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The effects of electricity and fuel prices on Swedish industry: A panel VAR approach☆

Hanna Lindström [a,b], Tommy Lundgren [a,c], Mattias Vesterberg [a,b,*]

[a] Centre for Environmental and Resource Economics, Sweden
[b] Umeå School of Business, Economics and Statistics, Umeå University, Sweden
[c] Department of Forest Economics, Swedish University of Agricultural Sciences, Sweden

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ABSTRACT

In this paper, we empirically examine the dynamic effects of electricity and fuel price changes on factor demand, utilizing detailed firm-level data from the Swedish manufacturing industry spanning 2004–2022. We employ a panel vector autoregressive model to analyze factor inputs and their associated prices. Our findings indicate that the demand for electricity and fuel is inelastic both immediately following a price change and over the following five years. Additionally, our results show that energy price shocks generally do not have statistically significant effects on labor demand, nor do they indicate any significant inter-fuel substitution.

1. Introduction

In this paper, we use unique firm-level data on the manufacturing industry in Sweden, spanning the period 2004 to 2022, to estimate how factor demand, and labor demand in particular, respond to the effect of changes in prices of electricity and fuels. Specifically, we use a panel-data vector autoregressive (hereinafter referred to as panel VAR) methodology, which combines the traditional VAR approach with the panel-data approach, which accounts for unobserved firm heterogeneity. From the estimated parameters, we compute dynamic multipliers to understand how changes to energy prices affect factor demand. This does not only provide new knowledge on the substitution possibilities among inputs, but also adds an intertemporal dimension allowing us to investigate effects over time.

Understanding the response of factor demand to energy price changes is important given the last few years' exceptionally high energy prices in Sweden and in Europe. For example, the annual average electricity price per kWh[1] in Sweden increased from less than EUR 0.025 to more than EUR 0.1 between 2020 and 2022 (see Fig. 1), and the price increases have been even larger in other European countries; see Fig. 2 for the percentage change in electricity prices for non-household consumers in European countries between the first half of 2021 and the first half of 2022. This rise in energy prices over the last years is primarily due to Russia's full-scale invasion of Ukraine and its ensuing energy crisis (Holmberg and Tangerås, 2023).

In the case of Sweden, increasing energy prices are likely to occur in the coming years as well, due to large investments in the green transition which will require large amounts of electricity. Electricity, generation in Sweden is dominated by hydro power, nuclear power and wind power, and Sweden is a net exporter of electricity. The Swedish electricity market was deregulated in 1996 and, as of today, approximately 90 percent of the electricity produced in the Nordic countries is traded on the Nordpool Nordic electricity stock exchange (see https://www.nordpoolgroup.com/). Forecasts on electricity consumption in 2030 indicate increases between 40 and 90 TWh compared to today's 140 TWh. The conservative scenario of a 40 TWh increase is expected

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* Corresponding author at: Umeå School of Business, Economics and Statistics, Umeå University, Sweden.
E-mail address: mattias.vesterberg@umu.se (M. Vesterberg).

[1] Because of the geographic transmission constraints, Sweden is, since the end of 2011, divided into four electricity price areas: Luleå (SE1), Sundsvall (SE2), Stockholm (SE3), and Malmö (SE4). The bidding areas are intended to enable better control of electricity transmission between different regions and to encourage the construction of new power plants and transmission capacity in and to regions with an electricity shortage.

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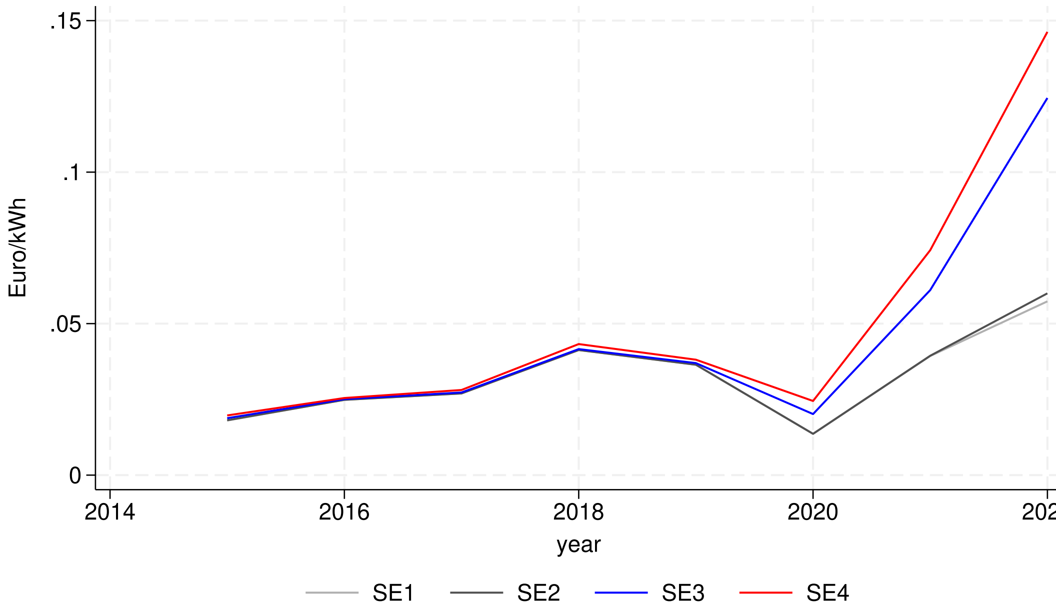

Fig. 1. Annual average electricity spot price, by price area. Note that price areas 1 and 2 (light and dark gray) faced almost identical prices during this period. *Source:* Nord pool (https://www.nordpoolgroup.com/en/Market-data1/Dayahead).

to result in almost doubled average spot prices on the Nordic electricity market compared to 2023 prices (Sundén, 2024). With a larger share of intermittent electricity production from e.g., windpower, prices are also expected to vary more (Bergman et al., 2022).

Rising energy prices can potentially have major repercussions on industry (UN, 2022). For example, high energy prices increase the cost for firms, who may respond by reducing the use of not only energy, but also other input factors (e.g., labor and capital) if these are complements to energy. This may in turn affect the economy as a whole, with the manufacturing industries playing an important role for both Sweden's and Europe's economic well-being.

This is particularly the case for Sweden, where the manufacturing and industrial engineering industry accounts for roughly 20 percent of the country's GDP, or approximately EUR 115 billion. Furthermore, the manufacturing industry in Sweden directly employs about 530,000 people (11 percent of the total workforce). At the EU level, the iron and steel, minerals, refineries and chemical industries combined employed an estimated 3.2 million people in the EU in 2019, accounting for about 11 per cent of total industrial employment (UN, 2022).

The magnitude and direction of the effect of high energy prices on firms' use of input factors depend on the own- and cross-price elasticities of input demand, and the output elasticity. It is therefore crucial to obtain measurements of these quantities, both for understanding the effects of changes in energy prices, and to be able to design efficient policies to, potentially, mitigate these effects (e.g., subsidies, vouchers and other support mechanisms). Furthermore, it is important to acknowledge that these substitution possibilities may differ across time, where, for example, firms have limited flexibility in the use of inputs in the short run, but adjust over time, due to adjustment costs. On the other hand, it may also be the case that firms reduce factor demand more in the short run, but after a while resume production and increase demand for factor inputs to stay in business. Substitution possibilities are thus ultimately an empirical question.

A key feature of our study is the ability to disaggregate energy consumption into two main categories: electricity and other fuels. This detailed breakdown allows us to gain a deeper understanding of how firms adjust their energy usage in response to price changes. Specifically, we can observe how firms substitute between different energy sources and whether labor demand responds differently to changes in the prices of electricity compared to other fuels. This distinction is particularly important given the current policy emphasis on electrification, which is seen as a crucial element in the green transition of industries and society at large. Understanding the potential for substitution between electricity and other fuels is vital for informing these policies. Our dynamic approach, which considers how these substitution possibilities evolve over time, offers a significant advantage over the static models commonly used in the literature (see, for example, Dahlqvist et al. (2021)).

Furthermore, Sweden's division into four distinct electricity price areas[2] adds another layer of complexity and richness to our data. The recent energy price shocks have affected these areas differently, resulting in substantial variation in energy prices, particularly electricity prices, within our dataset. This variation provides a unique opportunity to analyze firms' responses to these shocks. To the best of our knowledge, our paper is the first to investigate how firms have reacted to the recent fluctuations in electricity prices.

Another significant contribution of our study is the use of a panel VAR approach to capture the dynamic relationships between variables. This method is highly flexible and allows us to model the interactions between energy prices, energy consumption, and labor demand over time. This flexibility is a notable improvement over many previous studies that rely on structural models with Euler equations, which can be more rigid and less adaptable to changing conditions (see, for example, the discussions in Chatelain and Teurlai (2001) and Whited (1998))

In brief, our results reveal that (i) the own-price elasticities of electricity and fuels are negative and, for fossil fuels, relatively large (in absolute value), and the elasticity changes over time, with more inelastic demand in early periods after the price change, compared to subsequent periods; (ii) the demand for fuels is more elastic than the demand for electricity, both in the early periods after a price change, and the subsequent periods; (iii) there is no statistically significant effect of changes in energy prices on employment, neither for electricity nor fuels; (iv) we find no significant effect of electricity prices on

[2] These regional price differences arise due to variations in demand, generation mix, and transmission capacity constraints.

