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The Survival of the Energy-fittest: Evidence from French Manufacturing Firms

Ara Jo* ⓡ Sébastien Houde†

May 22, 2026

Abstract

This paper disentangles the roles of within-firm improvement and between-firm selection and market reallocation in determining aggregate energy intensity. Our analysis shows that selection and market reallocation play a stronger role than within-firm improvement in driving aggregate declines in energy intensity, despite the strong focus on within-firm response to climate policy measures in the existing empirical literature. We also find that these mechanisms, in particular the selection channel, can be leveraged by environmental policy.

JEL: Q40, Q52, Q58, L50.
Keywords: Industry dynamics; energy intensity; decarbonization; environmental policy; manufacturing sector.

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1 Introduction

Energy efficiency improvement is a central element of climate action that allows the economy to meet energy services demand without increasing energy consumption or emissions (IPCC, 2018). Accordingly, a large micro-empirical literature has emerged in an attempt to understand how various climate policy instruments affect energy efficiency and generally found a positive and statistically significant relationship between energy efficiency and climate policy measures within firms (Dechezleprltre et al., 2019). These empirical findings are in line with a substantial decrease in energy use per unit of output in many sectors and economies (Metcalf, 2008; Mulder and De Groot, 2012; Levinson, 2021). However, there exist alternative, less emphasized channels of selection and market reallocation that could also contribute to the improvement in aggregate energy intensity. Environmental policy or subsequently higher energy prices lead to a cost advantage to less energy-intensive firms, which can result in the reallocation of resources from more energy-intensive to less energy-intensive firms. This resource reallocation may force the most energy-intensive firms to exit the market and increase the market share of the least energy-intensive firms, improving energy intensity at an aggregate level.

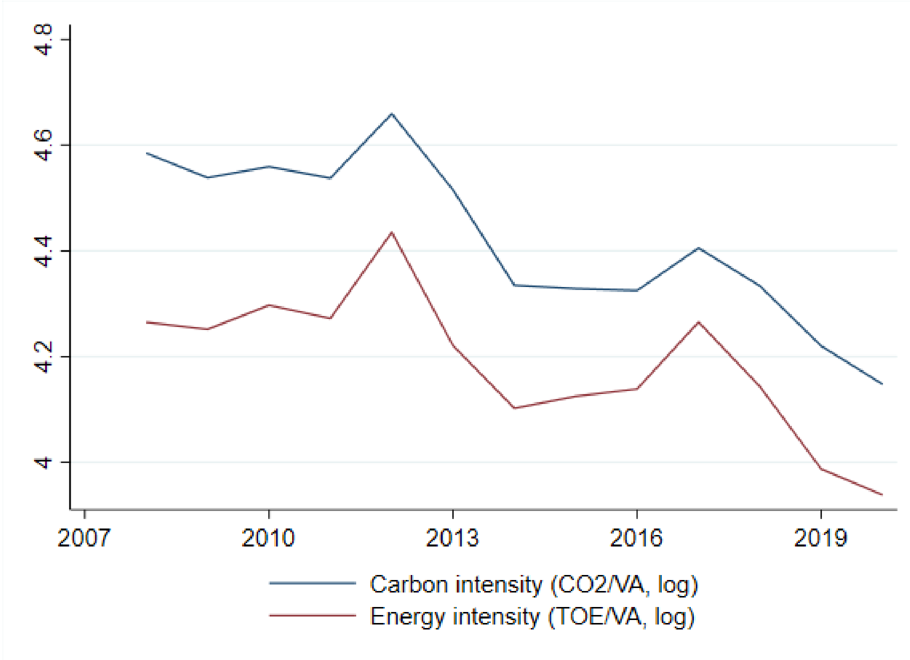
This paper disentangles the roles of within-firm improvement and between-firm selection and market reallocation in determining aggregate energy intensity and investigates their relative importance. Although all these channels may improve aggregate energy intensity, they operate at two distinct margins and represent different sources of energy intensity reduction. Within-firm improvement in energy intensity works at an intensive margin, which may arise from investing in abatement technologies or changing product mix in continuing firms. On the other hand, between-firm selection and reallocation operate at an extensive margin, whereby higher energy prices induce the exit of the dirtiest firms and allow the cleanest firms to grow larger. Importantly, the relative strength of these channels in driving the change in aggregate energy intensity has diverging policy implications: within-firm improvement in energy intensity emphasizes the importance of policy measures targeting individual firms, whereas selection and reallocation may be better facilitated by improving market conditions for stronger competition at the industry level. Thus, understanding the relative importance of each margin is essential for designing effective climate policies.

Our analysis proceeds in three steps. First, we decompose the evolution of aggregate energy intensity into the contribution of within-firm improvement, reallocation, exit, and entry in order to quantify their relative importance. For the purpose, we leverage firm-level administrative data on energy consumption, output, and firm status (exiting, continuing, or entering) from the French manufacturing sector that has experienced a substantial decline in aggregate energy intensity as shown in Figure 1.

Next, we investigate to what extent energy prices, as a proxy for the stringency of environmental policy, influence the adjustments at the extensive margin, in addition to within-firm improvement that has been extensively documented in the literature. Specifically, we estimate the impact of energy prices on exit probability and market shares of firms. In our main specification, we consider heterogeneity in the response to energy price shocks by distinguishing firms along the distribution of energy intensities. These specifications allow us to examine whether energy-intensive firms are more likely to exit or experience changes in market shares in response to energy price shocks. We use the shift-share instrument as our main empirical strategy to address the potential endogeneity of firm-level energy prices. Finally, we use our reduced-form estimates to quantify whether future energy price evolution can drive economically significant reductions in aggregate energy intensity through the channels of selection and market reallocation.

Our decomposition exercise yields surprising results. Despite the emphasis on the within-firm improvement of energy intensity in the existing literature, we find that the relative importance of the within-firm component is small, accounting for less than 10 percent of the total reduction in aggregate energy intensity. The contribution of selection and reallocation were significantly stronger: of the 33 percent reduction in aggregate energy intensity over the sample period, 23 percent is attributable to reallocation cumulatively, accounting for 70 percent of the total change. In other words, less energy-intensive firms grew larger over time, lowering the industry-level average energy intensity weighted by market shares. The exit of energy-intensive firms also induced a further 5 percent reduction, accounting for 16 percent of the total change. Entry was the least

Figure 1: Energy and Carbon Intensity in French Manufacturing



strong contributor, accounting for 6 percent of the total change.

We also find causal evidence that energy prices have an impact on the selection mechanism. Rising energy prices have strong positive effects on exit probability of the most energy-intensive firms (the top 75% of the distribution or above), while having no significant impact on other less energy-intensive firms. This suggests that shocks and policy changes that drive up energy prices induce the exit of dirtiest firms, improving the average industry energy intensity. Looking at reallocation, we find suggestive evidence that higher energy prices have a positive impact on the revenue shares of the least energy-intensive firms (25% or below), while having no or a negative impact on more energy-intensive firms. However, the magnitude of the impact is not economically large enough to explain the strong contribution of the reallocation channel observed in the decomposition exercise.

Finally, we use our reduced-form estimates on the impact of energy prices on firm exit and energy intensity within firms to simulate how an increase in future energy prices would affect aggregate energy intensity through different channels. Regardless of the assumption of how the released market shares of the least energy-efficient firms are captured by continuing firms, we observe that over three quarters of the total reduction in aggregate energy intensity is attributed to the adjustments at the extensive margin (selection and reallocation). This exercise corroborates the importance of between-firm adjustments behind the reduction in aggregate energy intensity.

This paper contributes to the existing literature by providing novel evidence on the process of energy intensity improvement at an aggregate level. Some studies relate changes in energy (or pollution) intensity at the national level to three channels: changes in the aggregate level of output, changes in the composition of output across different industries, and changes in pollution intensity within an industry (Gamper-Rabindran, 2006; Metcalf, 2008; Levinson, 2009; Mulder and De Groot, 2012; Marrero and Ramos-Real, 2013; Levinson, 2021). Shapiro and Walker (2018) and Rottner and von Graevenitz (2024) provide analyses that are closer to ours in spirit disentangling changes in aggregate pollution intensity into the total scale of output, composition of products within firms, and product-level energy intensities. In contrast, we explore the importance of selection and market reallocation *between firms* in improving aggregate energy intensity. Our decomposition exercise suggests that between-firm adjustments at the extensive margin were a major driver behind the decline in aggregate energy intensity, rather than improvements within firms.

A large number of studies have analyzed the impact of various policy instruments on environmental and economic outcomes within firms. The consensus is that climate policies, especially in the context of the EU-ETS, induced firms to lower emissions or energy consumption without detrimental effects on output and employment (Martin et al., 2014; Jaraitė and Maria, 2016; Löschel et al., 2019; Klemetsen et al., 2020; Dechezleprêtre et al., 2023; Colmer et al., 2024), whereas others estimate negative effects on both emissions and economic performance of firms (Greenstone et al., 2012; Dussaux, 2020; Marin and Vona, 2021; Bretschger and Jo, 2024). The novelty of our analysis is to look beyond the within-firm outcomes and investigate the impact of energy prices on the channels of between-firm selection and market reallocation that contribute to energy intensity improvement at an aggregate level. Our findings suggest that adjustments at the extensive margin, in particular the selection mechanism, can also be leveraged by policy instruments such as fuel excises.

