conseil d'analyse
économique
French Council of Economic Analysis

Focus
No 94
May 2023

Cost Pass-Through and the Rise of Inflation*

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After more than a decade of price moderation, inflation is back. We examine the role of external factors, specifically the pressure on import prices and the surge in energy costs, in driving the increase in French producer prices from January 2021 to July 2022. We use micro-level price data that underlies the French producer price index, along with external measures of firms' exposure to imported inputs and energy cost shocks to document the dynamics of producer prices in the manufacturing sector. Over the period from 2018 to mid-2022, we find that manufacturing firms pass through 30% of changes in the price of imported inputs and 100% of changes in energy costs to their downstream partners. Once we consider the contribution of these costs to the firm's operational costs, our estimates imply that, for the average firm in our data, a 10% increase in foreign costs leads to a 0.74% increase in output prices, while a 10% energy cost shock leads to a 0.73% increase in prices.

We examine how pass-through rates vary across firms within and across industries, depending on their size and exposure to shocks. We find strong evidence that the pass-through rate is asymmetric, with positive cost shocks inducing significantly more pass-through than negative shocks. In the case of energy, the pass-through rate for positive shocks is above 100%, while the transmission of negative cost adjustments is much lower, at 58%. The asymmetry implies that the reduction in energy prices in 2023 should not counteract the inflationary pressure of the 2022 energy shock. The heterogeneity across firms in their exposure to external shocks drives important differences in inflation dynamics along the distribution of firms.

We use our empirical model to quantify the contribution of cumulated imported inputs and energy price shocks between January 2021 and July 2022. The impact of these shocks is highly heterogeneous across firms, even within the same sector. Seventy percent of the variation in the predicted impact of these shocks is found among firms in the same 2-digit industry. Overall, the surge in imported input prices is estimated to contribute 1.9 percentage points to the inflation of producer prices in the manufacturing sector, while energy is estimated to add another 1.6 percentage points. The chemical and metal industries are the most exposed to both external shocks, with a combined impact on sectoral inflation above 10%. Together, these shocks explain 20% of the observed PPI inflation over the period.

* We are grateful to Philippe Martin, Pauline Givord, Sophie Guilloux-Nefussi, and Matthieu Lequien, as well as seminar participants at various institutions for helpful suggestions. The paper has greatly benefited from insightful discussions on the data with Nicolas Studer, Camille Carré, and Grégory Verriest. Isabelle Mejean gratefully acknowledges support from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (grant agreement No. 714597).

JEL Classification: F1, F4, L1.

This publication has also been published in French by Insee, under the reference: Raphaël Lafrogne-Joussier, Julien Martin et Isabelle Méjean, "La transmission directe des coûts des intrants importés et de l'énergie aux prix de production", *Insee Analyse* n°84, May 2023.

1. Introduction

After years of price moderation, inflation is back, characterized notably by a large increase in the price of physical goods (Lane, 2022). Since 2020, the dynamics of goods prices have often been explained by a combination of an increase in demand (relative to services) and an increase in costs - in the European context, mostly energy prices and foreign input prices (Seiler, 2022, di Giovanni et al., 2022).[1] In this context, manufacturing firms are under scrutiny: they are directly exposed to energy and foreign input cost shocks, and their behavior may attenuate or amplify the downward transmission of these shocks to consumers.

This paper estimates the pass-through of imported inputs and energy costs shocks into producer prices and discusses the role of these external factors in the 2021-2022 inflation surge. We leverage the rich micro data underlying the French Producer Price Index (PPI) to study the behavior of manufacturing prices at the firm- and product level between January 2018 and July 2022. We tackle two questions: What are the pass-through rates of energy and foreign input shocks into manufacturing prices? What sectors and firms have been the most impacted by these two types of shocks in the post-pandemic period, and by how much?

We start by establishing four stylized facts about producer price-setting behavior in our data. First, micro-price movements are for the most part idiosyncratic: The degree of price synchronization across firms within a month, within industries, or narrow product markets, is very low. Second, the 2021-2022 rise in producer prices comes with both more frequent and larger price changes. Third, while larger firms tend to adjust their prices more frequently, either upward or downward, the pattern changes after 2021. The probability of upward price changes becomes similar across larger and smaller firms, whereas the differential in downward adjustments is now twice as large as before 2021. Last, output price volatility appears higher among firms that are more exposed to cost shocks.

We then estimate pass-through rates of energy and imported input cost shocks to manufacturing prices. We exploit a sample of 2,352 manufacturing firms that account for one-fifth of France's manufacturing production and report the monthly prices of 10,242 items sold domestically. The prices are observed from January 2018 to July 2022. We supplement the price dataset by incorporating firm-level measures of exposure to external shocks, which are obtained from Customs and energy consumption data. We create two distinct firm samples, one consisting of firms for which we have information on exposure to imported input costs and the other consisting of firms for which we can measure exposure to energy price shocks.

To study the relationship between cost shocks and producer prices, we follow Burstein and Gopinath (2014) and estimate conditional pass-through rates: We estimate by how much prices respond to cost shocks, conditional on a price adjustment. To do so, we exploit the vast heterogeneity across firms *within* product markets and periods in their exposure to external shocks to control for any market- and time-specific unobserved determinants of price changes. Because imported inputs account for 32% of total variable costs on average in the sample of importers, whereas energy accounts for only 2.6% of costs, we apportion both types of shocks to total variable costs so that point estimates are comparable and can be interpreted as pass-through rates after a 1% cost shock. We find a conditional pass-through of foreign input prices into domestic prices of 30%. The pass-through of energy prices is higher, and not statistically different from full pass-through (100%). Unconditional on the share of foreign inputs in total costs, a 10% increase (decrease) in foreign costs leads to a .74% increase (decrease) in domestic prices. Similarly, a 10% increase (decrease) in energy prices leads to a .73% price increase (decrease).

