Robust standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are logged. All columns are estimated with the OLS estimator. Average energy cost equals the log of the ratio between energy expenditure and energy use. Regressors are lagged one period. Energy use is the sum of electricity, natural gas, heating oil, and butane propane consumption. CO_2 emissions are emissions from energy consumption. Table shows the summary statistics for the estimation sample.

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Table A.12: OLS estimates for energy intensity and input substitution

	Real energy intensity	Energy use per worker	Energy use per material	Energy use per capital	Electricity / fossil fuel
ln(avg. energy cost)	-0.108***	-0.117***	-0.131***	-0.106***	0.267***
	(0.039)	(0.038)	(0.042)	(0.038)	(0.055)
Firm age in years	0.008	0.006	0.006	0.005	-0.013
	(0.007)	(0.006)	(0.008)	(0.008)	(0.009)
ETS (0/1)	-0.078*	-0.038	-0.034	-0.043	-0.125**
	(0.041)	(0.038)	(0.080)	(0.049)	(0.061)
Firm FE	X	X	X	X	X
Industry x Year dummies	X	X	X	X	X
Observations	32,132	32,132	32,132	32,132	28,717
Number of firms	6,346	6,346	6,346	6,346	5,615

Robust standard errors clustered at the firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are logged. All columns are estimated with the OLS estimator. Average energy cost equals the log of the ratio between energy expenditure and energy use. Regressors are lagged one period. Energy use is the sum of electricity, natural gas, heating oil, and butane propane consumption. CO_2 emissions are emissions from energy consumption. Table shows the summary statistics for the estimation sample.

Table A.13: Difference between large firms and SMEs

	Large firms	SMEs	Difference
Average energy cost	-0.64	-0.46	-0.17***
Energy intensity	-3.78	-4.26	0.49***
ETS (%)	4.00	0.94	3.03***
Electricity use / fossil use	0.26	0.34	-0.08***
Energy use per capital	-2.80	-3.08	0.28***
Energy use per material	-2.66	-3.10	0.44***
Energy use per worker	1.48	0.82	0.66***
Real output	11.39	9.47	1.93***
Employees	6.14	4.38	1.76***
Energy use	7.62	5.20	2.42***

Statistics computed on the estimation sample. All variables are logged except ETS.

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3. The impact of costs and prices on collective energy choices and respective CO2 emissions in the German manufacturing sector based on company data

3.1. Introduction

Decreasing CO2 emissions in all nations and economic sectors are indispensable in order to meet the goals of the 2015 Paris Agreement. Achieving this goal requires a shift away from emissions-intensive energy sources and improving the efficiency of energy usage. As such, the IEA (2017) finds that energy efficiency improvements are the main effect that attenuate the growth of global greenhouse gas emissions, counteracting the impact of rising energy demand due to income and population growth. Most governments in the world have introduced measures to reduce their CO2 emissions, often emphasizing the energy sector and manufacturing sector as a starting point. In many developed countries, the manufacturing sector remains a prime contributor to GDP and still accounts for a large share of emissions. In order to meet reduction targets for emissions, energy-efficiency policies promote an optimized energy behavior, endorsing sustainability and energy security while not corrupting economic efficiency. Firms are encouraged to optimize their energy behavior, adopt new technology or utilize fuel-switching possibilities. A current example is the German national action plan for energy efficiency under the slogan "Efficiency first" (Federal Ministry for Economic Affairs and Energy, 2014).

For the purpose of evaluation, emissions pathways of nations - or certain sectors of the economy – are often displayed as aggregated data. However, a detailed study of the channels via which a nation's - or sector's - emissions develop, is of utmost importance for the guidance of well-targeted policies. As such, a nearby explanation for declining emissions would be that agents adopt a more rational use of energy for production, or substitute for less emissions-intensive energy sources. At the same time, a less obvious explanation may be that total emissions mainly decline due to a change in the composition of the economy. A prime example would be a shift of economic activity towards less emissions-intensive sectors. If the output share of an energy intensive industry decreases while a less energy intensive industry's share increases, the total emissions decline, even though not a single production process has been technologically improved. Likewise, another potential key driver are structural changes within industries. As such, it may be the case that relatively emissions-intensive firms lose market shares, that new entrants are more energy-efficient than incumbents, or that the most inefficient firms exit the market. In case the latter explanations play a non-negligible role for emissions reductions on the aggregate level, one would have to question the sole focus of energy efficiency policies on technological improvements for existing firms only. The importance of market entry and exit of firms is highlighted by Linn (2008), who observes that the additional flexibility of entrants regarding new technology explains about a quarter of the observed decline in energy

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intensity of U.S. manufacturing from 1972 to 1982.[36]

Thus, the use of micro-level data is a prime tool to distinguish the channels that determine the development of emissions, such as the individual behavior of firms. Although the existing literature has made use of index decomposition analyses regarding energy usage and CO2 emissions, all studies rely on data that is aggregated at least at the sub-sector or industry level. Therefore, it is not possible to distinguish whether improvements on an industry-level are actually the result of increasing energy efficiency at the firm level, or rather due to the composition of and competition within industries.

Previous studies of emissions decomposition, often using the Logarithmic Mean Divisia Index (LMDI) approach (Ang et al., 1998, Ang and Liu, 2001, Ang, 2015), have either a different regional focus or a limited time period. Parker and Liddle (2016) decompose changes in energy intensity of manufacturing sectors across the OECD over the years 1980-2009. They confirm previous findings in the literature that sectoral energy intensity improvements are the major driver for observed reduction in aggregate energy intensity. In panel regressions analyses, a significant effect is found for rising prices on energy intensity improvements of industries.

Löschel et al. (2015) investigate drivers of a declining energy intensity in the EU27 between 1995-2009 based on the World Input Output Database (WIOD). Both structural change within national economies and changing sectoral energy intensities are found to be equally important drivers. Auxiliary panel regressions show that these effects are largely explained by energy prices, economic growth and capital intensity. Voigt et al. (2014) also use the WIOD to assess changes in energy intensity across 40 countries, both inside and outside the EU27, over the years 1995-2007. Results suggest that country-level reductions are largely attributable to technological change, i.e. energy intensity reductions at the industry level. On a global scale, energy efficiency improved mainly due to the technology effect, while structural change of economic activity was less important in most countries. In a decomposition of Chinese CO2 emissions from 1980 until 2003, Ma and Stern (2008) confirm the role of technological improvement as the main reason for declining energy intensity. Hammond and Norman (2012) find that emissions in the U.K decreased by 2 percent p.a. from 1990 to 2007 due to a reduction in energy intensity. The authors suggest that major drivers for improvements are technological improvements and fuel-switching behavior.