Our findings have strong implications for policy debates on climate change mitigation as understanding the drivers of the reduction in aggregate energy intensity is critical to designing climate policy (Levinson, 2021). Specifically, the strong contribution of selection and reallocation to the improvement in aggregate energy intensity shown in our study suggests a novel policy approach that complements traditional climate policy instruments targeting individual firms such as carbon pricing or abatement subsidy: policies that foster competitive market conditions can accelerate decarbonization by inducing the exit of dirtiest firms and and facilitating the reallocation of resources from dirty to clean firms.

The rest of the paper proceeds as follows. Section 2 introduces the data. Section 3 presents a statistical decomposition that breaks down the trend in aggregate energy intensity observed in our data. Section 4 performs analyses on the relationship between energy prices and the channels of industry dynamics. Section 5 provides simulation exercises that quantify the extent to which energy prices can drive economically significant reductions in aggregate energy intensity. Section 6 concludes.

2 Data

We compile a dataset of French manufacturing firms for each year between 2008 and 2020 using two main sources. First, we rely on the Annual Structural Statistics of Companies (FARE) collected by the French National Institute of Statistics and Economic Studies (INSEE) and the Ministry of Finance (DGFiP), which is the fiscal census that covers the universe of French businesses. The dataset provides general information about the firm and detailed financial information. The exhaustive coverage of the FARE allows us to accurately keep track of firms' lifespan and measure firm status as continuing, entering, or exiting with minimal measurement errors, compared to surveys based on a sampling pool.

We obtain detailed information on energy consumption and expenditure by fuel from the Annual Survey of Industrial Energy Consumption (EACEI), a survey conducted annually by the INSEE on a representative sample of manufacturing plants. The fuel-specific consumption and expenditure information allows us to also compute emissions for each firm. To merge with the firm-level information from the fiscal census, we aggregate plant-level information from the EACEI to the firm level. The final sample of the merged dataset is determined by the representative sample of the EACEI. Keeping industries that are continuously surveyed throughout the sample period leaves us 17 industries defined according to the two-digit NAF rev.2. Appendix A1 provides more information on our data and the construction process.

To obtain a measure of energy intensity, we divide total energy consumption by output measured in value added. Carbon intensity is calculated similarly. We construct a measure of overall firm-level energy price by dividing total energy expenditure by total energy consumption. We also calculate unit prices of different fuels defined as expenditure per unit of consumption of each fuel. Figure A1 shows the movement in unit prices of main fuels used in manufacturing firms, which are electricity, natural gas, and heavy fuel oil (accounting for 61, 28, and 4 percent, respectively), and their average in log. We observe an increasing trend in the average price of energy, which reflects the introduction of carbon pricing and rising fuel excises over the sample period in France. Table A1 presents summary statistics of key variables.

3 Decomposition Exercise

3.1 Methodology

In this section, we decompose the changes in energy intensity in French manufacturing into four different components: the effect of exit, entry, changes within and reallocation across continuing firms. To begin, we first define the energy intensity of industry i in year t is as:

$$\log E_{it} = \sum_{j \in i} s_{jit} \log e_{jt} \tag{1}$$

where s_{jit} is the share of firm j's revenue in industry i and e_{jt} is the firm's energy intensity. The evolution of this measure in Figure 1 shows a downward trend with approximately 30 percent reduction over the 12-year period.

To decompose the observed decline, we follow the methodology in Foster et al. (2001) (henceforth FHK). The change in energy intensity at the industry level between t and $t-1$ is defined as:

$$\Delta \log E_{it} = \log E_{it} - \log E_{i,t-1}. \tag{2}$$

The industry-level change in energy intensity can be written as the sum of two terms:

$$\Delta \log E_{it} = \Delta \log E_{it}^{NE} + \Delta \log E_{it}^{C} \tag{3}$$

where $\Delta \log E_{it}^{NE}$ is the change in industry-level energy intensity driven by net entry (entry and exit of firms) and $\Delta \log E_{it}^{C}$ captures the change driven by continuing firms. The first term in (3) is further decomposed as below:

$$\Delta \log E_{it}^{NE} = \underbrace{\sum_{j \in N_{it}} s_{jit} \left(\log e_{jt} - \log E_{i,t-1}\right)}_{\text{entry term}} - \underbrace{\sum_{j \in X_{it}} s_{ji,t-1} \left(\log e_{j,t-1} - \log E_{i,t-1}\right)}_{\text{exit term}} \tag{4}$$

where N_{it} is the set of entering firms and X_{it} is the set of exiting firms. We define a firm as *entering* if it is only active (records non-zero revenue and employees) in t and not active in $t-1$ and *exiting* if it is only active at $t-1$ and not active in t. The first component, the entry term, lowers aggregate energy intensity if entering firms' energy intensity levels are lower than the initial industry average. The second component, the exit term, lowers aggregate energy intensity if the exiting firms' energy intensity levels are higher than the industry average. The second term in (3) can also be further decomposed as below:

$$\Delta \log E_{it}^{C} = \underbrace{\sum_{j\in C_{it}} s_{ji,t-1}\,\Delta \log e_{jt}}_{\text{within term}} + \underbrace{\sum_{j\in C_{it}} (\log e_{jt} - \log E_{i,t-1})\,\Delta\, s_{jit}}_{\text{reallocation term}} \tag{5}$$

where C_{it} is the set of continuing firms. A *continuing* firm is defined as such if it is active in both $t-1$ and t. The first term, the within term, measures changes in industry-level energy intensity driven by changes in the energy intensity of existing firms, holding their sizes fixed. The second term, the reallocation term, measures changes in industry-level energy intensity that are due to the reallocation of output shares among existing firms.[1] Once we decompose energy intensity for each 2-digit industry, we compute the aggregate manufacturing-wide change in energy intensity by calculating the average across all industries.

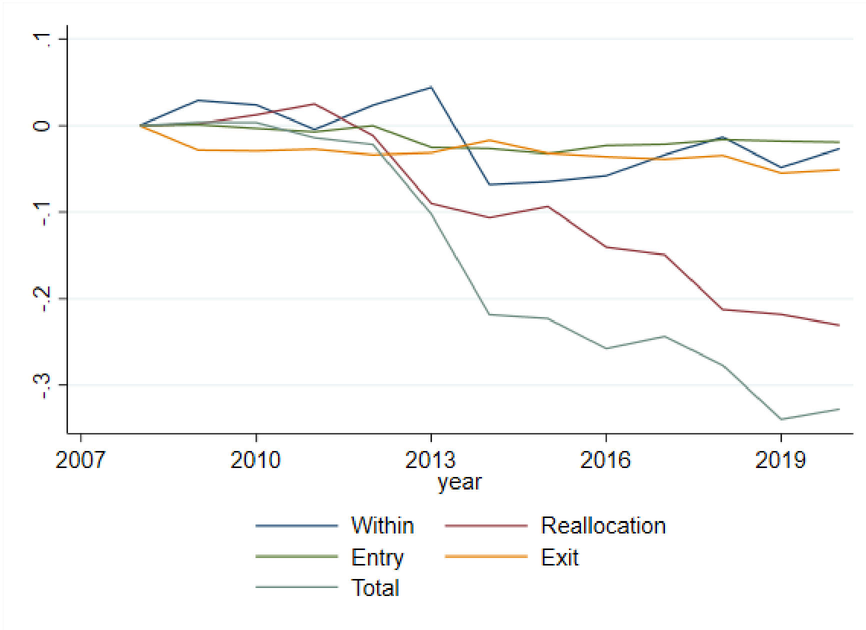
Although we are able to accurately measure firm status based on the fiscal census that covers the population of firms, information on energy intensity is only available for the representative sample of firms in the energy survey (EACEI). Thus, applying this decomposition method to the sample of firms in our panel data might be noisy as the method tracks the same firms over time and not all firms are observed every year in the survey. We investigate the magnitude of measurement error in our context and find that the error disappears cumulatively as most firms in our sample are observed over at least two consecutive years. Appendix A2 explains this in detail.

3.2 Results

Figure 2 depicts the cumulative change in aggregate energy intensity driven by four different elements, namely, improvement within firms, reallocation between firms, exit, and entry. Despite the strong focus on the reduction of energy intensity within firms in the existing micro-empirical literature, we find that the contribution of within-firm improvement in energy intensity accounts for a relatively small share, 8 percent, of the total reduction. Instead, the alternative channels of

[1] This term can be further decomposed into a between term ($\sum_{j\in C_{it}} (\log e_{j,t-1} - \log E_{i,t-1})\,\Delta\, s_{jit}$) that captures changing market shares weighted by the deviation of the firm's energy intensity from the industry average in the previous period, and a covariance term ($\sum_{j\in C_{it}} \Delta \log e_{jt}\,\Delta\, s_{jit}$).