We then study heterogeneity in pass-through behaviors. First, we complement our study of conditional pass-through rates by examining how external cost shocks affect the *frequency* of price adjustments. A 1% shock to imported input (energy) prices leads to a 1.6 (1.8) percentage point higher probability of adjusting prices. Such extensive adjustments can contribute to the increase in the frequency of price adjustments observed in the last year of the dataset.

Second, we explore non-linearities in pass-through rates, depending on the sign and size of cost shocks. We find strong evidence that the pass-through of negative and positive shocks is asymmetric: Firms pass through a larger share of cost increases to their customers. This asymmetry may suggest that the current and expected decline in energy prices should not contribute as much to inflation as during the energy price boom. However, as our period of study is characterized by more positive than negative cost shocks, it is unsure whether firms would behave similarly in an environment with mostly negative cost shocks. Besides, large cost shocks seem to be passed-through more, even though the supplementary pass-through associated with large cost shocks is imprecisely estimated.

[1] Labor shortages and wage pressures are also important factors, particularly in the US (see, e.g., Hobijn et al., 2022, Amiti et al., 2022).

Last, we estimate pass-through rates along the firm size distribution. Previous literature suggests that firms with market power have a tendency to pass a lower share of cost shocks, thus gaining market shares over their competitors in a period of rising costs (Amiti et al., 2019). On the other hand, evidence in Brauning et al. (2022) suggests that cost pass-through may be magnified in more concentrated industries. We do not find strong evidence consistent with either of these findings. However, we may lack identification power in this specific exercise as the survey is restricted to the largest firms in each product market.

Whereas firms do not display much heterogeneity in their pass-through rates, they do differ substantially in their *exposure* to shocks. In the last section of the paper, we dig into the consequences of this heterogeneity. We use the predictions of our econometric model to quantify the direct transmission of external cost shocks to producer prices, across firms and sectors, and use the actual imported inputs and energy price changes that occurred between January 2021 and June 2022. Over the period, input prices increased for most firms – they decreased for less than 1% of firms in our sample – and energy costs rose by 72% on average – the average increase in costs due to energy costs is about 1.28%. In manufacturing industries, the average price increase from imported and energy cost shocks that our model predicts is about 1.90 and 1.62% respectively, which represent about 20% of the observed inflation over the period. This number hides strong heterogeneity across firms. For the median firm in our sample, the two shocks increased output prices by about 0.93 and 0.81%.[2] For the 1% of firms most exposed to each of these shocks, the impact on producer prices is 14.7% and up to 12.4%. Again, heterogeneity within industries matters: 73% (72%) of the variance in predicted price adjustments induced by imported inputs (energy) is across firms within the same 2-digit industry. The heterogeneity in exposures also matters for cross-sectoral predictions. The four industries most affected by imported inputs cost shocks in 2021-2022 are textile, chemical, paper, and metal products. In these sectors, imported input cost shocks may have directly increased industry-level prices by up to 8.2%. Metal products and the chemical industry were also exposed to the surge in energy prices. In the chemical industry, energy cost shocks may have directly contributed to an additional 5.7% of inflation.

Our paper contributes to three strands of the literature. First, we participate in the growing efforts to understand the factors behind the 2021-2022 inflation surge. Several recent studies emphasize the dominant role of supply-side factors: for instance, energy prices (Bunn et al., 2022); foreign shocks and supply-chain disruptions (Amiti et al., 2022, di Giovanni et al., 2022); and stock-outs (Cavallo and Kryvtsov, 2021). Our paper uses micro-data on the pricing of manufacturing firms to shed light on the importance of both imported inputs and energy cost shocks and the role of their heterogeneity along the distribution of firms.

Furthermore, we contribute to the literature on cost pass-through.[3] Previous papers using microprice data have studied cost pass-through in the context of specific industries such as the coffee or beer industries (Nakamura and Zerom, 2010, Goldberg and Hellerstein, 2013). Closer to our work, Ganapati et al. (2020) estimated a pass-through rate of 70% of energy-driven cost shocks on manufacturing prices. We obtain slightly larger estimates using a different methodology - we exploit direct information on the energy use of firms - at a different level - we identify pass-through rates across firms within a product market in all manufacturing industries. Finally, Fontagné *et al.* (2018, 2023) use earlier vintages of the energy data to study the impact of energy price shocks on French firms' output. Consistent with us, they find full pass-through of energy price shocks on export unit values.

Martin (2011, chap.4) uses the micro data underlying the French PPI for an earlier period to study the pass-through of imported input shocks into domestic prices.[4] We augment this work by considering pass-through behaviors during a high-inflation period, and we further explore the pass-through of energy cost shocks. In a related paper, Dedola et al. (2022) explore the extensive and intensive margins of price adjustments to cost shocks using price data underlying the Danish PPI. They find that selection issues have a small impact on estimated pass-through, and they document a strong heterogeneity in pass-through across firms and sectors. Our analysis in the French context covers a more recent period, which allows us to study the role of imported and energy cost shocks in the 2021-2022 inflation surge. In addition, we can study not only oil shocks but also any price shock on the energy bill.

Last, we contribute to the macro literature on price setting behavior of producers (Nakamura and Steinsson, 2008, Gautier, 2008, Loupias and Sevestre, 2013, Bhattarai and Schoenle, 2014). We highlight two factors behind the recent inflation surge: The frequency of price changes and their absolute magnitude have increased, and the probability of upward adjustments conditional on price changes has risen significantly. These new findings complement existing evidence on the role of the extensive margin of prices for inflation dynamics (Gagnon, 2006, Klenow and Kryvtsov, 2008, Nakamura et al., 2018, Alvarez et al., 2019).

[2] We focus on the direct incidence of the shocks and do not take into account further transmission through the production network.
[3] More broadly, our paper relates to the literature on exchange rate pass-through (see, *e.g.*, Gopinath and Itskhoki, 2010, Burstein and Gopinath, 2014).
[4] About the transmission of foreign shocks to domestic prices see also Auer et al. (2019) and Goldberg and Campa (2010).

