Environment and the Economy:

Firm-level responses to energy price shocks

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Abstract

Although raising the carbon price is an effective tool for decreasing reliance on carbon-intensive production sources, it has also raised substantial concerns among policymakers that higher energy costs will render manufacturing firms less competitive and potentially lead to increased consumer prices. Using detailed firm-level data from 2006 to 2014 and a novel combination of shift-share instruments and dynamic difference-in-differences estimation, I identify the causal impact of energy prices on energy consumption, CO_2 emissions, productivity, employment, and cost pass-through. I find that a 10% increase in energy prices leads to an 8.6% reduction in energy use and a 5.9% decline in emissions, highlighting the effectiveness of energy taxation in promoting environmental goals. However, higher prices also reduce firm-level productivity by 2% and employment by 3%, especially among high-skilled workers. I also find evidence of partial cost pass-through to consumers, with a 10% marginal cost increase resulting in a 2% rise in output prices. Overall, the results provide new micro-level evidence that the economic incidence of energy pricing is heterogeneous, and the trade-off between environmental and economic goals is far from straightforward.

Keywords: Energy Price, Manufacturing firms, Productivity, Employment, Pass-through
JEL: D24, Q50, Q55, O47, O31

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1 Introduction

The design of carbon pricing remains central to achieving climate targets while minimizing economic disruption (Golosov et al., 2014; Sterner et al., 2019; Rockström et al., 2017). [1] Despite its strong theoretical appeal, there remains a shortage of comprehensive microeconometric evidence on how carbon pricing affects firm-level CO_2 emissions and broader economic performance. This gap stems largely from the limited availability of suitable microdata and credible identification strategies (Venmans et al., 2020; Martin et al., 2014).

Sweden, which has maintained the world's highest carbon tax for over three decades, offers a unique setting to examine the microeconomic effects of carbon pricing. Using a decade of matched employer-employee and firm-level panel data, this paper studies how rising energy prices – driven by domestic energy tax reforms and EU ETS policies—affect manufacturing firms' behavior.[2] I provide new causal evidence on how energy price shocks affect firm-level emissions, productivity, employment, and cost pass-through. To identify these effects, I exploit exogenous variation in firms' exposure to energy taxes using a shift-share instrumental variable approach and a dynamic difference-in-differences estimator. This strategy isolates plausibly exogenous firm-level price shocks resulting from changes in sector-level energy tax burdens. I then quantify firms' behavioral responses along several margins: energy consumption and CO_2 emissions (environmental outcomes), productivity and employment (economic outcomes), and output prices (cost pass-through)[3]. Understanding these adjustment mechanisms is crucial for evaluating the trade-offs embedded in climate policy and for designing energy pricing instruments that are both environmentally effective and economically efficient.

To examine the impact of energy pricing, I first construct firm-level energy prices, by combining data on annual energy expenditures and quantities purchased by each firm. This allows me to compute unit value energy prices and observe how these prices evolve in response to energy tax reforms and broader policy changes. From the perspective of a firm, exposure to carbon pricing and energy taxation primarily materializes through higher energy prices. As a result, firms are likely to respond to these shocks in ways similar to how they react to changes in other input prices in production.[4] Compared to output taxes, input-based carbon pricing allows firms some flexibility in adjusting their production mix– substituting away from more carbon-intensive inputs to minimize costs. In addition to adjusting input use, firms may also pass on increased energy costs to consumers through higher product prices.

[1]At its core, pricing carbon emissions makes fossil fuel-based energy more expensive, thereby discouraging reliance on carbon-intensive production sources (Ganapati et al., 2020; Goulder et al., 2019).

[2]Swedish manufacturing firms are especially relevant for this analysis: they contribute significantly to global GHG emissions, operate in highly tradable sectors exposed to international competition, and are particularly sensitive to energy costs, which may influence investment, labor demand, and firm viability.

[3]I consider that the incidence of an energy tax is independent of who bears the initial financial burden. If the tax leads to higher final product prices, the burden is shifted forward to consumers. Alternatively, if it stimulates investment in energy-efficient technologies, firms may reduce their exposure to rising costs.

[4]Energy is a particularly relevant input in this context due to its strong association with environmental externalities. In many countries, including Sweden, a large share of the manufacturing sector's CO_2 emissions stems directly from energy consumption (Dechezleprêtre and Sato, 2020).

A key empirical challenge in estimating the effects of energy prices is that observed energy expenditures are endogenous: firms that adopt energy-saving technologies or face lower demand may simultaneously reduce both energy consumption and costs, biasing estimates of price impacts. To address this, I construct a shift-share instrumental variable that isolates exogenous variation in firm-level energy prices . The instrument combines time-varying industry-level median energy prices—driven largely by national tax reforms and market conditions—with each firm's pre-determined energy mix (see e.g., Goldsmith-Pinkham et al. 2020; Borusyak et al. 2022a; Barrows and Ollivier 2021). This strategy leverages the fact that Swedish energy taxes vary across fuel types and sectors, creating plausibly exogenous shocks to firms based on their historical input structure. To capture dynamic firm responses and ensure robustness, I complement the IV approach with a dynamic difference-in-differences (DiD) specification that traces outcomes in the years before and after energy price shocks. This estimator allows for flexible treatment timing and controls for firm and industry-year fixed effects, helping rule out differential pre-trends and confounding shocks (Barrows and Ollivier, 2021). Together, these two approaches allow me to estimate both the contemporaneous and dynamic effects of energy price shocks in a unified empirical framework, allowing me to attribute variation in firm-level energy prices to Sweden's evolving carbon tax design.

My findings suggest that energy pricing has been effective in reducing emissions, but it also imposes significant and uneven economic costs across firms and labor groups. A 10% increase in firm-level energy prices leads to an 8.6% reduction in energy consumption and a 5.9% decline in CO_2 emissions, with effects that are stronger in the long run. These environmental gains are accompanied by a 2% drop in firm productivity and a 3% decline in employment, particularly among workers with university degrees. To understand the extent of cost incidence, I estimate the degree of pass-through from energy prices to product prices. A 10% increase in marginal costs results in a 2% increase in unit prices, indicating a pass-through rate of approximately 0.8. However, this rate varies substantially across firms. Energy-intensive firms, as well as those that are highly productive, multiproduct, or subject to the EU-ETS, tend to absorb more of the cost increase and pass on less to consumers.

Importantly, the economic burden of higher energy prices is not uniformly distributed. I find that low-productivity firms experience larger declines in productivity, while high-productivity firms remain relatively resilient. Overall, the results indicate that an increase in energy prices leads to a crowding-out effect. This means that regardless of whether it enhances energy efficiency or not, a higher energy price hinders other possible productivity improvements in firms. Employment effects also differ by occupation: while overall employment declines, workers with high school degrees see slight increases in employment, whereas those with university degrees experience declines. These results highlight that energy pricing creates a complex mix of winners and losers, shaped by firm characteristics and market structure, rather than a simple environmental-economic trade-off.

The results carry several implications for the design of carbon pricing mechanisms. While energy taxes effectively reduce emissions, their economic effects vary widely across firms and workers. This suggests a need for complementary fiscal policies to mitigate regressive impacts – especially in energy-intensive sectors and among vulnerable labor groups (see e.g. Känzig 2023). For example, revenue recycling or targeted subsidies for energy-efficient technologies may help alleviate the productivity losses faced by low-performing firms, without undermining environmental gains. Given the incomplete cost pass-through, policymakers should also be cautious about inflationary effects and ensure that consumer prices do not rise disproportionately in the short term. More broadly, the findings show the importance of designing carbon pricing systems that recognize heterogeneity in firm capacity and market power, in order to maximize efficiency while minimizing unintended distributional consequences.

Related Literature and contribution. This study makes three contributions. Firstly, I contribute to an expanding body of literature investigating the environmental effects of carbon policies, particularly focusing on energy pricing. There exists a mounting evidence supporting the effectiveness of carbon policies for reducing emissions. However, such assessments have predominantly been conducted at the macro-level (national and sector level) (Andersson, 2019; Golosov et al., 2014; Green, 2021; Leroutier, 2022), and we have little understanding of how climate policy shocks affect emissions at the micro-level such as firms-level emissions. Exceptions are studies such as Martin et al. (2014) and Martinsson et al. (2022) that show carbon policy can reduce emissions considerably at the firm-level. While Martin et al. (2014) exploited the United Kingdom's climate tax levy by using the exogenous variation in eligibility as instruments for climate policy, Martinsson et al. (2022) used the climate tax shocks in Sweden with fixed effect models and reduced form calibrations to estimate the importance of emission elasticities. In contrast, this paper contribute to the micro-level evidence by providing new causal estimates based on firm-level energy prices, employing both shift-share instruments and dynamic DiD techniques. These methods enable me to isolate the exogenous variations in firm-level energy prices while allowing for the assessment of both short- and long-term impacts.

This paper also contributes to a growing body of literature that studies the economic effects and trade-off of climate policy. A number of studies have analyzed the macroeconomic impacts of the British Columbia carbon tax, finding no significant effects on GDP and employment Bernard and Kichian (2021); Konradt and Weder (2021). Similarly, (Metcalf and Stock, 2020) examined the macroeconomic impacts of carbon taxes in European countries, discovering no robust evidence of a negative effect on employment or GDP growth. Konradt and Weder (2021) also concluded that carbon taxes in Europe and Canada do not appear to cause inflation. In contrast, Känzig (2023) found potentially significant economic costs through lower output and higher unemployment using the EU-ETS. Dechezleprêtre et al. (2023) on the other hand found no effect on employment and profit of firms. Previous theoretical studies based on computable general equilibrium models also tend to reveal contractionary output effects (see, e.g., McKibbin et al. 2017; Goulder and Hafstead 2017). Thus, evidence regarding the macroeconomic effects of carbon policies and pricing remains mixed. I contribute to this literature by examining the microeconomic effects on the labor market and identifying scale-down effects at the firm level. In particular, the impact of energy prices on labor demand is still not fully understood, as conflicting mechanisms can offset each other (Marin and Vona, 2021). Higher energy prices might negatively affect labor demand, but they can also prompt the substitution of energy for other inputs such as labor and capital. By examining the heterogeneity in skill groups and compositional changes, I contribute to explaining the mechanisms through which energy price affects total employment. I find that firms may substitute high-skilled costly labour for low-skilled cheap labour. This findings offers valuable supplementary insights to studies such as Marin and Vona (2021) and Dechezleprêtre et al. (2023). Additionally, by examining how energy prices affect the productivity of firms, I contribute to studies that explore such relationships (Andersson, 2020; Dechezlepretre et al., 2017; Venmans et al., 2020). By extension, I also contribute to studies examining how ambitious climate policies could lead to carbon leakage, where higher energy prices may induce firms to substitute towards foreign-sourced inputs for a given level of firm output. Using shocks in Swedish electricity prices in the 2000s, Ferguson and Sanctuary (2019) found that imports declined for firms with most electricity-intense firms but increased for firms in the second electricity intensity quartile. A potential mechanism for such effect could be that some firms are able to pass-through the marginal-cost to consumers.

This paper brings together two dimensions of firm response that are often studied separately: the substitution of inputs in production and the pass-through of energy costs to consumers. In doing so, to the literature on cost pass-through, namely, changes in prices resulting from cost shocks (Sijm et al., 2008; Fabra and Reguant, 2014; Hintermann, 2016). In particular, I offer estimates for the cost pass-through rates across various sub-sectors of the economy will prove beneficial for policymakers in shaping future regulations on free allowance allocation. A significant finding of this paper is that although higher energy prices may decrease manufacturing firms' international competitiveness, not all firms adjust prices of their final products to counteract the impact of energy inflation. Manufacturing firms with higher productivity levels, multi-product structures, those categorized as "dirty" firms, and those regulated under the EU-ETS exhibit greater capability in absorbing energy price inflation. My results shares close association with Ganapati et al. (2020), who estimated the pass-through and incidence of energy costs in selected U.S. manufacturing industries. Focusing on single-product plants, the authors found that firms passed on approximately 70% of cost shocks associated with energy prices. However, my approach diverges not only in geographical scope but also in examining energy cost pass-through for both single and multi-product firms and exploring various heterogeneous effects, rather than focusing solely on selected industries. My findings also highlight the complexities of pricing and cost-sharing behaviors among productive firms, multi-product firms, those considered 'dirty', and those regulated under the EU-ETS.

Roadmap. The paper proceeds as follows. In the next section, I provide institutional background of energy use and energy costs in the Swedish manufacturing sector. Section 3 introduces five hypotheses of how firms respond to an energy price shock. Sections 4 and 5 describe the data and the empirical strategy, respectively. I present the findings and robustness checks in Sections 6, and section 7 concludes.

2 Institutional Background

Energy, although an essential input in the manufacturing process[5], is typically considered a limited direct cost. For example, a study by Ganapati et al. (2020) highlights that energy expenses can exceed 20% of the total revenues in some energy-intensive sectors. However, the extent of energy cost for individual firms will vary depending on factors such as the industry's energy intensity, production scale, and energy efficiency measures implemented by firms.[6]

Figure 1: Energy Cost Burden

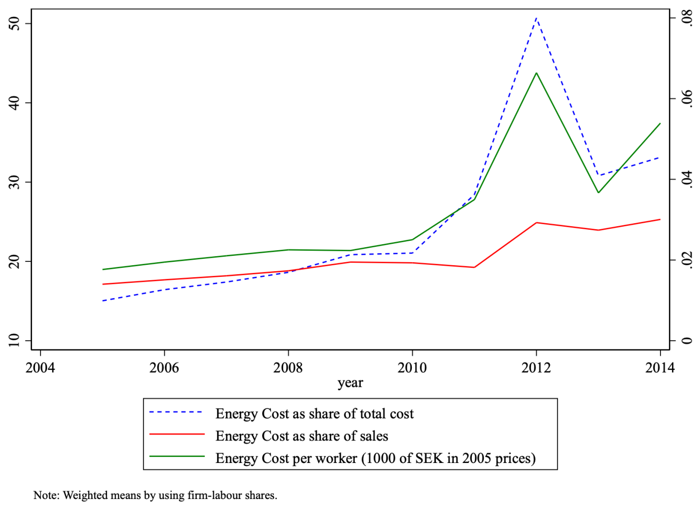


Figure plots the raw data for the total firm energy expenditure as a share of total cost of firm (blue dotted line), as a share of sales (red line) and as energy cost per worker (1000 of SEK in 2005 prices), shown in green line. from 2005 to 2014. The average means of are weighted by firm-labour shares

To see the energy-cost burden of Swedish manufacturing firms, I plot (see Figure 1) the total energy cost of firms as (i) a share of total cost (blue dotted line), (ii) a share of sales (red line) and (iii) per worker (in real terms). The overall pattern suggests that energy cost burden increased for an average firm between 2005 to 2014, with a particularly pronounced upward shock observed in 2011/2012. This is perhaps, unsurprising. In 2011/2012, the Swedish government changed the tax rates for all industries, even those in the EU Emissions Trading System (ETS). This revision meant that all industries pay a fixed 30% energy tax, whether or not they were part of the EU ETS. Additionally, firms outside the EU ETS had to pay an additional 30% of the regular carbon dioxide tax on fossil fuels. Shocks in energy prices may also be due to a number of factors, including other external factors, such as global political events , economic

[5]Industrial energy consumption constitutes a significant portion, approximately 38%, of Sweden's overall end-use energy consumption, according to data from the Swedish Energy Agency.