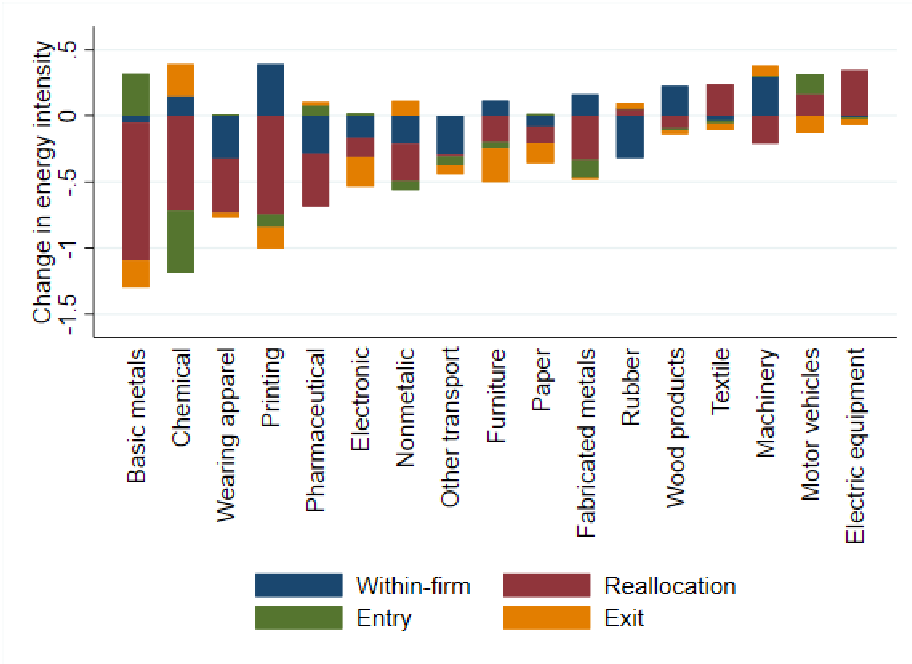
Figure 2: Decomposition of the Change in Energy Intensity in the Manufacturing Industry



selection and market reallocation contributed significantly to the total reduction in aggregate energy intensity. Of the 33 percent reduction in aggregate energy intensity over the sample period, 23 percent is attributable to reallocation, accounting for 70 percent of the total change. The contribution suggests that less energy-intensive firms grew larger over time, lowering the industry-level average energy intensity weighted by market shares. Next, we observe that exit contributed to reducing aggregate energy intensity, which suggests that exiting firms are more energy-intensive than industry average. As the second most important driver after reallocation, it accounts for 16 percent of the total reduction in aggregate energy intensity. Entrants appear to have lower energy intensities than the industry average, although the overall contribution accounts for only 6 percent of the total reduction.

We find similar patterns with respect to the reduction in aggregate carbon intensity with reallocation and exit contributing significantly to decreasing industry-level carbon intensity (Figure A2). Examining heterogeneity in the strength and operation of selection and market reallocation across sectors, we continue to observe strong contributions of adjustments between firms at the extensive margin. In 13 out of 17 sectors, the joint contributions of selection and reallocation far

Figure 3: Decomposition of the Change in Energy Intensity by Sector



outweigh that of the within component (Figure 3), which suggests that the significant contributions of selection and reallocation at the aggregate manufacturing level are not driven by a few specific sectors.

3.3 Robustness Checks

To examine the robustness of our decomposition results, we consider alternative decomposition methods by Griliches and Regev (1995) and Melitz and Polanec (2015), henceforth GR and MP, respectively. These two methods are similar to the FHK approach except for the choice of a reference energy intensity level against which the contribution of different terms are measured. The FHK approach uses the average industry average energy intensity from the previous year as a reference point, whereas GR use the average between the current and previous year as a reference point. On the other hand, MP extend the cross-sectional decomposition approach in Olley and Pakes (1996) to incorporate the contribution of entry and exit. This method uses the average energy intensity of the firms surviving into the next period to measure the contribution of exiting firms, and use the average energy intensity of incumbents to measure the contribution of entering firms. The contribution of within and reallocation is calculated from the cross-sectional decomposition in Olley and Pakes (1996). Appendix A3 provides detailed discussions on these alternative methods.

Table A9 shows that the contributions of selection and reallocation remain strong relative to the within-firms component across different methodological approaches. Reallocation account for 45 and 69 percent of the reduction in aggregate energy intensity according to the GR and MP method, respectively. Selection is an important driver in both methods, accounting for 28 and 9 percent of the decrease in GR and MP, respectively.

4 The Impact of Energy Prices on Selection and Reallocation

The previous section documents that adjustments between firms at the extensive margin significantly contributed to the reduction in aggregate energy intensity in the French manufacturing sector. However, to what extent were the observed patterns driven by policy initiatives for decarbonization? This section explores the causal impact of environmental policy, proxied by energy prices, on the channels of selection and reallocation in reducing aggregate energy intensity.

4.1 Identification

To study how energy prices affect the channels of selection and reallocation, we consider the following specification:

$$y_{jit} = \alpha + \beta \ln p_{jit} + \lambda_j + \delta_t + \epsilon_{jit}, \tag{6}$$

where y_{jit} represents the outcome variables of firm j in sector i in year t. Using this specification, we examine the following three outcomes. The first outcome of interest is exit probability of firm j in sector i that takes 1 if it exits in the following year or 0 if it continues to remain active. The second outcome variable is the market share of the firm measured within its sector, which allows us to examine the patterns of reallocation of output across firms. Finally, the third outcome of interest is energy intensity which will capture the element of within-firm improvement. The firm-level unit price of energy p_{jit} is constructed by dividing total energy expenditure by total energy consumption that we use as a proxy for the stringency of environmental regulation (Linn, 2008; Marin and Vona, 2021; Dussaux, 2020; Bretschger and Jo, 2024). The coefficient of interest β captures the impact of energy prices on our outcome variables. To account for unobservable firm characteristics, we include firm fixed effects, λ_j. Year-specific shocks are absorbed by year fixed effects, δ_t. Standard errors are clustered at the firm level to allow for correlation within each firm.

To address the potential endogeneity of firm-specific energy prices, we rely on the shift-share instrument:

$$\ln p_{jit}^{iv} = \sum_f \omega_{ji,t=0}^f \ln p_{it}^f \tag{7}$$

where $\omega_{ji,t=0}^f$ is the share of fuel f in the total energy consumption of firm j in the pre-sample period and p_{it}^f is the median price of fuel f in sector i in year t.[2] We examine the mean and standard deviation of different fuel shares across firms and observe substantial dispersions, which provide strong firm-level variation in the instrument (Table A2). Furthermore, Figure A3 shows sufficient variation arising from sector-level fuel prices in the demeaned instrument that captures the annual deviation from the within-firm average, which we exploit for identification in our fixed-effects specifications.

The validity of the instrument relies on two identifying assumptions. First, sector-level fuel prices must be uncorrelated with firm-specific unobservables, which we find plausible given the large number of firms in each sector (around 3,900 firms on average). Second, firm-specific fuel shares from the pre-sample period should be uncorrelated with potential confounding factors in the future. To check the salience of the bias arising from this assumption, we control for a number of channels through which pre-sample fuel shares might affect the outcome variable as robustness checks.

[2] For example, one might worry about unobserved demand or productivity shocks that may affect firms' economic performance such as exit decisions and market shares and unit prices of energy simultaneously through quantity discounts (Dussaux, 2020; Marin and Vona, 2021).

Table 1: The Impact of Energy Prices on the Probability of Exit

	All	Bin 1 ($< 25\%$)	Bin 2 (25-50%)	Bin 3 (50-75%)	Bin 4 ($> 75\%$)
	(1)	(2)	(3)	(4)	(5)
Energy price	0.153***	0.089	-0.002	0.018	0.378**
	(0.057)	(0.139)	(0.059)	(0.091)	(0.151)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	24,076	4,942	5,751	6,354	6,621
F-stat	486.39	29.69	168.95	153.05	118.08

Notes: The estimates are from linear probability models. The dependent variable is the binary firm status that takes 1 if it exits in the following year or 0 if it continues to remain active. Standard errors are clustered at the firm level.

4.2 Exit Probability

We begin by examining the relationship between energy prices and exit probabilities. To probe heterogeneity in exit behavior of firms with different levels of energy intensity, we estimate equation (6) by either using a pooled sample of firms or dividing firms into four bins based on quartiles of the distribution of initial energy intensity.