The rest of the paper is organized as follows. In Section 2, we describe the data and provide novel stylized facts on the behavior of micro-level prices in the 2021-2022 inflation surge. Section 3 presents our strategy and results for the estimation of cost pass-through. We explore the heterogeneity of pass-through rates in Section 4. Then in Section 5 we run a quantification exercise to evaluate the role of foreign inflation and energy prices in the dynamics of producer prices in 2021-2022. Section 6 concludes.

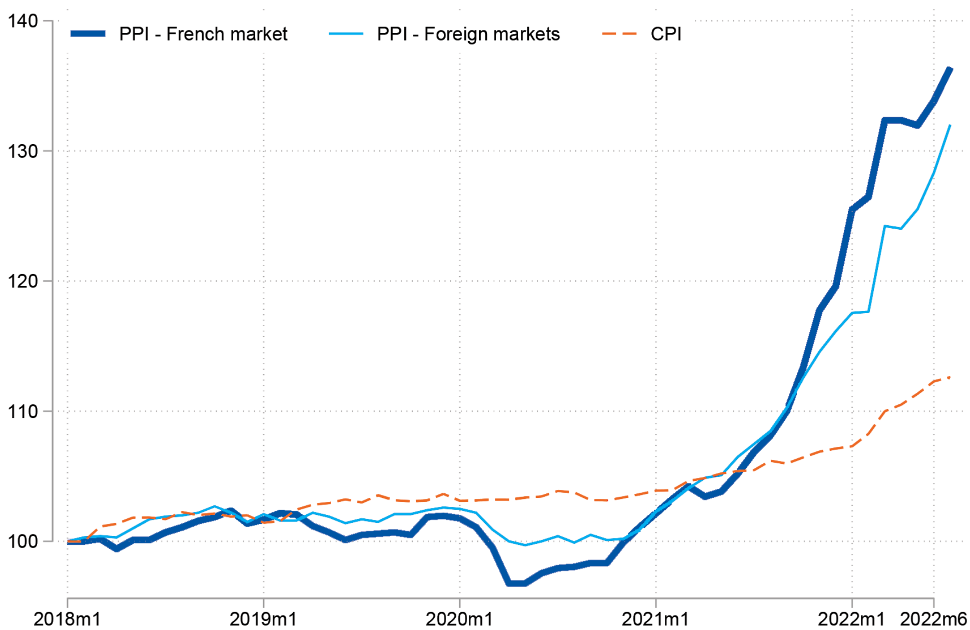
2. Data and context

2.1. The French context

Since the beginning of the 2000s, France has experienced low and stable levels of inflation. In 16 years, from January 2005 to December 2020, producer prices have increased by 17% (an annual rate of 1%). The great price moderation stopped in the aftermath of the Covid-19 pandemic. From January 2021 to June 2022, producer prices have increased by 31%, a monthly rate of 1.6%. The recent inflation surge affects domestic and export prices, although the growth of export prices is slightly lower than the rise of domestic prices (Figure 1). The increase in manufacturing firms' producer prices then contributes to overall CPI inflation.

The recent acceleration of inflation is largely attributed to external factors, namely imported inflation and energy cost shocks (Bunn et al., 2022, di Giovanni et al., 2022). Both import prices and energy prices began to rise at an accelerating pace at the end of 2020 - beginning of 2021 (Figure 2).[5] The surge in import prices has been fed by supply chain disruptions and rising freight costs following the first wave of Covid-19, as well as accelerating inflation in the US, after President Biden announced a $1.9 trillion rescue plan in January 2021. The continuous depreciation of the Euro against the dollar since the beginning of 2021 has further fuelled imported inflation.

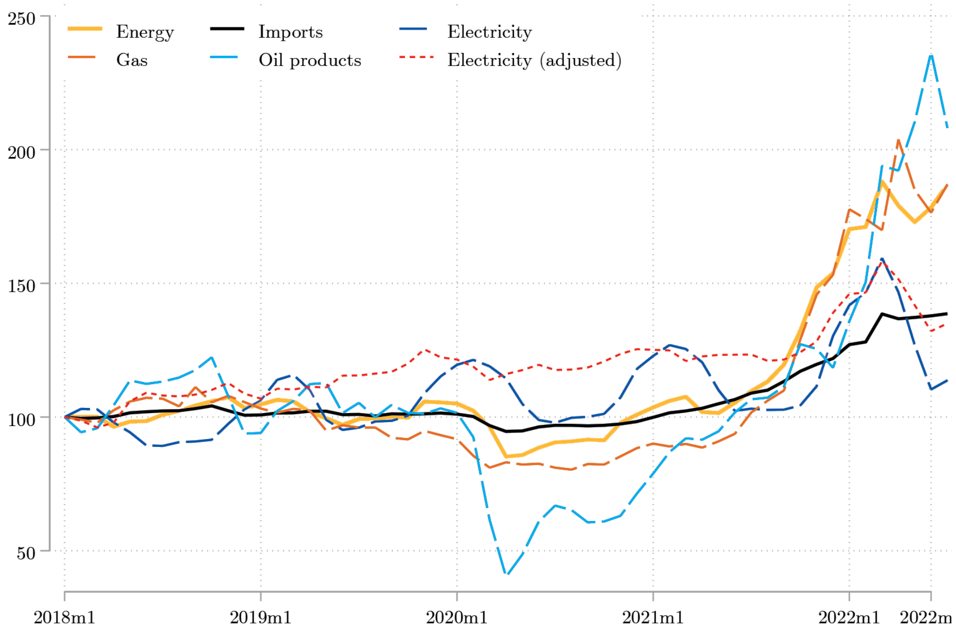
Figure 1: French PPI, January 2018 - July 2022



Notes: This figure shows price indices, normalized to 100 in January 2018. "PPI – French Market" and "PPI - Foreign markets" are the producer price indices of the French manufacturing industry, for domestic and foreign sales, respectively. "CPI" is the French Consumer Price Index. Source: Insee.

[5] Here, the import price index is constructed from data on firms' direct imports and does not include imported energy as a consequence.