To date and to our best knowledge, there are only two studies that build upon micro-level (firm-level) data to explore the role of compositional changes within industries: The first, Fisher-Vanden et al. (2004) uses panel data on Chinese firms to investigate declining emissions using index decomposition and regression analysis. They find that sectoral energy efficiency improvements account for almost half the change in energy consumption, but do not further split this factor into firm-level improvements vs. firm output shares. The second study by Petrick (2013) is also based on firm-level data for the German manufacturing sector but refers to the historic 1995-2007 period. A main finding is that certain industries, especially some of the most energy intensive ones, did not significantly reduce their energy intensity,

[36] Investigating the link between energy efficiency and energy prices (in the U.S. manufacturing sector between 1967-1997), Linn (2008) finds that entrants are more flexible in adopting more energy efficient technology than incumbents and thus show a significantly larger energy efficiency. However, this difference is relatively small. A 10 percent increases in the energy price is found to reduce the energy intensity of entrants, relative to incumbents, by one percent. In the long run a large price elasticity of firms is found, but entrants only explain a small fraction of this effect.

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but that reductions are rather a result of structural changes within those industries.

An investigation of the more recent development of CO2 emissions in Germany makes sense for several reasons. First, the country is the world's 6th largest emitter of greenhouse gas emissions (Boden et al., 2017, UNFCCC, 2017, BP, 2017) and is often considered as a leading actor in climate policy with ambitious reduction goals and various energy efficiency policies in place. In recent years, the German energy system has seen significant changes: its energy and manufacturing sector are covered by the EU ETS since 2005, where the binding phase II started in 2008. As an overlapping regulation, in 2007 the federal government has set up a voluntary reduction target for territorial emissions of 40% until 2020 (relative to 1990). Moreover, resource and energy prices have seen a historic spike in the early 2000s, while costs for renewable energy technologies have fallen dramatically owing to economies of scale and learning curves. Globally, installations of renewables have seen a dramatic increase worldwide, and especially in Germany the feed-in-tariffs have led to a large penetration of the energy market by renewable power. Meanwhile, the phase-out of nuclear power ("Energiewende") was decided shortly after the Fukushima catastrophe in 2011. Despite ambitious fiscal policy measures, the financial crisis of 2008/09 also affected the German economy, although to a lesser extent than other countries.

In our analysis, we focus on the German manufacturing sector that is directly responsible for about 20% of national emissions (Federal Environment Agency, 2016a). The sector generates a large share of national value added and it shows a high level of diversification between different industries. From 2006 to 2014, the CO2 emissions in the manufacturing sector show a stable trend, which is remarkable given a steady increase of gross output. Our aim is to understand the main drivers of how this decoupling of emissions and economic activity could be achieved. Therefore, we apply index decomposition analysis to firm-level data with information on fuel-specific energy consumption. This allows for an accurate estimate of firm-level CO2 emissions. Another advantage of the dataset is that we can well handle industry heterogeneity.

We conduct a two-step approach, that is closely related to Parker and Liddle (2016) and Löschel et al. (2015). First, we decompose changes in aggregate CO2 emissions of the German manufacturing sector into five main drivers using the Index Decomposition Analysis (IDA). We estimate the contribution that each of these drivers had on the change in aggregate CO2 emissions via the well-established Logarithmic Mean Divisia Index (LMDI) method. Contrary to other approaches, its formula yields a perfect decomposition without a residual term.

Based on the decomposition, we further analyse driving factors across industries and thus distinguish different innovation patterns: Whereas firm-level energy efficiency innovations may be key driver for improvements in some industries, other industries may innovate mostly via changes in market shares and market entry or exit of firms. Further, substitution of energy carriers may be a driving force. The results will shed light on the potential for energy efficiency policies in certain industries.

Further, we apply panel regressions to assess the drivers of the decomposed effects, with a special emphasis on energy prices and energy costs, besides other industry dynamics.

At last, we further investigate the difference in firm-level energy intensity across incumbent firms, newcomer firms and those firms that leave the market. Therein we assess structural differences across small-and-medium enterprises (SME) and large firms.

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The remainder of the analysis is structured as follows. Section 2 describes the dataset and we explain the methodology in Section 3. In Section 4, we present and discuss main results of the decomposition analysis. Section 5 concludes.

3.2. Data

The analysis builds upon the German production census firm-level data AFiD (Amtliche Firmendaten für Deutschland – Official firm data for Germany) provided by the Research Data Centres of the Statistical Offices Germany (2014). The dataset is confidential and, due to its high reliability, has been used in previous studies on the effects of energy policy (e.g. Löschel et al., 2018, Lutz et al., 2017, Petrick, 2013). Our unbalanced panel covers the years 2006-2014 and consists of several modules.

The AFiD-Panel Industrial Units contains annual data from the Production Census, the Monthly Report on Plant Operation and the Investment Census. Participation is mandatory for all German manufacturing plants within firms of more than 20 employees. It provides economic indicators such as the number of employees, wages, gross output, revenue and revenue from exports.

From the AFiD-Module Use of Energy we obtain plant-level data on the consumption, acquisition and sale of electricity and 14 major fuel types. The Module further distinguishes between electricity from the grid and own generation via fossil fuels or renewable energy sources. This way we can calculate the total energy consumption of a plant in each year. Using fuel-specific CO2 emission factors, we can estimate direct CO2 emissions of production at the plant level (see Appendix). We define CO2 intensity (energy intensity) as emissions (energy consumption) per economic activity, which we measure in terms of gross output.[37]

The AFiD-Module Environmental Protection Investments provides the value of investments made for the protection of the environment (Air, Water, Waste, Noise, Landscape, Soil and Noise) and the climate (Energy Efficiency, Greenhouse Gas Mitigation, Renewable Energy).

In addition, the Cost Structure Survey (CSS) provides information on intermediate inputs and respective costs, including the costs for energy usage. All firms with more than 500 employees permanently report to the CSS, whereas only random samples of firms with 20-500 employees are included. The latest random samples in our dataset were drawn in 2008 and 2012. As only a subset of firms in our panel report to the CSS, we include CSS covariates only in extended models of the regression analyses in Section 4.

We aggregate all plant data to the firm level in order to combine all datasets and to avoid any bias from firm-specific internal accounting methods or firm-internal shifting of resources across plants.

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[37] Intensities can also be defined as the ratio between energy use and value-added, in order to avoid double-counting of intermediate goods. However, there are a number of reasons why our study uses gross output as the preferred indicator as in Voigt et a. (2014) and Löschel et al. (2015): First, using gross output better reflects disembodied technological change. Second, it does not require the assumption of separability between intermediate goods and value added. At last, value added (from the CSS) is only reported in all years of our panel for large firms with more than 500 employees. It is vital that we have a complete set of firms over time, since otherwise we would misinterpret firms merely leaving the sample as closing down completely. The analysis presented in this paper is therefore based on gross output figures.

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We investigate on the 2-digit industry level (NACE rev. 2). This means we distinguish between 24 different manufacturing industries. All monetary variables are deflated to 2010-€ using industry-specific deflators from product-level producer price indices.[38] Thus, we account for industry specific business cycles in line with the critique of Ma (2010) that using GDP deflators will lead to biased results.

To date and to our best knowledge, this plant-level dataset is the most promising way to investigate the determinants of changes in the industrial energy and emissions intensity.

3.3. Decomposition Method

The methodology followed here is index decomposition analysis, the multiplicative Logarithmic Mean Divisia Index (LMDI) as proposed by Ang and Liu (2001), Ang (2015), Ang et al. (1998).[39] The approach is well-established in the literature (Xu and Ang, 2013), as it yields perfect decomposition of results, i.e. no residual term.