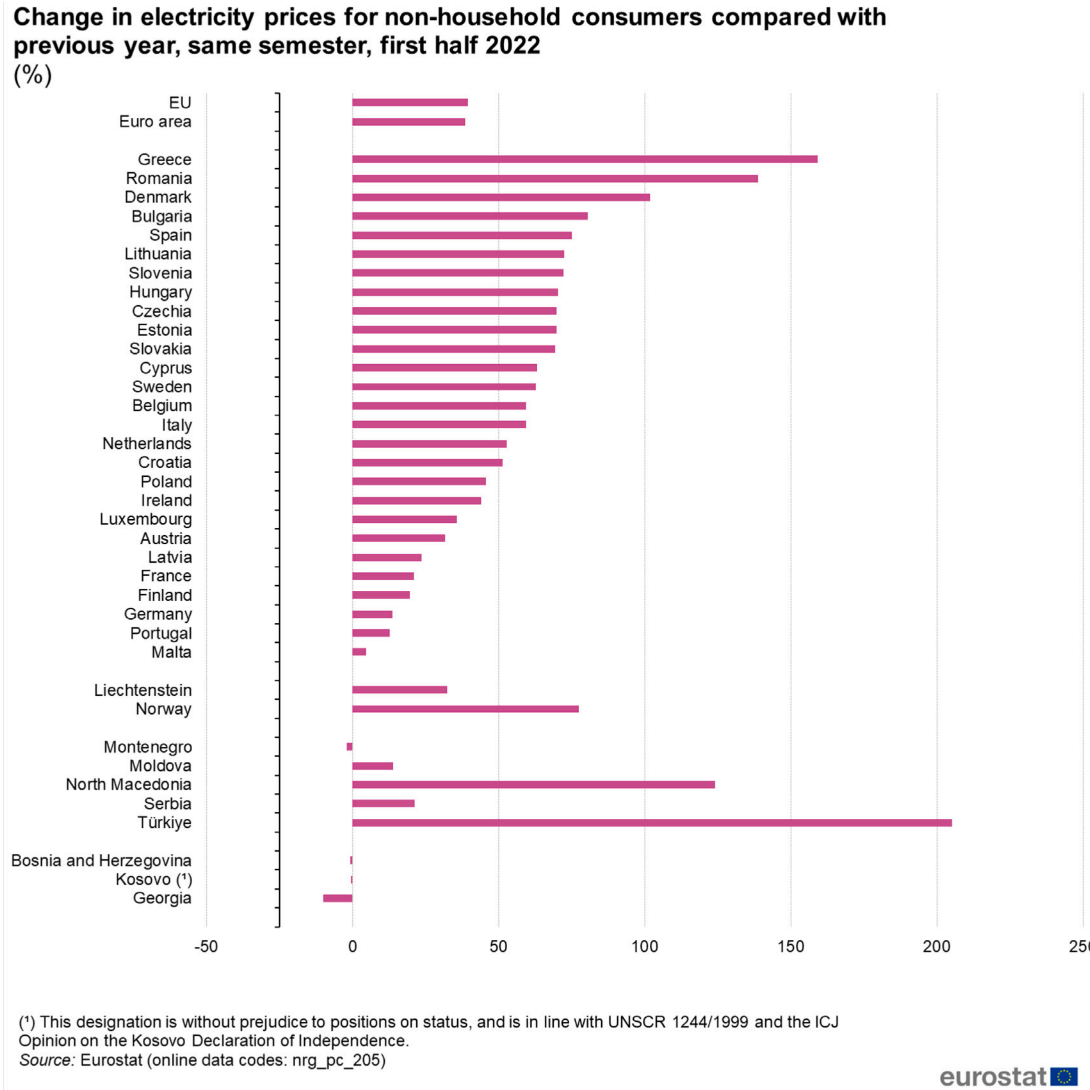

Fig. 2. Percentage change in electricity prices for non-household consumers between first half of 2021 and first half of 2022.

fuel use, and we find no significant effect of fuel prices on the use of electricity.

Our empirical results have important policy implications; first, they suggest that even in the face of large energy price shocks, policy makers should not worry too much about spillover effects on labor markets, given that the elasticity of employment with respect to energy prices is not statistically different from zero. Furthermore, given Sweden's ambitious climate and energy policy goals, which most likely will lead to higher electricity prices (driven by an increased demand for electricity), our results indicate that such policies will have no or limited effect on labor market outcomes. Finally, one interpretation of the lack of substitution between electricity and fuel is that the effects of, for example, carbon taxes on fuels will have little impact on electrification in the short run. Similarly, our results indicate that electricity price shocks does not appear to lead to more use of fuels and thereby more emissions.

The rest of this paper is structured as follows: We review the existing literature on firm-level effects of changes in energy prices in Section 2. Next, in Section 3, we describe our firm-level data, and in Section 4, we detail our empirical approach. Section 5 presents results and Section 6 concludes.

2. Previous literature

While the literature on the economics of industry factor demand is relatively large, results are mixed and study designs differ with respect to the context studied (e.g., country or sector), data (aggregate or micro data, disaggregation of energy types) and empirical method (factor demand analysis, reduced form or time-series analysis).

Berndt and Wood (1975), use a static translog specification and U.S. manufacturing data, and find the own-price elasticity of aggregate energy demand to be −0.47. Furthermore, they show that energy and labor, and capital and labor, are substitutes but with cross-price elasticities close to zero, whereas energy and capital are complements with a rather negative cross-price elasticity of −3.2.

Cox et al. (2014) estimate a static translog cost function using German data, with a special attention on the effects of electricity prices on labor demand. When estimating conditional cross-price elasticities, i.e., holding the production level of firms constant, they find a low substitutability between electricity and labor. Conditional cross-price elasticities of labor demand with respect to electricity prices are positive, but small, ranging between 0.09 and 0.31 for different skill levels of labor. However, when allowing for changes in production levels due to rising overall production costs, the authors find negative unconditional cross-price elasticities ranging between −0.06 and −0.69, thus suggesting moderate complementarity between labor and electricity. Hille and Möbius (2019) use cross-country multi-sector data and a reduced-form specification, and find the elasticity of labor demand with respect to energy prices to be positive, 0.32 on average across sectors, but statistically insignificant for the manufacturing sector.

Next, a number of papers have in different ways introduced dynamics to the study of firm performance and factor demand. Pindyck and Rotemberg (1983) analyze dynamic factor demands and the effects of energy price shocks using the same data as in Berndt and Wood (1975), but allow for dynamics through the inclusion of Euler equations. They show that the own-price elasticity of energy is −0.66 in the short-run and −0.93 in the long-run, and that energy and labor are complements both in the short- and long-run.

Lundgren and Sjöström (1999) specify a translog cost function and, similar to Pindyck and Rotemberg (1983), model dynamics through Euler equations. They apply their model to Swedish data for the pulp and paper industry and show that the own-price elasticity of labor is −0.71 in the short-run and roughly the same in the long-run. The elasticity of labor demand with respect to energy prices is negative and relatively small, around −0.16 to −0.19, both in the short- and long-run, thus suggesting weak complementarity between the two input factors.

Gamtessa and Olani (2018) use data from Canada to explore how energy-capital, output-capital, and energy-output ratios are affected by energy price. Similar to the current paper, they employ a panel VAR model to study these relations. They show that an increase in energy prices reduces energy-capital and energy-output ratios both in the short- and the long-run. They also show that industry-specific impulse responses of energy intensities to an oil price shock is negative in most cases.

Hesse and Tarkka (1986) break down energy input into fuels (coal, gas, fuel oils) on the one hand and electricity on the other hand. They specify a static translog cost function and estimate the parameters using data on manufacturing industries in a number of Western European countries in the 1960's and 1970's. They find that the demand is own-price inelastic for all inputs (labor, capital, electricity and fuels), with estimated elasticities ranging from −0.3 for electricity and fuel, to −0.8 for capital. Furthermore, the cross-price elasticities indicate that labor and electricity are substitutes for all countries in both periods and labor and fuels are substitutes for most countries in the 1960's period. Electricity and fuels are found to be strong complements in the 1960's period, but this relationship is completely altered in the 1970's with positive elasticities ranging from 1.20 to 1.51.

For the Swedish context, Brännlund and Lundgren (2004) study inter-fuel substitution between wood fuel, non-gaseous fossil fuels (e.g., oil and coal), gaseous fossil fuels (e.g., natural gas and propane) and other fuels (e.g., waste, peat and industrial hot water) for Swedish heating plants during the period 1990 to 1996. They estimate a system of demand equations for these four different fuels using a linear logit model, allowing for the level of total fuel use to adjust. They find that all estimated own-price elasticities are negative and all cross-price elasticities are positive. However, this is for a very limited sample of heating plants where electricity is not included among the fuels.

Brännlund and Lundgren (2007) use Swedish firm-level data for the base industry (eight manufacturing sectors), for the period 1990–2001, and differentiate between electricity and fuel. They employ a structural approach by specifying a quadratic profit function and estimate a system of factor demand equations for each sector. By allowing all inputs to be flexible, their model can be viewed as a long-run model. They find that the elasticity of labor demand with respect to electricity price is negative for most sectors, but very small, ranging between −0.37 and 0.20. A similar pattern holds for demand for labor with respect to fuel price. Demand is own-price inelastic for all inputs, with fuels showing, generally, larger elasticities in absolute value compared to electricity. The cross-price elasticity of electricity with respect to fuel price ranges between −1.60 and 0.17 and is, generally, negative thus indicating complementarity between the two energy types.

In a more recent study, Dahlqvist et al. (2021) employ firm-level data on the four most energy-intensive manufacturing sectors (Paper and pulp, Chemical, Iron and Steel, Mining) for the years 2001 to 2012 and differentiate between electricity and fossil fuels. They assume a static normalized quadratic profit function and find that the own-price elasticity for electricity ranges between −1.62 and −0.85, and between −0.80 and −0.24 for fossil fuels. Furthermore, they find that the cross-price elasticities for labor demand with respect to electricity price range between −1.20 (indicating complementarity) for the mining sector and 0.065 (indicating substitute) for the Chemical sector. The cross-price elasticities for labor demand with respect to fossil fuel price range between −0.55 (indicating relatively weak complementarity) for the mining sector and 0.078 (indicating substitute) for the Chemical sector. Regarding inter-fuel substitution, the demand elasticity for electricity with respect to fuel prices ranges between −0.73 for the mining sector and −0.14 for the chemical sector.

Our study also relates to a body of literature starting with Davis and Haltiwanger (2001), looking at oil price shocks and job flows in US manufacturing. Two studies that look specifically into energy price fluctuations (mainly oil) and its relation to employment are Herrera and Karaki (2015) and Herrera et al. (2017). These papers extends Davis and Haltiwanger's sectoral job flow analysis by confirming the importance of oil shocks for labor-market dynamics, while questioning earlier claims of nonlinear (asymmetric) effects. By linking energy price shocks to cross-industry employment flows, they highlight how oil price downturns can simultaneously shrink employment in energy-producing sectors and boost it in energy-consuming sectors, with an overall dampening of labor market churn. Other studies look more generally at oil price shocks and effects on the economy. For example, Baumeister and Kilian (2016) analyze the macroeconomic impact of the 2014–2016 oil price collapse on the U.S. economy. The authors find that the positive effects of cheaper oil on consumers and non-oil businesses were largely offset by negative effects on the oil sector, leaving the net impact on GDP close to zero.[3]

To summarize, while there is a relatively large literature on industry factor demand, estimates vary substantially across studies. This variation in findings may be due to differences in context studied (e.g., country, sectors, time-period), data (e.g., aggregate or micro data, disaggregation of energy type) and methods (e.g., reduced form or structural models, static or dynamic models). We also note that relatively few studies examine the dynamics of factor demand, and that these few studies typically rely on Euler equations, which have been criticized for being restrictive and fitting the data poorly (e.g., Chatelain and Teurlai (2001) and Whited (1998)).