[6]Primary energy sources utilized in the manufacturing sector comprise biofuels, electricity, and fossil fuels, with respective proportions of 38%, 37%, and 22% in 2011, and 43%, 34%, and 20% in 2020. Within the manufacturing sector, energy usage primarily falls into two categories: electricity and primary fuels, namely oil, natural gas, and coal. Manufacturing plants allocate energy for four primary tasks, including process production accounting for 40% of energy use, boiler fuels constituting approximately 25%, feedstock representing another 25%, and the remaining 10% allocated to other on-site purposes.

crises, and market speculations.

Prior to the tax revision in 2011/2012, Sweden has implemented several tax reforms and energy policies, aimed at addressing carbon emissions and promoting energy efficiency. Most fossil fuels utilized in the manufacturing industry are subject to both the energy and the CO_2 tax. In 1991, a tax on CO_2 was introduced, initially set at SEK 0.25 per kilogram of emissions. Subsequently, in 1993, an energy tax reform resulted in significant increases in energy and CO_2 tax rates. However, to safeguard the competitiveness of the manufacturing industry in international markets, the firms in the mining and manufacturing sectors were exempted from paying energy tax and instead required to pay only 25% of the statutory CO_2 tax rate.[7] In 1997, the CO_2 tax rate for the manufacturing industry was increased to 50% of the statutory CO_2 tax rate. Throughout the 2000s, the statutory tax rate experienced substantial stepwise increases, rising from SEK 0.37 in 2000 to SEK 1.12 in 2015. Notably, for industries included in the EU Emissions Trading System (ETS), the CO_2 tax was gradually phased out, beginning in 2008 and completely eliminated by the end of 2010. However, these entities are still liable for the energy tax. Currently, Sweden has the highest nominal carbon tax rate in the world (SEK 1,409 (US$129.89)).

The evolution of tax reforms and energy policies in Sweden has played a crucial role in shaping the manufacturing industry's energy landscape. These measures have aimed to strike a balance between environmental objectives and maintaining competitiveness in global markets. However, ongoing evaluation and refinement of these policies are essential to ensure effective outcomes, foster technological advancements, and encourage sustainable energy practices within the manufacturing sector. There are legitimate concerns that high energy taxes resulting in high energy costs may directly and indirectly lead to economic costs of manufacturing industries as well as leakage of green house emissions to a less environmentally stringent regions. In this paper, I investigate how the changes in the firm-level energy prices have affected the emissions, firms productivity, the labour market, and consumer prices.

3 Firms' Responsiveness to Energy Shocks

In any economy, the supply of goods and services relies on various factors, such as the availability and costs of inputs like labor, raw materials, capital, and foreign resources. However, unexpected shocks can upset this balance, leading to significant changes in production factors. One such shock is energy taxes, intentionally designed to raise energy prices. Compared to output taxes, input taxes offer firms the opportunity to shift away from specific inputs, potentially reducing the rise in marginal costs and thereby lessening the impact on profits. Consequently, a cost-push shock in energy prices can significantly influence firms' demand for inputs and their production methods. There are different theoretical perspectives of how firms respond to energy price shocks

[7] For further details on the institutional settings, see Martinsson et al. (2022)

3.1 Environmental Effect

One option for reducing the impact of higher carbon prices on production costs is to reduce energy dependency and/or implement abatement measures using existing technologies. First, reducing energy dependency can help to insulate firms from the volatility of energy prices and reduce their exposure to supply disruptions. If firms reduce the their dependence on carbon-intensive energy sources, then we could expect a fall in firms' total emissions as well (Martinsson et al., 2022).

Hypothesis 1: *In response to energy price shocks, firms will reduce their dependency on energy. If a proportionate reduction in carbon-intensive energy occurs, firms' emissions will fall.*

3.2 Economic Effect

Cost-Cutting Measures. Firms may be forced to implement cost-cutting measures such as reducing their workforce or scaling back production, which can have negative impacts on employment levels and output. Energy prices can also have a significant impact on the substitutability between domestic and foreign inputs for firms (Albrizio et al., 2014; Dechezleprêtre and Sato, 2020). As every firm aims to maximize profits, firms will use a production technique that produces output but also produces a "bad output" (CO_2) in an efficient way. Subsequently, each firm selects a combination of inputs that minimizes costs for a given output decision and all input and output prices remain exogenous to the firm.

Hypothesis 2: *In response to energy price shocks, firms will substitute energy with non-energy inputs such as labour and /or capital.*

II. Investment.

The impact of energy cost shocks on firms can also depend on their ability to adapt to the changing environment. Firms can invest in more energy-efficient technologies or alternative sources of energy and may be better positioned to mitigate the negative impacts of cost-push energy shocks and remain competitive in the market. *A priori*, it is not clear how and if energy prices affect competitiveness. Although there is a conventional view that an increase in the regulation stringency entails a trade-off between firm or sectoral competitiveness (e.g productivity growth) and environmental protection (Dechezleprêtre and Sato, 2020; Jaffe and Palmer, 1997; Jaffe et al., 1995), some studies argue that energy taxes can spur innovation and thereby improve firms' productivity – the so called *Porter Hypothesis* (Porter, 1991; Porter and Van der Linde, 1995). Porter and Van der Linde (1995) argue that regulations can even lead to innovation that fully offsets the costs of compliance, improving overall production costs and competitiveness. This can happen if cleaner technologies improve productivity, result in input savings, and lead to innovations that offset regulatory costs over time and improve export performance and market share. In the theory, the evolution of the total factor productivity (TFP) distribution hinges on profit- maximizing firms seeking to upgrade their technology, thus it is still unclear how energy prices via carbon tax stringency can lead to higher productivity. [8] For firms that are

[8]The Porter hypothesis has been criticised to be incompatible with the assumption of firms' profit

able to internalize the positive externalities from technology and innovation spillovers, energy price shocks can improve their productivity (Greaker, 2006). However, energy intensive firms with higher production and abatement costs may experience a reduced productivity as a result of an energy price shock (Andersson, 2020). Firms that pollute more typically must invest more in abatement, such as upgrading outdated machinery. On the other hand, those with lower pollution levels might only need to implement minor modifications to their production processes and practices. As such productivity for firms in cleaner industries is likely to increase whereas those in the dirtiest industry may fall as the the marginal cost of adopting abatement technology is expected to be higher and may outweigh the marginal benefits (Lu and Pless, 2021).

Hypothesis 3: *Energy cost shocks may incentivize firms to innovate their technological processes, which could improve their productivity.*

Hypothesis 4: *Productivity of energy-intensive firms may fall if marginal abatement costs outweigh the benefits*

IV. Cost Pass-through. Firms may seek to pass on the higher costs to consumers in the form of higher prices, leading to inflationary pressures in the economy. To provide an example, let's consider a manufacturing plant that faces an increase in carbon taxes. Economists have established that the impact of a tax on the welfare of producers versus consumers, also known as its incidence, is independent of who actually pays the tax (Ganapati et al., 2020). This principle also applies to production cost shocks resulting from factors such as political events in oil-producing countries or fracking. Such changes in production costs affect the prices and quantities of both inputs and outputs. In the example of a carbon tax levied on a manufacturing plant, the tax physically applies only to the plant, as the government directly collects tax revenue from it. If the tax leads to higher prices, then the tax burden will shift forward to consumers. On the other hand, if the tax encourages the plant to invest in energy-efficient production technologies, producers will have to pay less in energy taxes, minimizing their burden. Thus, pass-through and input substitution represent ways in which the party paying the tax can either pass on its effects to others or avoid paying the tax altogether. When firms pass on tax increases to consumers, they can preserve their profit margin and continue production. The ability to pass on tax increases is influenced by various factors, such as the competitive environment of the market and the degree of product differentiation, or substitutability.[9] Monopolistic competition is a prevalent market structure, particularly within manufacturing firms. In this context, firms produce similar goods with distinctions in quality, brand, and design. Despite the similarities, firms operating under monopolistic competition possess some degree of market power, allow-

maximization (see for example, Palmer et al. 1995). A comprehensive review of the extensive work on the environmental policy-productivity nexus by Kozluk and Zipperer (2015) and Dechezleprêtre and Sato (2020) indicates that there is no clear strong evidence in support of the effect of environmental policies on productivity. Also, Cohen and Tubb (2018) conducted a meta-analysis of 108 studies. They revealed that older studies tend to find a negative relationship between environmental regulation and productivity at the more aggregated country or regional level than at the sectoral and firm level. Notable contributions include attempts to explain the US productivity slowdown in the 1970s with environmental regulation (Gray, 1987; Barbera and McConnell, 1990).

[9] See Appendix A for the model of incidence of energy tax

ing them to set prices and impact economic profit in the short run. Manufacturing firms are therefore confronted with the decision of either absorbing the rise in costs or raising their prices. Thus, my last hypothesis is as follows:

Hypothesis 5: *Manufacturing firms may be more likely to pass on the increased costs to consumers by increasing their prices.*

4 Data and Measurement

To examine how energy prices affect firms' environmental performance, competitiveness and the possibility of cost pass-through, I draw information from three major databases in Sweden that cover all individuals, plants, and firms in the country. I obtained panel data of about 3800 firms for the period 2005-2014 from Statistics Sweden (SCB)[10], the Swedish government's statistical agency. The selection of the firms and time period, as well as the composition of sectors are determined mainly by the availability of energy price information and study setting. Thus, the sample does not extend to current years. The first database, FEK (Structural Business Statistics), provides detailed information on all firms and their subordinate plants, including the number of employees, industry, spatial location, sales, cost, assets, investments, and trade (imports and exports at the 8-digit product level for each destination). I then merge this dataset with data on energy consumption from manufacturing firms in Sweden. The energy dataset presents firms' energy expenditures, energy quantities and energy inputs. The last database, LISA (longitudinal integration database for health insurance and labor market studies), provides a wealth of socio-economic information on each individual, including income, occupation, employment in full-time equivalents, education, as well as information on their place of work, including the plant and firm where they are employed. Using this information, I can construct a matched employee-employer database covering all manufacturing firms and their establishments for the period 2006-2014 by linking them to all working-age individuals above the age of 16. This dataset allows me to decompose the skill-set of workers into high-skilled, low-skilled, as well as the share of workers with a university degree and high-school degree. To ensure the validity of the findings, I restrict my sample to firms with positive sales, thereby eliminating inactive firms from my analysis.

Aside from employment (which is given), key variables of interest such as energy prices, firms' Total Factor Productivity (TFP), marginal cost and markup require significant attention in terms of measurement.

Energy Prices. To correctly capture energy price and its variation, it is important to understand the energy tax scheme in Sweden. The energy tax systems usually have three basic components: a charge on fossil fuels based on their CO_2 emissions and global damage, additional charges on fuels used in power generation and heating based on local air pollution emissions, and charges on motor vehicles for local air pollution, congestion, accidents, and pavement damage. Although energy taxes are typically imposed to discourage carbon-intensive activities,

[10] I use year 2005 as a pre-sample year.

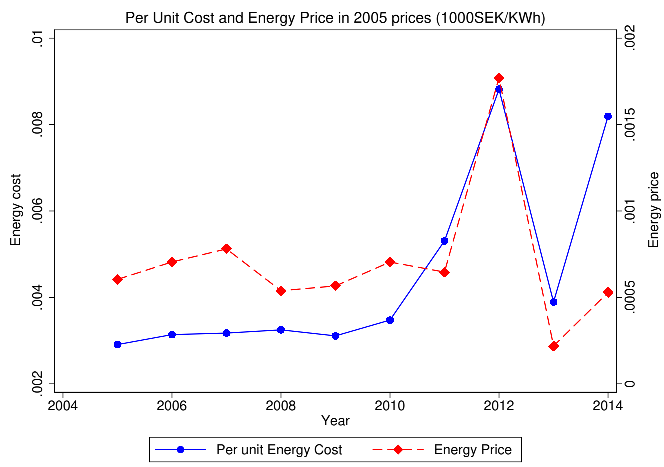
the specific bases and rates of these taxes can vary due to a variety of political and regulatory factors. As a result, general energy or electricity prices may not fully reflect the nuances of these variations, and may fail to capture the true cost of carbon taxes in different jurisdictions. A unique advantage of my data is that I have access to all plant-specific information on firms' energy mixes, their heat contents and their yearly expenditures over a long time span as compared to studies such as Fabra and Reguant (2014), Sijm et al. (2008), and Hille and Möbius (2019). By considering a broad measure of energy prices instead of just electricity prices, I can create specific exposure to shocks in specific energy inputs, allowing me to study price shocks to inputs with varying carbon content.

Given that firm-use of energy is different for each energy input, I can calculate the energy price (EP) of each firm as follows:

$$EP_{it} = \sum_{j=1}^{n} \omega_{it}^{j} EC_{it}^{j}$$

where ω_{jit}^{j} is the share of energy consumption of input $j = 1 \ldots n$ (i.e., natural gas, electricity, etc.) in total energy consumption, whereas EC_{it}^{j} is the average unit value cost of energy input j paid by firm i at time t. Energy consumption for all energy inputs is converted into kWh equivalent values. With this approach, it becomes possible to assess the cost of energy for each individual firm based on its specific usage patterns.

Figure 2: Trend of per unit energy cost and energy price.



This Figure plots the raw data for the energy price (red line (axis 1), and per unit energy cost of firms in real terms (blue line (axis 2) from 2005 to 2014. The unit cost represents the firm's total energy expenditure divided by its total energy consumption. Conversely, the energy price adjusts for the proportion of energy consumption attributed to specific energy types or inputs (such as electricity, natural gas, etc.).

Figure 2 shows the evolution of the yearly energy cost and energy prices for an average firm from 2005 to 2014 (all values expressed in 1000 of SEK in 2005 price). A visual inspection indicates that both energy costs and prices remained relatively stable until around 2011/2012, after which a sharp increase is evident. This surge coincides in time with a significant event - the introduction of a tax rate update by the Swedish Government, affecting all industries, including those covered by the EU Emissions Trading System (ETS). I explore the industrial level shocks to create an instrument that is correlated with firm-level energy expenditure and energy prices but uncorrelated with specific shocks affecting individual firms such as technological adoption and negative demand shocks.

Total Factor Productivity. For firms' productivity, I consider, TFP, which is the closest proxy of the a firm's level of input efficiency. Several approaches exist in measuring firms' TFP, going back to the seminal paper by Solow (1957) as well as Olley and Pakes (1992) and Levinsohn and Petrin (2003) who show that, under certain assumptions, investment and intermediate inputs, respectively, can be used as a proxy variable for unobserved, time-varying productivity. However, these proxies may suffer from identification issues if all inputs (including labor usage) are determined by a productivity shock (and hence optimally chosen by firms). [11] In this paper, I deal with these measurement issues by using a semi-parametric control function suggested by Wooldridge (2009)[12]. This approach essentially consists of using input demand functions to proxy for unobserved firm TFP via a unified Generalized Method of Moment (GMM). This approach has several advantages over standard semi-parametric estimation methods, such as the ability to calculate robust standard errors without using bootstrapping methods and greater efficiency in correcting for errors. Additionally, GMM estimation allows for testing the model's identification assumptions and can address the first-stage identification problem.