Our variable of interest is the sum of CO2 emissions in the German manufacturing sector due to energy usage in year t. It can be defined as a weighted average of emissions by firm j:

$$CO2_t = \sum_i \sum_{j \in i} Y_t \cdot \frac{Y_{j,t}}{Y_t} \cdot \frac{Y_{i,t}}{j,t} \cdot \frac{E_{ij,t}}{Y_{ij,t}} \cdot \frac{CO2_{ij,t}}{E_{ij,t}} = \sum_i \sum_{j \in i} A_{ij,t} B_{ij,t} \cdot W_{ij,t} \cdot E_{ij,t} \cdot F_{ij,t}$$

with the following notation:

- Industries: $i = 10, \ldots, 33$ [NACE 2-digit industry Codes]
- CO2 emissions of firm j in year t: $CO2_{ij,t}$
- CO2 emissions of industry i in year t: = $CO2_{i,t} = \sum_{j \in i} CO2_{ij,t}$
- CO2 emissions of sector in year t: $CO2_t = \sum_i \sum_{j \in i} CO2_{ij,t}$
- Energy use of firm j in year t: $E_{ij,t}$
- Energy use of industry i in year t: = $E_{i,t} = \sum_{j \in i} E_{ij,t}$
- Energy use of sector in year t: $E_t = \sum_i \sum_{j \in i} E_{ij,t}$
- Gross output of firm j in year t: $Y_{ij,t}$

[38] The price indices data is available on the website of the Federal Statistical Office: https://www-genesis.destatis.de/genesis/online (Producer Price Index 61241-0003).

[39] Another decomposition methodology is structural decomposition analysis (SDA) that relies on input-output analysis (see Wang et al. (2017) for a comparison).

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- Gross output of industry i in year t: = $Y_{i,t} = \sum_{j\in i} Y_{ij,t}$
- Gross output of sector in year t: $Y_t = \sum_i \sum_{j\in i} Y_{ij,t} = A$
  (Activity effect)
- Industry share of gross output in year t: $\frac{Y_{j,t}}{Y_t} = B$
  (Between-industry structure effect)
- Firm share of industry gross output in year t: $\frac{Y_{ij,t}}{Y_{j,t}} = W$
  (Within-industry structure effect)
- Energy intensity per gross output of firm in year t: $\frac{E_{ij,t}}{Y_{ij,t}} = E$
  (Energy-intensity effect)
- CO2 emissions from energy usage of firm in year t: $\frac{CO2_{ij,t}}{E_{ij,t}} = F$
  (Fuel-mix effect)

In a next step, we disentangle the changes in total CO2 emissions (from year t towards year $t+1$), denoted as the total effect $D_{Tot,t}$ using the multi-factor decomposition:

$$D_{Tot,t} = \frac{CO2_{t+1}}{CO2_t} = D_{Act,t} \cdot D_{Bet,t} \cdot D_{Wit,t} \cdot D_{EInt,t} \cdot D_{FMix,t}$$

Each component yields the hypothetical change in total CO2 emissions if only that one component had changed over time. A multiplication of these ceteris paribus (c.p.) effects yields the total change in CO2 emissions again.

We obtain each effect by aggregating the change in that respective component from the firm level to the total level, calculating the weighted average change over all firms and industries. Effects are defined as follows:

1) The Activity effect: c.p. change in total CO2 emissions if only industrial activity had changed

$$D_{Act} = exp \sum_i \sum_{j\in i} \omega_{ij} \cdot \ln(\frac{A_{ij,(t+1)}}{A_{ij,t}})$$

2) The Between-sector Structural effect: c.p. change in total CO2 emissions if only shares of sectors among manufacturing gross output had changed:

$$D_{Bet} = exp \sum_i \sum_{j\in i} \omega_{ij} \cdot \ln(\frac{B_{ij,(t+1)}}{B_{ij,t}})$$

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3) The Within-sector Structural effect: c.p. change in total CO2 emissions if only the relative market shares of firms among that sector's gross output had changed:

$$D_{Wit} = exp \sum_{i} \sum_{j \in i} \omega_{ij} \cdot \ln(\frac{W_{ij,(t+1)}}{W_{ij,t}})$$

4) The Energy-Intensity Effect: c.p. change in total CO2 emissions if only the firm-level energy intensity of production had changed:

$$D_{EInt} = exp \sum_{i} \sum_{j \in i} \omega_{ij} \cdot \ln(\frac{E_{ij,(t+1)}}{E_{ij,t}})$$

5) The Fuel-Mix Effect: c.p. change in total CO2 emissions if only the fuel mix of total energy consumption had changed:

$$D_{FMx} = exp \sum_{i} \sum_{j \in i} \omega_{ij} \cdot \ln(\frac{F_{ij,(t+1)}}{F_{ij,t}})$$

Note that effects 3), 4) and 5) constitute this paper's contribution to the existing literature. Only via the use of firm-level data, we can distinguish effects of changing firm market shares and entry/exit from energy-efficiency improvements of the firm and from fuel-switching behavior.[40]

Respective weights ω_{ij} for each firm-year are determined by the firm's share of CO2 emissions among total emissions:

$$\omega_{ij} = \frac{\dfrac{CO2_{ij,t} - CO2_{ij,t-1}}{\ln(CO2_{ij,t}) - \ln(CO2_{ij,t-1})}}{\dfrac{CO2_{\,t} - CO2_{\,t-1}}{\ln(CO2_{t}) - \ln(CO2_{t-1})}}$$

We can obtain total changes ($D_{Tot,t}$) and changes via effects 1)-5) on a rolling, annual basis (i.e. via changes from 2006 to 2007, ... , 2013 to 2014). These annual effect values yield a time series, but we can also "chain" them to obtain overall effects from period 0 to period T, i.e. the change from year 2006 to 2014.

A major caveat to LMDI applications on micro-data is the existence of zero-values that may hinder a perfect decomposition and generate a residual term. In our case, problematic zero values arise when firms enter or exit the market or due to missing values on either gross output or energy and thus CO2. Ang et al. (1998) propose the replacement of zero values

[40] Implicitly, the Fuel-Mix factor also absorbs changes in a fuel's emission factor over time. Although our dataset would allow for a further decomposition into changes in fuel shares and changes in a fuel's emissions intensity. However, these changes are negligible, with exception for electricity from the grid where the emission factor decreases by 4% from 2006 to 2014 (623 to 598 g/kWh). The maximum annual change rate is -6% from 2007 to 2008 (643 to 607 g/kWh) and the range is 575 (2010) to 643 (2007) g/kWh (UBA 2016b). Nonetheless, we decided that it is plausible to subsume this effect when firms can substitute between grid electricity and other fuels for their energy needed, especially when own electricity generation capacities are available.

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with small values (e.g. 10^{-20}). The critique by Wood and Lenzen (2006) shows that, depending on the amount of zero-values, a substantial residual remains and recommends the use of Analytical Limits, as derived by Ang et al. (1998), as a remedy. We follow this approach and achieve a perfect decomposition without residual, as previously shown in related decomposition studies such as Pothen (2017) or Kaltenegger et al. (2017).