3. Data

To measure the dynamic effects of energy prices on factor demand, we use annual firm-level unbalanced panel data, covering the years 2004–2022. The data is sourced from the "Frida" database from

[3] Research on the macroeconomic effects of oil price shocks identifies several key transmission mechanisms. Early DSGE models (e.g., Kim and Loungani (1992)) argued that oil's small share in GDP limited its impact via production costs. However, later studies, such as Edelstein and Kilian (2009), emphasize household spending reallocation — particularly away from non-energy goods — as the dominant channel. This view is further refined by Baumeister and Kilian (2016) and Baumeister et al. (2018), who provide empirical evidence on how oil shocks influence consumption patterns. Kilian and Vigfusson (2011) also challenge earlier assumptions of asymmetric effects, offering a more nuanced view of oil-macroeconomy dynamics.

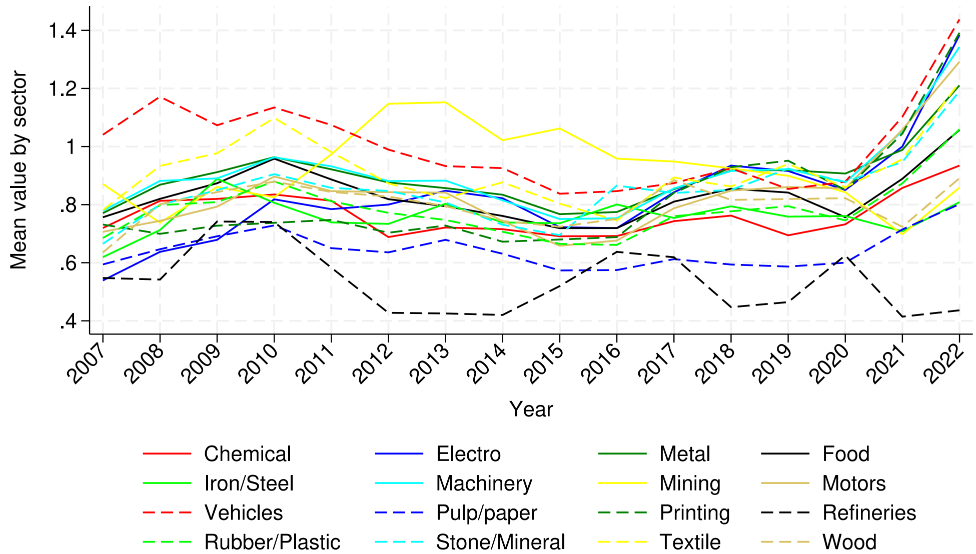

Fig. 3. Electricity price (in 1000 sek/MWh) across sectors.

Statistics Sweden[4] and covers all manufacturing industries in Sweden: Chemical, electro, fabricated metal, food, iron and steel, machinery, mining, vehicles, paper and pulp, printing, refined petrol products, rubber and plastic, stone and mineral, textile and wood.[5] The dataset comprises approximately 8700 firms and 60,000 observations in total.[6]

While all of the sectors in our data use relatively large quantities of energy in their production processes, some of these sectors are to be considered as relatively more energy-intensive: for example, sectors such as paper and pulp, chemical, iron and steel, mining, and stone and mineral all use large amounts of energy in their production. To give a sense of magnitude, the average cost share for energy is approximately 0.05 in our sample, and for firms in the 95th percentile, this share is more than 0.24. For the relatively more energy-intensive sectors, the corresponding shares are 0.08 and 0.42, respectively.

Our analysis focuses on the demand for the inputs electricity, fuels, labor and capital, and on output. Fuels consists of coal, petroleum products, biofuels, gaseous fuels, district heating and other fuels. Statistics Sweden converts fuel quantities to energy equivalents (MWh) using the same conversion rates for all sectors.

For the inputs electricity and fuel, our dataset includes firm-level data on both expenditure (in swedish kronas, sek) and quantity used. This enables us to calculate average prices by dividing total expenditure by total quantity consumed—for electricity and similarly for fuel. When visualizing the data using boxplots over time, we identify a small number of outliers in electricity and fuel prices and quantities. Our main specification retains all observations, including these outliers. However, as a robustness check, we estimate an alternative model that excludes outliers. Specifically, we define outliers as values for labor, fuel, and electricity prices or quantities that fall below the 1st percentile or exceed the 99th percentile within each sector.

Furthermore, for each firm, we also observe labor quantity, which is defined as the sum of a firm's number of full-time and part-time employees. Labor price (in 1000 sek), is calculated for each firm by dividing yearly total salary costs over the firm's number of employees, thus reflecting the average salary paid to an employee that year. While it would have been interesting to be able to distinguish between, e.g., blue and white collar labor, and full-time and part-time employees, our data does not allow for such disaggregation. This should be kept in mind when interpreting the results, especially when it comes to substitution possibilities between labor and other input factors.

The input factor prices for electricity, fuel and labor are deflated using sector-specific producer-price index (PPI) with base year 2020.

The data includes firm-specific capital gross investments, which allows us to create a firm-specific capital stock by applying the perpetual inventory method (Berndt, 1991).[7] Specifically, we compute the capital stock in time t as $K_{it} = I_{it}+(1-\delta)K_{it-1}$ where K_{it} denotes capital at time t, I_{it} denotes gross investments in inventories and machinery, and δ the depreciation rate which we, following Dahlqvist et al. (2021), assume to be 0.087.[8] For the first observation per firm i, we set $K_{i0} = I_{it}/\delta$

The data does not contain information about the user cost of capital at the firm level. While we in principle can compute such a price at the sector level,[9] such a price will only have limited variation, and in particular no variation across firms within a sector; see Fig. A.2 in the Appendix. More generally, measurements of the user cost of capital is known to be contentious (e.g., Inklaar (2010)), and previous research has shown that empirical results may be sensitive to how the user cost is computed (e.g., Oulton (2007)). Furthermore, our data suffers

[4] The source material has been anonymized and identification of firms is not possible. This dataset is owned by Statistics Sweden, and Statistics Sweden has released the data to us under many conditions: The database shall be used solely for research, exclusively and solely by us, and with an explicit instruction regarding not sharing the database with any third party. We have signed an undertaking to this effect prior to obtaining the data. As a result, we are unable to provide the dataset to other researchers. However, researchers can access the data by contacting Statistics Sweden at mikrodata@scb.se. For further information, please contact the authors.

[5] Older versions of this data-set has been used in a number of previous papers; for example, Amjadi et al. (2018) and Dahlqvist et al. (2021) use this data to study the rebound effect in Swedish heavy industry.

[6] Although the time period covered is relatively short, the large number of cross-sectional units (firms) suggests that our context is consistent with a large N, small T framework.

[7] This requires at least two observations on capital gross investments over two consecutive years for each firm. When this is not available, observations have been excluded.

[8] For example, Edquist and Henrekson (2017) show that depreciation rates are very similar across sectors within the manufacturing industry. Figures from Statistics Sweden confirm this, see https://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START_NV_NV0109_NV0109O/BNTT01/. This motivates our assumption of a uniform depreciation rate.

[9] E.g., $p_K = p_I/p_Y(r+\delta)$ where p_I and p_Y denote the investment good price index and the output price (sector-specific Producer Price Index), respectively, r denotes the long-term market capital interest rate and $\delta = 0.087$ the depreciation rate.

Table 1
Descriptive statistics all sectors.

	Mean	Std.dev	Min	Max	N
Number of employees	134.7	628.3	6	20 318	28 086
Electricity use (MWh)	17 829.9	125 597.4	0.0500	3 038 995	28 086
Other fuel use (MWh)	45 360.6.	491 723.2	0.0196	18 938 040	28 086
Yearly salary (Tsek)	596.7	295.0	0.000676	13 775.4	28 086
Price per MWh electricity (Tsek)	0.867	4.025	0.000563	672.9	28 086
Price per MWh other fuels (Tsek)	0.980	4.809	0.0000797	504.3	28 086
Capital stock (Tsek)	245 258.3	1 690 767.5	276.3	55 997 680	28 086
Net sales (Tsek)	636 895.3	4 680 516.2	3.885	196 718 784	28 086

from similar problems when it comes to measurement of the price of outputs: while we in principle can use, e.g., the sector-level producer price index, this price varies very little over time, and again, has no variation within sectors in a given year; see Fig. A.3 in the Appendix. In Section 4, we detail how we model capital and output in our empirical work, given this data limitation. Finally, output, Y, is calculated as a firm's net sales (in 1000 sek), divided by a sector-specific producer price index, using 2020 as base year, in order to deflate values.

Summary statistics for our key variables are presented in Table 1. A first thing to notice in Table 1 is the very large heterogeneity in firm size, illustrated, for example, by the range of net sales. The use of the four input factors (electricity, fuels, capital and labor) indicate similar heterogeneity in firm size. In Figs. 3 to 5, we illustrate the sector-level variation in the price of input factors electricity, fuels and labor, respectively. Remember that in our data, these input prices vary not only across sectors, but also across firms within sectors. Also keep in mind that fuels and labor are aggregates over various types of fuels (e.g., biofuel, oil and coal) and various types of labor (e.g., skill level), respectively, with different sectors possibly using different fuels and labor mixes.

A first thing to notice is that input prices are relatively similar across sectors, especially for fuels and labor. Even though electricity is a homogeneous good, there is some variation across sectors (and to some extent also within sectors). One plausible explanation to the variation in electricity price across firms and sectors is that Sweden is divided into four electricity price areas (to reflect bottlenecks in transmission capacity), and that the across-firm variation in prices reflects these regional differences in the electricity price.