Marginal Cost and Markups. My approach to determining marginal costs involves combining plant-level production data with assumptions about cost minimization by the firm. This methodology, originally introduced by Hall et al. (1986) and later developed by Loecker and Warzynski (2012), uses a firm's first-order condition to derive a plant's multiplicative markup (i.e., its price divided by its marginal cost), which equals the output elasticity of a variable input such as energy or materials divided by that input's revenue share. In other words, if we can identify the output elasticity of a variable input, we can determine the markup. I can then use price data to calculate marginal costs by dividing price by the markup. Appendix A provides a formal description of this approach. Essentially, I compute a time-varying, plant-level markup utilizing the estimated output elasticity of a variable input and that input's revenue share. I then recover marginal costs from the accounting identity that price equals markups times marginal costs

4.1 Characteristics of Firms

Table 1 presents the descriptive statistics of all variables used in this study. Each firm's energy price (EP) is calculated in in SEK/kWh, with an average EP of 6.0 SEK/kWh. The standard deviation of about 349SEK/kWh means that the energy price is highly spread out and also

[11] See Appendix B.1 for a detailed discussion.

[12] It is important to mention that I generated the productivity index using a Cobb-Douglas production function that uses labor, capital, and materials as inputs. I also measure output in physical quantities, and compute output elasticities and industry-level cost shares, assuming constant returns to scale.

skewed as the top 90% spent about 9.5SEK/kWh and the median is about 0.907SEK/kWh.

Table 1: Summary Statistics at firm level

Variables	N	Mean	Std. Dev	Min	p10	Median	p90	Max
Energy Price (SEK/kWh)	31,909	6.035	349.4	0	0.410	0.907	9.505	54,895
Employment	35,703	140.2	679.4	10	13	38	226	20,492
Total factor productivity (/1000)	35,703	1,237	5,271	0	425.7	743.8	1,676	488,780
Firm sales (SEK million)	35,703	471.8	3,438	0.001	16.78	68.54	603.4	120,555
Firm cost (SEK million)	35,703	443.6	3,341	0	15.71	64.02	554.5	117,061
Firm Investment(SEK million)	35,703	16.68	126.7	0	0.050	1.149	18.28	7,106
Markup	35,703	3.480	337.829	0	0.106	1.063	5.077	1064.7

The average firm employs about 140 workers, which accounts for relatively medium- and large-size firms. SCB collects information on the energy consumption of all manufacturing plants with 10 or more employees, thus I consider relatively large firms. On average, firms spent SEK 16.68 million on machine investment, made a sale of SEK 471.8 million, and incurred a total cost of production of about SEK443.6million.

5 Empirical Approach

I divide my empirical approach into two subsections. The first subsection elaborates on capturing the effect of energy prices on firms themselves. Here, I look at firm-specific outcomes variables such as energy use and emissions, productivity, and employment. The second subsection, then focuses on the propensity of the marginal cost pass-through effect to consumers.

5.1 Environment, Productivity and Employment

I begin by providing a unified empirical model for testing **hypotheses 1 to 4**. That is, exploring the effect of firms energy prices (EP_{it}) on firm level environmental outcomes (energy consumption and CO_2 emissions) and economic outcomes (employment and TFP). I specify the following linear model:

$$y_{it} = \gamma_i + \delta_{st} + \beta_1 EP_{it} + \lambda Z_{it} + \epsilon_{it} \tag{1}$$

where y_{it} are my outcome variables (energy use, CO_2 emissions, employment, TFP) by firm i at time t.[13] The main variable of interest EP_{it} measures the firm-level energy price at period t. To reduce omitted variable concerns, I include different controls including year-specific EU-ETS dummies, firm cost, and machine investment Z_{it}.

Possible Biases. Identifying β_1 from equation (1) is challenging for three reasons. First, observe that energy price is an equilibrium outcome that conflates supply and demand, so firms that demand less energy are also less-likely to be affected by energy price inflation. Also,

[13]Note that all variables are in logs, which leads to a direct interpretation of the estimated coefficients as elasticities.

if firms face a unique negative demand shock (such as bulk reduction in energy discount), then output and input demand (including energy and labor demand), are reduced. Subsequently, a decrease in energy demand raises the average cost per unit of energy (see e.g., Marin and Vona (2021)). Secondly, there is a risk of energy-saving technological change by firms which may be unobserved. This technological adoption can simultaneously reduce the energy consumption and energy discount offered to firms and hence increase the unit cost of energy. Lastly, the measurement of the constructed energy price used in the analysis may be subject to some degree of error, as actual energy prices at the firm level are not available. This lack of precise data on energy prices can introduce attenuation bias, potentially leading to underestimation of the estimates. Overall, the direction of bias is unclear and depends on the specific outcome variable that is being assessed.

For example, to provide insight into the expected sign of the omitted variable for energy (E), employment L, and total factor productivity (TFP), we can refer to the omitted variable bias formula proposed b by Angrist and Pischke (2009):

$$\hat{\beta}_y = \frac{\text{Cov}\left(y_{it}, EP_{it}\right)}{\text{Var}\left(EP_{it}\right)} = \beta_y + \underbrace{\gamma_{y,dd}\delta_{p,dd}}_{-E,-L,-TFP} + \underbrace{\gamma_{y,tech}\delta_{p,tech}}_{-E,+L,+TFP} + \underbrace{attenuation}_{?}, \tag{2}$$

First, notice that both the demand shocks dd_{it} and technological change $tech_{it}$ are positively correlated with EP. Thus $\delta_{p,dd}$ and $\delta_{p,tech} > 0$. This means that the sign of the biases depends only on the correlations between the dependent variable and the omitted variables $\gamma_{y,dd}$ and $\gamma_{y,tech}$ (assuming no attenuation bias). Now, because a domestic demand shock reduces output, all the outcome variables are expected to fall ($\gamma_{y,dd} < 0$). This means that if the true parameter is negative, (especially for E, L and TFP), then this omitted demand shock will overestimate the impact of energy prices. Additionally, energy-saving technological adoption is expected to correlate negatively with E but positively with TFP and L (via substitution effect). This source of bias will therefore exacerbate the negative energy price effect on energy-use, but reduce the demand shock bias on L, and TFP. Innovation and green technology are endogenous decisions, taken at firm-level; thus, I expect the impact on firms' L, and TFP to be larger; thereby diminishing the negative effect of energy prices. Coupled with measurement error, I expect the OLS to overestimate the expected impact on energy consumption and underestimate the effect on employment, and TFP.

Shift-Share Instrument. To overcome the possible multiple omitted biases and measurement errors, I combine a rich data on energy mixes and energy cost at both the firm and industry-levels to construct a shift-share-style instrument that is correlated with exogenous variation in unit energy cost but uncorrelated with firm-specific demand shocks and endogenous technological change. Specifically, for each firm, I use the variation in median industry-level energy prices net of firm prices (p^j_{st}). The reason for using industry level energy price is because, Swedish climate policies are not firms-targeted but rather industry-targeted. [14] As fuel

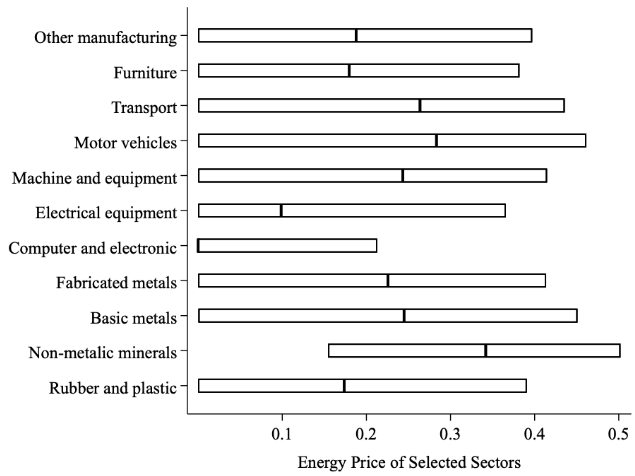
[14]Studies such as Sato et al. (2015) show that energy taxes are a significant determinant of energy prices at the industry level. The study reports that taxes account for a considerable portion of the variability in

prices vary substantially across sectors, the differences in marginal fuel input shares causes the industrial energy prices variations to differently affect firms who are dependent on those fuels (see Figure 3).

I then use pre-sample weights ($\omega^j_{i,t=t_0}$)[15] of different types of energy-use to block the energy-mix dependencies before the entry of firms in the estimation sample. The dot product of these two terms gives each firms exposure to energy price shocks. Formally;

$$EP^{IV}_{it} = \sum_{j=1}^{n} \omega^j_{i,t=t_0} p^j_{st}.$$

Figure 3: Median energy prices of selected sectors



The figure shows boxplots of energy prices of some selected sectors. With each vertical line in each box representing the median (or the 50% percentile) of the energy price.

The identifying assumptions are that (a) the instrument is a good predictor of energy prices at the firm-level and (b) the exclusion restriction holds. I show that the first assumption is met in Table 2. Specifically, the result show that the instrument turns out to be strong at first stage with a positive and statistically significant coefficients. The instrument remains strongly correlated with the firm-level energy prices even in a more demanding specification where I control for a large set of fixed effects including firm, industry-year, and municipal-year fixed effects (column 4).

For the second assumption, there are two primary approaches to ensuring that the instrument is satisfied when analyzing the relationship between energy prices and firm-level outcomes. The first approach assumes that shock exposure weights $\omega^j_{i,t=t_0}$, which measure the sensitivity of each firm to changes in energy prices, are exogenous and non-random, and that the data are identically and independently distributed. This approach was demonstrated in a

energy prices, with coal prices being 80-90% explained by taxes, electricity prices being explained by 60%, and oil prices being explained by 50-80%. However, the relationship between taxes and natural gas prices is weaker, with only about 20% of the variability being attributable to differences in taxes.

[15] Note that the pre-sample year is 2005.

Table 2: First stage results

	EP_{it}			
	(1)	(2)	(3)	(4)
EP_{it}^{IV}	0.162***	0.107***	0.113***	0.108***
	(0.006)	(0.009)	(0.009)	(0.010)
Control	×	√	√	√
Year Fixed Effect	×	√	×	×
Firm Fixed Effect	×	√	√	√
Industry-Year Fixed Effect	×	×	√	√
Municipal-Year Fixed Effect	×	×	×	√
Observations	31,170	29,807	29,592	29,410

Note: Standard errors are clustered at firm-level. *,**,***denotes significant at the 10% , 5% and 1% level respectively.

study by Goldsmith-Pinkham et al. (2020) using the Bartik framework. The second approach, developed by Borusyak et al. (2022a), treats the shocks as random variables and assumes that they are exogenous conditional on the shock-level residuals and exposure weights. My preferred instrument is based on this latter approach. The identifying assumption is that firms did not sort into sectors such that industry characteristics were correlated with energy prices. Though this seems tenable in my empirical setting, there are concerns of market speculations by managers. I therefore, allow firm energy mix to be lagged by at least 2 years with respect to the first observation in which the firm joins the estimation sample.

I also include firm fixed effect (γ_i) and industry-year fixed effect (δ_{st}) to capture the within-firm response to a change in energy prices and not the effects of different price levels. This is important given that firms may be able to secure individual energy supply contracts, with prices that differ in levels from the industry prices. The fixed effects help control for level differences across firms. Also the industry-year dummies remove confounding factors such as global supply shocks and global price trends in energy prices (e.g. increases in oil prices). Once the global drivers of energy prices are controlled for, the remaining variation of energy prices reflects primarily domestic changes in post-tax prices that are subject to energy taxes or emission limits imposed at the energy sector (Sato et al., 2019), as well as other regulatory policy and domestic energy supply shocks (e.g., deregulation of energy markets). In some specifications, I also include different controls including year-specific EU-ETS dummies, firm cost, and machine investment (Z_{it}) to further diminish omitted variable concerns.

5.2 Marginal Costs and Pass-through

I now turn to describe the methodological approach in testing **hypothesis 5**, (i.e, assessing the pass-through effect of energy prices). I do this in two major steps. First, I examine the relationship between energy price variation and firm-level output prices, marginal cost and markups. Second, I use my data on unit prices, retrieved estimates of marginal costs, to compute the degree of marginal cost pass-through to consumers. I therefore begin with the regression model:

$$q_{it} = \gamma_i + \delta_{st} + \beta_1 EP_{it} + \lambda Z_{it} + \epsilon_{it} \tag{3}$$

Equation (3) describes a regression of outcome q in logs (unit prices, marginal costs, or markups) for firm i and year t. I control for firm fixed effect, and industry-by-year fixed effects. Some specifications also control separately for differential trends by firm, including region-by-year fixed effects and industry-by-year fixed effects. Following Ganapati et al. (2020), I then estimate the marginal cost pass-through elasticity from the following firm-level regression of (log) output price on (log) marginal costs:

$$p_{it} = \gamma_i + \delta_{st} + \rho_{MC,\epsilon} mc_{it} + \lambda Z_{it} + \epsilon_{it} \tag{4}$$

The main coefficient of interest, $\rho_{MC,\epsilon}$, measures the elasticity of unit prices with respect to marginal costs. Note that $\rho_{MC,\epsilon}$ differs from the marginal cost pass-through rate ρ_{MC}, which represents pass-through in levels. To calculate ρ_{MC}, I multiply $\rho_{MC,\epsilon}$ by the markup: $\rho_{MC} = \rho_{MC,\epsilon} \times P/MC$. My regression model, shown in Equation (4), includes the same vector of controls Z_{it} as before, along with firm fixed effects η_i, industry-year fixed effects δ_{st}, and an idiosyncratic error ϵ_{it}. I also provide additional regression estimates that control for differential trends by firms, region-by-year fixed effects, and industry-by-year fixed effects.

Because price equals the product of markups and marginal costs ($P_{it} = MC_{it} * \mu_{it}$), one might expect the elasticity $\rho_{MC,\epsilon}$ in Equation (4) to be one. However, this is not the case. The pass-through regression does not explicitly control for markups, so the markup term is in the regression error. Pass-through estimates therefore capture the extent to which marginal costs do not perfectly predict product prices due to variability of markups.