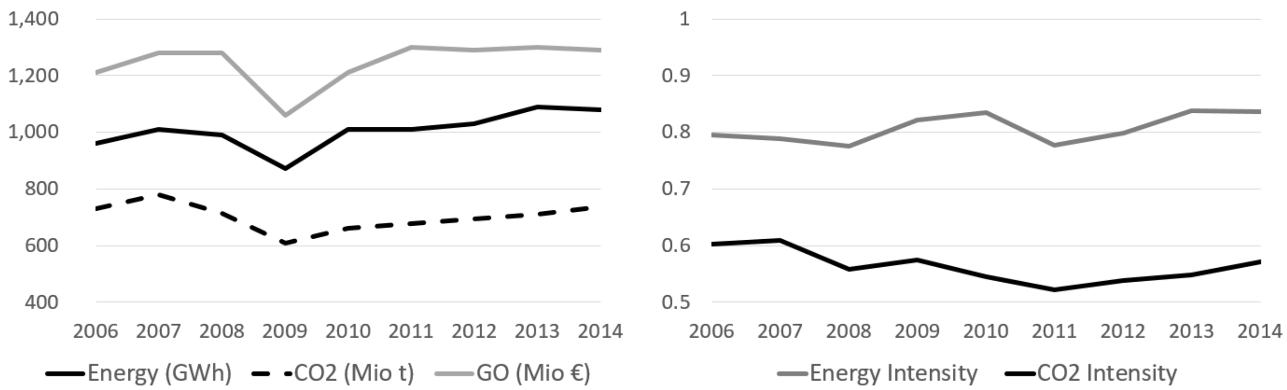
3.4. Results

3.4.1. Sector-wide analysis

The left panel of Figure 1 shows the development of gross output and required energy usage, as well as respective direct CO2 emissions. The latter increased slightly by 1.12 percent between 2006 and 2014, with a short dip during the financial crisis in 2008 and 2009. However, over the whole sample period one can detect a slow decoupling of emissions from gross output. This is more visible in the right panel of Figure 1, where we relate emissions to gross output, yielding the CO2 intensity of production indicator. It slightly decreased over the period of our dataset, from 0.6 to 0.57 tons of CO2 per 1000€ of gross output.

The main question of our paper is to assess why this indicator decreased over time. The decomposition indicates how total CO2 emissions would have changed over time, if only one component had changed ceteris paribus (Table 1, Figure 2).

Figure 1: Total gross output, energy usage and emissions (left); Energy and CO2 Intensity (right)



We investigate the chained decomposition (i.e. the overall change from 2006 and 2014) as well as the annual changes, because the contribution of effects may vary over time. For comparison, the last row of Table 1 shows the median for the annual values. Overall, the direction (positive vs. negative) of the median of changes is consistent to the chained decomposition values (except for the fuel mix effect). Note that positive values in column "Total" indicate a percent increase of emissions, and negative values indicate a percent decrease. In all further columns, positive values indicate the effect's contribution to an emission increase in percent, whereas a negative value indicates the percent contribution

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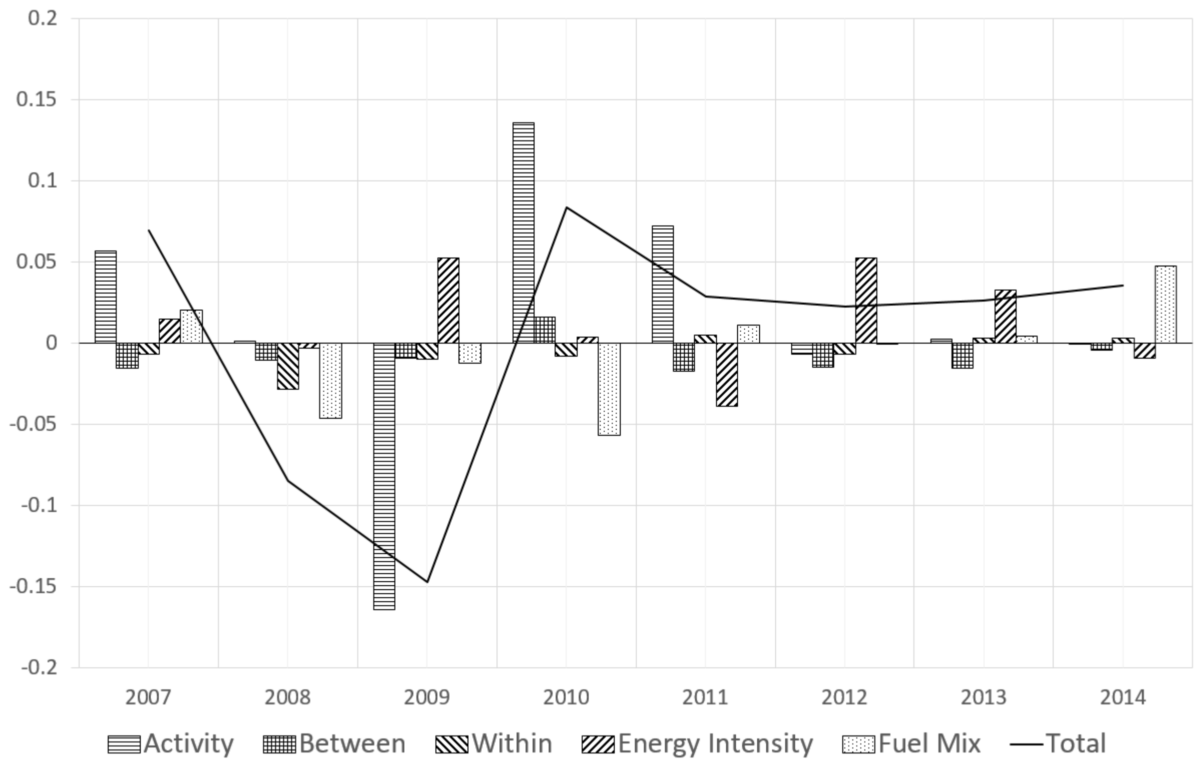
to emissions reductions.

FIGURE 2: PERCENT CHANGES IN ANNUAL CO2 EMISSIONS - TOTAL AND DECOMPOSITION EFFECTS



Line shows the percent change in CO2 emissions and bars show the c.p. change of each effect (in percent). Source: Research Data Centres of the Statistical Offices Germany (2014): Official Firm Data for Germany (AFiD) – Cost Structure Survey, AFiD-Panel Industrial Units, AFiD Module Use of Energy, AFiD Module Environmental Protection Investments, own calculations.

Thus, had we only observed an increase in economic activity, emissions would have increased by 7.12 percent c.p. from 2006 until 2014. The activity effect mirrors the business cycle, with a boom around the year 2006 and, due to the financial crisis, the large dip towards 2009 and the following recovery of the economy. From 2001 onwards, the effect is rather stable, which is why the median value is slightly positive.