Table 1 reports the IV estimates from linear probability models. The estimate in column (1) suggests higher energy prices, on average, increase the probability of exit: a 10 percent jump in energy prices in a given year increases the probability of firms exiting in the following year by 1.5 percent. However, the overall effect appears to be entirely driven by the most energy-intensive firms (Bin 4) in column (5). Given that energy costs account for a larger share of total operating costs in more energy-intensive firms, higher energy prices imply a larger increase in operating costs and subsequently, higher probabilities of exit among these firms. As a robustness check, we only consider a firm's final exit as genuine exit for firms that leave the market more than once in our sample (e.g., exit one year, re-enter, and exit again).[3] This alternative classification of firm status does not affect the result that only most energy-intensive firms experience a higher likelihood of exit

[3]Exit rate is 5.5 percent with our baseline measure of firm status, whereas the alternative classification leads to a lower rate of 4.6 percent.

in response to higher energy prices (Table A3). In addition, we try a more conservative specification that adds sector by year fixed effects, which yields similar results (Table A4).

To further examine the magnitude of selection on the basis of energy intensity, we also consider the following specification:

$$\ln e_{jit} = \alpha + \beta\, survival_{jit} + \beta'\, survival_{jit} * \ln p_{jit} + \lambda_{it} + \epsilon_{jit}, \tag{8}$$

where e_{jit} denotes energy intensity of firm j in sector i in year t and $survival_{jit}$ is a binary indicator of whether firm j survives in the next period. λ_{it} is sector by year fixed effects, thus achieving identification through variation across firms within a given sector and a year. We expect β' to be negative if energy prices lead to tougher selection on firms. Column (1) of Table 2 shows the result from estimating the equation above, which again provides strong evidence of selection based on energy intensity driven by energy prices. Not only are surviving firms on average have lower energy intensities than exiting firms in the same sector and year, the energy intensity difference between the two groups is much larger when energy prices are higher, as shown by the negative coefficient on the interaction between the survival indicator and energy prices. In column (2), we instrument for energy prices with our shift-share instrument and find similar estimates.

4.3 Reallocation

Next, we examine the impact of energy prices on the reallocation of market shares. To understand the extent to which energy price shocks affected the pattern of reallocation across firms with different energy intensities, we estimate equation (6) with firms' market shares as the dependent variable on all firms as well as separately by groups of firms divided according to their initial energy intensity similarly as above. As measures of market share, we look at the revenue, employment, and value added share of a firm within its sector. We continue to apply the shift-share instrument to address the endogeneity of firm-level energy prices.

Table 2: The Energy Intensity Difference of Surviving and Exiting Firms

	(1)	(2)
Survival	-0.916***	-1.112***
	(0.043)	(0.056)
Survival × energy price	-2.042***	-2.575***
	(0.048)	(0.096)
Sector by year FE	✓	✓
Observations	33,742	26,223
F-stat		5,234

Notes: The dependent variable is energy intensity in log. Column (1) estimates the specification in (8) and column (2) estimates the same specification but instruments the energy price measure with the shift-share instrument. Standard errors are clustered at the firm level.

Table 3 reports the estimates.[4] In column (1) of panel A, we find that rising energy prices are negatively correlated with revenue across all firms, although the impact is statistically insignificant. Estimating the regressions separately for groups of firms with different levels of initial energy intensity shows that the least energy-intensive firms (Bin 1) experienced an increase in the share of revenue, while other firms had a statistically insignificant fall in their market shares in response to higher energy prices. However, the increase in market shares experienced by the least energy-intensive firms is economically very small. A 100 percent increase in the energy price increases the revenue share of the cleanest firms by 0.003 pp from the baseline 0.4 percent.

Panel B and C report the reallocation impact of energy prices by using the employment and value added share as alternative measures of a firm's market share. The pattern of the cleanest firms growing larger and other firms shrinking continues to hold, although the impact is statistically insignificant and very small in size. Overall, the findings suggest that energy prices were not a major driver behind the channel of reallocation driving the decline in aggregate energy intensity.

[4] There are more observations in these regressions as the market share is regressed on the energy price variable in the same period, whereas the specifications in Table 1 relate the exit status of the firm in the current period to the energy price in the previous period.

Table 3: The Impact of Energy Prices on Market Shares

	All	Bin 1 ($< 25\%$)	Bin 2 (25-50%)	Bin 3 (50-75%)	Bin 4 ($> 75\%$)
	(1)	(2)	(3)	(4)	(5)
Panel A: Revenue share					
Energy price	-0.002	0.008*	-0.004	-0.007	-0.005
	(0.002)	(0.004)	(0.005)	(0.007)	(0.005)
Panel B: Employment share					
Energy price	-0.003	0.001	-0.005	-0.005	-0.004
	(0.002)	(0.004)	(0.004)	(0.006)	(0.004)
Panel C: Value added share					
Energy price	-0.004	0.003	-0.006	-0.008	-0.004
	(0.003)	(0.004)	(0.006)	(0.007)	(0.005)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	37,203	8,592	9,089	9,375	9,260
F-stat	466.07	51.07	152.85	92.37	137.27

Notes: The dependent variables are the market share of firms within their sectors measured by revenue, employment, and value added in Panel A, B, and C, respectively. Standard errors are clustered at the firm level.

4.4 Within-firm Improvement

The impact of energy prices on energy intensity within firms is well-documented in the literature (e.g., Metcalf, 2008; Mulder and De Groot, 2012; Steinbuks and Neuhoff, 2014; Antonietti and Fontini, 2019; Dussaux, 2020; Levinson, 2021). Estimating the impact in our sample using the specification (6) and the shift-share instrument, we find the elasticity of -0.21 (column (1) of Table A5), which is comparable to the existing estimates that range between -0.11 (Metcalf, 2008) and -0.52 (Dussaux, 2020). Across the distribution of initial energy intensity, we find that the most energy-intensive firms (Bin 4) reduced their intensities more than less energy-intensive firms, as expected from their large energy cost shares.

4.5 Sensitivity Analysis and Discussion

4.5.1 Robustness checks

We examine the robustness of our results based on the discussions provided in Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022) on the validity of shift-share instruments. The main concern is that pre-sample fuel shares may predict outcomes (exit probability, market shares, and energy intensity) through channels other than energy price shocks. Thus, we begin by exploring the relationship between fuel shares and other firm characteristics that may be correlated with innovations in our outcome variables in the pre-sample period. Specifically, we look at labor productivity, firm age and value added as potential channels through which pre-sample fuel shares may predict the changes in our outcome variables.

Table A6 reports the the correlations between initial firm characteristics and the share of the top 3 fuel shares (electricity, natural gas, and heavy fuel oil). We note that R^2 in these regressions are very small (between 1 and 3 percent), mitigating the worry that these variables are strong sources of omitted variable bias. Although correlations in levels do not violate the identifying assumption, they can be a concern if these factors predict the *change* in exit probability or market shares, not just levels. Thus, we directly control for these factors in the regressions and examine the change in the estimates as a simple way to test the extent to which they are biasing the estimation Goldsmith-Pinkham et al. (2020). Table A7 shows that our estimates of the impact of energy prices are stable across our outcome variables even when these potential confounders are directly controlled for.

4.5.2 Relocation

Our analysis shows that higher energy prices induce the most energy-intensive firms to exit the market. However, one might worry that exiting firms simply relocate to a foreign location in response to more stringent environmental regulation in the domestic market, rather than exiting due to a larger increase in operating costs. Although estimating the patterns of relocation using data on full ownership structure of firms is beyond the scope of this study, our data allows us to explore signs of financial distress leading up to exit, which would suggest that firms decide to leave the market due to operational and financial constraints rather than to move their business elsewhere. This observation would corroborate the importance of selection effects in reducing aggregate emissions.

As signs of financial distress, we consider three measures: profits, and loans and unpaid bills relative to revenue. The information is available from the FARE. We regress these variables in log on dummies for x years before the firm's exit for up to five years. With firm and year fixed effects, the dummies capture whether there are changes in financial distress in years leading up to exit compared to other years within firms. Table A8 provides support that exit behavior recorded in our data is likely to be due to operational and financial constraints rather than relocation: profits tend to fall, while liability and unpaid bills grow in size relative to their revenues over time before firms leave the market.

Prior studies that investigate the impact of environmental regulation on firm or production relocation also find little evidence of carbon leakage through relocation (aus dem Moore et al., 2019; Naegele and Zaklan, 2019; Dechezleprêtre et al., 2022). For example, Dechezleprêtre et al. (2022) study whether multinationals subject to the EU Emissions Trading Scheme reduce emissions in Europe only to increase them elsewhere through production relocation, using data on multinational firms that operate across a wide range of jurisdictions. They do not find evidence that the EU ETS has led to a displacement of carbon emissions from Europe toward the rest of the world within multinationals. The finding provides strong evidence against leakage given , despite the fact that these firms are likely tomight be particularly responsive to environmental regulations that impose higher production costs in a given location by shifting production to less-regulated regions in which they already operate.