5.3 Dynamic Treatment Effect

A key concern for identification in this context is the potential influence of energy-specific technological trends on both energy price and firm-level output and emissions. If such a scenario were true, my shift-share instrument would be unable to separate the exogenous shift in energy prices from pre-existing systematic differences in trends among firms with different initial compositions. To address the estimation concern, I use a dynamic DID approach to evaluate the pre-trends. A rapidly growing amount of literature in DID has shown that two-way fixed effects regressions could deliver consistent estimates only with strong assumptions about the homogeneity of treatment effects, and may be biased when treatment effects vary over time or by firms (Cengiz et al., 2019; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Borusyak et al., 2022c). For instance, firms may take time to adjust to energy price shocks in which case its impact in the first year may be bigger. Alternatively, the energy price shocks of later firms may be smoother, so that their treatment effects may be smaller. I study the dynamics of treatment effects using the "shocks view" by Borusyak et al. (2022b) and base my identification on the exogeniety of industry-wide energy price shocks.[16] The identifying assumption is that, after accounting for industry-by-year trends and firm-fixed effect, variations in the instrument are unrelated to energy-specific technological shocks and firm characteristics (see e.g. Borusyak et al. 2022b,c; Barrows and Ollivier 2021; Freyaldenhoven et al. 2021). Falsification tests of correlations between future shocks and contemporaneous changes in firm-specific outcomes support the identifying assumption. Subsequently, I run the following DID equation

$$\Delta y_{it} = \gamma_{st} + \sum_{m=-G}^{M} \beta_m \Delta EP_{i,t-m} + Z'_{it}\psi + \varepsilon_{it} \tag{5}$$

Where y_{it} represents the outcome variables. The term $\sum_{m=-G}^{M} \beta_m EP_{i,t-m}$ means that the firm-level energy prices have dynamic effects. I normalize $\beta_{-1} = 0$ so β_m is in normalized differences. I use four years prior to the shock and four years after $M = 4$, to examine the dynamic effect. I then instrument each $\Delta EP_{i,t-m}$ using $\Delta EP^{IV}_{i,t-m}$. To account for industry-specific trends like labor regulations, income shocks, and general technological progress, I include an industry indicator interacted with year interval fixed effects α_{st}. I also include the firm-fixed effect to obtain within-firm responses devoid of unobserved firm-heterogeneity. Consequently, this specification has the advantage of reducing the likelihood of correlation between changes in energy price shocks and observable or unobservable firm characteristics, making it less susceptible to potential issues. As a consequence, this specification allows for the assessment of pre-trends and facilitates the estimation of the cumulative long-run impact of energy prices. Lastly, in shift-share instruments regressions, it is crucial to consider the correlation among error terms across observations sharing similar exposure profiles (Borusyak et al., 2022a,b). In my case, firms with comparable energy mixes exhibit what I term “correlated exposure.” To tackle this correlation across units and over time, I cluster standard errors at the firm level.

6 Results

Having described the theory, data, and methodology, I will now present different sets of results, all providing answers to my study hypotheses. The first set includes the effect of energy prices on emissions and pollution abatement (environmental goals). This set tests my hypothesis 1 of how an increase in energy price can reduce energy dependency and emission but increase investment in pollution abatement. The second set reports results to hypotheses 2 to 4 (on TFP and employment) and the third set then reports results for my hypothesis by presenting findings on marginal cost pass-through of energy cost to consumers.

[16] This is different from the one proposed in Sun and Abraham (2021), De Chaisemartin and d’Haultfoeuille (2020), and Callaway and Sant’Anna (2021) using the interaction weighted (IW) estimator. For example, Sun and Abraham (2021) show that this estimator is consistent assuming parallel trends, no anticipatory behavior, and firm-specific treatment effects that follow the same dynamic profile.

Environmental Goals

Table 3 assesses the impact of energy prices on firm energy consumption and CO_2 emissions. I show both the OLS and IV results. Recall, the OLS may overestimate the effect of energy price and emissions, hence the use of the instruments IV and IV* (where I lagged the pre-sample energy mix 2 years). Also recall the the main identifying assumption behind the instrument is that the instrument is correlated with firm-level energy price but uncorrelated with other structural shock at the firm-level. However, to be able to conduct a standard inference, the instrument must be sufficiently strong at first stage. To analyse whether this is the case, I perform the weak instrument test by Kleibergen and Paap (2006). The shift-share instrument turns out to be strong with KP F-stats greater than the conventional critical values of 10.

Table 3: Energy Prices effect on Environmental Goals

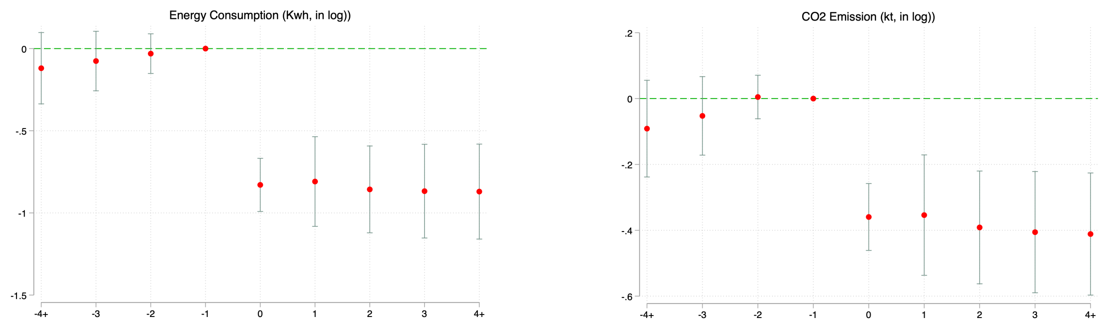
	Energy Consumption			**CO_2 emissions**		
	1	2	3	4	5	6
EP_{it}	-2.775***	-1.729***	-0.861***	-1.012***	-0.590**	-0.586**
	(0.723)	(0.005)	(0.020)	(0.538)	(0.262)	(0.259)
Observations	29,487	29,702	24,184	29,487	29,702	24,184
Estimation Strategy	**OLS**	**IV**	**IV***	**OLS**	**IV**	**IV***
KP F-stats		15.90	13.73		15.90	13.73
Control	√	√	√	√	√	√
Firm Fixed Effect	√	√	√	√	√	√
Industry-Year Fixed Effect	√	√	√	√	√	√

Note: The data covers the period from 2006 to 2014, with 2005 utilized as a pre-sample year. I include firm fixed effects to control for time-invariant unobservable differences across firms. I also include lag values of firm controls with the assumption that firms with different initial energy mixes may exhibits different pre-trends. Further, I account for sector-year fixed effects to purge the residual from all time-varying industry shocks. Notwithstanding, there is a concern that forward-looking managers could forecast the evolution of input-specific energy prices in the coming years and choose the energy mix in the year t accordingly. To mitigate this concern, the pre-sample measure of the firm energy mix is lagged by at least 2 years with respect to the first observation in which the firm joins the estimation sample (IV^*). Thus, my preferred specification is columns 3, 6 and 9. The instrument passes the relevance assumption with F-stats passing the usual rule of thumb of 10. Standard errors are clustered at the firm-level. *,**, and *** denotes significance at the 10% , 5% and 1% levels respectively.

Having established that the instrument's relevance, I can now turn to the discussion of the environmental impact of energy price shocks. Table 3 columns 1-6 find support for the *first hypothesis* that increases in energy prices will result in lower firm-level energy consumption and emissions. The negative coefficients in columns 1-3 suggest that the average firms' energy consumption falls considerably due to an increase in energy prices. Unsurprisingly, the the OLS estimate reports a larger negative coefficient as compared to the instrumental variable approach. By controlling for forward-looking managers in column 3, I estimate that a 10% increase in energy prices leads to about 8.6% reduction in energy consumption. Accounting for how this affects the carbon content of energy and overall emissions, I find that the same 10% increase in energy prices will lead to a 5.9% decline in emissions. This suggests that firms' energy use does not equate one-to-one with pollution. It may be that firms make higher investments in energy-saving as compared pollution reducing technologies, or firms relatively reduce the less-carbon-intensive energy.

Further, energy price shocks can have a dynamic effect on energy consumption and emis-

Figure 4: **Dynamic Effect:** Energy Price and Firms' Environmental Variables



A. Energy Consumption B. CO_2 emissions

Note: Estimates of coefficients β_m for $m = -4, \ldots, 4$ from equation (5) are reported graphically. Panel A. reports these coefficients for energy consumption (KwH, in logs), and panel B. for CO_2 emissions, all at the firm level. The x-axis represents the value of m, the dots the point estimates of β_m, and the bar the 95% confidence intervals. Estimates are obtained from instrumental variable regressions where endogenous energy prices are instrumented by industry-level median energy prices weighted by pre-sample shares of energy mix. I used a balanced sample spanning 2006-2014. Standard errors are clustered at the firm-level.

sions. Such shock can lead to a strong, immediate effect and a persistent increase in environmental quality. I present this in Figure 4, plotting the coefficient estimates from the regression presented in Equation (5), accompanied by their 95% confidence intervals. By using this regression, I can explicitly test for pre-trends in firm characteristics, which is crucial for my identifying assumption in the IV estimates. First, the analysis shows that there is no significant differential pretrends, as the point estimates leading up to the pre-sample are statistically indistinguishable from zero. This pattern aligns with the parallel trends assumption, which strengthens the validity of my identification strategy. Notice that the point estimates for the impact of an energy price shock on energy consumption and CO_2 emissions are initially negative but statistically insignificant in year zero. However, they become statistically significant one year after the shock. Specifically, the estimated coefficient shows a decline of -0.52 log points for energy consumption and an increase of 0.41 log points for CO_2 emissions one year after the shock. These results are close to the those in estimated in Table 3. The values remain relatively stable in the long run. Conclusively, the support for *hypothesis 1* is stronger in the longrun as the dynamic effects suggest that an energy price shock had a prolonged effect on environmental improvements by reducing energy consumption and pollution emissions in Swedish manufacturing firms.

Economic Effects

Table 4 presents my second set of results describing how increases in energy price affect total factor productivity (TFP), and employment for Swedish manufacturing firms. Here, I start by the hypotheses' that firms responsiveness to an energy price shock is to substitute labour for energy or other inputs such as capital and machine (*hypothesis 2*). In effect, employment will fall. Overall, the results show a significant reduction in firms' employment due to an energy price shock. The results indicate that a 10% increase in the energy price shocks will lead to an approximately about a 3% decline in firm employment. The point estimate implies an economically significant decrease in employment by about 0.24%.[17]

Table 4: Energy Prices effect on Economic Goals

	IV		IV*	
	TFP	**Employment**	**TFP**	**Employment**
	1	2	3	4
EP_{it}	-0.184***	-0.493***	-0.172***	-0.270***
	(0.005)	(0.150)	(0.013)	(0.008)
Observations	29,596	29,809	22,815	22,815
KP F-stats	15.84	15.80	16.17	16.21
Control	√	√	√	√
Firm Fixed Effect	√	√	√	√
Industry-Year Fixed Effect	√	√	√	√

Note: The data covers the period from 2006 to 2014, with 2005 utilized as a pre-sample year. I include firm fixed effects to control for time-invariant unobservable differences across firms. I also include lag values of firm controls with the assumption that firms with different initial energy mixes may exhibits different pre-trends. Further, I account for sector-year fixed effects to purge the residual from all time-varying industry shocks. Notwithstanding, there is a concern that forward-looking managers could forecast the evolution of input-specific energy prices in the coming years and choose the energy mix in the year t accordingly. To mitigate this concern, the pre-sample measure of the firm energy mix is lagged by at least 2 years with respect to the first observation in which the firm joins the estimation sample (IV^*). Thus, my preferred specification is columns 3, 6 and 9. The instrument passes the relevance assumption with F-stats passing the usual rule of thumb of 10. Standard errors are clustered at the firm-level. *,**, and *** denotes significant at the 10% , 5% and 1% levels respectively.

Looking at the dynamic effects in Figure 5, I find that employment in the short-run is rather smaller in magnitude compared to the estimates reported in previous studies such as Kahn and Mansur (2013) and Marin and Vona (2021), whose estimates range from -0.08 to -0.21. However, in the long term, our estimates converge to approximately -0.17 (see Figure 5, Panel A). The negative impact of energy prices on employment theoretically aligns with the idea that such shocks directly increase firm costs, potentially leading to workforce downsizing.[18]. This may suggest that firms substitute energy with labour; however, to fully test the *second hypothesis*, I investigate how the workforce downsizing affects different occupations and skill-groups and also test the effect of energy prices on other non-energy inputs such as capital.

Occupation and Skill-Group. Recently, there has been a significant debate regarding the distributional effects of climate policy and energy prices (Känzig, 2023; Bernard and Kichian, 2021). If specific groups are left behind, this could potentially undermine the success of energy pricing. For instance, various occupational and labor-skilled groups may be disproportionately affected by the rise in energy prices. To investigate this composition effect, I categorize employment into full-time employment (which excludes part-time and secondary jobs or moonlighting), as well as high-skilled and low-skilled groups. I define high-skilled employment as consisting of workers with skill levels 3 and 4 determined by the SSYK 2012 classification by SCB. Examples of such workers include managers, commissioned officers, and occupations requiring advanced or higher levels of education. Conversely, low-skilled workers are those

[17] To find the percentage effect, I multiply each point estimates by the mean value of energy price and then divide the result by the mean sample of each dependent variable.

[18] Results in Table E.6 shows that the cost elasticity is about 8%.

categorized as having only skill level 1, primarily comprising elementary occupations. I find that energy price shocks have an adverse impact on both low- and high-skilled employment but a small positive effect on those in full-time positions (see Table E.2). However, there was a notable increase in the employment of workers with high school degrees (Figure 5, Panel D). Consequently, the findings suggest a potential degree of substitutability between high-skilled labor (including individuals with university degrees) and low-skilled labor and/or capital.[19] One underlying mechanism is that wage offers fall considerably (see Figure 5 Panel B), leading to a lower supply of skilled workers who command higher wages. In terms of occupation, the results show that professionals and workers in marketing, sales, and services are more likely to experience a decline in employment compared to technicians, mechanics, and engineers (Table E.4). Therefore, the overall results do not fully support the *second hypothesis* that in response to energy price shocks, firms will substitute energy with all non-energy inputs. Only high-skilled labour, and workers in sales, marketing, and professional occupation groups are negatively affected.