Figure 2: External factors of inflation, January 2018- July 2022



Notes: This figure shows price indices, normalized to 100 in January 2018. "Energy" is the producer price index of French energy sectors computed over their domestic sales. "Imports" is the price index of imported intermediate products. "Gas" is "Trade services of gas to final consuming businesses", "Electricity" is "Electricity sold to final consuming businesses", and "Oil products" is "Coke and petroleum products". "Electricity (adjusted)" is the price index for Electricity, once seasonality is controlled for. Source: Insee.

Cost inflation has also been fed by energy prices, which have increased by about 70% between January 2021 and July 2022. The rise in energy prices is particularly pronounced for oil products, whose prices have almost continuously increased since March 2020, but is also very steep on gas. Electricity prices have started to rise in 2021, although the trend is less clear due to important price seasonality in the European electricity market. Once seasonality is controlled for, the trend is clearer, although not as steep as for oil and gas.

How do these prices translate to firms' costs? Whereas oil prices are priced in spot markets, the diffusion of electricity and gas price shocks to firms is slowed down by the prevalence of long-term, fixed-price contracts, that smooth the transmission of energy cost shocks to manufacturing companies. Insee (2022) estimates that less than 20% of French manufacturing output is produced by firms whose electricity or gas contract is indexed on spot prices. Besides, 15% of manufacturing output is produced by relatively small producers that are offered a fixed regulated electricity price. In between these extremes, 40% of manufacturing firms benefit from long-term electricity contracts and 60% from long-run gas contracts. Among these firms, 48% (resp. 36%) will have their electricity contract (resp. gas contract) renegotiated before the end of 2022. Thus, when nationwide electricity and gas prices are increasing, only a subset of firms faces an actual rise in energy costs. Moreover, the high seasonality of electricity prices observed in Figure 2 is not expected to have consequences on manufacturing firms, beyond the small share which prices are indexed on spot prices. For this reason, our empirical analysis uses electricity prices which are adjusted for seasonality to measure firms' exposure to energy prices.

Whereas the role of external cost shocks on domestic prices is well-understood qualitatively, measuring its quantitative impact requires a finer view of firms' exposures to these shocks and their incidence on their pricing strategies. This paper brings together micro data on both dimensions to tackle these questions.

2.2. Data

Individual prices

We use micro-level data on firm- and product-level prices, collected by the French statistical institute (Insee) in the OPISE survey (*Observation des prix dans l'industrie et les services*, Price Observation in Industry and Services). The data cover the period from January 2018 to July 2022.[6] The survey's primary objective is to calculate producer price indices, which are predominantly used as deflators, such as for measuring industrial production in real terms and contract indexation clauses. The survey targets a group of companies that report their most representative product prices on a monthly basis. The data collected includes prices for domestic and export sales, as well as import prices for firms that source inputs from overseas. The survey also collects information on the total value of domestic sales, exports, or imports of the product. The survey covers both manufacturing and service products, but our study focuses on manufactured products.

The sample of surveyed firms is composed of relatively large firms, that are chosen via a cut-off method. The cut-off is performed within each market (domestic, export, and import) and "branche", a "branche" gathering the production of all products within a 4-digit category (Classification des Produits Français, CPF4). For each one of the 240 4-digit categories, the largest firms in terms of their sales are included, until at least 40% of the product sales are covered (30% on exports and imports). Beyond the coverage, the sample also targets a minimum and a maximum number of units per product market. Once a firm is selected, it remains surveyed until the next renewal of the sample in the market, which happens once every five years on average.

In a typical year, around 5,000 firms are selected in manufacturing sectors. Once the sample is constituted, the firm and the statistician identify a list of its core products, selected to reflect at best the evolution of its output, export, and import prices. The firm is due to report the last four prices of the identified core products, mostly by filling out a web form. The raw data are then used to construct monthly price indices for each firm×product, correcting for non-response, quality changes, product substitution, or atypical evolutions. In 2021, the survey produces 28,000 price series, including 14,200 domestic prices and 9,400 import price series. All prices are defined before taxes. Import and export prices are converted to current euros when needed. Import prices include the cost of insurance and freight, up to the border of the importing country. Some of the export and import price series can reflect intra-group transactions, as discussed in Martin (2011).

In the rest of the paper, we will call "items" the individual price series, that are firm- and product-specific. We study output price series in the manufacturing sector, excluding tobacco, energy products, extraction, water, and steam supply. We end up with 10,242 items, corresponding to 2,352 firms. When studying the pass-through of import cost shocks, we further restrict the sample to 250 firms that also report at least one import price.

Energy consumption

We use the Insee-EACEI survey to build a measure of exposure to energy cost shocks.[7] The EACEI survey provides detailed plant-level information on the nominal and real consumption of energy, by type of energy, in a subset of manufacturing firms.[8] The purpose of the survey is to compute aggregate energy consumption statistics at the industry and regional level, by categories of firms' size. When we merge individual observations of the EACEI survey with the price data, we recover a dataset composed of 1,130 firms. We use energy consumption by energy types to measure firms' heterogeneous exposure to various energy cost shocks. Table A1 in the appendix displays statistics about the relative share of various types of energy in firms' real consumption. Electricity, gas, and oil products account for 99% of energy consumption.

Other data

We use the firm's identifier to merge the price data with two additional microlevel datasets.[9] First, we recover balance-sheet information over the firm using the Insee-FARE dataset. The dataset is constructed from the firm's tax forms and contains information about the firm's main activity, its production, value-added, and employment, as well as the structure of its costs. Throughout the paper, we measure total variable costs as the sum of the firm's wage bill and intermediate consumption (raw materials, merchandises, and services). Variable costs are used in the denominator of all cost-share variables. Second, we retrieve information on firm-level imports using the French customs database (DGDDI, DEB, and DAU files). The ratio of nominal imports (excluding capital goods) over variable costs is used as a

[6] Earlier vintages of this dataset have been used in Gautier (2008), Martin (2011).
[7] EACEI stands for "Enquête annuelle sur les consommations d'énergie dans l'industrie". See, for instance, Fontagné et al. (2018, 2023), Aghion et al. (2020) for recent studies using the same dataset.
[8] The activity of multi-establishment firms may not be fully covered by the survey as some plants of the firm are surveyed while others are not. We, therefore, include in our sample only firms that have all their manufacturing plants surveyed.
[9] See details in Appendix A.

measure of the firm's exposure to foreign input shocks. We also draw 2-digit industry-level labor costs and production levels from quarterly national accounts. These variables are used as controls in pass-through regressions.