Changes in the output shares of industries among the total manufacturing sector's output (the between-industry effect) have had a decreasing effect of about 7 percent on total CO_2 emissions, ceteris paribus. This attenuating effect is seen throughout the sample period, except for the change from 2009 to 2010. At the median, the effect contributes to a total emissions reduction of 1.26 percent. However, with the decomposition analysis we cannot further investigate whether this is rather driven by less emissions-intensive sectors becoming more competitive, or by the decrease of emissions-intensive industries. The latter could be a result of carbon leakage, i.e. the shifting of business abroad due to stringent climate policy.

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Table 1: Decomposition of CO2 emissions - Chained and Annual

	Total	Act	Bet	Wit	EInt	FMix
CHAINED						
2006-2014	1.12	7.12	-6.89	-4.9	10.61	-3.61
ANNUAL						
2006-2007	6.97	5.65	-1.56	-0.69	1.48	2.06
2007-2008	-8.50	0.10	-1.05	-2.85	-0.33	-4.60
2008-2009	-14.71	-16.42	-0.91	-0.97	5.27	-1.21
2009-2010	8.36	13.58	1.62	-0.83	0.39	-5.70
2010-2011	2.88	7.22	-1.72	0.48	-3.88	1.09
2011-2012	2.25	-0.68	-1.47	-0.68	5.26	-0.06
2012-2013	2.63	0.27	-1.55	0.29	3.25	0.40
2013-2014	3.54	-0.08	-0.43	0.28	-0.94	4.78
MEDIAN	2.76	0.19	-1.26	-0.69	0.94	0.17

Figures indicate percent changes. Chained effect is the overall change from 2006 to 2014. Total is the change in total emissions of the manufacturing sector, and all further columns show the impact of each decomposition effect. Negative values indicate decreasing emissions or a decreasing effect on emissions. Source: Research Data Centres of the Statistical Offices Germany (2014): Official Firm Data for Germany (AFiD) – Cost Structure Survey, AFiD-Panel Industrial Units, AFiD Module Use of Energy, AFiD Module Environmental Protection Investments, own calculations.

At the same time, changes of the composition within industries also exerted an attenuating effect on total emissions, albeit at a smaller scale, by about 5 percent from 2006 to 2014. In 5 out of 8 years, the effect contributed to emissions reductions, yielding an annual reduction of 0.7 percent at the median. This result shows the relevance of micro-level data analysis to uncover the importance of entry-exit effects, mergers and acquisitions, and other changes in firm size for aggregated emissions.

While both the between-industry and the within-industry effects had an attenuating effect in most years, we observe the contrary for the firm-level energy intensity effect. It had an increasing effect over the whole study period and in most years.

Thus, our study shows that, contrary to previous findings in the literature, emissions reductions by an industry are not necessarily the mere results of a more efficient use of energy. This finding may be explained by surviving firms having more energy-intensive production processes, e.g. more high-tech and capital-intensive production systems. Nonetheless, it is noteworthy that the industry-level energy intensity effect is mostly larger in magnitude than the within-industry effect, which is why it still dominates the changes on the industry level.

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At last, we find that over the whole sample period time, CO2 emissions would have decreased owing to the energy mix of firms. However, the annual effects (and its median) do not suggests a strong substitution towards less CO2-intensive fuels, especially in the early years of our sample.

Contrary to our finding, the existing literature mostly reports an emission or energy saving effect of energy intensity changes. A review of decomposition analyses by Liu and Ang (2007) also comprises 20 studies for Germany of which only one finds an emissions-increasing intensity effect. However, only the total effect, i.e. chained over the whole study period, is reported, which is why the remaining 19 studies may have also found single years with an expansive intensity effect. Nonetheless, among all studies in the review, including other countries outside Germany, those reporting an expansive intensity effects are outnumbered by contractive intensity effects (48 vs. 274 studies). As our analysis suggests, the reason for emission- or energy-saving intensity effect found in studies with aggregated data may not be due to actual intensity improvements on the firm level, but rather competition among firms with different levels of energy efficiency. In the review, the number of studies reporting an energy-saving effect from structural change is 17 out of 20 among the studies on Germany, and 98 out of 322 studies on all countries. We confirm this majority result in our analysis, too.

Another review of decomposition studies by Xu and Ang (2013) comprises 10 studies on the German industry sector. In all these studies, the energy intensity effect and the fuel mix effect exert decreasing effects on aggregate carbon intensity of production. Again, our result rather contradicts this meta-level findings.

3.4.2. Industry-specific analysis and innovation patterns

In this section, we focus on industry-specific decomposition of effects and investigate different innovation processes towards a more efficient use of energy.

Manufacturing companies in highly developed economies face a limited set of options for coping with increasing energy prices and complying with regulation aimed at reducing industrial emissions of greenhouse gases. The severity of this problem varies across industries, but it is especially serious in energy intensive industries such as metal manufacturers, chemicals, or the pulp and paper industry. Ideally, firms can identify cost-efficient options for increasing the efficiency of energy and resource usage. To some extent, firms with own electricity generation capacities can benefit from fuel-switching opportunities. Otherwise, the only options left is the adoption of more energy-efficient investments or investments into renewable energy source.

The second column in Table 2 shows the absolute CO2 emissions in 2014 by industry. The largest emitters are Chemicals and Basic Metals, followed by Motor Vehicles and Electrical Equipment.

In order to disentangle the development of emissions within each industry, we use the same decomposition formula as before, but do not sum up across all industries i. This yields industry-specific activity effects, within-industry-effects, energy intensity effects and fuel mix effects. In the last five columns of Table 2, we display the median value of annual total change in emissions, as well as the median of annual effects. We chose the median

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because the contribution of changes varies over years and is not accurately reflected by the chained effect from 2006 until 2014. Further, we highlight (in **bold**) whether industries reduced emissions (at the median) and we do the same for effects with a negative contribution (i.e. it would have reduced emissions at the median).