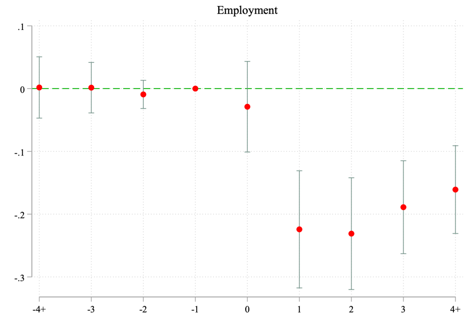
Next, I turn to *hypothesis 3*, where I test whether such reallocation leads to firms' improved productivity. The results in Table 4 show a significant reduction in firms' productivity due to an energy price shock. The results indicate that a 10% increase in the energy price shocks will lead to about a 2% decrease in TFP, which reflects an economically significant decrease of TFP by about 0.57%. Figure 6 shows that these effects are persistent over time, and short-term elasticities are smaller as compared to long-term elasticities. The estimated effect of energy price on TFP aligns with Marin and Vona (2021), who found the elasticity to be around 0.175%. The results that productivity falls rejects the *third hypothesis*, which is rather surprising, given that capital and machine increase for the average firm.[20]

It is possible that average estimate conceals heterogeneity across firms with different initial productivity levels. To investigate this further, Table E.2 presents estimates for how energy price shocks might affect high-productive and low-productive firms. The analysis reveals that low-productivity firms suffer greatly from energy price shocks, whereas high-productivity firms (those in the 90th percentile and above) experience a substantial boost in productivity. Consequently, I find that median firms' total productivity is negatively impacted, albeit statistically insignificant. As suggested by the factor demand framework (see e.g. Brännlund and Lundgren 2010), efficient firms tend to respond to energy prices by substituting energy demand with other technological demands to counter the adverse effects of energy price shocks. However, my findings suggest that this is not the case for average and low-productivity firms. Despite the reduction in energy dependency and CO_2 emissions due to energy price changes, the average firm does not significantly increase investments in pollution abatement technologies (see Figure E.1). I interpret this as a crowding-out effect – that is, higher energy prices, regardless of whether they result in enhanced energy efficiency or not, hinder other feasible productivity

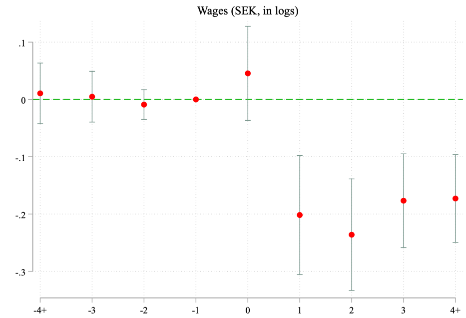
[19] For example, Table E.6 depicts a considerable increase in both actual capital and machinery investment in response to the increased energy prices.

[20] See for example, Table E.6 where both actual capital and machinery investment increase in response to the increase energy prices.

Figure 5: **Dynamic Effect:** Energy Price and Employment and Wages

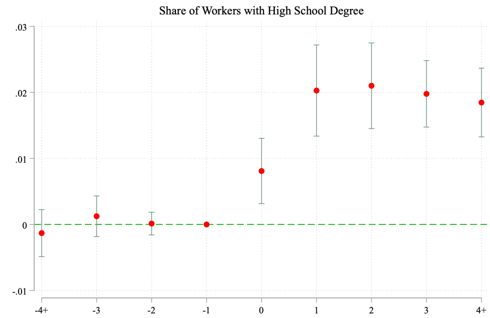


A. Employment



B. Wages

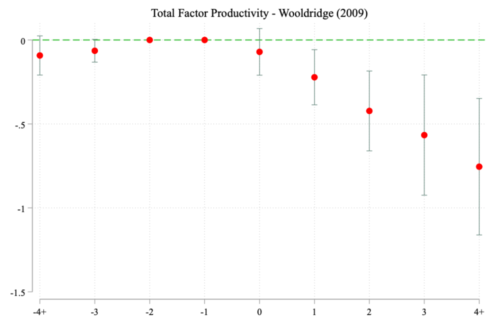
C. Share of workers with University degree



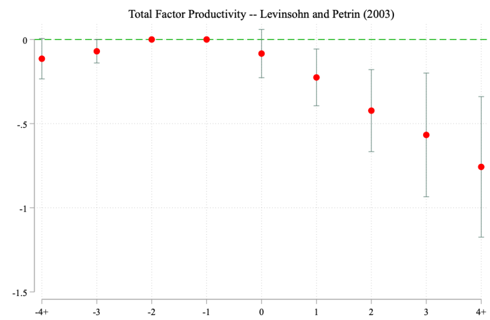
D. Share of workers with high school degree

Note: Estimates of coefficients β_m for $m = -4, \ldots, 4$ from equation (5)are reported graphically. Panel A. reports these coefficients for employment, panel B. for share of workers with university degree in total firm employment, panel C. for share workers with high school degree in total firm employment, and panel D. wages (monthly full-time equivalent earnings). The x-axis represent the value of m, the dots the point estimates of β_m, and the bar the 95% confidence intervals. Estimates are obtained from instrumental variable regressions where endogenous energy prices are instrumented by industry-level median energy prices weighted by pre-sample shares of energy mix. Standard errors are clustered at the firm-level.

Figure 6: **Dynamic Effect:** Energy Price and Firms' Total Factor Productivity



A. TFP – Wooldridge (2009)



B. TFP – Levinsohn and Petrin (2003)

Note: Estimates of coefficients β_m for $m = -4, \ldots, 4$ from equation (5) are reported graphically. Panel A. reports these coefficients for TFP measured by Wooldridge (2009) approach, and panel B. for TFP measured by Levinsohn and Petrin (2003) approach. The x-axis represents the value of m, the dots the point estimates of β_m, and the bar the 95% confidence intervals. Estimates are obtained from instrumental variable regressions where endogenous energy prices are instrumented by industry-level median energy prices weighted by pre-sample shares of energy mix. I used a balanced sample spanning the periods 2006-2014. Standard errors are clustered at the firm-level.

enhancements for the average firm. In effect, the results do not entirely reject *hypothesis 3*. I find that although productive firms tend to dynamically see an improvement in their TFP, low-productive firms are unable to invest in abatement technologies and reallocate resources that will increase their TFP as a result of energy price shock.

EU-ETS firms. Energy prices could reflect domestic alterations in environmental policies. However, global policies such as the EU-ETS exert varying effects on both domestic and foreign investments, thereby shaping the competitive landscape of domestic firms. Understanding such heterogeneity among EU-ETS and non-EU-ETS firms is crucial for climate policy exemptions. For example, Andersson (2020) shows that EU ETS could have a varying effect on upstream, and downstream industries as it can change their innovation, energy efficiency, and competitiveness. To check these heterogeneous responses, I augment regression model (1) with and interaction of EU-ETS with energy prices to capture how EU-ETS firms respond to energy price shocks. I present the results in Table 5. I find that although productivity is comparatively positive with ETS firms (column 1), the results are statistically insignificant in a more demanding specification (column 2). Additionally, employment remain negative but statistically insignificant from zero (column 4). Therefore, I do not have enough evidence to conclude that both energy prices and EU-ETS can lead to improved productivity. Moreover, the employment levels of an average EU-ETS firm show no significant difference compared to non-EU-ETS firms. This finding aligns with the majority of ex-post studies on carbon pricing effects on EU-ETS firms (see, for instance, Dechezleprêtre et al. 2023; Venmans et al. 2020). These outcomes imply that providing climate tax exemptions to EU-ETS firms could potentially mitigate their adverse economic effects, albeit at the expense of environmental considerations.

Table 5: Productivity and Employment Effect of Energy Prices – EU-ETS firms

	TFP		**Employment**	
	1	2	3	4
EP_{it}	-0.395*	-0.324*	-0.294***	-0.246**
	(0.223)	(0.175)	(0.103)	(0.124)
EP_{it} × ETS firms	0.185**	0.057	0.055	-0.084
	(0.077)	(0.061)	(0.108)	(0.106)
Observations	29,586	29,403	29,610	29,427
KP F-Stats	9.98	10.12	9.98	10.09
Control	√	√	√	√
Firm Fixed Effect	√	√	√	√
Industry-Year Fixed Effect	√	√	√	√
Municipal-Year Fixed Effect	×	√	×	√

Note: The data covers the period from 2006 to 2014, with 2005 used as a pre-sample year. I include firm fixed effects to control for time-invariant unobservable differences across firms. I also include lag values of firm controls with the assumption that firms with different initial energy mixes may exhibits different pre-trends. Further, I account for sector-year fixed effect to purge the residual from all time-varying industry shocks. I also include municipal-year fixed effect to control for changes in the labour market at the municipal-level. Standard errors are clustered at the firm-level. *,**, and *** denotes significance at the 10% , 5% and 1% levels respectively.

Dirty firms and sectorial energy intensity. The EU-ETS extends its coverage to all combustion installations with a power generation capacity exceeding 20 MW, regardless of their industrial categorization. Because my analysis focuses on individual firms, it is possible that certain firms, lacking any regulated installations, could potentially exhibit higher emissions levels compared to some firms falling under the scope of the EU-ETS. As a result, I manually compute for sectors with energy-intensive firms in two ways. First, I generate a dummy variable for "dirty" firms, which I classify as firms whose energy intensity exceeds a normalized sector-specific energy intensity. Second, I use the actual energy intensities of all sectors (3-digit SIC codes) to explore heterogeneity across sectors. As suggested by the descriptive evidence in Figure C.2, the incidence of energy prices varies substantially across sectors. Thus, in line with previous studies such as Kahn and Mansur (2013), Marin and Vona (2021) and Ferguson and Sanctuary (2019), I expect that dirty firms and energy-intensive sectors will be more sensitive to changes in energy prices. This section also enables me to test for *hypothesis 4* of whether productivity of energy-intensive firms will fall.

Table 6: Effect of energy prices by dirty firms and sectoral energy intensity

	TFP		**Employment**	
	1	2	3	4
EP_{it}	-0.182***	-0.548***	-0.033	-0.071***
	(0.064)	(1.054)	(0.022)	(0.014)
EP_{it} × Dirty firms	-0.843***		-0.241***	
	(0.100)		(0.038)	
EP_{it} × Energy intensity		-0.338***		-0.092***
		(0.084)		(0.026)
Observations	29,799	29,799	29,825	29,825
KP F-stats	60.18	19.99	60.09	19.98
Control	√	√	√	√
Firm Fixed Effect	√	√	√	√
Industry-Year Fixed Effect	√	√	√	√
Municipal-Year Fixed Effect	√	√	√	√

Note: The data covers the period from 2006 to 2014, with 2005 used as a pre-sample year. I include firm fixed effects to control for time-invariant unobservable differences across firms. I also include lag values of firm controls with the assumption that firms with different initial energy mixes may exhibits different pre-trends. Further, I account for sector-year fixed effect to purge the residual from all time-varying industry shocks. I also include municipal-year fixed effect to control for changes in the labour market at the municipal-level. Standard errors are clustered at firm-level. *,**,and *** denotes significance at the 10% , 5% and 1% levels respectively.

Results in Table 6 confirm that the impact of energy prices increases with sectoral energy intensity for all two outcome variables considered at the firm-level. An important finding is that firms in 'dirty' industries tend to be lower in employment and productivity due to energy prices increases, and hence corroborate with hypothesis 4. Additionally, the effect is negative and statistically significant for sectors in the top decile of energy intensity. I find that this significant negative effect is driven by sectors such as Coke, chemicals and pharmacy, and furniture (see Figure E.3). In summary, higher prices for intermediate inputs like energy will have significant negative economic effect of firms in energy-intensive sectors because they depend largely on energy and hence must accommodate the rise in energy costs.

Marginal Cost Pass-Through

The extent to which manufacturing firms pass on changes in their marginal production cost, resulting from changes in energy cost, remains largely unknown. In this subsection, I *test hypothesis 5*, by examining how the fluctuations in energy prices influence marginal cost, and whether firms can successfully transfer this cost to consumers. First, I estimate the effect of energy price shock (the instrument) on firm's unit price, marginal cost, markup and output. Second, I use the combined estimated relationship between energy prices and marginal costs into a pass-through regression model. The first set of regressions are presented in Table 7. Note that I only present the coefficients obtained from the preferred instrument, where I incorporate a lag up to 2 years in the firm's energy mix relative to the first observation when the firm becomes part of the estimation sample. The regression models also include firm fixed effects, as well as industry-year and municipal-year fixed effects.

Table 7: Energy Prices effect on unit price, marginal cost, markup and output

	Price	**Marginal Cost**	**Markup**	**Output**
	(1)	(2)	(3)	(4)
Energy Price Shock	0.518**	0.617***	-0.100*	-0.018**
	(0.222)	(0.213)	(0.057)	(0.008)
KP	179.27	179.27	163.05	163.05
Firm Fixed Effect	√	√	√	√
Industry-Year Fixed Effect	√	√	√	√
Municipal-Year Fixed Effect	√	√	√	√

Note: The data covers the period from 2006 to 2014, with 2005 used as a pre-sample year. I include firm fixed effects to control for time-invariant unobservable differences across firms. I also include lag values of firm controls with the assumption that firms with different initial energy mixes may exhibits different pre-trends. Further, I account for sector-year fixed effect to purge the residual from all time-varying industry shocks. I also include municipal-year fixed effect to control for changes in the labour market at the municipal-level. Standard errors are clustered at firm-level. *,**, and *** denotes significance at the 10% , 5% and 1% levels respectively.

The regression results show that the estimated coefficients for unit price and marginal costs are positive, as anticipated, indicating that energy price shocks tend to raise firm prices and the marginal costs of production. Specifically, the results show that energy price shocks leads to an increase of approximately 5% and 6% in goods prices and marginal costs, respectively. This provides initial evidence that energy price shocks are pass-through to firm-level unit prices. The sign and precision of the markup estimates in column 3 provide further support for these findings. As markups are defined as the ratio of prices to marginal costs, the effects of changes in energy prices on markups are approximately equal to the difference between their effects on marginal costs and unit prices. The point estimates suggest that higher energy prices result in modest decreases in markups by about 1% and a higher long run effect of about 2.4% (see Panel B of Figure 7). Lastly, I find a small but statistically significant reduction in firm output as a result of energy price – reflecting the possibility of firms scaling down production and increasing prices to counteract the high cost of production.

To concretize the effect of marginal cost pass-through effect, I incorporate the estimated relationship between energy prices and marginal costs into a pass-through regression model.

Specifically, I regress unit prices on marginal costs, thus examining how changes in marginal costs influence the transmission of costs to unit prices. Table 8 presents OLS regression estimates (with the usual fixed effects) and IV estimates of equation (4). The estimates in column 1 suggests that a 1% increase in marginal cost is associated with a 0.08% increase in the firm-level unit price. Following Ganapati et al. (2020), I convert this pass-through elasticity into the pass-through rate by multiplying the elasticity by the average markup in the sample of 3.48. This gives a pass-through rate of 0.28. Columns 2 and 3 show that the pass-through elasticities sits between 0.49 and 0.23, which translates into a pass-through rate of 1.7 and 0.8 respectively. In addition, I find that there is a possibility of a delayed pass-through effect as the pass-through rate in the long-run is larger in magnitude (see Panel C of Figure 7).

Table 8: Marginal cost pass-through effect

	Price		
	(1)	(2)	(3)
Marginal cost	0.084***	0.490***	0.228***
	(0.025)	(0.301)	(0.013)
KP		8.78	7.42
Estimation	**OLS**	**IV**	**IV***
Firm Fixed Effect	√	√	√
Industry-Year Fixed Effect	√	√	√
Municipal-Year Fixed Effect	√	√	√

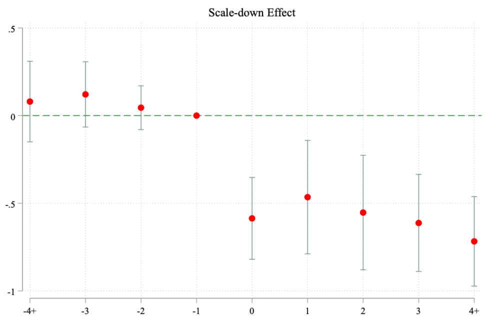
Note: The data covers the period from 2006 to 2014, with 2005 used as a pre-sample year. I include firm fixed effects to control for time-invariant unobservable differences across firms. I also include lag values of firm controls with the assumption that firms with different initial energy mixes may exhibits different pre-trends. Further, I account for sector-year fixed effect to purge the residual from all time-varying industry shocks. I also include municipal-year fixed effect to control for changes in the labour market at the municipal-level. Standard errors are clustered at firm-level. *,**, and *** denotes significance at the 10% , 5% and 1% levels respectively.