Beginning with electricity in Fig. 3, we see that for most sectors, the price increased in the beginning of the sample until 2010, after which there was a downward trend until around 2015, when prices started to increase. Some sectors have seen rather sharp price increases after 2015, and almost all sectors have seen increasing prices since 2020. Turning to fuels in Fig. 4, prices has been relatively stable up until 2020, after which prices started to increase sharply. The development is similar for most of the sectors, although some sectors experience years with relatively high prices. Finally, there is a relatively large heterogeneity in wage across sectors (Fig. 5), although most sectors see decreasing wage costs in the beginning of the sample period and slightly increasing wage costs in the second half of the sample. It is important to note that our data does not distinguish between blue-collar and white-collar wages. However, as shown in Fig. A.1 in the Appendix — based on aggregate data from Statistics Sweden — wage developments have been relatively similar across skill levels. Moreover, our wage data closely aligns with these aggregate trends. Table 2 presents the distribution of unique firms across sectors and years for the estimation sample. The data reveal that the metal and machinery sectors consistently host a large number of firms. In contrast, sectors such as mining and refineries are characterized by a relatively small number of firms, reflecting their more specialized or capital-intensive nature. Over time, we observe a modest but noticeable decline in the total number of firms. While our data is uninformative about the reasons for this attrition (we only observe whether a firm is present or not in the data for each year), one plausible explanation is that this downward trend is attributable to broader economic disruptions. Furthermore, the COVID-19 pandemic during 2020–2021 had a relatively large impact on business continuity, leading to both temporary and permanent plant closures and reduced activity across many industries. Here, it is important to emphasize that most closures were primarily driven by reduced demand rather than by temporary lockdowns (see, for example, Regeringen (2022)). These developments underscore the importance of considering macroeconomic shocks when interpreting firm-level dynamics over time. In our subsequent empirical analysis in Section 4, we detail how we account for factors that are specific to years and common to all firms.

Results from a unit root test are presented in Table 3. To accommodate the fact that the panel is unbalanced, we employ a Fisher-type unit root test proposed by Choi (2001).[10] For all inputs, the null hypothesis of a unit root is rejected.

4. Empirical approach

We assume that firms are cost-minimizing, and that they operate in a corporate environment where prices are taken as given. This is in line with previous literature on industry factor demand (e.g., Pindyck and Rotemberg (1983), Lundgren and Sjöström (1999), Brännlund and Lundgren (2007), Cox et al. (2014), Hille and Möbius (2019) and Dahlqvist et al. (2021)). We argue that it is a reasonable assumption based on the following: for labor, it seems likely that workers can move freely between firms within and between sectors, and we also see relatively little wage variation across sectors.

For energy prices, this assumption is motivated by several factors: First, regarding electricity prices, approximately 90% of all electricity produced in the Nordic countries is traded competitively on the Nordic electricity exchange, Nord Pool. Only a small share of firms' electricity consumption is procured through bilateral agreements, which limits their ability to influence prices. Although electricity prices vary somewhat across sectors, these differences primarily reflect geographical variation in firm locations. In Sweden, this is further shaped by the country's unique electricity market structure, which has been divided into four pricing zones since 2011. These zones introduce spatial price differentials, but firm-level influence remains minimal. While firms could theoretically sort into different pricing areas, our data show that few firms relocate across zones, and most were already established before the introduction of the pricing zones in 2011, when Sweden operated under a single national price. Second, fossil fuel prices are determined on global markets.[11] As with electricity, individual firms are too small to exert any meaningful influence on these prices. Third, the treatment of energy prices as exogenous is well-established in the literature on factor demand in the Nordic context. Numerous studies adopt similar reasoning to justify this approach; see, for example, Dahlqvist et al. (2021), Lundgren and Sjöström (1999), Brännlund and Lundgren

[10] We implement the test using the Stata 17 `xtunitroot` package, using the Phillips–Perron unit-root test.

[11] Kilian and Zhou (2024) discuss that the relationship between oil and fuel prices tends to be unstable, at least for the U.S. This is not necessarily the case for Sweden, and it is out of the scope of this study to examine this in detail.

Table 2
Number of firms per year and sector.

Year	Chem.	Elec.	Metal	Food	Iron	Machine	Mining	Motors	Vehic.	Pulp	Print.	Refin.	Rubber	Mineral	Textile	Wood	All
2007	78	116	526	162	76	288	22	107	28	76	86	6	138	70	46	166	1991
2008	77	105	603	173	77	301	24	118	29	78	90	6	139	65	53	189	2127
2009	66	95	586	184	66	270	22	106	26	76	80	6	136	72	42	198	2031
2010	62	90	547	192	66	257	25	107	28	73	66	5	125	71	36	187	1937
2011	60	99	521	186	72	255	26	102	33	68	63	6	124	77	38	179	1909
2012	64	88	485	183	71	238	27	100	27	70	63	5	115	81	35	169	1821
2013	67	93	487	181	77	237	28	98	29	66	60	6	111	79	32	163	1814
2014	66	99	496	173	73	217	24	98	29	61	66	6	106	74	35	164	1787
2015	68	87	475	177	78	212	22	92	30	62	58	5	94	74	31	178	1743
2016	60	87	429	161	70	215	18	83	25	53	46	5	92	66	30	160	1600
2017	58	81	418	153	69	204	16	75	25	56	39	5	86	67	30	157	1539
2018	59	81	416	151	60	200	19	81	23	57	37	7	94	65	26	159	1535
2019	62	84	453	148	62	221	18	88	24	60	41	6	105	66	30	168	1636
2020	57	81	444	145	61	231	20	78	26	56	38	3	112	69	31	164	1616
2021	58	68	383	126	52	199	19	72	24	53	31	1	99	68	29	164	1446
2022	62	81	421	130	53	222	20	83	28	56	33	1	102	68	32	162	1554

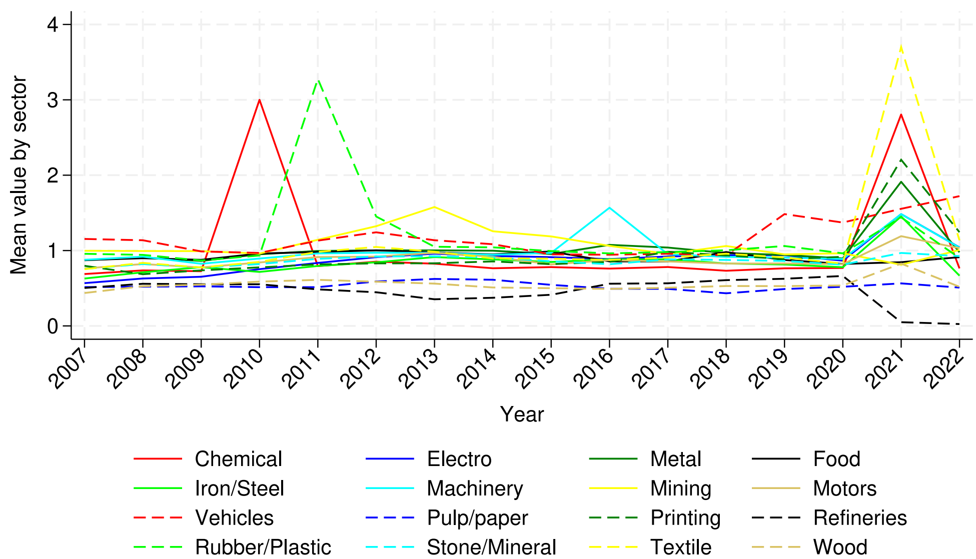

Fig. 4. Fuel price (in 1000 sek/MWh) across sectors.

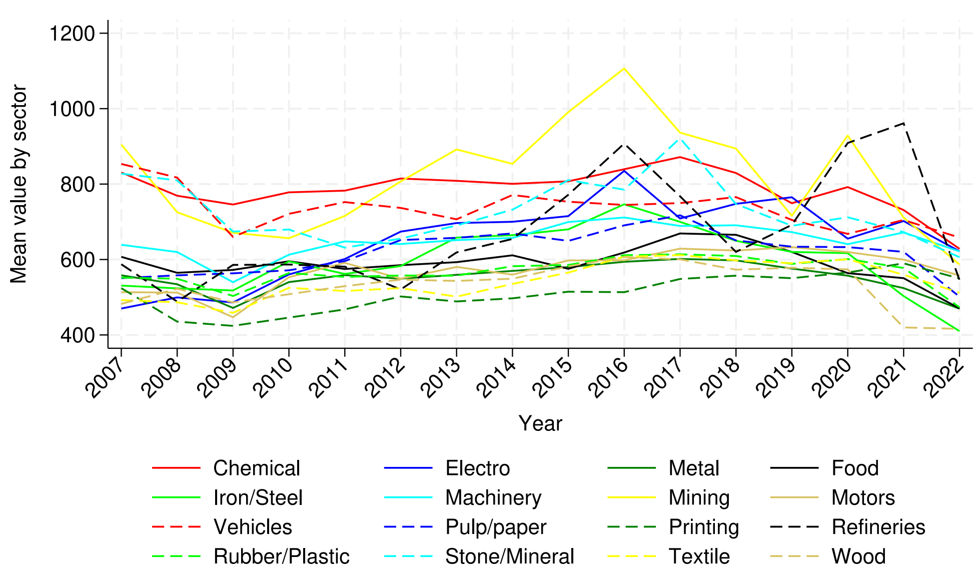

Fig. 5. Labor price (in 1000 sek) across sectors.

Table 3
Unit root tests.

	Inv. Chi-sq	Inv. Normal	Inv. Logit
lnL	1.71e+0.4	−3.422	−20.276
	(0.000)	(0.000)	(0.000)
lnE	3.15e+04	−43.808	−89.171
	(0.000)	(0.000)	(0.000)
lnF	3.38e+04	−54.228	−101.506
	(0.000)	(0.000)	(0.000)

Fisher-type tests using the Phillips–Perron unit root test. p-values in parentheses. H0: All panels contain unit roots.

(2010) and Amjadi et al. (2018). Nonetheless, we also estimate a specification in which electricity prices are treated as endogenous. In this case, we use lagged values of electricity prices as instruments (see Section 5.1). However, this alternative specification yields less precise parameter estimates.

The firms are assumed to produce their output using capital K, labor L, fuels F and electricity E as inputs, and capital K is assumed quasi-fixed in the short run. With these assumptions, the standard way to proceed would be to specify a technology (cost function) and use Shephard's lemma to derive the conditional factor demands:

$$y_j(\boldsymbol{p}, Q, K) = \frac{\partial c(\boldsymbol{p}, Q, K)}{\partial p_j} \tag{1}$$

where y_j is the factor demand for input $j = K, L, F, E$, $\boldsymbol{p}$ is a vector of input prices, Q is output, c is the cost function and p_j is the price of input j.