TABLE 2: INDUSTRY-SPECIFIC CO2 EMISSIONS AND CONTRIBUTIONS FROM DECOMPOSITION EFFECTS

	Emissions (Mio tons)	**Effects (Median values)**				
Industry	**2014**	**Total**	**Act**	**Wit**	**EInt**	**FMix**
10) Food products	29,929	**-1.68**	1.44	**-0.84**	0.85	**-2.44**
11) Beverages	5,154	4.01	1.01	1.24	**-4.04**	0.38
12) Tobacco	280	**-2.35**	**-3.85**	0.26	3.48	**-0.07**
13) Textiles	2,111	**-4.79**	0.00	**-1.56**	**-1.00**	**-1.56**
14) Wearing apparel	124	**-8.40**	**-1.49**	**-8.47**	8.89	**-3.19**
15) Leather	153	**-2.64**	**-0.41**	1.06	**-2.84**	**-0.18**
16) Wood products	4,357	**-5.42**	0.74	**-1.82**	0.91	**-6.55**
17) Paper	27,137	**-0.12**	**-0.79**	**-0.49**	**-1.45**	**-0.18**
18) Printing	2,270	**-1.45**	0.23	0.02	**-2.69**	0.38
19) Coke; refinery	33,609	5.93	0.27	2.89	4.17	**-0.95**
20) Chemicals	222,459	3.83	0.49	**-1.20**	5.19	**-4.19**
21) Pharmaceuticals	2,816	1.43	4.76	**-0.53**	**-3.64**	**-1.05**
22) Rubber, plastic	19,415	**-1.44**	2.21	**-0.68**	0.51	**-0.68**
23) Non-metallic minerals	51,946	**-2.25**	1.13	1.16	**-2.92**	**-1.14**
24) Basic metals	141,548	2.40	**-1.95**	**-0.96**	3.74	0.01
25) Fabricated metals	15,365	3.56	2.31	**-0.32**	**-1.81**	1.00
26) Electronics	6,473	**-0.59**	2.19	0.02	**-2.54**	**-1.59**
27) Electrical equipment	58,915	**-6.91**	0.19	**-1.44**	**-3.36**	**-2.60**
28) Machinery	42,445	**-1.23**	4.85	**-4.18**	**-3.65**	2.05
29) Motor vehicles	63,371	1.32	4.96	0.86	**-2.68**	**-2.09**
30) Other transport	2,291	**-4.89**	5.87	**-2.97**	**-3.73**	**-4.16**
31) Furniture	1,000	**-2.63**	**-1.08**	**-0.74**	**-2.34**	**-2.02**
32) Other manuf.	1,559	**-0.25**	3.13	**-0.99**	**-2.20**	**-0.03**
33) Repair, installation	2,572	5.12	4.88	**-0.02**	**-1.79**	1.99

Column Total is the median of annual percent changes of an industry's emissions, and all further columns show the median for of each decomposition effect. Negative values indicate decreasing emissions or a decreasing effect on emissions. Source: Research Data Centres of the Statistical Offices Germany (2014): Official Firm Data for Germany (AFiD) – Cost Structure Survey, AFiD-Panel Industrial Units, AFiD Module Use of Energy, AFiD Module Environmental Protection Investments, own calculations.

As an example, the largest emitters in our sample period, the Chemicals industry and the Basic Metals industry, increased emissions by 4 percent (at the median) over our sample period. In the Chemicals industry, this was mostly due to an increase in output and firm-level energy intensity, whereas inter-fuel substitution and the within-industry composition both

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exerted attenuating effects. In the Basic Metals industry, emissions mainly increased due to firm-level energy intensity, which counteracted potential reductions from the activity and within-industry effect, and inter-fuel substitution hardly showed any influence.

In 16 out of the 24 industries, the median change of emissions was negative (values for Total < 0 in Table 2).

In most industries (18 out of 24), increasing output would have led to increased emissions in most years, as indicated by an activity effect larger than zero.

Overall, in 16 industries the within-industry effect showed an attenuating effect in most years, especially among large emitters such as Chemicals, Basic Metals, Paper, Electrical Equipment, or Machinery. In another 16 industries, changes in firm-level energy intensity effect had a reducing effect on emissions, such as in Motor Vehicles, Electrical equipment, and Non-metallic minerals. However, in only 10 industries both effects simultaneously would exert an attenuating effect on emissions, such as Electrical Equipment, Machinery, and Paper. In 6 industries emissions would decline via shifting market shares, but not via firm-internal energy intensity improvements. Examples are Basic Metals, Chemicals, and Food products. The opposite case, that firm-level energy intensity improvements would reduce emissions but not within-industry changes, is only found in 5 industries, such as Motor Vehicles or Non-metallic minerals. Thus, our analysis clearly shows the importance of micro-level data to disentangle such sectoral improvements for better-guided policies. Overall, as in the aggregate decomposition, the energy-intensity effect is larger in magnitude than the within-industry effect (at the median) in 20 industries. This shows that industry-level changes are primarily driven by firm level-energy intensity, and only secondly by within-industry composition.

At last, for almost all industries we find that the composition of energy sources in use would have an attenuating effect on emissions. This effect is especially strong in the Chemicals industry, while we see an almost zero effect in the Basic metals industry.

3.4.3. Determinants of industry-specific effects

Having identified the main channels of industry-specific effects on emissions, we follow the approach by Löschel et al. (2015) and Parker and Liddle (2016) by using panel regressions to further investigate the driving forces of annual effects. For this purpose, we construct a panel of annual industry-level effects (as in Section 4.2) for each year. We focus on the within-industry structural effect, the energy-intensity effect and the fuel-mix effect. Per effect, the panel has 192 observations (24 industries, 8 years), i.e. the unit of observation is an industry-year. Recall that a positive contribution of an effect would increase emissions, while negative contributions would imply decreasing emissions.

We then regress each of the three effects $D_{Y,jt}$ ($Y \in \{Wit, Eint, FMix\}$) on its lagged value $D_{Y,j(t-1)}$, a vector of industry covariates X_{jt} and year-dummies τ_t as follows:

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$$D_{Y,jt} = D_{Y,i(t-1)} + \boldsymbol{X_{it}} + \tau_t + \theta_{i,t}$$

where $\theta_{i,t}$ is a robust standard error term.

In a baseline model we include the following covariates, where values are always the mean per industry each year: We define *Energy Intensity* as the total Energy Consumption (in MWh) per Gross Output (in 1000€). As in Löschel et al. (2018) we estimate direct *CO2 Emissions* (in tons) of the firm from the fuel-specific consumption data (see Appendix). Both *Energy Intensity* and *CO2 Emissions* enter the model in natural logs. The *Export Ratio* is the value of exports divided by the value of total revenue. *Energy Cost Share* is the share of costs from energy usage. Dividing energy costs by energy consumption yields *Energy Price*, the average price per unit of energy. A dummy indicates firms using renewable energy (*Renewables*), e.g. by solar, wind and hydropower. We calculate the Hirshman-Herfindahl Index (*HHI*) to account for industry concentration, and the share of R&D spending per revenue (*RD share*) to proxy the tendency to innovate. At last, we calculate *Profits* as revenue minus total costs.

In an extended set of covariates, we further include the total *Revenue*, the share of firms with investments into the protection of the environment and climate (*Eco-Investments (%)*), as well as the monetary value of these investments (*Eco-Investments (€)*).

Our results in Table 3 show that the lagged dependent effect variable is not significant for all three effects. Thus, the effects do not seem to follow a trend over time and other variables may better explain their direction and magnitude. Overall, the (log of) energy intensity has strong explanatory power for all three effects. Emissions reductions via the within-industry effect correlate with a larger average log energy intensity of an industry (visible by the negative coefficient). This result seems plausible, as entry and exit of firms in energy intensive industries may shape the aggregate emissions more easily than in less energy intensive industries. The coefficient is significant at the one percent level in the baseline model and remains significant at the five percent level when including more controls.

On the contrary, for the energy intensity effect, we find a positive coefficient for the average energy intensity of an industry. This means that in industries that are more energy-intensive, the energy-intensity effect rather contributes to increasing emissions. In other words, we find that, especially in energy-intensive industries, firms have become more energy-intensive in production. Our finding is robust to the inclusion of more control variables and the coefficient remains significant at the one percent level.