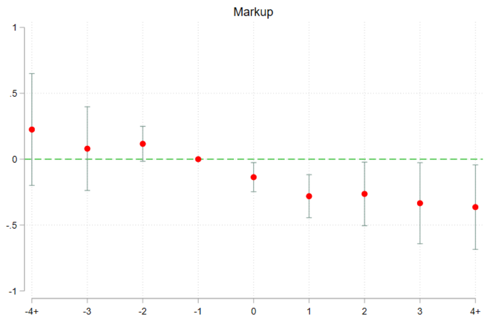
Observe that pass-through rates exceeding unity suggest that the average firm's producer surplus may increase due to a change in energy tax, potentially leading to over-shifting (see Delipalla and Keen (1992); Ganapati et al. (2020); Seade (1985)). However, it remains unclear in which market the average firm is operating, as the results show that pass-through rates range from below unity to above unity depending on the specific instrument used.[21]

Empirical evidence suggests that higher pass-through rates are typical in firms or industries with relatively inelastic demand and higher markups (Delipalla and Keen, 1992; Seade, 1985) as firms can reduce their own output and increase prices. My preferred specification in column 3 of Table 8 suggests that there is no over-shifting of tax-induced energy cost, which occurs in market environments with more elastic demand relative to a firm's supply. Interestingly, for the average firm, I find that tax-induced energy cost leads to a scale-down effect (Panel A of Figure

[21]Notice that these instruments exhibits some variation in strength across the different specifications, as indicated by the first-stage partial F statistics ranging from 7.4 to 8.7. As shown in Appendix D, though, lags of the instrument may reduce expectation bias, so it is also more likely to exacerbate the selection bias in the estimation sample, thus making the instrument relatively weak in the first-stage relationship. In such cases, the bias tends to favor the ordinary least squares (OLS) estimation. As also seen in Figure 7 Panel C, the pre-trends at period 4 are marginally violated. Thus, the relationship here may not be purely causal and should be interpreted with caution.

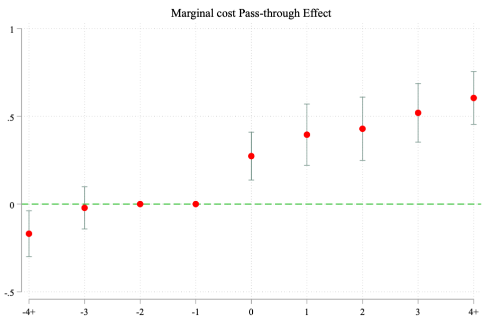
Figure 7: **Dynamic Effect:** Scale-down effect, Markup and Marginal Cost Pass-through





A. Output

B. Markup



C. Marginal cost effect on unit price

Note: Estimates of coefficients β_m for $m = -4, \ldots, 4$ from equation (5) are reported graphically.Panel A. reports these coefficients for output, panel B. for markup, and panel C. marginal cost pass-through elasticity. The x-axis represent the value of m, the dots the point estimates of β_m, and the bar the 95% confidence intervals. Estimates are obtained from instrumental variable regressions where endogenous energy prices are instrumented by industry-level median energy prices weighted by pre-sample shares of energy mix. Standard errors are clustered at the firm-level. Kleibergen-Paap rk LM statistics for the scale-down effect, markup and marginal cost pass through effect are 140.84, 123.06 and 8.72 respectively.

7), which is a common characteristics of oligopoly firms. However, it is crucial to consider that in this empirical setting, the firms might be unable to excessively increase unit prices due to the expenses associated with foregoing profits. Thus, the scale-down effect observed could indicate that a firm's supply is inelastic to energy prices and/or the tax-induced cost increase induces a form of collusion among producing firms that they are individually unable to achieve (see e.g., Seade (1985)). Additionally, it is essential to highlight that the markup falls, indicating that over-shifting may not be feasible in this particular case.

One crucial implication is that the average effect may conceal significant heterogeneity responses among firms. For example, the pricing behavior of firms with varying levels of productivity and product diversification can provide valuable insights into the mechanisms underlying cost pass-through in different market settings. To capture the non-linearity in productivity responses, I interact firms productivity with marginal cost in column 1 of Table 9. The estimated coefficients of the interaction are negative and statistically significant, suggesting that productive firms pass on a lower share of their cost to buyers. I also check how the effect differs between multi-product and singe-product firms. The interactive effect of marginal cost and multi-product dummy[22] in column 2 suggest that multi-product firms are also less likely to shift the increase in marginal cost to consumers.

Table 9: Heterogeneity: Marginal cost pass-through effect

	Price			
	(1)	(2)	(3)	(4)
Marginal cost × TFP	-0.205***			
	(0.050)			
Marginal cost × Multi-product firms		-0.118***		
		(0.032)		
Marginal cost × ETS firms			-0.175**	
			(0.076)	
Marginal cost × Dirty firms				-0.208***
				(0.045)
KP	10.50	7.52	7.36	14.84
Firm Fixed Effect	√	√	√	√
Industry-Year Fixed Effect	√	√	√	√
Municipal-Year Fixed Effect	√	√	√	√

Note: The data covers the period from 2006 to 2014, with 2005 used as a pre-sample year. All specifications include marginal cost. I include firm fixed effects to control for time-invariant unobservable differences across firms. I also include lag values of firm controls with the assumption that firms with different initial energy mixes may exhibits different pre-trends. Further, I account for sector-year fixed effect to purge the residual from all time-varying industry shocks. I also include municipal-year fixed effect to control for changes in the labour market at the municipal-level. Standard errors are clustered at firm-level. *,**, and *** denotes significance at the 10% , 5% and 1% levels respectively.

In considering another source of heterogeneity, I examine firms with high energy intensity and those subject to the EU-ETS regulation. As previously mentioned, not all energy-intensive firms fall under the EU-ETS; therefore, the response of EU-ETS firms may differ from that of the average energy-intensive firm. The interactive effects of EU-ETS firms and energy-intensive

[22]I generate a dummy = 1 if a firm produces multi-products over the entire period of study, and 0 if a firm produces a single product. About 80% of my sample are multi-products firms who produces and sell more than one type of product. These firms diversify their offerings to include a variety of goods within their portfolio. This diversification strategy allows them to target different market segments, mitigate risks associated with dependence on a single product, and take advantage of economies of scope.

(dirty) firms are presented in columns 3 and 4, respectively. The results indicate that firms covered by the EU-ETS pass on a lower share of their costs compared to non-covered firms. Also, dirty firms are less likely to shift a larger proportion of the carbon cost to consumers compared to cleaner firms. Interestingly, dirty firms have a higher cost absorption rate than EU-ETS firms. This might explain why carbon cost shock leads to a larger negative effect on dirty firms compared to EU-ETS firms. I attribute the low and incomplete pass-through effect by EU-ETS and dirty firms to the essential role of energy as a production input for these firms, coupled with their relatively large size and market power, which creates incentives for absorbing part of the cost increase.

Overall, the findings support *hypothesis 5*, and indicate that there is a pronounced heterogeneity of marginal cost pass-through in the manufacturing sector. Firms with higher productivity levels, multi-product firms, dirty firms, and those regulated under the EU-ETS are more capable of absorbing the energy price inflation. A major takeaway is that although higher prices of energy may decrease firms' international competitiveness, not all firms adjust prices of their final goods and products to offset the impact of energy inflation. This result has significant implications for understanding the dynamics of firms' pricing behavior in response to changes in input costs.

7 Conclusion

This study presents new findings on the impact of energy price inflation on manufacturing firms. I examine the impact of energy prices on a firms' competitiveness and environmental outcomes in a scenario that replicates what would occur with ambitious carbon pricing policies. I use a shift-share instrumental variable and dynamic difference-in-difference approaches to account for the potential endogeneity of energy prices.

The empirical findings presented in this study provide nuanced insights into the complex dynamics of energy price inflation on both environmental and economic dimensions. My analysis uncovers a dual impact of energy price shocks, revealing their role in driving positive environmental outcomes through reductions in energy consumption and CO_2 emissions, but have detrimental effects on firms' productivity, employment levels, and the potential risk of carbon leakage. Additionally, firms exhibit a tendency to pass on cost burdens to consumers, which could lead to increases in general inflation within the economy. My results also showcase varying levels of heterogeneity across manufacturing sectors, including energy-intensive and EU-ETS firms.

Considering these outcomes, my study highlights the existence of a trade-off between pursuing environmental and economic objectives amidst changing energy taxes. The findings underscore the need for careful consideration and strategic policy design to strike an optimal balance between achieving environmental sustainability and promoting economic growth. As energy price inflation continues to impact both environmental and economic indicators, policymakers must navigate these trade-offs to formulate effective measures that foster long-term sustainability and prosperity. This paper contributes significantly to the quantitative assessment of energy pricing, offering crucial empirical evidence for informed policy decision-making and sustainable development in the context of energy price fluctuations in the manufacturing sector.

Although this study leverages on the intensity of the energy price shock resulting from changes in energy taxes in Sweden, it is important to acknowledge that this approach does not permit the explicit identification of firms that were not exposed to this shock in comparison to those that were exposed. In future research, investigating environments where firms are exclusively exempted from paying energy taxes in other jurisdictions could serve as an interesting source of exogenous variations.

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Appendix

A Theory of Incidence

Existing studies primarily focus on the incidence of output taxes, but I extend this analysis to examine changes in input taxes or input costs. I begin by discussing incidence in scenarios of perfect competition and monopoly, which highlight how market power influences incidence. I then consider a more general framework that accommodates various forms of competition. I draw extensively from the work of Ganapati et al. (2020), which centers on taxes imposed on variable input costs rather than fixed costs. My emphasis is on providing economic intuition and presenting the model's primary aspects. For a more comprehensive understanding, interested readers are directed to refer to the original paper.

A.1 Model Overview

Let's assume goods outside the industry of interest, including the market for the taxed input, are supplied perfectly competitively, allowing me to disregard the welfare implications for producers resulting from consumer substitution to these goods. Additionally, let's assume the supply of the taxed input is perfectly elastic. Let's begin by introducing essential definitions. The incidence of a marginal increase in the tax rate τ is denoted by I, defined as the ratio of its effects on consumer surplus (CS) and producer surplus (PS):

$$I \equiv \frac{dCS/d\tau}{dPS/d\tau}$$

An incidence value above one indicates that consumers bear most of the welfare loss, whereas a value below one suggests that producers bear more. Next, the pass-through rate of an energy tax, denoted by ρ, is defined as the marginal change in output prices P resulting from a change in energy tax rates:

$$\rho \equiv \frac{dP}{d\tau}$$

Let γ denote the cost-shift rate, which signifies the marginal effect of the energy tax rate τ on marginal costs:

$$\gamma \equiv dMC/d\tau$$

The cost-shift rate γ can either be less than or greater than one. Lastly, let denote the change in average variable costs, $dAVC/d\tau$, which is the result of a marginal increase in the tax rate.

For the purposes of generalization, let's assume all firms in the market are identical. Let $\epsilon_D \equiv -[dQ/dP][P/Q]$ represent the elasticity of demand, which describes the change in total market-wise sales in response to a change in the prevailing market price. $L \equiv (P - MC)/P$ denotes the Lerner index, a measure of markups, calculated as the gap between price and marginal cost divided by price.

For the incidence of an input tax under arbitrary forms of competition, four statistics play a role: the pass-through rate ρ, the cost-shift rate γ, the Lerner index L, and the demand elasticity ϵ_D. Notably, perfect competition is a special case with $L\epsilon_D = 0$, and monopoly is a special case with $L\epsilon_D = 1$.

Proposition 1 *under generalized oligopoly, assuming N symmetrical firms and AVC=MC, provides the following form for incidence:*

$$I = \frac{\rho}{\gamma - (1 - L\epsilon_D)\,\rho} \tag{6}$$

Proof: Each of the N symmetrical producers maximizes profits by selling Q_i units at price P:

$$\pi = (P - MC)Q_i$$

Differentiating profits with respect to an input tax τ and substituting the definitions of L, ϵ_D, ρ, and γ yield the following relationship:

$$\frac{d\pi}{d\tau} = Q_i\left[(1 - L\epsilon_D)\,\rho - \gamma\right]$$

CS is given by $dCS/d\tau = -Q\rho$. By aggregating across all producers, the incidence can be written as:

$$I = \frac{dCS/d\tau}{dPS/d\tau} = \frac{-Q\rho}{N \cdot Q_i\left[(1 - L\epsilon_D)\,\rho - \gamma\right]},$$

where $Q = N \cdot Q_i$ represents the total quantity produced by all N symmetrical producers. This term simplifies to equation (6). Equation (6) can be intuitively explained as follows: The loss to consumers is represented by the change in product price, ρ, whereas the loss to producers is determined by the change in marginal costs, γ, minus the change in product price, ρ. The firm's change in product prices depends on the term $1 - L\epsilon_D$.

In perfectly competitive markets with input taxation, the tax incidence is fully characterized by the pass-through rate and cost-shift rate. Specifically, the incidence is given by the pass-through rate divided by the difference between the cost-shift rate and pass-through rate:

$$I^{Comp} = \frac{\rho}{\gamma - \rho} \tag{7}$$

Similar results are applicable when considering an input tax imposed on a monopolist. The incidence of a tax on an input for a monopolist is given by

$$I^{Mon} = \frac{\rho}{\frac{dAVC}{d\tau}} = \frac{\rho}{\gamma} \tag{8}$$

These equations enable us to compare input and output taxes. Across all three cases - perfect competition, monopoly, and general oligopoly - the incidence of input taxes varies from that of output taxes. In the case of an output tax, $\gamma = 1$ since firms cannot easily replace the taxed product. Conversely, for an input tax, the most probable scenario is $\gamma < 1$, indicating that marginal costs increase by less than 1 for every 1 unit of tax imposed on a single input. This occurs because firms can substitute away from the taxed input.

As a result, given a fixed pass-through rate, input taxes are likely to place a larger burden on consumers (and a smaller burden on firms) compared to output taxes. Relative to output taxes, input taxes afford firms the opportunity to substitute away from certain inputs, mitigating the potential rise in marginal costs and thereby reducing the impact on profits

B Data and Measurements

In this section, I describe methodology to estimate the parameters of the production function, including TFP and markups, both of which are unobserved.

B.1 Total Factor Productivity

TFP at the firm level is typically estimated as the residual in the functional relationship between output and inputs the firm employs and its productivity . However, using traditional methods like OLS to estimate the TFP introduces simultaneity because productivity and inputs are correlated. Also, entry and exit of firms in the sample may introduce selection bias. Several estimators have been proposed, including fixed effects, instrumental variables and GMM, Olley and Pakes' semi-parametric algorithm, and Levinsohn and Petrin's semi-parametric estimator to tackle these problems. However, the fixed-effect estimator still assumes that the inputs (such as labor, capital, and various intermediate inputs) are strictly exogenous, which is conditional on the heterogeneity of firms' productivity. This assumption implies that inputs of production should not be selected in response to productivity shocks, which is a severe and unrealistic limitation for analyzing firm behavior.