Dynamics could be introduced assuming there are adjustment costs ("frictions") in changing some of the factor inputs; e.g., the Euler equation approach by Pindyck and Rotemberg (1983). Instead, we specify a panel VAR model of factor demands that accounts for endogeneity of the inputs, and where dynamics are explicitly introduced through lagged endogenous variables but with a minimal set of restrictions (see, e.g., Holtz-Eakin et al. (1988), Juselius (2006) and Love and Zicchino (2006)).[12] This approach is less tractable in terms of offering a complete characterization of the technology and the economic interaction between the choice of inputs to generate output, i.e., we do not explicitly specify a technology/production function. However, the panel VAR approach has advantages when it comes to simplicity, especially in terms of introducing dynamics. Furthermore, it avoids many of the restrictions and associated critique from using the Euler equation approach (e.g., Chatelain and Teurlai (2001) and Whited (1998)) and is generally considered to fit data relatively well (Juselius, 2006).

In the next section, we detail the panel VAR approach and how it applies to our specific context.

4.1. Panel vector autoregression

Holtz-Eakin et al. (1988) pioneered dynamic panel VAR estimation by differencing data and using instruments, laying the foundation for later GMM methods. Arellano and Bover (1995) introduced a system GMM to improve efficiency in dynamic panel estimation, addressing weak instruments in the difference GMM. Blundell and Bond (1998) developed and validated system GMM further, showing its advantage over difference GMM for persistent data and short panels.

We consider a homogeneous panel VAR (Holtz-Eakin et al., 1988; Abrigo and Love, 2016; Love and Zicchino, 2006) of order p with firm-fixed effects, represented by the following system of equations:

$$\boldsymbol{Y}_{it} = \boldsymbol{Y}_{it-1}\boldsymbol{\beta}_1 + \boldsymbol{Y}_{it-2}\boldsymbol{\beta}_2 + \cdots + \boldsymbol{Y}_{it-p}\boldsymbol{\beta}_p + \boldsymbol{X}_{it}\boldsymbol{\theta} + \boldsymbol{u}_i + \boldsymbol{\epsilon}_{it} \tag{2}$$

[12] If the time series were cointegrated, a more appropriate way to proceed would be to specify, e.g., an error correction model.

where $i = 1, \dots, N$ index firms, $t = 1, \dots, T$ index time (in our case year), $\boldsymbol{Y}$ is a $(1 \times k)$ vector of endogenous variables; in our case, factor demand, and $\boldsymbol{X}$ is a $(1 \times l)$ vector of factor prices, capital and output. All variables are in logs. The two $(1 \times k)$ vectors $\boldsymbol{u}_i$ and $\boldsymbol{\epsilon}_{it}$ are the firm-specific fixed effect and idiosyncratic errors, respectively, with the following characteristics: $\mathbb{E}[\boldsymbol{e}_{it}] = 0$, $\mathbb{E}[\boldsymbol{e}'_{it}\boldsymbol{e}_{it}] = \boldsymbol{\Sigma}$ and $\mathbb{E}[\boldsymbol{e}'_{it}\boldsymbol{e}_{is}] = 0$ for all $t > s$. The firm-specific fixed effects capture, for example, sector and location of firms. $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are vectors of parameters to be estimated. This specification loosely corresponds to a structural model's conditional factor demands (cost minimizing firm) with K quasi-fixed in the short term.

To address firm-specific, time-invariant heterogeneity in our panel data, we apply a first-difference (FD) transformation. This approach effectively removes unobserved fixed effects that could otherwise bias the estimation results. In addition, we include firm output as a control variable to account for differences in firm size, which may influence pricing behavior and other outcomes of interest.[13] An alternative approach would be to use the forward orthogonal deviation (FOD), where one subtracts the average of all future available observations of a variable. A key advantage of FOD is its ability to minimize data loss in unbalanced panels. Regardless of how many gaps exist in the data, it remains computable for all observations except the final one for each individual. However, since we see most price variation in the latter periods, we prefer the FD approach in order to not loose the last year observed.

Furthermore, to account for factors that are specific to years and common to all firms, we subtract from each variable in the model its cross-sectional mean before estimation to remove common time fixed effects from all the variables prior to any other transformation.

Ideally, one would want to allow for sector-specific dynamic responses to changes in energy prices. However, our analysis is constrained by data limitations: estimating separate models for each subsector would significantly reduce the number of observations, particularly given the relatively short time dimension (annual data over about 20 years). This would make it difficult to obtain precise and robust estimates of dynamic responses at the sub-sector level. Nevertheless, in Section 5.1, we estimate our specification separately for energy-intensive firms.

Under the assumption that the error terms are serially uncorrelated, our model can be consistently estimated using the Generalized Method of Moments (GMM). A key feature of this approach is the use of lagged levels of endogenous variables as instruments for their differenced forms. This instrumental strategy is grounded in the orthogonality conditions that arise from the dynamic structure of the model: past values of endogenous variables are uncorrelated with the contemporaneous error term, making them valid instruments for the differenced equations. The transformation of the model into first differences eliminates unobserved individual-specific effects, but it also introduces endogeneity due to the correlation between the differenced endogenous variables and the lagged error terms. To address this, lagged levels — typically two or more periods behind — are employed as instruments. These lags are assumed to be predetermined or exogenous with respect to the differenced error term, thereby satisfying the moment conditions required for consistent estimation. System GMM extends this framework by combining the differenced equations with the original equations in levels, using lagged differences as instruments for the level equations. This dual system improves efficiency, especially when the instruments in the differenced equations are weak due to persistent time series. To further enhance the efficiency of the estimator, additional lags of the

[13] Our dataset does not provide precise geographic coordinates for firms; instead, it identifies the municipality in which each firm is located. Firm mobility across municipalities is rare during the sample period, and no firm switches sector classification, ensuring consistency in firm characteristics over time.

endogenous variables can be included as instruments. However, this comes at a cost: the number of available observations may decline, particularly in unbalanced panel datasets where not all units have complete time series. To mitigate this loss of information, we adopt the approach proposed by Holtz-Eakin et al. (1988), which allows missing values among the lagged instruments to be replaced with zeros. Observations with no valid instruments are excluded. This pragmatic solution preserves the instrument matrix structure while maintaining the consistency of the estimator.[14]

While estimating a panel VAR model equation-by-equation using GMM yields consistent parameter estimates, estimating the system jointly can lead to efficiency gains (see Holtz-Eakin et al. (1988)). Let the common set of instruments be denoted by the row vector Z_{it}, where $M \geq kp + l$ and $X_{it} \in Z_{it}$. Each equation in the system is indexed using a superscript. We now consider a transformed version of the panel VAR model—based on Eq. (2), expressed in a more compact form. In this representation, an asterisk indicates that the variable has been first-differenced.

$$
\begin{aligned}
\boldsymbol{Y}_{it}^{*} &= \tilde{\boldsymbol{Y}}_{it}^{*}\boldsymbol{\beta} + \boldsymbol{e}_{it}^{*}\\
\boldsymbol{Y}_{it}^{*} &= \begin{bmatrix} y_{it}^{1*} & y_{it}^{2*} & \dots & y_{it}^{k-1*} & y_{it}^{k*} \end{bmatrix}\\
\tilde{\boldsymbol{Y}}_{it}^{*} &= \begin{bmatrix} \boldsymbol{Y}_{it-1}' & \boldsymbol{Y}_{it-2}' & \dots & \boldsymbol{Y}_{it-p+1}' & \boldsymbol{Y}_{it-p}' & \boldsymbol{X}_{it}' \end{bmatrix}\\
\boldsymbol{e}_{it}^{*} &= \begin{bmatrix} e_{it}^{1*} & e_{it}^{2*} & \dots & e_{it}^{k-1*} & e_{it}^{k*} \end{bmatrix}\\
\boldsymbol{\beta} &= \begin{bmatrix} \boldsymbol{\beta}_1' & \boldsymbol{\beta}_2' & \dots & \boldsymbol{\beta}_{p-1}' & \boldsymbol{\beta}_p' & \boldsymbol{\theta}' \end{bmatrix}
\end{aligned}
\tag{3}
$$

We stack observations over panels and then over time. The system GMM estimator is then given by

$$
\boldsymbol{\beta} = \left(\tilde{\boldsymbol{Y}}^{*'}\boldsymbol{Z}\hat{\boldsymbol{W}}\boldsymbol{Z}'\tilde{\boldsymbol{Y}}^{*}\right)^{-1}\left(\tilde{\boldsymbol{Y}}^{*'}\boldsymbol{Z}\hat{\boldsymbol{W}}\boldsymbol{Z}'\boldsymbol{Y}^{*}\right) \tag{4}
$$

where $\hat{\boldsymbol{W}}$ is an $(M \times M)$ weighting matrix assumed to be nonsingular, symmetric, and positive semidefinite. Assuming that $\mathbb{E}[\boldsymbol{Z}'\boldsymbol{e} = \boldsymbol{0}]$ and rank $\mathbb{E}[\tilde{\boldsymbol{Y}}_{it}^{*'}\boldsymbol{Z}] = kp + l$, the GMM estimator is consistent.

We estimate the model described in Section 4.1 using one-step GMM with robust weight matrix.[15]

4.2. Model selection

To assess our model, we use the Moment Selection Criteria, developed by Andrews and Lu (2001) specifically for Generalized Method of Moments (GMM) models. Their approach builds upon the J statistic introduced by Hansen (1982), which is used to test the validity of overidentifying restrictions in GMM estimation. The J statistic essentially measures how well the model's moment conditions are satisfied, and it plays a central role in evaluating model specification. The criteria proposed by Andrews and Lu (2001) all hinge on the use of Hansen's J statistic. A key requirement for applying this statistic is that the number of moment conditions must exceed the number of endogenous variables in the model—this ensures that the model is overidentified and that the J test is applicable. In practical terms, this overidentification allows researchers to assess the plausibility of the instruments and the overall specification of the model.[16]

Table 4
Lag order selection results.

Lag	J	J p-value	MBIC	MAIC	MQIC
1	39.880	0.002	−144.494	3.880	−43.877
2	8.689	0.467	−83.499	−9.312	−33.190

Note: No of obs 28086. No of panels 4479. Average no of years per panel 6.271.