Another robust result is that emissions reductions due to the within-industry effect increase with the export-orientation of an industry. However, larger R&D spending of an industry correlate with an expansive effect of within-industry changes on emissions. Otherwise, no other covariates significantly correlate with any of the three effects in both model specifications. Even the usage of renewable energy sources correlates only weakly with emissions reductions from the fuel mix effect. The effect is not significant at the ten percent level anymore in the extended model. Surprisingly, we also find no influence from investments into the protection of the environment and climate.

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TABLE 3: REGRESSION RESULT FOR DRIVERS OF INDUSTRY-LEVEL EFFECTS

Dependent Variable	Within industry effect		Energy Intensity effect		Fuel Mix effect	
Variable \ Model	**Baseline**	**Extended**	**Baseline**	**Extended**	**Baseline**	**Extended**
Lagged Dep. Var.	0.004	-0.001	-0.006	-0.012	-0.173	-0.179
	(0.111)	(0.109)	(0.114)	(0.108)	(0.106)	(0.111)
Energy Intensity (ln)	-0.021 ***	-0.022 **	0.036 ***	0.033 ***	-0.005	-0.005
	(0.008)	(0.009)	(0.012)	(0.010)	(0.005)	(0.005)
CO2 Emissions (ln)	0.033 ***	0.029	-0.004	0.025	0.011	0.009
	(0.012)	(0.023)	(0.019)	(0.045)	(0.010)	(0.023)
Energy Price	0.022	0.022	-0.010	0.003	-0.016	-0.022
	(0.038)	(0.044)	(0.068)	(0.075)	(0.030)	(0.033)
Export Ratio	-0.130 **	-0.133 **	0.021	0.082	-0.077	-0.083
	(0.053)	(0.066)	(0.112)	(0.133)	(0.091)	(0.095)
Renewables	0.041	0.046	0.101	0.125	-0.162 *	-0.147
	(0.057)	(0.062)	(0.131)	(0.135)	(0.088)	(0.107)
HHI	-0.171	-0.181	0.720	1.147 *	-0.164	-0.137
	(0.155)	(0.317)	(0.472)	(0.653)	(0.160)	(0.339)
RD Share	1.182 ***	1.113 **	0.232	0.707	0.696	0.665
	(0.415)	(0.513)	(0.895)	(1.070)	(1.135)	(1.278)
Energy Cost Share	2.556	2.273	-5.467	-6.270	10.260	10.281
	(6.883)	(7.073)	(10.744)	(11.286)	(6.562)	(6.572)
Profits (ln)	-0.019	-0.020	-0.012	0.007	-0.008	-0.018
	(0.021)	(0.019)	(0.033)	(0.038)	(0.016)	(0.022)
Revenue (ln)		-0.001		-0.046		0.001
		(0.029)		(0.046)		(0.032)
Eco-Investments (%)		0.085		-0.220		0.089
		(0.216)		(0.452)		(0.127)
Eco-Investments (€)		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
Prob > F	0.0517	0.0980	<0.0001	<0.0001	0.0004	0.0008
R^2	0.2675	0.2714	0.3188	0.3284	0.2302	0.2354

Estimates over the whole sample period 2006-2014. Robust standard errors shown in parentheses. Unit of observation is the 2-digit industry each year. Nr. of observations: 142. All models include year dummies. P values: *: p<0.1, **: p<0.05, ***: p< 0.01. Source: Research Data Centres of the Statistical Offices Germany (2014): Official Firm Data for Germany (AFiD) – Cost Structure Survey, AFiD-Panel Industrial Units, AFiD Module Use of Energy, AFiD Module Environmental Protection Investments, own calculations.

In general, the models yield sufficient explanatory power. Three covariates are significant explanatory variables for the within-industry effect. However, none of the covariates except for average energy intensity seems to determine the industry-level energy intensity effect. At last, the fuel mix effect does not significantly correlate with the industry-level covariates, where the year dummies explain most of the variance.

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3.4.4. Influence of industry composition effects

In a final part of the analysis, we further uncover the determinants of the within-industry and energy-intensity effect. Therefore, we examine on the firm level whether firms, entering, leaving or staying in the market differ in their energy and CO2 intensity. Note that instead of the decomposition effect panel from Section 3.4.3, we now use the whole firm-level panel again. Thus, the unit of observation is a firm-year and the number of observations is much larger now.

In relation to the approach by Linn (2008), we regress the relative difference in log energy intensity $Y_{ij,t}$ on an Entry dummy $Entry_{ij,t}$ (that is equal to one for a firm in its first year appearing in the panel), an dummy $Exit_{ij,t}$ for firms leaving the market (that is equal to one for a firm in its last year in the panel in years prior to 2014, the last year of the panel), and an SME dummy $SME_{ij,t}$ (that is equal to one for small-and medium size firms). We further control for a vector of firm-level covariates $\boldsymbol{X}_{ij,t}$, and absorb industry-specific dynamics via industry-year fixed effects $\gamma_i \cdot \tau_t$. The error term $\epsilon_{ij,t}$ is clustered on the firm level. The model can be written down as follows:

$$Y_{ij,t} = \alpha + \beta_1\, Entry_{ij,t} + \beta_2\, Exit_{ij,t} + \beta_3\, SME_{ij,t} + \beta_4\, \boldsymbol{X}_{ij,t} + \gamma_i \cdot \tau_t + \epsilon_{ij,t}$$

The vector of controls comprises the (log of) *Revenue*, the (log of) *Labor Intensity* (employees per gross output), a dummy for firms generating own electricity from fossil fuels (*Fossil*), a dummy for firms using renewable energy sources (*Renewables*), the share of revenue from exports (*Export Ratio*), the *Nr. of Products* manufactured by the firm, and a dummy for an *International Firm*.

In an extended model, we also include covariates from the CSS for further explanatory power. However, this requires using the smaller CSS subsample, where smaller firms are only included as a (representative) random sample. We include the average *Energy Price*, the *Energy Cost Share* among total costs, a dummy for public or private ownership (Corporation), and the *RD share*.

In the regression results (Table 4) the coefficient for new entrants is always negative and suggests that entrant firms generally use about 5 percent less energy, and generate up to six percent less emissions, per unit of output than existing firms. For energy intensity, the result is significant at the one percent level in the full sample, and on the five percent level in the CSS subsample where we include more control variables. For CO2 intensity, the coefficient is only significant at the ten percent level in the full sample, but highly significant when we include the CSS covariates. On the contrary, firms that leave the market seem to produce more energy and CO2 intensive than firms remaining in the market. The coefficients are highly significant in the full sample, which is why market exit may also explain some part of the within-industry effect. However, the results are not robust in the CSS subsample, potentially because of the explanatory power of the average energy price variable. As such, we find that firms with a one-euro larger average energy price (per MWh) have a lower energy and CO2 intensity, by about two percent. The energy cost share, however, does not significantly influence any of the outcome variables.