5 Policy Implications

Our decomposition exercise shows that market-share reallocation is the primary driver of changes in aggregate energy intensity. Concurrently, we also find little evidence that energy prices have a direct effect on this reallocation. This suggests that the ability of policies, such as carbon pricing or energy taxes, that raise energy prices and induce sector-wide reductions in energy intensity might be limited. However, this logic excludes the fact that energy prices have an indirect effect on market-share reallocation through their impact on firm exit. As energy price shocks tend to drive energy-intensive firms out of the market, the production of these exiting firms will be captured, in part, by surviving firms. To determine the economic importance of rising energy prices on reducing sectoral energy intensity, we must then consider how surviving firms benefit from their competitors' exit. This is what we do next.

Specifically, we quantify how an increase in energy prices affects sectoral energy intensity through their direct effects on within-firm improvements in energy intensity and firm exit, while considering different scenarios of how market shares of exiting firms are reallocated to surviving firms. We simulate a 20% increase in the price of fossil-fuel energy. Because firms differ in their reliance on clean energy, the effective firm-level price change is $0.20 \cdot (1 - \omega_{jt})$, where ω_{jt} denotes firm j's clean-energy share. Cleaner firms therefore face a smaller effective shock, consistent with the heterogeneity that underlies our identification strategy in the previous section.

We use our reduced-form estimates to translate this price shock into counterfactual changes in exit and within-firm energy intensity. For the impact on exit, we use the quartile-specific IV coefficient (0.378) for the dirtiest firms (those above the 75th percentile of energy intensity in their sector), and zero for the three lower quartiles, whose estimates are statistically indistinguishable from zero. For the within-firm response, we apply the pooled IV elasticity (-0.21) uniformly across quartiles.[5] Rather than predicting both baseline and counterfactual outcomes from the model, we anchor the baseline at the observed exit indicator and observed energy intensity, and add only the model-implied change to construct the counterfactual. Finally, we take entry as given, as we do not want to impose additional structure to model how selection based on entry unfolds.

For market-share reallocation, we consider three scenarios with the aim of bounding our quantification exercise. Note that in our scenarios, market-share reallocation is driven entirely by the exit of dirtier firms in response to the energy price shock—none of the other three quartiles experience additional exit. We thus need to determine which surviving firms benefit from this exit. In the first scenario, the market shares freed by exiting firms are allocated proportionally across all firms in the same sector, based on baseline market shares. Firms with larger market shares thus gain a little more than firms with smaller market shares. In the second scenario, only firms with the lowest energy intensity (the first quartile) "receive" the reallocated market shares. This is an extreme scenario where firms' exit benefits only cleaner firms. The third scenario does the opposite: the most energy-intensive surviving firms (the fourth quartile) capture the reallocated shares. This is plausible if, within a sector, production is a closer substitute for firms with a similar level of energy intensity.

The main outcome of interest is the expected (log) energy intensity of industry i in year t, where the expectation considers the probability that firm j will survive to year t. In the baseline scenario, denoted by the superscript 0, the expected energy intensity corresponds to:

$$\mathbf{E}\left[\log E_{it}^{0}\right] = \sum_{j\in i}(1 - T_{jit}^{0}) \cdot s_{jit}^{0} \cdot \log e_{jt}^{0}. \tag{9}$$

[5] To obtain these coefficients, we ran a separate IV regression for each energy intensity quartile to estimate the impact of energy price shocks on exit probabilities. For the within-firm energy intensity response, we use the same IV strategy on the full sample. Remember, that firm-level quartile assignment is based on each firm's position in the sector-year distribution of energy intensity in the first year it appears in the panel, and is then held fixed over its lifetime.

As in equation (1), s_{jit} is the share of firm j's revenue in industry i and e_{jt} is the firm's energy intensity. The variable T_{jit} is the exit probability, so that $(1 - T_{jit})$ is the probability that firm j survives in year t. The baseline quantities T^0_{jit} and e^0_{jt} correspond to the observed exit indicator and observed energy intensity. Once we construct each counterfactual outcome, we can compute the expected energy intensity for, say, scenario 1, which we denote $\mathbf{E}\left[\log E^1_{it}\right]$:

$$\mathbf{E}\left[\log E^1_{it}\right] = \sum_{j \in i} (1 - T^1_{jit}) \cdot s^{\text{scenario}}_{jit} \cdot \log e^1_{jt}, \tag{10}$$

where $s^{\text{scenario}}_{jit}$ are the market shares computed under one of the three scenarios outlined above, and T^1_{jit} and e^1_{jt} are, respectively, the counterfactual exit probability and counterfactual energy intensity obtained by adding the reduced-form effect of the firm-specific energy-price change to the observed baseline.

This approach allows us to decompose the change in energy intensity along the different margins. To quantify the contribution of exit, we simulate the expected energy intensity using the counterfactual exit probabilities T^1_{jit} and the reallocated market shares $s^{\text{scenario}}_{jit}$—both of which are driven by exit—while holding within-firm energy intensity at its baseline value $\log e^0_{jt}$. The within-firm channel is computed symmetrically, by letting only $\log e^1_{jt}$ vary while holding exit probabilities and market shares at their baseline values. We thus report results showing the overall change in energy intensity and, then, the change induced solely by exit (inclusive of its associated share reallocation), allowing us to gauge the importance of selection relative to within-firm improvements.

5.1 Results

Table 4 presents results. We first report how a 20% increase in fossil fuel prices affects the average energy price across sectors. Next, we show the percentage change in sectoral energy intensity, accounting for the direct effects of prices on exit and within-firm improvement. The next column only takes into account exit, i.e., we shut down the impact of energy price shock on within-firm energy intensity improvement. For both sets of results, market shares are adjusted due to exit. The main results are for the scenario where market shares are allocated proportionally to all firms. In brackets, we present the two scenarios where all market shares are allocated to the cleaner firms, or dirtier firms, respectively. Finally, in the last two columns, we replicate the same exercise, but we reduce the impact of the energy price shock on the exit probability of the dirtier firms by half.

There are five important takeaways. First, for most sectors, the energy prices have an economically significant impact on energy intensity. Across all sectors, the implied elasticities is -1.01 and range from -1.25 to -0.86. Second, while the effects depend on the market share reallocation process, the estimates have rather tight bounds. Third, most of the reductions, for instance, more than 85% of the overall change, are driven by the impact of energy prices on exit. Within-firm changes in energy intensity tend to have a second-order effect for most sectors. Fourth, there is substantial heterogeneity across sectors. The magnitude of the effects is determined by our estimate of the impact of energy price shocks on firms in the most energy-intensive quartile, with respect to exit. For some sectors, metals for instance, the impact is very large. How these estimates translate to other regions, evolve over time, and can be impacted by policies that aim to protect firms from large price shocks would have an important impact on firm dynamics and, ultimately, decarbonization of these sectors. Fifth, the magnitude of the impact of energy price on exit probability is economically important. In the appendix (Table A10), we show that even reducing its magnitude by half still leads to large improvement in energy intensity. The average elasticity is reduced to -0.63, from -1.01, which is still economically large.

6 Conclusion

This paper provides new evidence on the sources of aggregate energy intensity reduction by shifting the focus from within-firm adjustment to industry dynamics. While the existing empirical literature on climate policy has largely emphasized improvements in energy efficiency within firms, we show that the fall in aggregate energy intensity is driven primarily by adjustments between firms operating at the extensive margin. In particular, our analysis demonstrates that firm selection and

Table 4: Impact of 20% Fossil Fuel Price Increases and Decomposition of Energy Intensity Changes

Sector	Δ Energy Price	Δ Energy Intensity	Δ Energy Intensity w/o Within-Firm
Textile	9.9%	-6.2% [-7.1%, -5.4%]	-4.5% [-5.5%, -3.7%]
Apparel	8.3%	-5.9% [-6.5%, -5.3%]	-4.3% [-4.9%, -3.7%]
Wood	7.1%	-12.0% [-14.7%, -10.2%]	-10.6% [-13.3%, -8.8%]
Paper	8.5%	-15.5% [-19.3%, -14.8%]	-13.9% [-17.8%, -13.2%]
Printing	5.2%	-6.5% [-7.5%, -5.7%]	-5.5% [-6.4%, -4.7%]
Chemical	9.0%	-7.6% [-9.2%, -6.3%]	-6.1% [-7.7%, -4.8%]
Pharma	8.5%	-2.2% [-2.3%, -2.1%]	-0.6% [-0.8%, -0.5%]
Rubber	4.8%	-2.4% [-2.7%, -2.2%]	-1.1% [-1.4%, -1.0%]
Non-metalic	9.4%	-24.3% [-31.1%, -23.0%]	-22.5% [-29.5%, -21.1%]
Basic metals	8.9%	-14.2% [-17.8%, -13.4%]	-12.6% [-16.3%, -11.9%]
Fabricated metals	7.1%	-9.5% [-11.4%, -8.5%]	-8.1% [-10.1%, -7.1%]
Electronic	4.8%	-1.9% [-2.1%, -1.6%]	-1.2% [-1.4%, -0.8%]
Electric equip	8.1%	-8.2% [-10.4%, -7.6%]	-6.9% [-9.1%, -6.3%]
Machinery	9.5%	-4.5% [-5.1%, -4.1%]	-3.0% [-3.6%, -2.6%]
Motor vehicles	7.5%	-3.9% [-4.1%, -3.5%]	-2.2% [-2.4%, -1.9%]
Transport	8.6%	-5.0% [-5.4%, -5.0%]	-3.6% [-4.0%, -3.5%]
Furniture	9.2%	-5.3% [-5.9%, -4.8%]	-3.6% [-4.1%, -3.0%]
Average	7.9%	-8.0% [-9.9%, -6.8%]	-6.7% [-8.7%, -5.5%]
Implied ε		-1.01 [-1.25, -0.86]	-0.85 [-1.10, -0.70]

Notes: The first column presents the percentage change in energy price in each sector when fossil prices increase by 20%. The second column is the percentage change in the (log) energy intensity. The main estimates consider a proportional reallocation of market shares when firms exit. The estimates in brackets consider that market shares are reallocated to the less energy intensive firms, or more energy intensive firms, respectively. In the last column, the impact of energy prices on within-firm energy intensity improvements is shut down. The bottom panel presents the (unweighted) averaged and implied elasticity.

market reallocation account for the majority of the decline in aggregate energy intensity in French manufacturing.