In Table 4, we present the lag order selection results: the table presents J-statistics and selection criteria from the first- and second-order panel VAR models using the first three lags of the endogenous variables as instruments. We choose between first- and second-order panel VAR since 1–2 year lags are usually applied when using year-level data. Using more lags would reduce the degrees of freedom and increase the risk of overfitting. Based on the three model selection criteria by Andrews and Lu (2001), the second-order panel VAR is the preferred model because of MBIC and MQUIC being smallest for this specification. Furthermore, for the second-order model, the Hansen J-statistics p-value indicate that we cannot reject the null hypothesis that the instruments are valid. This means the instruments are likely uncorrelated with the error term and are correctly excluded from the estimated equation. Therefore, we opt for a lag order of 2 years.[17]

4.3. Dynamic multiplier analysis

Once the model is estimated, we can exploit the dynamic multiplier analysis to assess how the endogenous variables react to a change in exogenous energy prices over time. The dynamic multiplier function, or transfer function, measures the impact of a unit increase in an exogenous variable on the endogenous variables over time; see Lütkepohl (2005) for formal definitions of the dynamic multiplier function. Because our data covers a relatively short time period (approximately 20 years), we limit our analysis of the response to price changes to the first five time periods (years). While firms may take longer time to respond to prices, our data is not well-suited to study such effects. We return to this in our discussion of the results in Section 5.

We estimate confidence intervals for the dynamic multipliers using Gaussian approximation, based on 500 Monte Carlo draws from the fitted panel VAR model (Abrigo and Love, 2016).

5. Results

Parameter estimates from estimating Eq. (2) are presented in Table B.1 in Appendix B in the Appendix. Parameter estimates from panel VAR models are rarely interpreted in isolation, but instead operationalized as impulse response functions or dynamic multipliers. Prior to presenting the dynamic multiplier graphs, we discuss the model's stability.

Model stability is tested by calculating the modulus of each eigenvalue of the fitted model Lütkepohl (2005). This is done to ensure that the panel VAR is invertible and has an infinite-order vector moving-average representation, providing known interpretation to estimated impulse–response functions. In brief, all modulus are less than one, indicating stability of the model (see Table B.4 in Appendix B in the Appendix).

Dynamic multipliers are presented in Fig. 6 for the effects of energy prices on the demand for electricity, fuel and labor. The effects of wages on the factor inputs are all zero, and with large confidence intervals, and are therefore not included in our discussion of the results.

The solid lines show the percentage change of one input (response) variable (e.g., labor), in response to a percentage increase in the input price (impulse) variable (e.g., electricity price), whereas the shaded areas show a 95% confidence interval. The graphs reveal the following associations between prices and inputs:

[14] This method is based on the standard assumption that instruments are uncorrelated with the errors.

[15] Bond (2002) argues that the efficiency gains from using the two-step version are very modest, even in the presence of considerable heteroskedasticity, and that the dependence of the two-step matrix on estimated parameters makes the usual asymptotic distribution approximations less reliable (see Arellano and Bond (1991) and Blundell and Bond (1998)). For these reasons, the robust one-step estimator is employed in our estimation.

[16] Our review of the literature confirms that the methodology of using the J statistic to select among competing sets of moment conditions and lag structures is both widely accepted and frequently applied. Furthermore, this approach offers a framework for identifying the optimal configuration of instruments and model dynamics—an essential step in enhancing the reliability and efficiency of GMM estimators.

[17] Adding more lags, and/or changing the lag structure for the instruments does not change these conclusions.

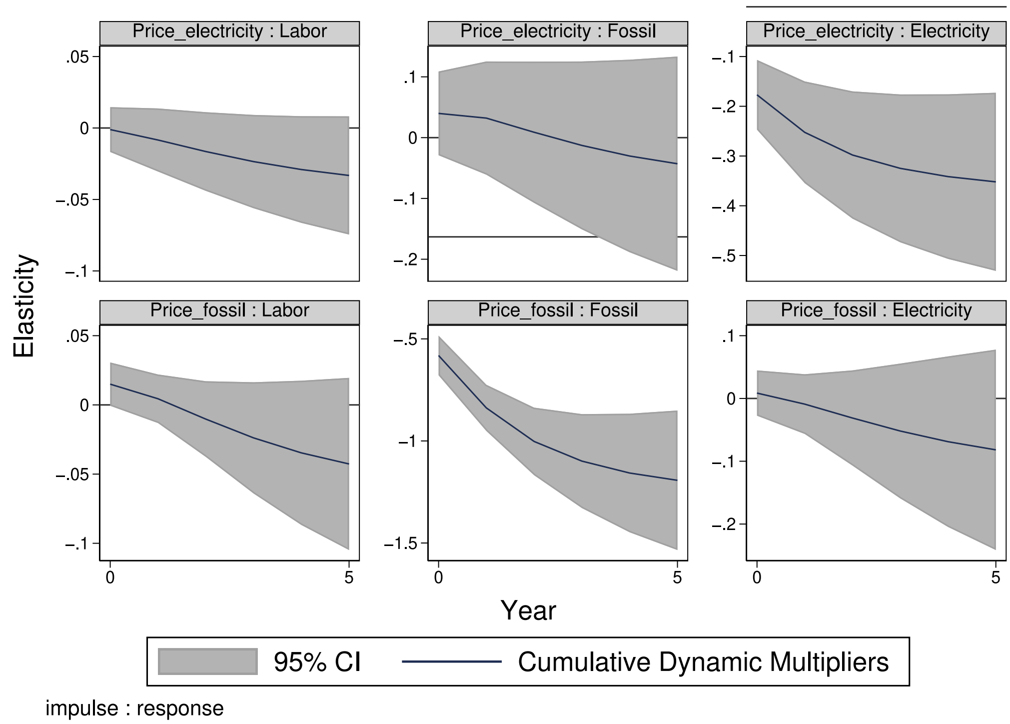

Fig. 6. Dynamic multiplier effects of prices on inputs.

In the top row of Fig. 6, we see that an increase in the price of electricity has no statistically significant effect on employment (left panel) or the use of fuel (middle panel), but leads to a reduction in the use of electricity (right panel). For the latter, the effect is relatively small, with an elasticity of approximately −0.2 in the first year and a cumulative effect (elasticity) of −0.35 in the fifth year. In the bottom row, we see that an increase in the fuel price has no statistically significant effect on employment (left panel) or electricity use (right panel), but a negative effect on the use of fuel, with own-price elasticities ranging from −0.55 in the first year to approximately −1.2 after five years.

To summarize, we find that the own-price elasticity for fossil fuel is relatively large, that the own-price elasticity of electricity is relatively small, and that all of the cross-price elasticities are statistically insignificant.

The finding of own-price inelastic electricity demand is in line with empirical findings on the industrial own-price elasticities of electricity of other countries (e.g., Cox et al. (2014)). Furthermore, our results regarding the cross-price elasticities for labor and energy (both electricity and fuels) are somewhat in line with previous findings, which usually identify a weak interrelationship between labor and electricity/energy (see, e.g., Cox et al. (2014), Berndt and Wood (1975) and Pindyck and Rotemberg (1983)).

Our findings also align with previous research by Herrera and Karaki (2015) and Herrera et al. (2017), who emphasize that energy price shocks affect sectoral dynamics without necessarily leading to large aggregate employment effects. However, unlike their results for U.S. manufacturing, we find limited evidence of significant sectoral employment changes in Swedish industry. This suggests that energy-intensive sectors in Sweden may adjust primarily through changes in input use rather than employment, reflecting institutional or structural differences between the two economies. However, it is important to note that differences in results may also arise from variations in empirical methodology. For instance, our approach assumes homogeneous coefficients across industries, while Herrera and Karaki (2015) and Herrera et al. (2017) allow for industry-specific variation.

Finally, we particularly wish to emphasize the statistically insignificant association between energy prices and labor demand, and the statistically insignificant inter-fuel substitutability/complementarity (e.g., no effect of the electricity price on fuel use), that our results reveal. Regarding the former, a likely explanation to this result is that the manufacturing industry is capital intense, and that it simply is difficult to power machines with manpower, conditional on capital. Furthermore, we note that the adjustment is relatively fast for both electricity and fuel, suggesting that there are relatively low adjustment costs for relatively small changes in inputs.

5.1. Robustness analysis

To assess the robustness of our results, we present estimates for two alternative specifications. In the first, we exclude outliers for which the values for the quantities and prices for labor, fuels and electricity exceed the sector's 99th percentile or fall below the 1st percentile. Not only does this allow us to understand the influence of outliers on our results, but it also means that very large firms, that possibly are large enough to influence input prices, will be dropped. For example, very large firms may be able to influence the electricity price or wages (most fossil fuels are priced on the world market), and excluding these firms strengthens our assumption of exogenous input prices.

In the second alternative specification, we restrict the sample to the sectors typically considered to be the most energy-intensive,[18] which are the chemical, iron and steel, paper and pulp and stone and mineral sectors. For this specification, the model selection criteria suggest a model of one lag, which allows us to use more data. This is especially valuable with the more narrow focus on the four specific sectors. However, it is important to note that this still reduces the sample size quite a lot: the main specification includes 4479 firms and 28,086 observations. In contrast, the specification limited to energy-intensive firms comprises only 5180 observations across 744 panels.

[18] For example, Dahlqvist et al. (2021) also focus on these four sectors.