Table 1: Summary statistics on the estimation sample

	# Firms	Variable	5 pctl	Mean	Median	95 pctl	St.dev.
Sample	2352	Employement	23	257.9	146	767	430.8
		# Products	2	7.2	5	19	6.4
× Importers	250	Employement	25	448.3	255	1453	722.9
		# Products	3	13.2	11	29	8.8
		Imp. Share	.041	.321	.304	.624	.18
× Energy	1130	Employement	32	227.1	148	652	314.7
		# Products	1	6.7	5	17	5.3
		Energy Share	.003	.026	.015	.096	.037
× Superstar	144	Employement	78	779.3	451.5	2434	1002.4
		# Products	2	13	10.5	33	11.7

Notes: This table reports statistics on the size, employment, number of products and cost shares of the population of firms in the sample, in the sub-sample of importers, in the sub-sample of firms that are also surveyed in the EACEI, and in the sub-sample of firms that we call "Superstar".

Table 1 displays statistics on the employment, number of products, and cost shares in the sample of firms described above. Our sample is composed of large firms (258 employees on average), that report the prices of several products (7.2 domestic products per firm, on average). The 250 firms that also report imported input prices are larger, both in terms of employment and the number of output prices surveyed. On average, imported inputs account for 32% of their costs. The 1,130 firms for which we have energy usage information are on average smaller. Energy accounts for 2.6% of their costs, on average.

2.3. Stylized facts on micro-level producer prices

Before digging into the transmission of external shocks to producer prices, this section reviews several stylized facts on the recent inflation surge.

Price setting behaviors are idiosyncratic

We first decompose monthly price variations observed at the level of each item into a set of common and idiosyncratic components. Formally, we regress the (log of) price changes on period fixed effects and examine the (adjusted) R-squared (R2).

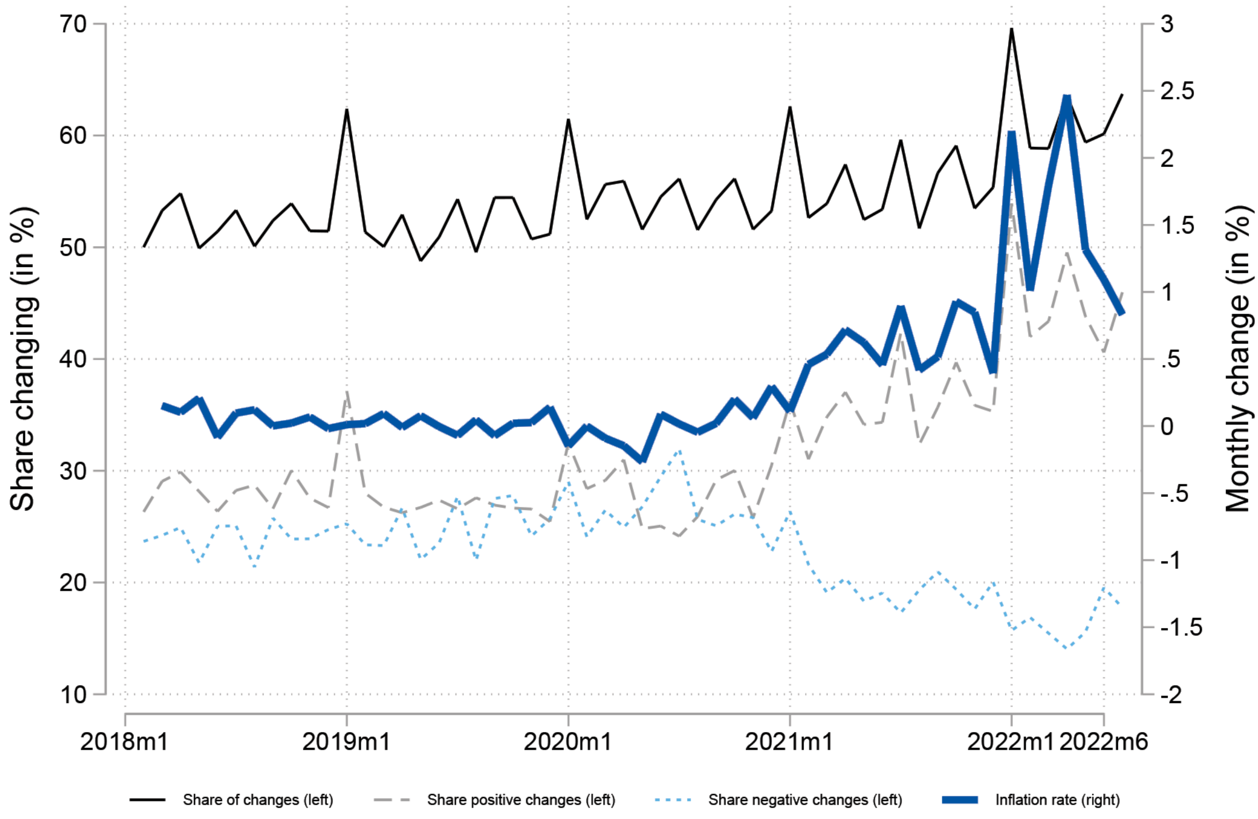
The higher this R2, the less variation in price changes there is around the average price change in a given month. In other words, a high R2 captures the general synchronization of prices across firms, and the residuals capture idiosyncratic (firm-level) movements in prices. Over the period between January 2018 and July 2022, we find a R2 of 1.19% (see Appendix Table A3). We then replicate the exercise using alternatively product × time and industry × time fixed-effects, using 2- or 4-digit categories. In these regressions, the R2 is informative of the degree of price synchronization across firms within an industry or a product market. 2-digit sector × time fixed effects explain 2.1% of the variance, while 4-digit product × time dummies explain 5 to 5.5%. The micro-level price data display massive heterogeneity, including across firms within a narrow product market. In the pass-through analysis, we will solely exploit this variation, using 4-digit product × time fixed effects to control for systematic trends across firms within a sector.