To consistently estimate the coefficients on variable inputs, both the Olley and Pakes (1992) and Levinsohn and Petrin (2003) methods use a two-step process. In the first step, semi-parametric methods are used to estimate the coefficients on variable inputs, as well as the non-parametric function that links productivity to capital and investment (or intermediate inputs). In the second step, the parameters on capital inputs can be identified based on assumptions about the dynamics of the productivity process, which is usually a one degree auto-regression process (i.e., AR(1)). Both methods have been widely used in recent studies on measuring firm-level TFP. However, the Levinsohn and Petrin (2003) method is often preferred over the Olley and Pakes (1992) method because it can save more observations when firms may not make long-term investments on an annual basis. However, these proxies may suffer from identification issue if all inputs (including labor usage) are determined by a productivity shock (and hence optimally chosen by firms). Thus, I use the Wooldridge (2009) approach of estimating the TFP. Specifically, I assume that the production function of Swedish manufacturing firms takes

Cobb-Douglas form with endogenous capital and labor usage.

$$Q_{it} = A_{it} L_{it}^{\beta_1} K_{it}^{\beta_k} M_{it}^{\beta_m} \tag{9}$$

where Q_{it} represents physical output of firm f in period t; $L_{it} K_{it}$ and M_{it} are inputs of labor, capital and intermediate inputs respectively and A_{it} is the Hicks neutral efficiency level of firm i in period t. Taking natural logs and differentiating the equation yields a linear production function as follows:

$$y_{it} = \ln A_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} \tag{10}$$

where lower-case letters refer to natural logarithms and $\ln A_{it} = \beta_0 + \omega_{it}$, and ω_{it} measures unobserved firm-level TFP over time. Based on equation (10), the unobservable firms' productivity $\omega_{it} = g\left(k_{it}, m_{it}\right)$ is assumed to be a three-degree polynomial of capital $\left(k_{it}\right)$ and intermediate inputs $\left(m_{it}\right)$, where the intermediate inputs are used as proxy (as in Levinsohn and Petrin (2003)). Under the assumption of $E\left(y_{it} l_{it},\ k_{it}, m_{it}\right) = 0$ (where $t = 1, 2, \ldots T$), I thus have the following regression function:

$$E\left(y_{it} \mid l_{it}, k_{it}, m_{it}\right) = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + g\left(k_{it}, m_{it}\right) = \beta_l l_{it} + h\left(k_{it}, m_{it}\right) \tag{11}$$

where $h\left(k_{it}, m_{it}\right) = \beta_0 + \beta_k k_{it} + \beta_m m_{it} + g\left(k_{it}, m_{it}\right)$.

Following Wooldridge (2009), I can rewrite the moment conditions for estimating β_l, β_k and β_m from equation (11) as a system of two equations and using a one-step GMM estimator. That is,

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + g\left(k_{it}, m_{it}\right) + \varepsilon_{it} \quad Vt = 1, \ldots, T \tag{12}$$

and

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + f[g(kit-1, mit-1)] + v_{it} \quad Vt = 1, \ldots, T \tag{13}$$

where $f(v)$ is approximated by a three-degree polynomial in v. With the assumption that productivity follows a random walk, identification is made with just current values and one lag in the conditioning set. Thus, to identify equations (12) and (13) in the GMM estimation, two groups of instruments are used which include (Ink k_{it}, the polynomials of $\ln k_{it}$ and $\ln m_{it}$ and its one-period lag) for the first equation and (lagged $\ln l_{it}$, lagged $\ln k_{it}$ and the lagged polynomials of $\ln k_{it}$ and lnm_{it}) for the second equation. The potential assumptions are (a) the firm-level productivity follows a random walk, so current values and one lag are independent in generating productivity shocks, and (b) there is no contemporaneous value of $\ln l_{it}$ and $\ln m_{it}$ being used and only one-period lag of the polynomial of $\ln k_{it}$ and $\ln m_{it}$, has been used. With the estimation of coefficients for labor, capital and intermediate inputs, the firm-level TFP can be estimated as follows:

$$\omega_{it} = y_{it} - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it} \tag{14}$$

where β_l, β_k and β_m are estimated by using the Woodridge GMM method.

B.2 Recovering Marginal Cost and Markup

This section describes the methodology for calculating marginal costs, and markups by closely following De Loecker et al. (2016). First, I define the production function for product j produced by firm i at time t as follows:

$$Q_{ijt} = F_{jt}\left(V_{ijt}, K_{ijt}\right)\exp\left(\omega_{it} + \epsilon_{ijt}\right) \tag{15}$$

In this equation, Q_{ijt} represents the physical output, F_{jt} is the product-specific production function, V_{ijt} denotes the variable inputs (inputs that can be easily adjusted by the firm), K_{ijt} denotes the fixed inputs (inputs that require adjustment costs), ω_{it} is the firm's firm-specific total factor productivity (TFP), and ϵ_{ijt} captures unexpected shocks to the firm's output or measurement error.

Equation 15 is built on several assumptions in the estimation procedure. Firstly, the production function F_{jt} is product-specific, as indicated by the notation. This assumption implies that the production technology used to manufacture product j is common across all firms, regardless of whether the firms are single- or multi-product. Secondly, productivity ω_{it} is firm-specific. Next, the firm-level expenditure is a sum of product-level expenditures. In other words, $W^v_{ijt}V^v_{ijt} = \tilde{\rho}ijt \sum_j Wijt^v V^v_{ijt}$, where $\tilde{\rho}ijt$ represents the share of the firm's expenditure on product j, ensuring that $\sum_j \rho ijt = 1$. This framework does not make any assumptions about market conduct or the demand system.

In this framework, firms are assumed to minimize costs by considering output quantity Q_{ijt} and input prices for variable inputs $\left(W^v_{ijt}\right)$ and fixed inputs $\left(W^k_{ijt}\right)$ as given. The firm's minimization problem for product j at time t leads to the following Lagrangian function:

$$\mathcal{L}\left(V_{ijt}, K_{ijt}, \lambda_{ijt}\right) = \sum_{v=1}^{V} W^v_{ijt}V^v_{ijt} + \sum_{k=1}^{K} W^k_{ijt}V^k_{ijt} + \lambda_{ijt}\left[Q_{ijt} - Q_{ijt}\left(V_{ijt}, K_{ijt}, \omega_{it}\right)\right] \tag{16}$$

This specification allows for the consideration that different firms may pay different prices for the same input, and that input quality (and hence the input price) might vary across products. Solving this problem leads to the following first-order condition, specifically for material inputs:

$$W^v_{ijt} = \lambda_{ijt}\frac{\partial Q_{ijt}}{\partial v_{ijt}} \tag{17}$$

The interpretation of λ_{ijt}, which is the shadow price of the firm's production constraint in the cost minimization problem, is the cost of producing another unit of Q_{ijt}. Multiplying by $\frac{V_{ijt}}{Q_{ijt}}$ and rearranging yields:

$$\frac{\partial Q_{ijt}}{\partial V_{ijt}}\frac{V_{ijt}}{Q_{ijt}} = \frac{1}{\lambda_{ijt}}\frac{W^v_{ijt}V_{ijt}}{Q_{ijt}} \tag{18}$$

Defining product-level markup μ_{ijt} as $\mu_{ijt} \equiv \frac{P_{ijt}}{\lambda_{ijt}}$ and rearranging Equation (18)results in the following expression for the markup:

$$\mu_{ijt} = \frac{\partial Q_{ijt}}{\partial V^v_{ijt}} \frac{V^v_{ijt}}{Q_{ijt}} \left(\frac{P_{ijt} Q_{ijt}}{W^v_{ijt} V^v_{ijt}} \right) = \theta^v_{ijt} \left(\alpha^v_{ijt} \right)^{-1} \tag{19}$$

where θ^v_{ijt} is the output elasticity of variable input V_{ijt} and α^v_{ijt} is the share of the firm's expenditure on input v attributed to product j in the sales of product j. From the definition of markups, marginal costs are obtained by dividing product level prices by markups:

$$mc_{ijt} = \frac{P_{ijt}}{\mu_{ijt}} \tag{20}$$

Thus, to obtain the markups and, in turn, marginal costs, I need two terms α^v_{ijt} and θ^v_{ijt}.$P_{ijt} Q_{ijt}$ (denominator of α^v_{ijt}) is available in the data. $W^v_{ijt} V^v_{ijt}$ (numerator of α^v_{ijt}) and θ^v_{ijt} need to be estimated. I discuss this in details below.

Output Elasticities. By taking the logarithm of the production function specified in Equation (15), we obtain the following expression:

$$q_{ijt} = i_j \left(\mathbf{v}_{ijt}, \mathbf{k}_{ijt}; \boldsymbol{\beta} \right) + \omega_{it} + \epsilon_{ijt} \tag{21}$$

where q, v, and k denote logs of correspondingly physical output, variable inputs, and fixed inputs. As it is standard in the literature, I assume that coefficients in the production function are time-invariant, which is reflected in the notation. It is possible to specify ω_{it} as varying on the firm-product-time level. However, this would compromise the ability to recover input allocation shares, which is critical for derivation of product level markups and marginal costs.

Equation (21) relates physical output on product-level q_{ijt} to the product level inputs $\boldsymbol{x}_{ijt} = \{\mathbf{v}_{ijt}, \mathbf{k}_{ijt}\}$. Physical output q_{ijt} is observed in the data. However, physical inputs $\boldsymbol{x}_{ijt}$ are unobserved and the best available counterparts to $\boldsymbol{x}_{ijt}$ are expressed in monetary values and are measured at firm level. Based on the assumption that firm-level expenditure is the sum of product-level expenditure on inputs, I can establish a relationship between product-level quantities $\boldsymbol{x}ijt$ and the corresponding monetary values for inputs (denoted as $\tilde{x}ft$) as follows:

$$x_{ijt} = \rho_{ijt} + \tilde{x}_{it} - w_{ijt} \tag{22}$$

where $\rho_{ijt} = \ln(\tilde{\rho}ijt)$, where $\tilde{x}ft$ represents firm-level expenditure on inputs (in logs), and w_{ijt} denotes the deviation of the product-specific input price from the industry average (in logs). By gathering all firm-product-specific input prices in logs into vector $\mathbf{w}_{ijt}$ and substituting Equation (22) into (21), I arrive at the framework's central equation:

$$q_{ijt} = f_j \left(\tilde{\mathbf{x}}_{ft}; \boldsymbol{\beta} \right) + M \left(\rho_{ijt}, \tilde{\mathbf{x}}_{ft}, \boldsymbol{\beta} \right) + N \left(\mathbf{w}_{ijt}, \rho_{ijt}, \tilde{\mathbf{x}}_{ft}, \boldsymbol{\beta} \right) + \omega_{it} + \epsilon_{ijt} \tag{23}$$

Terms $M(\cdot)$ and $N(\cdot)$ formalise biases that arise in the estimation of production function.

$M(.)$ represents the input allocation bias, which stems from the fact that product-level allocation of inputs is unobserved for multi-product firms. $N(.)$ is the input price bias, which arises from the unobserved input prices.

The solution proposed by De Loecker et al. (2016) here, is to separate the estimation divided into two steps: Firstly, I can estimate the production function parameters using single-product firms exclusively. In such firms, the input shares are equal to one by definition, thereby removing the need for ρ_{ijt} in both $M(\cdot)$. To obtain unbiased estimates, I account for both the unobserved productivity shock and the unobserved input quality. By assuming that the production function is product-specific, I can subsequently apply the parameter estimates to multi-product firms as well. Secondly, I can infer the input expenditure shares and the firm-level TFP by using the parameter estimates obtained from the first step and solving a system of simultaneous equations.

Since many firms in my dataset transition from being single-product to multi-product over time, it is crucial to address the potential selection bias that arises from this switching behavior. To handle the selection bias, I adopt the standard selection correction procedure introduced by Olley and Pakes (1992). To estimate the selection correction term, I calculate the probability that a firm continues to produce a single product in the next period. This probability is estimated nonparametrically, considering firm-level observable characteristics. Subsequently, I incorporate this selection correction term into the law of motion for more accurate and unbiased estimation.

Subsequently, I estimate and recover productivity for a single firm as follows:

$$\hat{\omega}_{ft} = \hat{q}_{it} - f\left(\tilde{\mathbf{x}}_{it}; \hat{\boldsymbol{\beta}}\right) + N\left(\hat{\mathbf{w}}_{it}, \tilde{\mathbf{x}}_{it}, \hat{\boldsymbol{\beta}}\right) \tag{24}$$

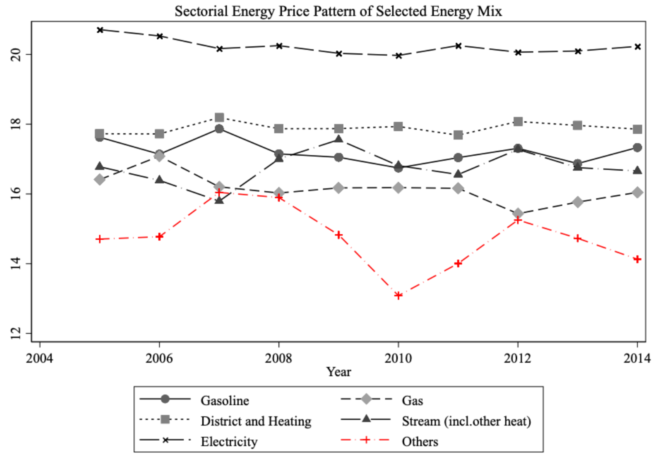
where $\hat{q}_{it}$ stands for the predicted physical output obtained from the projection of $\hat{q}_{it}$ on the covariates in the production function.

To calculate product-level markups and marginal costs for the entire sample, I must understand how multi-product firms allocate their inputs to different products. De Loecker et al. (2016) demonstrate that input allocation can be derived by leveraging the assumption that firm-level expenditure is a sum of product-level expenditure: $W_{ijt}^{v} V_{ijt}^{v} = \tilde{\rho} ijt \sum_j Wijt^{v} V_{ijt}^{v}$. Now, with estimates of output elasticities, Equation (23) can be restructured into two parts: one term with arguments independent of the input allocation variable ρ_{ijt} and another term solely dependent on ρ_{ijt}.

Considering the additional constraint $\sum_j \rho_{ijt} = 1$ (due to the assumption on expenditure allocation), I can formulate a system of equations that can be solved to determine ρ_{ijt}. Once I have the values of ρ_{ijt}, I know the input allocations, which then enable us to deduce firm-level productivity (essential for the discussion of mechanisms). Finally, I can use Equations (19) and (20) to obtain estimates of markups and marginal costs. In my calculations, I focus on the variable input of materials. As a result, I compute markups as the ratio between the output elasticity of materials and the share of materials in total sales. All product-level calculations are finally aggregated at the firm-level.