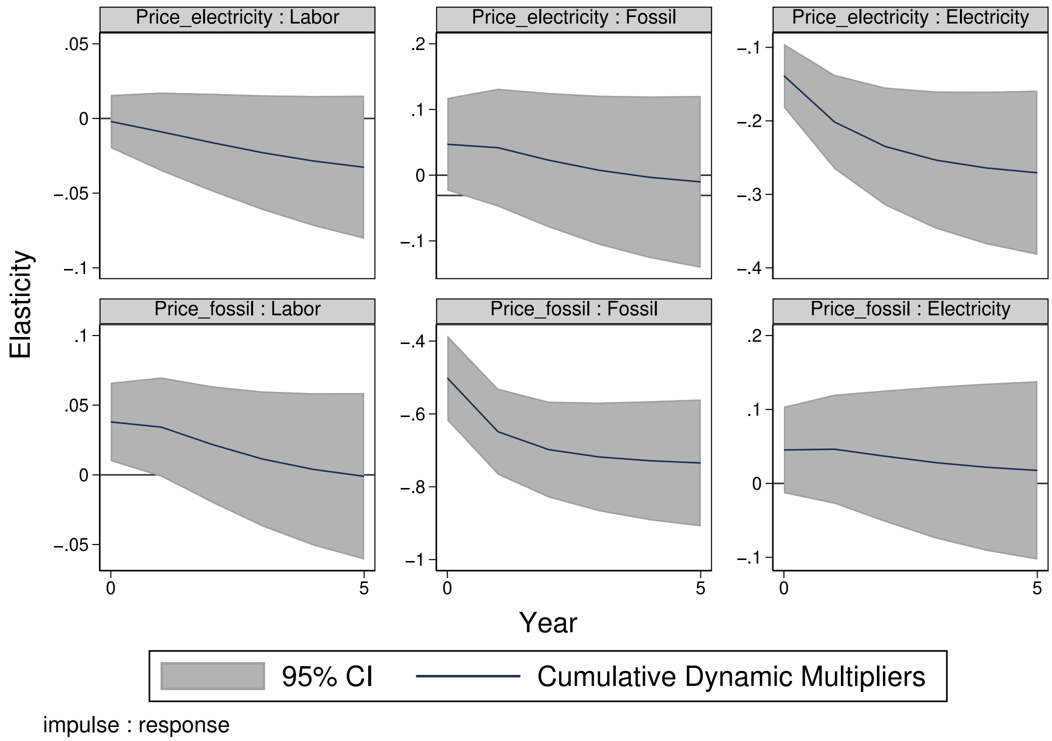

Fig. 7. Dynamic multiplier effects of prices on inputs, alternative specification 1 (excluding outliers).

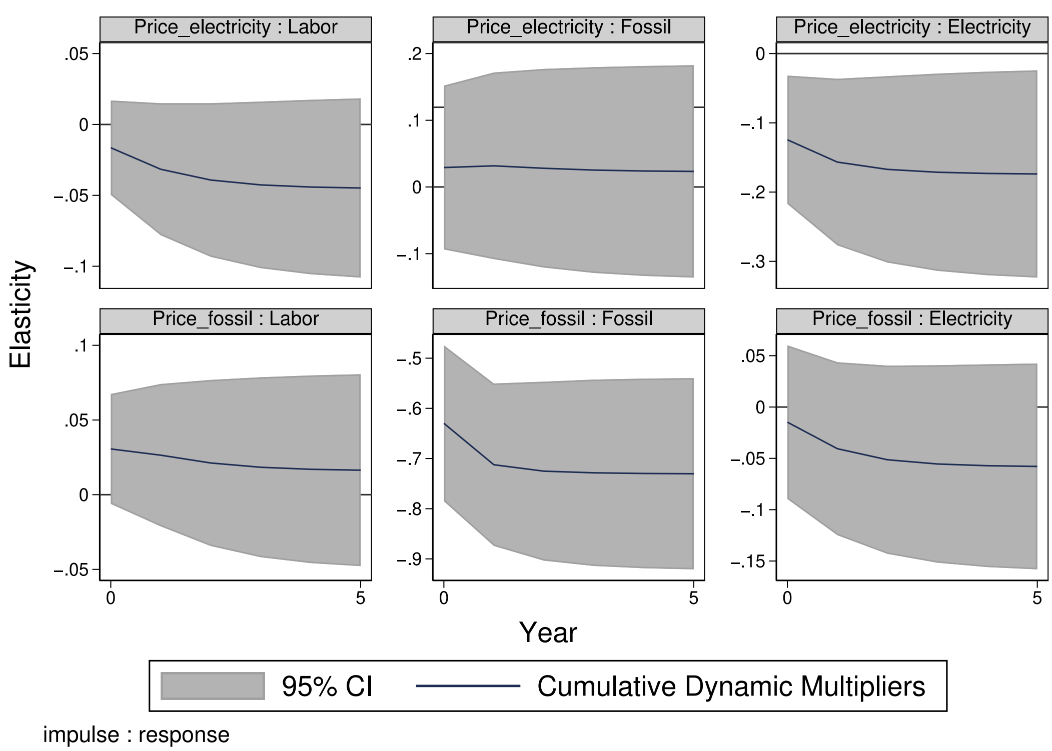

Fig. 8. Dynamic multiplier effects of prices on inputs, alternative specification 2 (only energy intensive sectors).

For simplicity, we only present dynamic multipliers for these alternative specifications and only briefly discuss additional results whenever relevant. Complete results of parameter estimates from these alternative specifications are presented in the Appendix in Table B.2 and Table B.3. Similar to our main specification, the Eigenvalue stability conditions are satisfied in these alternative specifications.

Beginning with the first alternative specification, presented in Fig. 7, the estimated effects are similar to our main specification. For example, we find negative own-price elasticities of similar magnitude as in Fig. 6 for both electricity and fuel, and that the effects of changes in input price increase over time. Furthermore, and similar to our main specification, we find no statistically significant effect of fuel prices on labor, or of electricity prices on labor, neither do we find any evidence for fuels and electricity being either complements or substitutes to each other.

In Fig. 8, we present results from the second alternative specification, where we focus on the energy intensive sectors. Again, we find negative own-price elasticities for both fuels and electricity, but especially for the latter, the estimated effect is closer to zero. The confidence intervals are also wider than in our main specification. The relatively small sample size for this alternative specification is likely the reason for why the estimates in the main specification are considerably more precise than those in this alternative specification.

In addition to the results presented here, we have estimated additional alternative specifications. For example, we have estimated a specification where we instead of dropping outliers use the winsorizing approach, replacing all observations above the 95th percentile and below the 5th percentile with the values of the 95th and 5th percentile, respectively. This does not change our results to any large extent. Furthermore, we have estimated a specification where we treat either output or electricity prices or both as endogenous variables, and this does not change any of our qualitative results, although estimates vary slightly. These results are available upon request.

To summarize, most of our key results are robust to alternative specifications. Most notably, in all specifications, the own-price effect of both fuel and electricity are negative; the magnitude of the statistically significant effects are relatively similar across specifications, and whenever the effects are significantly different from zero, the effect increases over time.

6. Conclusions

In this paper, we use a unique firm-level data on the manufacturing industry in Sweden, spanning the period 2004 to 2022, and time series analysis, to analyze the dynamic response of factor demand to changes to factor prices, and in particular to energy prices. Using the panel vector autoregressive model of Abrigo and Love (2016), we show that while own-price elasticity for fossil fuel is relatively large, the own-price elasticity for electricity is small and the cross-price elasticities are, generally, statistically insignificant. This suggests limited substitution possibilities between input factors in the short run.

These results have important policy implications: First, our results show that the effects of energy price shocks, like those many economies including Sweden experienced over the last few years, have relatively large effects on the demand for energy inputs; especially fuel use. Second, our results also reveal that the effects of such energy price shocks have limited effect on the number of employees: the effects we find are not statistically different from zero, not even at the end of a five-year period. Third, energy price shocks do not appear to lead to any substitution between energy sources. This means, for example, that the recent years' electricity price shocks did not lead to more use of other fuels and therefore more emissions. Fourth, our results suggest that the scope for green jobs appears limited. For example, if policy makers were to tax fuel even more than today, our results show that this will only have small effects on the number of employees. When interpreting labor demand effects, the reader should note that the measure available for labor is the number of full-time and part-time employees of firms currently active. That is, we do not observe the number of hours worked, and neither do we observe whether firms go out of business, i.e. decrease their number of employees to zero. These two factors may both be causes for underestimating effects on labor demand.

The findings presented in this study are likely to be relevant beyond the Swedish context, particularly for countries that share similar characteristics in terms of industrial composition, energy intensity, and market integration. This includes other Nord Pool member states — Norway, Finland, and Denmark — where manufacturing sectors operate under comparable regulatory frameworks and are exposed to similar dynamics in the integrated Nordic electricity market. As such, the empirical insights may inform broader regional discussions on the labor and productivity implications of energy price fluctuations and the design of climate and energy policy across these interconnected economies.

As discussed earlier, our study links to the foundational work of Davis and Haltiwanger (2001), who examined the effects of oil price shocks on job flows within U.S. manufacturing. Extending this line of research, Herrera and Karaki (2015) as well as Herrera et al. (2017) demonstrate that energy price fluctuations play a major role in shaping sectoral employment patterns. Collectively, these studies suggest that falling oil prices tend to decrease employment in energy-producing industries, increase it in energy-consuming ones, and overall lead to a smoothing of labor market dynamics. Our findings on the relatively inelastic response of energy demand to price changes align with previous studies such as Cox et al. (2014), who find limited short-term flexibility in industrial energy use. Similarly, Pindyck and Rotemberg (1983) report that US manufacturing sectors exhibit slow and muted adjustments to energy price shocks. Hesse and Tarkka (1986) further support this view, emphasizing that substitution away from energy inputs often occurs only gradually over time. Recent evidence from European manufacturing (Hille and Möbius, 2019) suggests that environmental regulation can influence factor demand patterns but does not drastically alter short-run energy dependencies. Together, these studies help frame our results within a broader literature showing that while industry can adapt to changing energy costs, the adjustment is often limited in the short to medium term (in our case 5 years).

Finally, we would like to highlight a number of caveats relating to the data used in this paper. First, the substitution possibilities between labor and energy may differ substantially across type of labor (e.g., white and blue collar). As already alluded to, our data is not informative about this aspect of labor, prohibiting such analysis, but this is a suggestion for future research.

Second, our data only covers factor demand up until 2022. It may be the case that the recent and extreme price shocks have had additional (long-run) effects on factor demand post 2022 that our model is unable to capture. Similarly, it is likely that some capital, such as a factory, are in place for a long time; likely longer than our available time period, and firms may respond to energy price shocks in the very long run by, for example, building a different type of factory that is more energy efficient or locating to a place where electricity prices are lower. This type of response would possibly require more data to understand, and is beyond the scope of the current paper.

CRediT authorship contribution statement

Hanna Lindström: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Tommy Lundgren:** Writing – original draft, Methodology, Conceptualization. **Mattias Vesterberg:** Writing – original draft, Methodology, Data curation, Conceptualization.

Appendix A. Additional descriptive statistics

See Figs. A.1–A.3.

Appendix B. Additional results

See Tables B.1–B.4.