The 2021-2022 inflation surge comes with more frequent and larger price changes

Figure 3 illustrates the evolution over time of the frequency and size of price adjustments. Together, these graphs shed light on the forces underlying the recent rise in producer prices. Has the recent inflation surge been driven by an increase in the share of firms adjusting their price up, by an increase in the size of positive price changes, or both?[10] In Figure 3, top panel, we see that the shares of positive and negative price changes have been stable until mid-2020.[11] Every month, about 50% of prices change, with a roughly equal proportion of positive and negative price adjustments. These statistics are in line with the frequency of price changes documented by Goldberg and Hellerstein (2009) using US data over the 2005-2008 period. From September 2020, the share of negative price changes has declined, from 25 to 20%, while the share of positive price changes increased, reaching about 45% in July 2022. Overall, the frequency of price adjustments has thus increased, although moderately. The bottom panel of Figure 3 focuses instead on the intensive margin of inflation, namely the average size of positive and negative price adjustments, over time. Whereas average price changes are roughly constant until 2021, around .75% for positive adjustments and -.6% when prices are adjusted down, the mean price increase starts rising in 2021, reaching around 2% in 2022.

Figure 3: The margins of price changes

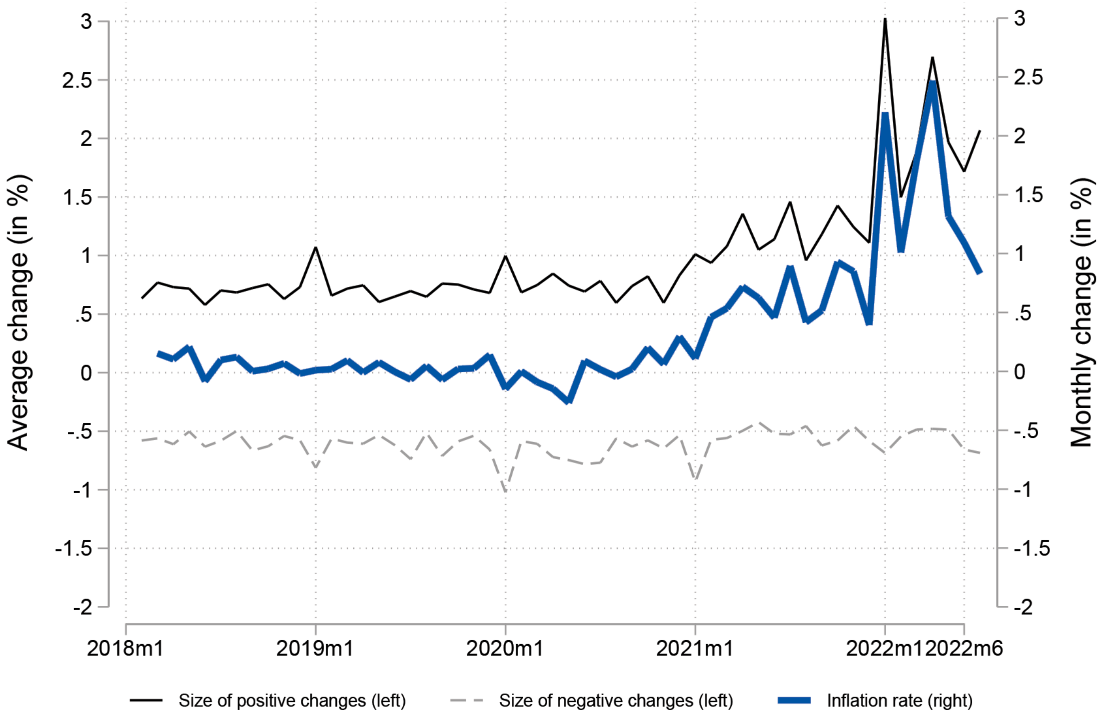
Panel A: Frequency of price changes



[10] The empirical literature on this question provides mixed answers. Nakamura et al. (2018) find that the frequency of price changes is strongly correlated with inflation whereas the size of price changes is flatter. Instead, Klenow and Kryvtsov (2008) attribute a larger share of inflation to changes in the size of price adjustments. In theoretical models of price rigidities, menu cost models point to firms being more likely to adjust their price in periods of high inflation whereas models à la Calvo assume the frequency of price adjustments is constant and the size of the adjustment is the main driver of inflation.

[11] Following Gautier (2008), price adjustments are restricted to variations in absolute values above .1%.

Panel B: Size of price changes



Notes: Panel A shows the share of prices increasing or decreasing in a given month, with respect to the last month. Panel B displays the average size of positive and negative price adjustments. Price changes concern only items in our sample. The inflation rate is the monthly percentage change of the price index of these items.