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TABLE 4: REGRESSION RESULT FOR DRIVERS OF FIRM-LEVEL ENERGY INTENSITY

Dependent Variable	Energy Intensity				CO2 Intensity			
Variable \ Sample	**Full sample**		**CSS subsample**		**Full sample**		**CSS subsample**	
Entry	-0.047	***	-0.049	**	-0.019	*	-0.059	***
	(0.011)		(0.021)		(0.011)		(0.021)	
Exit	0.077	***	-0.005		0.058	***	-0.043	
	(0.014)		(0.026)		(0.014)		(0.027)	
SME	0.361	***	0.352	***	0.367	***	0.362	***
	(0.017)		(0.036)		(0.017)		(0.034)	
Revenue (ln)	0.150	***	0.150	***	0.173	***	0.175	***
	(0.006)		(0.008)		(0.006)		(0.008)	
Labor intensity (ln)	0.455	***	0.389	***	0.386	***	0.294	***
	(0.010)		(0.014)		(0.011)		(0.015)	
Fossil	0.534	***	0.664	***	0.511	***	0.635	***
	(0.020)		(0.026)		(0.020)		(0.026)	
Renewables	0.230	***	0.230	***	-0.071	***	-0.024	
	(0.018)		(0.025)		(0.017)		(0.024)	
Export Ratio	0.154	***	0.138	***	0.067	***	0.017	
	(0.023)		(0.031)		(0.023)		(0.031)	
Nr. of products	-0.001		0.001	***	-0.002		-0.001	
	(0.002)		(0.002)		(0.001)		(0.001)	
International Firm	0.223	***	0.190	***	0.549	***	0.550	***
	(0.020)		(0.024)		0.021		0.025	
Energy Price			-0.020	**			-0.019	***
			(0.008)				(0.007)	
Energy Cost Share			1.452				0.955	
			(1.276)				(1.180)	
Corporation			0.005				-0.008	
			(0.014)				(0.014)	
RD Share			-0.842	***			-0.400	*
			(0.230)				(0.209)	
Prob > F	<0.0001		<0.0001		<0.0001		<0.0001	
R^2	0.3065		0.3237		0.3001		0.3182	
Nr. of observations	314,202		131,903		314,197		131,901	

Estimates over the whole sample period 2006-2014. Standard errors are clustered on the firm level and shown in parentheses. Unit of observation is the firm each year. All models include year-industry fixed effects.
P values: *: p<0.1, **: p<0.05, ***: p< 0.01. Source: Research Data Centres of the Statistical Offices Germany (2014): Official Firm Data for Germany (AFiD) – Cost Structure Survey, AFiD-Panel Industrial Units, AFiD Module Use of Energy, AFiD Module Environmental Protection Investments, own calculations.

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Another major finding is that SME show a much lower energy efficiency than large firms, which may be a result of fewer firm-internal resources. The coefficient is highly significant at the one percent level in all four models.

Other control variables also exert significant explanatory power in all models, such as revenue, labor intensity, as well as the own electricity generation from fossil fuels, and the International firm dummy. The renewable energy dummy is highly significant in all models except the CSS subsample analysis of CO2 emissions. Firms using renewables show a larger energy intensive but a relatively lower CO2 intensity, which is plausible owing to the impact of renewables on the fuel mix.

3.5. Conclusion

In this paper, we have investigated the development of direct CO2 emissions from energy use in the German manufacturing sector between 2006 and 2014. Based on firm-level data we apply the Logarithmic Mean Divisia Index Decomposition method in order to separate the major drivers of emissions over this period.

As a whole, the manufacturing sector managed to reduce emissions despite major changes in the energy market and a stabilization of output after the financial crisis.

In the decomposition of aggregate emissions, we find that the median contribution of the activity effect and the fuel mix effect are close to zero. At the same time, structural effects are dominantly contributing to reductions of emissions. On the one hand, changes in the output shares between industries are a major contributor. On the other hand, changes in the output shares of firms within industries also drive reduction of industries' emissions. Moreover, the energy-intensity of production in firms (remaining in our sample over time) seems to rather increase total emissions, which questions the effectiveness of efficiency policies to some extent. Further, this result contradicts the results of most existing decomposition analyses for Germany that were included in two major review studies (Liu and Ang, 2007, Xu and Ang, 2013).

One explanation for our finding might be that surviving firms are becoming more energy intensive due to increasingly specialized and capital-intensive production. In a regression of the decomposition effects, we find that the contribution of the within-industry structure effect can be explained by different firm characteristics. As such, the effect rather contributes to reductions in industries with more energy-intensive production and larger export ratios. To our surprise, the average price of energy as well as the share of energy costs do not show a significant influence.

In a final regression analysis on the firm level, we further explore the driving forces of the within-industry effect. Our regression results show that firms newly entering the market are significantly less emissions-intensive than incumbents (i.e. up to 6% less emissions per output). For this reason, energy efficiency policies could be further directed towards firms where the technology choice is still flexible and potentially yield substantial energy savings. We find

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that firms with relatively higher energy prices show a significantly lower energy and CO intensity, whereas the energy cost share does not significantly correlate with the two outcomes.

Another key result is that small-and-medium enterprises show a much lower energy efficiency of production than large firms. Hence, future energy efficiency policies could also be directed more towards SME in order to exploit yet untapped potential for cost-efficient improvements.

All in all, our analysis sheds light on the main channels of energy usage and emissions development, but any projection of future trends will require more updated data available for analysis.

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3.7. Appendices

3.7.1. Estimating direct CO2 Emissions of energy consumption

The AFiD-Module Use of Energy provides consumption data for electricity and eight different fuel types, e.g. natural gas, oil and coal products. We obtain fuel specific CO_2 emission factors (see Table A1) by the Federal Environment Agency (Federal Environment Agency 2016a). In Table A1 we display the average CO_2 emission factors over the years 1995-2014, whereas deviations across years and industries are not shown for brevity. The energy consumption variable for *coal products*, *other mineral oil products* and *other gases* are aggregated from more detailed fuels, which is why we weight the emission factor for each 3-digit industry and year according to the share of subsumed fuels consumed (AG Energiebilanzen). For electricity purchased from the grid, we refer to the CO_2 emission factor by the Federal Environment Agency (2016b) that accounts for international trade effects. Own generation of electricity is accounted for by the fossil fuel consumption. We set the emission factor to zero for electricity from renewables (wind, solar, hydro) and other energy from renewable sources, e.g. usage of biofuels. For district heating, we refer to values from the Federal Environment Agency (2008). Following the recommendation from a personal consultation of staff via phone in March 2017, we take the value of 2000 for 1995-2000, the value of 2005 for 2005-2014 and the mean of 2000-2005 for years 2001-2004.

TABLE A1: MEAN CO2 EMISSION FACTORS (G/KWH) OVER YEARS 2006-2014 FOR SPECIFIC ENERGY CARRIERS.

Fuel Type	**g/kWh**	**Fuel Type**	**g/kWh**
Electricity (grid)	620	Lignite raw	388
Natural gas	211	Lignite briquettes	357
Light heating oil	266	Other mineral oil products	279
Heavy heating oil	287	Other gases	441
District heat	218	Other coal products	355
Liquid gas	235	Other fuels and waste	265
Coal	337	Renewables	0
Coke	389		

Source: Federal Environment Agency 2016a, 2016b, 2008, AG Energiebilanzen.

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