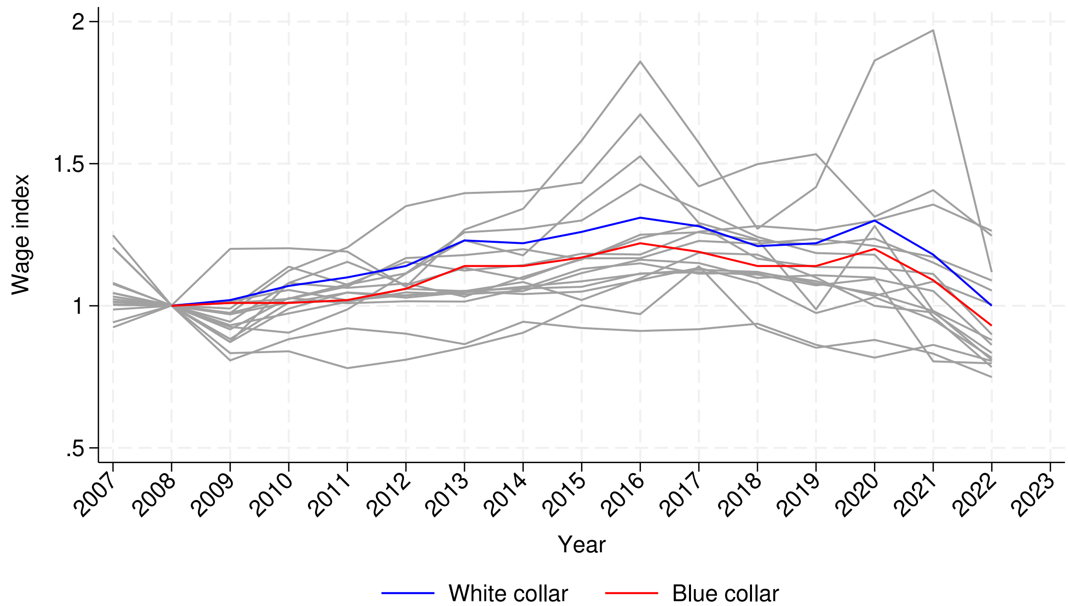

Fig. A.1. Wage index for our data and aggregate statistics across skill-level (blue and red lines, source: Statistics Sweden) and across each sector in the sample (gray lines).

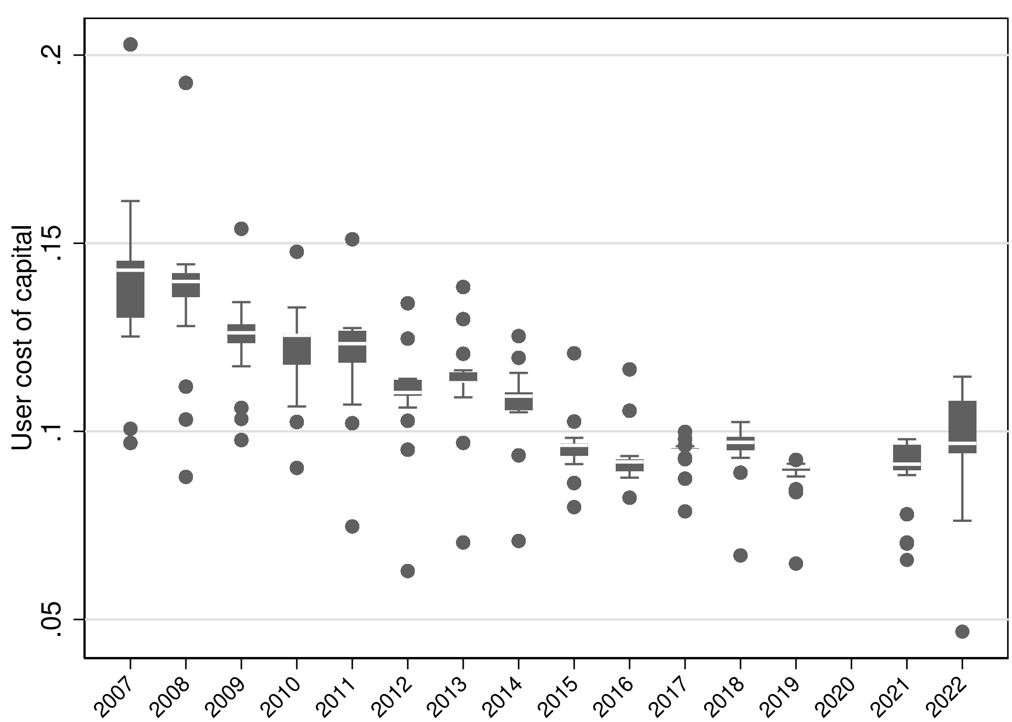

Fig. A.2. User cost of capital at the sector level.

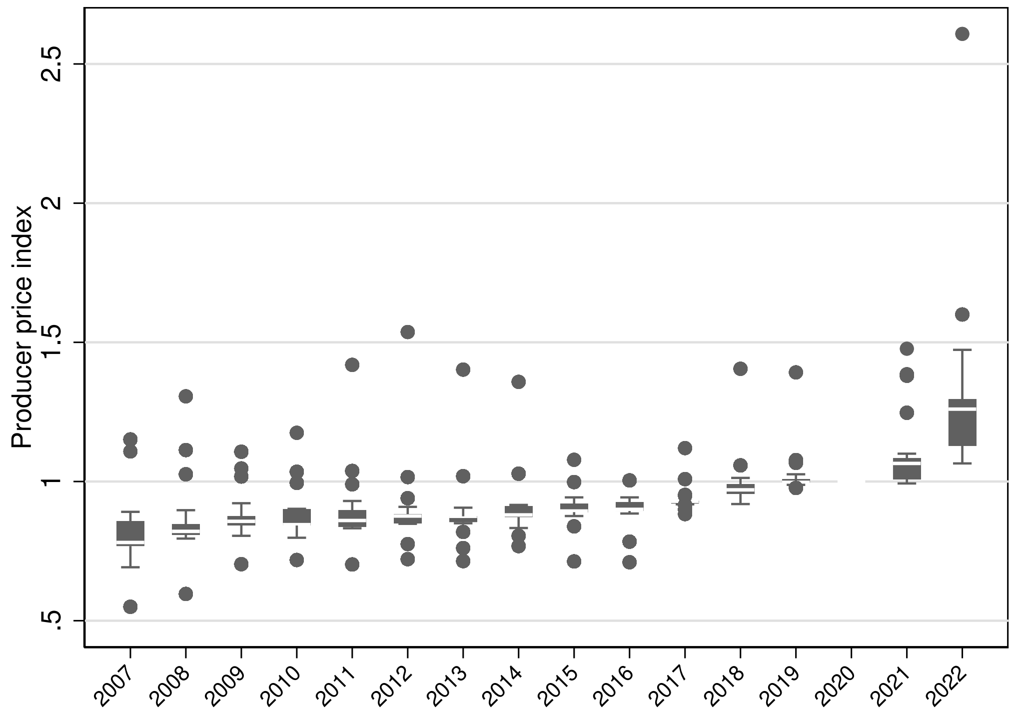

Fig. A.3. Producer price index at the sector level.

Table B.1
Parameter estimates, main specification.

	lnL	lnE	lnF
L.lnL	0.423*** (0.068)	0.141 (0.164)	−0.127 (0.255)
L2.lnL	0.030*** (0.011)	−0.010 (0.026)	−0.071* (0.042)
L.lnE	0.045** (0.019)	0.435*** (0.078)	0.144* (0.085)
L2.lnE	0.008 (0.007)	0.066** (0.029)	0.076** (0.031)
L.lnF	0.030** (0.014)	0.040 (0.036)	0.441*** (0.077)
L2.lnF	0.004 (0.004)	0.005 (0.012)	0.085*** (0.025)
lnPL	−0.345*** (0.046)	−0.005 (0.103)	−0.111 (0.166)
lnPE	−0.001 (0.008)	−0.177*** (0.033)	0.040 (0.034)
lnPF	0.015** (0.007)	0.009 (0.018)	−0.581*** (0.046)
lnK	0.039 (0.069)	0.131 (0.157)	−0.241 (0.250)
lnY	0.298*** (0.054)	−0.006 (0.124)	0.319* (0.183)
N	28 086	28 086	28 086

Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table B.2
Parameter estimates, alternative specification 1 (dropping outliers).

	lnL	lnE	lnF
L.lnL	0.508*** (0.080)	0.081 (0.179)	0.171 (0.285)
L2.lnL	0.014 (0.010)	−0.011 (0.020)	−0.003 (0.033)
L.lnE	0.060** (0.027)	0.469*** (0.076)	0.144 (0.098)
L2.lnE	−0.000 (0.008)	0.024 (0.025)	0.053* (0.031)
L.lnF	0.051*** (0.016)	0.047 (0.037)	0.320*** (0.076)
L2.lnF	0.007 (0.004)	0.007 (0.011)	0.008 (0.021)
lnPL	−0.326*** (0.088)	0.025 (0.190)	0.409 (0.316)
lnPE	−0.002 (0.009)	−0.139*** (0.021)	0.047 (0.036)
lnPF	0.038*** (0.014)	0.045 (0.029)	−0.501*** (0.059)
lnK	−0.125 (0.133)	−0.107 (0.296)	−1.220** (0.481)
lnY	0.367*** (0.093)	0.093 (0.200)	0.929*** (0.332)
N	23 871	23 871	23 871

Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table B.3
Parameter estimates, alternative specification 2 (energy-intensive sectors only).

	lnL	lnE	lnF
L.lnL	0.325***	0.181	0.326
	(0.094)	(0.209)	(0.325)
L.lnE	0.084**	0.245	−0.029
	(0.040)	(0.151)	(0.128)
L.lnF	0.020	0.044	0.148
	(0.019)	(0.035)	(0.097)
lnPL	−0.345***	−0.180	−0.136
	(0.081)	(0.147)	(0.225)
lnPE	−0.016	−0.124**	0.029
	(0.017)	(0.049)	(0.063)
lnPF	0.031*	−0.015	−0.630***
	(0.019)	(0.038)	(0.077)
lnK	0.088	0.095	−0.564
	(0.153)	(0.326)	(0.499)
lnY	0.335***	0.195	0.189
	(0.102)	(0.213)	(0.311)
N	5180	5180	5180

Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table B.4
Eigenvalue stability condition, main specification.

Eigenvalue	Modulus
0.667	0.667
0.480	0.481
0.480	0.481
−0.145	0.145
−0.114	0.114
−0.069	0.069

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