Investigating the impact of environmental policy proxied by energy prices on selection and reallocation, we find causal evidence that higher energy prices disproportionately increase the exit probability of the most energy-intensive firms, while having no impact on other firms. Energy prices have comparatively weak effects on market-share reallocation. We then use these reduced-form estimates to simulate the aggregate implications of future energy price increases. The simulations indicate that most of the decline in aggregate energy intensity would arise through firm exit and subsequent reallocation rather than through improvements within surviving firms.

These findings have important implications for policy design. If aggregate energy intensity reductions are driven largely by selection and reallocation, then policies that influence market structure and competitive dynamics may complement traditional instruments such as carbon pricing or abatement subsidies targeted at individual firms. More broadly, our results suggest that understanding decarbonization requires studying not only technological adjustment within firms, but also the evolution of industries through entry, exit, and changing market shares.

Finally, our analysis opens several directions for future research. An important question is why market-share reallocation toward cleaner firms appears quantitatively strong in the decomposition exercise, despite the relatively limited direct effect of energy prices on market shares. Future work could also investigate the welfare consequences of selection-driven decarbonization, including implications for productivity, employment, firm profits, and consumer surplus.

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Online Appendix

A1 Additional information on data

Our analysis draws on two sources of data. First, the fiscal census (FARE) provides general information about the firm (identifier, industry classification, total number of workers employed, age, etc.), the income statement (containing variables such as total turnover, total labor costs and value added) as well as balance sheet information (e.g., various measures of capital, debt and assets). The exhaustive coverage of the FARE allows us to accurately keep track of firms' lifespan and measure firm status as continuing, entering, or exiting with minimal measurement errors, compared to surveys based on a sampling pool.

The second source is the Annual Survey of Industrial Energy Consumption (EACEI), a survey conducted annually by the INSEE. Although not all plants in the manufacturing industry are covered, the survey includes all large plants (with over 250 employees) and a representative sample of plants with 20 employees or more in energy-intensive sectors with the response rate close to 90 percent. To merge with the firm-level information from the fiscal census, we aggregate plant-level information from the EACEI to the firm level. For multi-plant firms, it is important to ensure the energy use data across plants reported in the EACEI is representative of the entire firm. Thus, we keep observations in the EACEI when the sum of employment across plants belonging to the same firm is at least 90 percent or higher of the employment recorded in the fiscal census.

For carbon intensity, we use the information on energy consumption by fuel and CO2 conversion factors from the French Environment and Energy Management Agency (Ademe) to calculate CO2 emissions at the firm level which we then divide by output. Specifically, the emission factor is 2,750 kg CO2/toe for natural gas, 3,700 kg CO2/toe for domestic heating oil, 3,170 kg CO2/toe for butane/propane, and 582 kg CO2/toe for electricity (Dussaux, 2020).

Figure A1: Unit price of energy over time

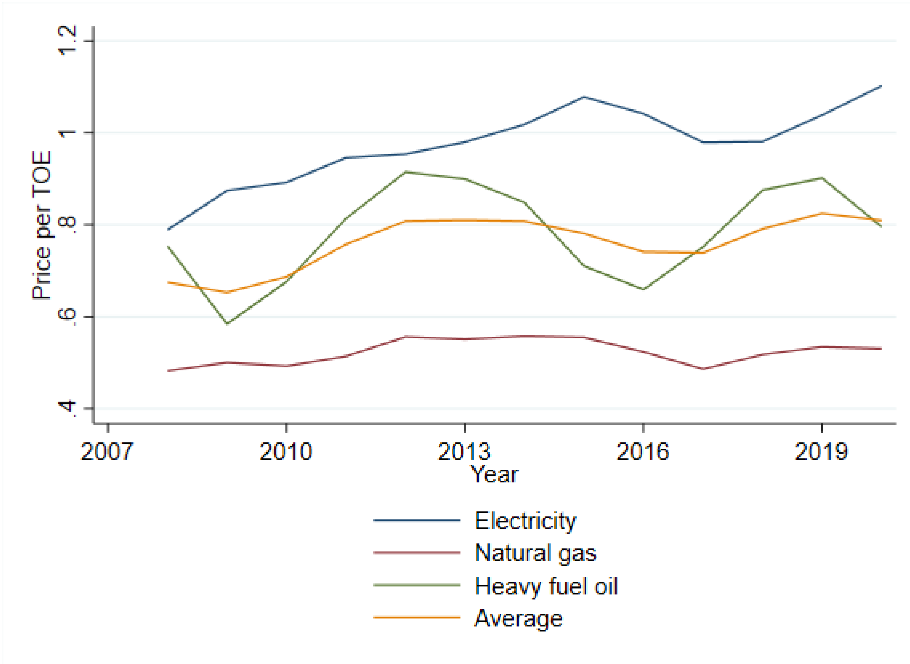


Table A1: Summary Statistics of Key Variables

	Mean	SD	P10	Median	P90
Energy intensity (TOE/VA)	142.27	306.67	12.43	50.09	300.37
Carbon intensity (CO2/VA)	213.08	530.15	12.50	62.92	450.27
Energy unit price	0.80	0.37	0.50	0.77	1.13
Revenue	50,675	243,962	3,070	13,957	89,597
Value added (VA)	14,237	67,401	1,143	4,312	25,853
Market share	0.004	0.021	0.000	0.001	0.006
Employees	178.2	566.4	24	75	341

Notes: The table reports the summary statistics of the key variables used in the analyses based on the EACEI sample.

Figure A2: Decomposition of the Change in Carbon Intensity

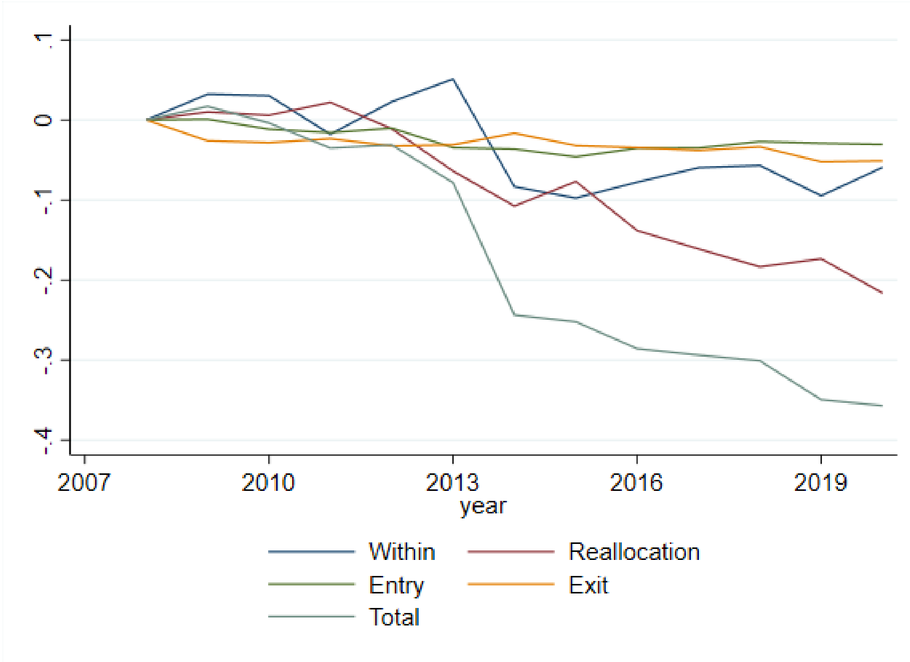


Table A2: Fuel Composition

Fuel	Electricity	Natural gas	Heating oil	Butane	Heavy fuel oil	Other gas
Average	0.61	0.28	0.04	0.04	0.00	0.00
(SD)	(0.276)	(0.282)	(0.113)	(0.124)	(0.044)	(0.043)

Table A3: The Impact of Energy Prices on the Probability of Exit:
An Alternative Measure of Exit

	All	Bin 1 ($<$ 25%)	Bin 2 (25-50%)	Bin 3 (50-75%)	Bin 4 ($>$ 75%)
	(1)	(2)	(3)	(4)	(5)
Energy price	0.142***	0.066	-0.058	0.053	0.363**
	(0.054)	(0.127)	(0.050)	(0.080)	(0.145)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	24,076	4,942	5,751	6,354	6,621
F-stat	486.39	29.69	168.95	153.05	118.08

Notes: The estimates are from linear probability models. The dependent variable is an alternative binary firm status that only considers final exit as exit for firms that leave the market more than once during the sample period. Standard errors are clustered at the firm level.