"Superstar" firms adjust their prices more frequently

An important question that microlevel data can help us address is the extent to which pricing behaviors vary along the distribution of firms' size. Is the price-setting behavior of large firms different from other firms? To what extent is the recent surge in inflation led by relatively large firms adjusting their prices more frequently and/or by a larger amount? Addressing these questions with the data at hand is not trivial as the sample of surveyed firms is biased towards relatively large firms. It is however possible to identify a subset of firms that are large among surveyed firms. To do so, we first select a subset of firms that belong to the top quartile of their (4-digit) industry in terms of employment. This selects 661 firms in the population of 2,352 firms surveyed over domestic prices. Because these firms may not be equally prominent in the various product markets that they serve, we then select the largest sellers in each product market. These are the firms whose total sales in the 4-digit product category account for at least 20% of the cumulated sales of firms in the survey. This criterion is thus specific to a "branche" in which the firm is producing. Using the double criteria, we end up with 144 firm×product pairs that we call "superstar".[12]

We then investigate the extent to which superstar firms' pricing behaviors differ from the rest of the sample using the following statistical framework:

$$y_{fpt} = \beta \times \mathbb{1}_{fp}^{\text{Super}} + \gamma \times \mathbb{1}_{fp}^{\text{Super}} \times \mathbb{1}_{t}^{2021} + \alpha_t + \mu_s + \epsilon_{fpt},$$

where y_{fpt} is a monthly firm×product-level price outcome, 1^{Super}_{fp} is a dummy identifying superstar firms, 1^{2021}_{t} is a dummy which is set to one starting from 2021. Finally, α_t and μ_s are period and 4-digit product fixed effects, respectively. In this equation, the β coefficient identifies any systematic difference between superstar firms and the rest of the sample in terms of the price outcome y_{fpt}. γ measures the extent to which the heterogeneity between superstar firms and the rest of the sample is more or less pronounced in 2021-2022.

Results are reported in Table 2.

[12] These 153 items correspond to 144 single firms. 9 firms are "superstar" in two product markets.

Table 2: Price changes

	Change		Change > 0		Change < 0 %		% Change	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Superstar	0.043***	0.045***	0.019***	0.027***	0.025***	0.017***	0.061	0.138**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.058)	(0.069)
Superstar ×≥ 2021		-0.004		-0.025***		0.022***		-0.215**
		(0.005)		(0.005)		(0.005)		(0.101)
Time FE	x	x	x	x	x	x	x	x
Branche FE	x	x	x	x	x	x	x	x
Top Obs.	35,570	35,570	35,570	35,570	35,570	35,570	21,874	21,874
Obs.	403,140	403,140	403,140	403,140	403,140	403,140	219,696	219,696
Average	0.545	0.545	0.314	0.314	0.231	0.231	0.390	0.390

Notes: The table displays results of regressions of item-level price outcomes on a dummy identifying superstar firms and its interaction with a post-2021 variable. The left hand side variable is the probability of a price adjustment in columns (1) and (2), the probability of a positive price adjustments in columns (3) and (4), the probability of a negative price adjustment in columns (5) and (6) and the percentage change in prices, conditional on a price adjustment, in columns (7) and (8). Robust standard errors in parenthesis. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

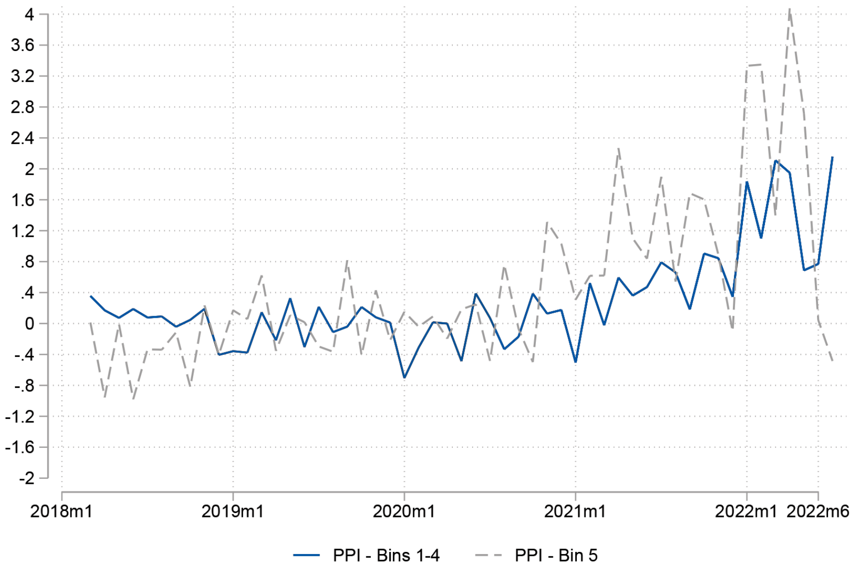
We estimate the model for four alternative outcome variables, the probability of a price adjustment (columns (1) and (2)), the probability of a positive price adjustment (columns (3) and (4)), the probability of a negative price adjustment (columns (5) and (6)), and the percentage change of prices, conditional on a price adjustment (columns (7) and (8)). The coefficients on the superstar firm dummy are always positive and strongly significant when the outcome variable is the probability of a price adjustment. In comparison with smaller firms in the same market, larger firms tend to adjust their prices more often, whether up or down. Goldberg and Hellerstein (2009) find a similar pattern in US producer price data. In 2021-2022, larger firms seem to exploit their market power to gain market share: They increase output prices as frequently as smaller firms, less than during the price moderation period, and downward price adjustments are more likely than before, relative to smaller firms. Last, conditional on changing output prices, larger firms seem to implement larger changes than smaller firms before 2021, and lower changes after. In the econometric analysis, we will further dig into this result, asking whether these systematically different price behaviors are driven by heterogeneous exposure to shocks in the 2021-2022 wave of inflation, or whether they instead reveal different pass-through behaviors.