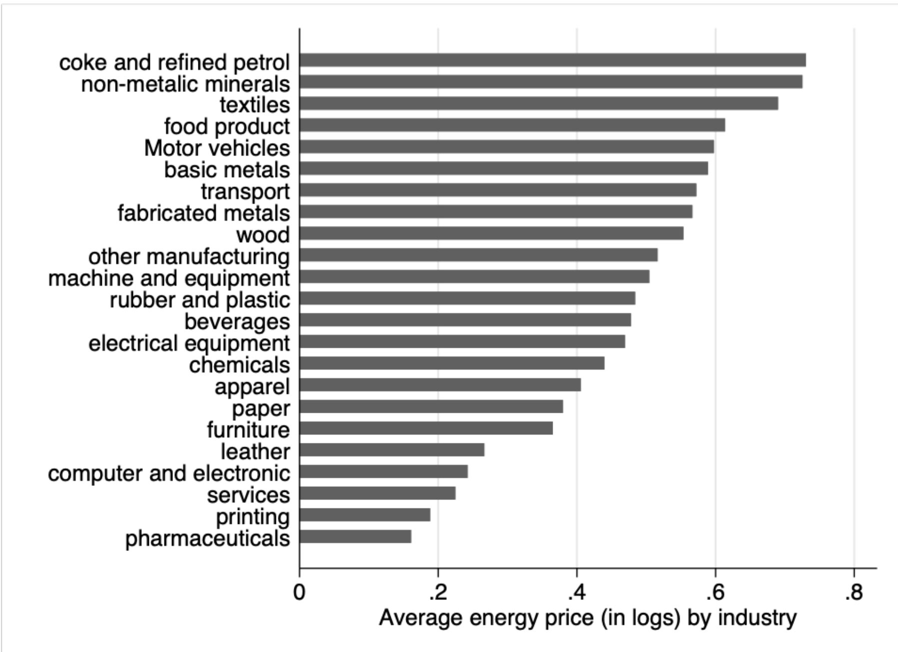
C Figures

Figure C.1: Sectorial Energy Mixes



Note: The results are my own elaboration of data obtained from SCB (Statistics Sweden). The calculation of the average energy mix considers sampling weights multiplied by energy consumption, ensuring a representative representation of energy usage

Figure C.2: Sectorial Energy Price



D Additional Robustness

I conduct two additional sensitivity analyses for the instrumental variable estimates on firms' TFP and employment. First, a concern regarding the validity of the instrument energy prices may be impacted by a worldwide shock, such as changes in demand, foreign cost shocks, and pricing to market. My benchmark approach is to contrast the results with a random trend model that accommodates a firm-product specific trend to capture even finer trends in energy prices, production and consumption patterns of firms. This is achieved by first eliminating firm-product specific effects through first-difference, and then utilizing fixed effects to account for individual trends. As shown in columns 1-3 in Table D.1, the result is robust to this demanding specification.

Table D.1: Robustness Results

	Random Trend Model		Dynamic Model					
	TFP	Employment	TFP			Employment		
	1	2	3	4	5	6	7	8
EP_t	-0.081**	-0.054**						
	(0.039)	(0.027)						
EP_{it-1}			-1.089***	-1.016*	-0.116***	-0.186***	-0.120	-0.077
			(0.122)	(0.558)	(0.009)	(0.017)	(0.093)	(0.126)
EP_{it-2}				-0.354	0.043		0.223	0.046
				(2.147)	(0.087)		(0.352)	(0.080)
EP_{it-3}					-0.059			0.102
					(0.096)			(0.062)
Observations	29,799	29,586	21,760	15,296	11,190	21,783	15,314	11,205
KP F-stats	11.15	11.01	99.11	8.22	8.81	98.67	8.22	8.84
Year Fixed Effect	√	√	√	√	×	√	√	×
Firm Fixed Effect	√	√	√	√	√	√	√	√
Industry-Year Fixed Effect	√	√	×	×	√	×	×	√

Note: Standard errors are clustered at the firm-level. *,**, and *** denotes significance at the 10% , 5% and 1% levels respectively.

Second, a specification issue arises if energy prices have a dynamic effect on firms' TFP and employment. It is not theoretically clear at what time energy price can affects firms' outcomes. I therefore include up to three yearly lags of energy prices in columns 3-8 to ascertain the the dynamic effects and the potential time lags in the regulatory effects. Interestingly, the results show a larger and statistically significant impact of energy cost on firms TFP, and employment with the inclusion of one lag. This extension conveys the crucial finding that long-term elasticities exhibit considerably larger values compared to short-term elasticities. However, when I add up to three consecutive lags in the model, I lose the statistical significance of the point estimates. This is expected as the the shock from the instruments are dampened at the first stage (see E.5). The higher the lags the less likely the instruments explain the variation in energy prices and the more likely they are to exacerbate the selection bias in the estimation sample, and hence the more similar the point estimate is to the OLS.

E Additional Results

Table E.1: Energy Price effect on Total Factor Productivity

	Woodldridge				L&P
	1	2	3	4	5
Energy Price	-0.003	-0.004*	-0.018	-0.147***	-0.169***
	(0.002)	(0.002)	(0.139)	(0.051)	(0.053)
KP			16.13	60.35	60.35
Control	×	√	×	√	√
Year Fixed Effect	√	×	√	×	×
Firm Fixed Effect	√	√	√	√	√
Industry-Year Fixed Effect	×	√	×	√	√
Municipal-Year Fixed Effect	×	√	×	√	√

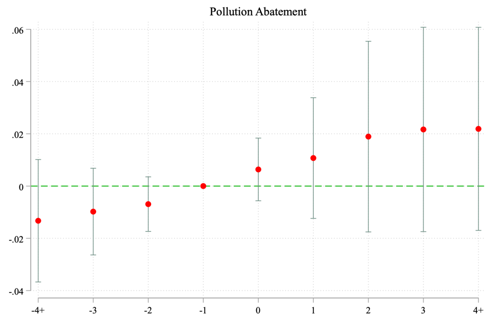
Note: I include firm fixed effects to control for time-invariant unobservable differences across firms. I also include lag values of firm controls with the assumption that firms with different initial energy mixes may exhibits different pre-trends. Further, I account for sector-year fixed effect to purge the residual from all time-varying industry shocks. The last specification includes municipal-year fixed effect to account for changes in the labour market at the regional level. L&P is TFP measured by the Levinsohn and Petrin (2003) approach. is Standard errors are clustered at firm-level. *,**, and *** denotes significance at the 10% , 5% and 1% levels respectively.

Table E.2: Energy Prices effect on Total Factor Productivity and Employment

	Total Factor Productivity			Employment		
	0-10th percentile	10-50th percentile	90-100th percentile	Full-time	Low-skilled	High-skilled
	1	2	3	4	5	6
EP_{it}	-1.180***	-0.105	0.221***	0.006**	-0.003*	-0.019***
	(0.325)	(0.272)	(0.062)	(0.002)	(0.002)	(0.004)
KP	16.22	9.79	40.55	16.17	16.17	16.17
Control	√	√	√	√	√	√
Firm Fixed Effect	√	√	√	√	√	√
Industry-Year Fixed Effect	√	√	√	√	√	√

Note: The data covers the period from 2006 to 2014, with 2005 used as a pre-sample year. I include firm fixed effects to control for time-invariant unobservable differences across firms. I also include lag values of firm controls with the assumption that firms with different initial energy mixes may exhibits different pre-trends. Further, I account for sector-year fixed effect to purge the residual from all time-varying industry shocks. Firms productivity is cut between the 0-10th percentile, 10-50th percentile and 90-100 percentile respectively, in columns 1, 2 and 3. High-skilled employment encapsulates workers with skill level 3 and 4 of the SSYK 2012 by Statistics Sweden. An example of workers here includes managers, commissioned officers, and occupation requiring advanced or higher level of education. Workers in skill level 1, comprising of elementary occupations are classified as low-skilled employment. Standard errors are clustered at the firm-level. *,**, and *** denotes significance at the 10% , 5% and 1% levels respectively

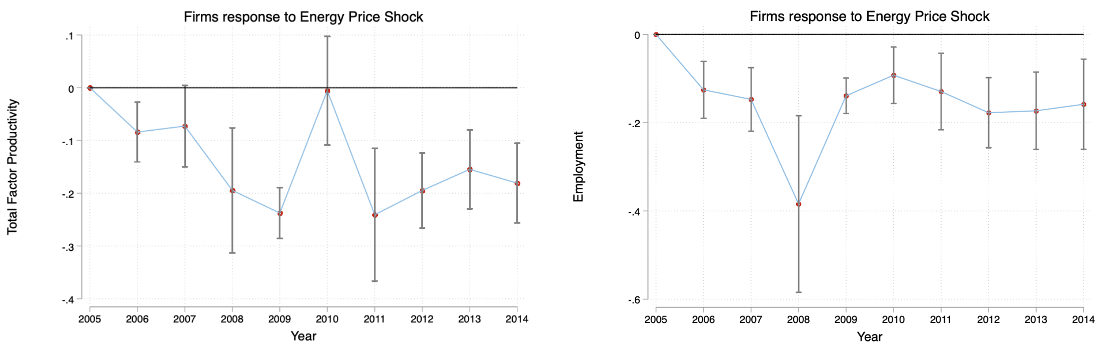
Figure E.1: **Dynamic Effect:** Energy Price and Firms' Pollution Abatement



A. Pollution Abatement

Note: Estimates of coefficients β_m for $m = -4, \ldots, 4$ from equation (5) are reported graphically. This figure reports the coefficients for pollution abatement investments, all at the firm level. The x-axis represent the value of m, the dots the point estimates of β_m, and the bar the 95% confidence intervals. Estimates are obtained from instrumental variable regressions where endogenous energy prices are instrumented by industry-level median energy prices weighted by pre-sample shares of energy mix. Note that my data on firm abatement covers only a few large firms, and I retain about 600 observations which may have contributed to losing statistical power in my dynamic difference-in-difference estimation. Standard errors are clustered at the firm-level.

Figure E.2: Yearly estimates of impact of energy price of firm employment and produtivity



Note: The figure plots the yearly estimates of energy prices on total factor productivity and and employment.

Table E.3: Energy Prices effect on Employment (FDB)

	1	2	3	4
Energy Price	-0.010***	-0.011***	-0.276**	-0.404***
	(0.003)	(0.003)	(0.113)	(0.124)
KP		19.64	45.93	19.64
Estimation	**OLS**	**OLS**	**IV**	**IV***
Control	×	√	×	√
Year Fixed Effect	√	×	√	×
Firm Fixed Effect	√	√	√	√
Industry-Year Fixed Effect	×	√	×	√
Municipal-Year Fixed Effect	×	√	×	√

Note: Employment(FDB) is employment defined by the business registry (FDB) dataset. In this context, an employed individual is defined as someone who engaged in work for at least one hour during a specific week (reference week) as an employee, a self-employed individual, or as an assistant in a family-owned business. Additionally, individuals who were temporarily absent from their employment or work during the entire reference week due to reasons such as vacation or illness are also included in the count of employed persons. My preferred specification is column 4, which includes set of controls, firm fixed effect, industry-year fixed effect and municipal-year fixed effect. The data covers the period from 2006 to 2014, with 2005 used as a pre-sample year. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

Table E.4: Energy Prices effect on Employment of Workers in Different Occupation

		Share of					
	Engineers	Marketing	Sales	Professionals	Managers	Technicians and Mechanics	Services
Energy Price	0.035	-0.011*	-0.091**	-0.279**	-0.004	0.179**	-0.144**
	(0.054)	(0.007)	(0.043)	(0.140)	(0.022)	(0.085)	(0.068)
KP	12.40	12.40	12.40	12.40	12.40	12.40	12.40
Control	√	√	√	√	√	√	√
Firm Fixed Effect	√	√	√	√	√	√	√
Industry-Year Fixed Effect	√	√	√	√	√	√	√
Municipal-Year Fixed Effect	√	√	√	√	√	√	√

Note:I include firm fixed effects to control for time-invariant unobservable differences across firms. I also include lag values of firm controls with the assumption that firms with different initial energy mixes may exhibits different pre-trends. Further, I account for sector-year fixed effect to purge the residual from all time-varying industry shocks. The data covers the period from 2006 to 2014, with 2005 used as a pre-sample year. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

Table E.5: First stage results

	EP_{it}						
	(1)	(2)	(3)	(4)	EP_{it-1}	EP_{it-2}	EP_{it-3}
IV_t	0.162***	0.107***	0.113***	0.108***	0.022*	0.016	0.010
	(0.006)	(0.009)	(0.009)	(0.010)	(0.011)	(0.012)	(0.015)
Control	×	√	√	√	√	√	√
Year Fixed Effect	×	√	×	√	√	√	√
Firm Fixed Effect	×	√	√	√	√	√	√
Industry-Year Fixed Effect	×	×	√	×	×	×	×
Municipal-Year Fixed Effect	×	×	×	√	√	√	√
Observations	31,170	29,807	29,592	29,410	22,379	18,655	15,112

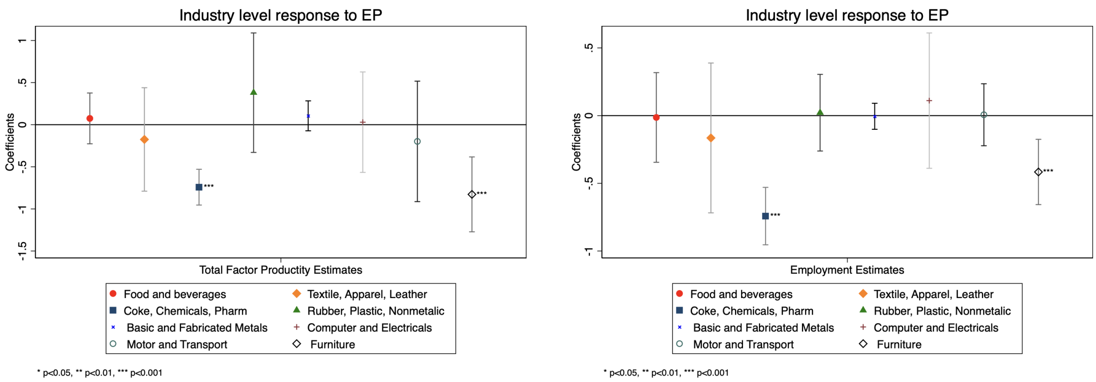
Note: Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

Table E.6: Energy Prices effect on other economic outcomes

	Firm Sales (1)	Machine investment (2)	Real Capital (3)	Total Cost (4)
EP_{it}	-0.602***	0.637**	0.928***	0.087**
	(0.163)	(0.312)	(0.232)	(0.034)
Observations	29,835	29,835	29,835	29,825
KleibergenPaap	15.79	15.798	15.79	15.81
Year Fixed Effect	√	√	√	√
Firm Fixed Effect	√	√	√	√
Industry-Year Fixed Effect	√	√	√	√

Note: Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

Figure E.3: Sectoral estimates of impact of energy price of productivity and employment



Note: The figure plots the yearly estimates of energy prices on total factor productivity and and employment.