Figure A3: Variation in the Instrument over Time within Firms

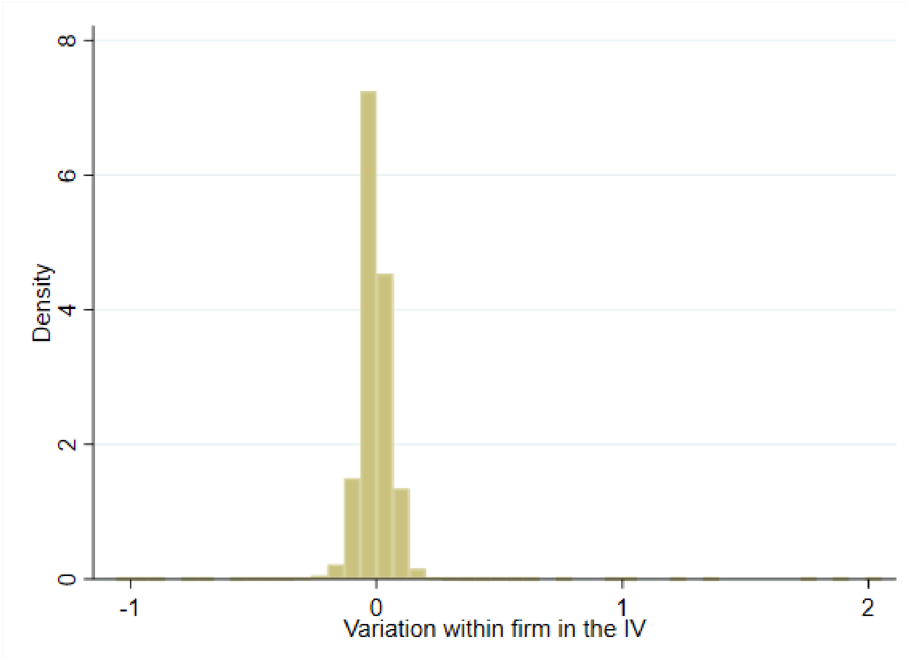


Table A4: The Impact of Energy Prices on the Probability of Exit:
An Alternative Specification

	All (1)	Bin 1 (< 25%) (2)	Bin 2 (25-50%) (3)	Bin 3 (50-75%) (4)	Bin 4 (> 75%) (5)
Energy price	0.303*	0.501	-0.023	0.053	0.554*
	(0.169)	(1.306)	(0.169)	(0.340)	(0.335)
Firm FE	✓	✓	✓	✓	✓
Sector by Year FE	✓	✓	✓	✓	✓
Observations	24,076	4,942	5,751	6,354	6,621
F-stat	85.61	1.96	21.05	9.06	29.75

Notes: The estimates are from linear probability models. The dependent variable is the binary firm status that takes 1 if it exits in the following year or 0 if it continues to remain active. Standard errors are clustered at the firm level.

Table A5: The Impact of Energy Prices on Energy Intensity within Firms

	All (1)	Bin 1 ($<$ 25%) (2)	Bin 2 (25-50%) (3)	Bin 3 (50-75%) (4)	Bin 4 ($>$ 75%) (5)
Energy price	-0.211*	-0.398	-0.310	-0.222	-0.432*
	(0.127)	(0.366)	(0.208)	(0.311)	(0.224)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	37,203	8,592	9,089	9,375	9,260
F-stat	466.04	50.95	152.89	92.31	137.04

Notes: The dependent variable is energy intensity (log). Standard errors are clustered at the firm level.

Table A6: The Correlates of Pre-sample Fuel Shares

Fuel	Electricity (1)	Gas (2)	Fuel oil (3)
Labor productivity	-0.010	-0.016	0.020***
	(0.009)	(0.010)	(0.004)
Value added	-0.016***	0.037***	-0.020***
	(0.003)	(0.003)	(0.002)
Age	-0.000**	-0.000	0.000***
	(0.000)	(0.000)	(0.000)
Observations	5386	5386	5386
R^2	0.01	0.02	0.03

Notes: Standard errors are clustered at the firm level.

Table A7: Robustness Checks: Testing the Identifying Assumption

	All	Bin 1 ($<25\%$)	Bin 2 (25-50%)	Bin 3 (50-75%)	Bin 4 ($>75\%$)
	(1)	(2)	(3)	(4)	(5)
Panel A: Exit probability					
Energy price	0.183***	0.123	0.047	0.099	0.360**
	(0.055)	(0.149)	(0.059)	(0.086)	(0.145)
Observations	24,076	4,942	5,751	6,354	6,621
$F-stat$	488.68	28.91	172.07	151.45	119.08
Panel B: Revenue share					
Energy price	-0.003	0.007*	-0.006	-0.008	-0.005
	(0.002)	(0.004)	(0.005)	(0.007)	(0.005)
Observations	37,203	8,592	9,089	9,375	9,260
$F-stat$	468.53	50.69	155.80	91.73	138.13
Panel C: Within-firm improvement in energy intensity					
Energy price	-0.024	-0.106	0.005	0.148	-0.397*
	(0.116)	(0.366)	(0.187)	(0.267)	(0.206)
Observations	37,203	8,592	9,089	9,375	9,260
$F-stat$	468.53	50.69	155.80	91.73	138.13

Notes: Standard errors are clustered at the firm level. All specifications include firm and year fixed effects, and additionally controls for potential confounders including log labor productivity, firm age, and log value added. The bins are based on the quartiles of the distribution of initial energy intensity.

Table A8: Profit and Financial Distress Leading Up To The Year of Exit

	Profit (1)	Loans (2)	Bills to pay (3)
1 year before exit	-0.301***	0.285***	0.066***
	(0.026)	(0.102)	(0.025)
2 years before exit	-0.187***	0.132	0.073***
	(0.021)	(0.099)	(0.021)
3 years before exit	-0.134***	0.202**	0.062***
	(0.019)	(0.092)	(0.020)
4 years before exit	-0.084***	0.132	0.007
	(0.017)	(0.086)	(0.018)
5 years before exit	-0.042***	0.054	0.011
	(0.015)	(0.070)	(0.016)
Obsrevations	45,896	42,589	45,889

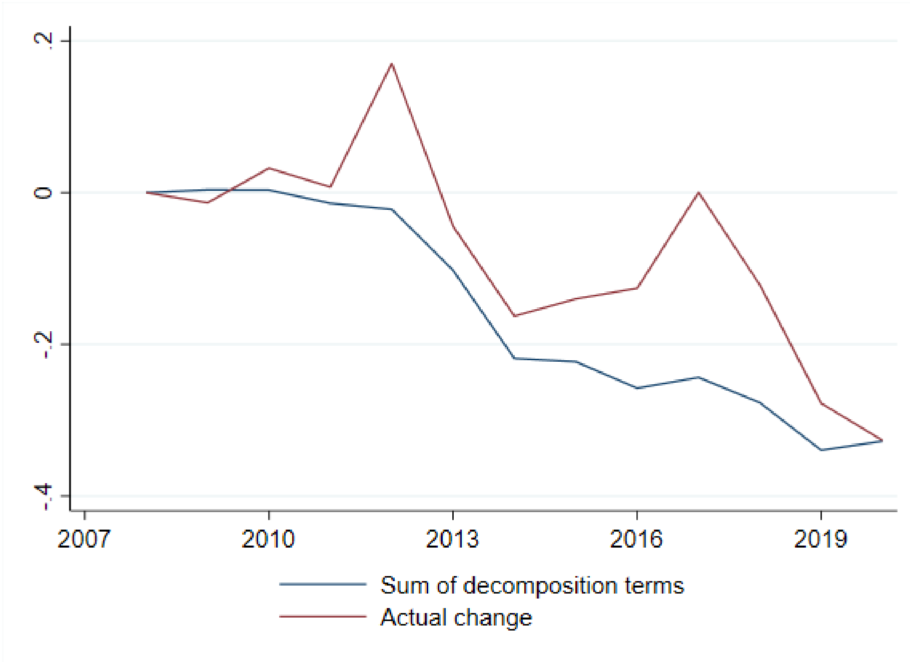
Notes: Dependent variables are specified in each column. All specifications include firm and year fixed effects. Standard errors are clustered at the firm level.

A2 Investigating measurement error in the decomposition

Although we are able to accurately measure firm status based on the fiscal census that covers the population of firms, information on energy intensity is only available for the representative sample of firms in the EACEI. Thus, applying the decomposition exercise to the sample of firms in our panel data might be noisy as the decomposition methods tracks the same firms over time and not all firms are observed every year. To explain, consider a continuing firm in t in our sample that was not observed in $t-1$ and hence its energy intensity is missing despite it being active in $t-1$. This firm's energy intensity is reflected in the change in energy intensity at the industry level in (2) through E_{it}. However, the firm will not be captured in the reallocation and within terms in (5) as both terms require information from the previous period. This introduces measurement error between the sum of the four terms in the decomposition exercise and the change in the average industry energy intensity in (2) calculated directly from the data. Note that entrants and exiters do not contribute to the measurement error. By definition, entrants do not have information on its energy intensity from the previous period. Although some exiters might be missing their energy intensities the year before they exit, they affect neither the decomposition term nor the change in the average industry energy intensity in (2) calculated directly from the data.

However, Figure A4 shows that the discrepancy between the two measures disappears cumulatively over the sample period. This is because the firm-year observations in t not captured in the decomposition of the change between $t-1$ and t due to the missing information in $t-1$ are captured in the decomposition of the change between t and $t+1$ if the firm is observed in $t+1$. In other words, only firm-year observations that do not have both preceding and succeeding observations will be dropped in the decomposition exercise, which tends to be rare in our data (over 90 percent of firm-year observations are over at least two consecutive years).

Figure A4: Measurement Error in the Decomposition Exercise



A3 Alternative decomposition methods

To check the robustness of our decomposition results, we consider alternative decomposition methods suggested by Griliches and Regev (1995) and Melitz and Polanec (2015), henceforth GR and MP, respectively.

The GR decomposition is similar to the FHK method except the reference point against which the contributions of entry and exit, as well as reallocation are measured. The FHK method uses the average industry energy intensity in $t-1$, $E_{i,t-1}$, as the reference point, whereas the GR method uses the average between the two periods, $(E_{it} + E_{i,t-1})/2$, as the reference point. Thus, defining the new reference point $\bar{E_{it}} = (E_{it} + E_{i,t-1})/2$, the GR decomposition is written as:

$$\Delta \log E_{it} = \underbrace{\sum_{j \in N_{it}} s_{jit} (\log e_{jt} - \log \bar{E_{it}})}_{\text{entry term}} - \underbrace{\sum_{j \in X_{it}} s_{ji,t-1} (\log e_{j,t-1} - \log \bar{E_{it}})}_{\text{exit term}}$$

$$+ \underbrace{\sum_{j \in C_{it}} \bar{s_{jit}} \, \Delta \log e_{jt}}_{\text{within term}} + \underbrace{\sum_{j \in C_{it}} (\log \bar{e_{jt}} - \log \bar{E_{it}}) \, \Delta \, s_{jit}}_{\text{reallocation term}} \quad \text{(A1)}$$

where the within and reallocation terms also feature an average firm share $\bar{s_{jit}} = (s_{jit} + s_{ji,t-1})/2$ and an average energy intensity $\bar{e_{jt}} = (e_{jt} + e_{j,t-1})/2$.

MP extends the cross-sectional decomposition in Olley and Pakes (1996) to accommodate the role of entry and exit. A key different to FHK and GR is that they use different reference energy intensity levels to measure the contribution of entry and exit. First consider the beginning-of-the-window energy intensity of industry i at time $t-1$ as

$$\log E_{i,t-1} = s^C_{i,t-1} \log E^C_{i,t-1} + s^X_{i,t-1} \log E^X_{i,t-1} \quad \text{(A2)}$$

where $s^C_{i,t-1} = \sum_{j \in C} s_{ji,t-1}$ represents the aggregate market share of continuing firms and $\log E^C_{i,t-1} = \sum_{j \in C} (s_{ji,t-1}/s^C_{i,t-1}) \log e_{jt}$ denotes the aggregate energy intensity of continuing firms. Similarly, $s^X_{i,t-1}$ and $\log E^X_{i,t-1}$ represent the aggregate market share and energy intensity of exiting firms, respectively.

The end-of-window industry energy intensity at time t is written as:

$$\log E_{it} = s^N_{it} \log E^N_{it} + s^C_{it} \log E^C_{it} \quad \text{(A3)}$$

where $s^N_{it} = \sum_{j \in N} s_{jit}$ represents the aggregate market share of entrants and $\log E^N_{it} = \sum_{j \in N} (s_{jit}/s^N_{it}) \log e_{jt}$ denotes the aggregate energy intensity of entrants.

Table A9: The Relative Contributions of Industry Dynamics:
Alternative Decomposition Methods

	Within	Reallocation	Entry	Exit
GR	21.9	45.1	5.0	28.0
MP	21.0	69.4	0.3	9.3

Notes: The table reports the relative contributions of each element measured in percent of the total change over the sample period.

From this, we obtain the change in aggregate energy intensity in terms of these components:

$$\Delta \log E_{it} = \underbrace{s_{it}^{N} \left(\log E_{it}^{N} - \log E_{it}^{C}\right)}_{\text{entry term}} - \underbrace{s_{ji,t-1}^{X} \left(\log E_{j,t-1}^{X} - \log E_{i,t-1}^{C}\right)}_{\text{exit term}} + \underbrace{\left(\log E_{it}^{C} - \log E_{i,t-1}^{C}\right)}_{\text{continuing term}} \quad \text{(A4)}$$

where the continuing term can be further decomposed according to the method in Olley and Pakes (1996) into the change in the unweighted average of continuing firms' energy intensities $\Delta \log \bar{e_{it}}^{C}$ and the change in the covariance between market share and energy intensity $\Delta \sum_{j \in C_{it}} (\log e_{jt} - \log \bar{e_{jt}}) (\log s_{jt} - \log \bar{s_{jt}})$. Note that the contribution of entry is measured against aggregate energy intensity of continuing firms at t, while the contribution of exit is measured against aggregate energy intensity of continuing firms at $t-1$. The use of different reference points in different decomposition methods will affect the relative contribution of each term.

Table A9 reports the results from these alternative decomposition approaches. The strong contribution of between-firms adjustments in reducing aggregate energy intensity relative to the contribution of within-firm improvement is apparent in both methods. Reallocation accounts for 45 and 70 percent of the total improvement in aggregate energy intensity in GR and MP method, respectively. As in FHK, net entry continues to be important in GR decomposition (accounting for 33 percent of the total change), while the magnitude of the contribution is smaller in MP.

A4 Policy Implications: Additional Results

Below, we reproduce the main estimates of the impact of 20% energy price shock presented in the main text, which we compare to simulation where we reduce the impact of energy price on exit probability. We cut the estimate of 0.378 for the dirtiest quartile by half to illustrate what a weaker link between energy prices and exit probability can do on overall energy intensity.

The impacts are non-linear. For instance, the overall implied elasticity goes from -1.01 to -0.63, which is still economically significant.

Table A10: Impact of 20% Fossil Fuel Price Increases and Decomposition of Energy Intensity Changes (proportional market share re-allocation case)

		Main Text Estimates		Exit Prob. Dirtier Firms Cut by Half	
Sector	Δ Energy Price	Δ Energy Intensity	Δ Energy Intensity w/o Within-Firm	Δ Energy Intensity	Δ Energy Intensity w/o Within-Firm
Textile	9.9%	−6.2%	−4.5%	−4.0%	−2.3%
Apparel	8.3%	−5.9%	−4.3%	−3.9%	−2.2%
Wood	7.1%	−12.0%	−10.6%	−7.0%	−5.5%
Paper	8.5%	−15.5%	−13.9%	−9.0%	−7.2%
Printing	5.2%	−6.5%	−5.5%	−3.9%	−2.8%
Chemical	9.0%	−7.6%	−6.1%	−4.6%	−3.1%
Pharma	8.5%	−2.2%	−0.6%	−1.9%	−0.3%
Rubber	4.8%	−2.4%	−1.1%	−1.8%	−0.6%
Non-metalic	9.4%	−24.3%	−22.5%	−14.2%	−12.0%
Basic metals	8.9%	−14.2%	−12.6%	−8.2%	−6.5%
Fabricated metals	7.1%	−9.5%	−8.1%	−5.7%	−4.2%
Electronic	4.8%	−1.9%	−1.2%	−1.3%	−0.6%
Electric equip	8.1%	−8.2%	−6.9%	−4.9%	−3.5%
Machinery	9.5%	−4.5%	−3.0%	−3.1%	−1.5%
Motor vehicles	7.5%	−3.9%	−2.2%	−2.8%	−1.1%
Transport	8.6%	−5.0%	−3.6%	−3.3%	−1.8%
Furniture	9.2%	−5.3%	−3.6%	−3.6%	−1.8%
Average	7.9%	−8.0%	−6.7%	−5.0%	−3.7%
Implied ε		−1.01	−0.85	−0.63	−0.47