Price volatility is higher among firms exposed to cost shocks

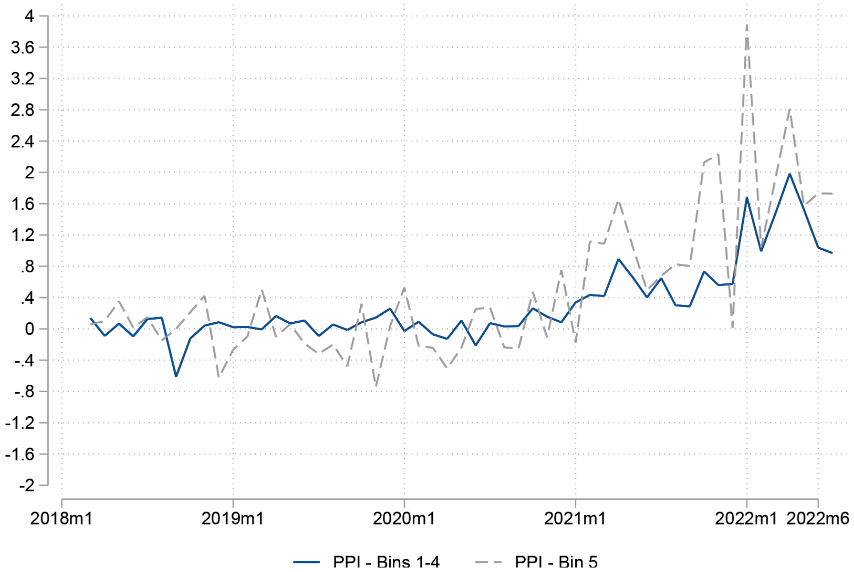
Finally, Figure 4 provides suggestive evidence of firms' heterogeneous price strategies in response to external shocks. We compare the dynamics of prices across firms with low and high exposures to imported inputs (top panel) and energy cost shocks (bottom panel). In general, average producer prices in the top quintile of exposures are more volatile than in the rest of the sample, due to less smoothing across firms. However, the figures confirm that, after 2021, monthly growth rates are almost systematically larger in the sub-sample of most exposed firms. This is consistent with the view that their exposure to external shocks has generated upward price pressures in a period of rising costs. We examine this conjecture in the rest of the paper.

Figure 4: Heterogeneous price dynamics and heterogeneous exposure to external shocks

Panel A: Exposure to imported inputs



Panel B: Exposure to energy



Notes: Panel A shows the monthly growth rate of the producer price index of firms exposed to imported inputs in our sample. Firms are split between highly exposed firms and others. Panel B shows the monthly growth rate of the producer price index of firms exposed to energy prices in our sample. Firms are split between highly exposed firms and others. In both cases, exposure is measured by the share of the corresponding inputs in total variable costs.

3. The role of external factors

In the current context, a natural question is the extent to which the surge in inflation is driven by external factors. Specifically, we examine two potential sources of producer price inflation: inflation in foreign markets and the rise in energy prices. To tackle this question, we first estimate the pass-through of foreign input price shocks and energy costs onto producer prices. We begin by describing our cost-shock variables (Section 3.1). We then estimate the pass-through of cost shocks into producer prices in Section 3.2. Whereas these estimates reflect pass-through conditional on price changes, Section 3.3 reports the impact of cost shocks on the extensive margin, that is the decision to change prices.

3.1. Measuring firm-level cost shocks

Imported input shocks

Our data offer a unique opportunity to match producer price adjustments with shocks to import prices. Among producers surveyed on domestic output, we use the sub-sample of 250 firms that also report import prices. For these firms, we build an import price shock between any two periods t and t' as:

$$\Delta_{t',t}p^M_{ft} = \sum_m w^m_{f0}\Delta_{t',t}p^M_{fmt}$$

where m indexes the firm's imported product, and $\Delta_{t',t}p^M_{fmt}$ denotes the (log) change in the price of this input between period t and t'. The weights are firm-level import shares of product m, collected when firm f enters the survey and constant throughout the period. The $\Delta_{t',t}p^M_{ft}$ variable is an input price shock that varies at the firm level but is common to all products sold by the firm.

In some of the regressions, we will further normalize the import price shock by the size of imported inputs in the firm's overall costs. To this aim, we combine the customs and balance sheet data to measure the ratio of the firm's nominal imports (excluding capital goods) over variable costs.[13] Normalizing Δ by this ratio amounts to measuring the marginal cost adjustment that firm f is facing as a consequence of the price of foreign inputs changing. Figure A1 (Top panel) in Appendix shows the distribution of these shares in the estimation sample. Our sample is biased towards relatively large manufacturing firms which explains that exposure to foreign inputs is high, on average, at 32%. There is however substantial heterogeneity across firms, with a standard deviation of 18% and two-thirds of the dispersion across firms within the same 4-digit industry.

Energy cost shocks

We combine firm-level energy consumption by type of energy with the nationwide evolution of energy prices to build a measure of energy costs that varies a the firm level. We use monthly price indices reflecting changes in the price of energy faced by French firms over the observation period (see Figure 2). Firms' exposure to various sources of energy is recovered from the EACEI survey on energy consumption. For each firm f, the energy cost shock computed between period t and t' is defined as a shift-share:

$$\Delta_{t',t}p^E_{ft} = \sum_e w^e_{f0}\Delta_{t',t}p^e_t$$

w^e_{f0} is the share of energy e in firm f's consumption of energy, in real terms (tons of oil equivalent). It is calculated as an average over 2014-2017 to maximize coverage while using pre-sample data. $\Delta_{t',t}p^e_t$ is the growth of the price index for energy e between t and t'. The shock on energy prices is calculated based on variations in the price of electricity, natural gas, and oil products, which are the three main sources of energy consumption (Table A1).

As discussed in Section 2.1, the price index of electricity is strongly affected by the seasonality of prices in European markets (Figure 2). This, together with evidence that a majority of firms are covered by long-run, fixed-term contracts, implies that the evolution of electricity prices recovered from the raw electricity price index may be a bad proxy of the actual price changes that manufacturing firms face. To deal with this issue, we remove the (monthly) seasonal component of the series of electricity prices.[14]

In several specifications, we normalize the energy cost shock by the firm's exposure to these shocks. Exposure is measured as the ratio of the firm's nominal consumption of energy over variable costs.[15] The bottom panel of Figure A1 shows the distribution of these shares in the estimation sample. In comparison with import shares, exposure to energy cost shocks is severely dampened by the limited contribution of energy to overall costs. On average, electricity, gas, and oil purchases account for 2.6% of the value of a firm's variable costs in our sample. There is however substantial

[13] We use the average ratio over 2014-2017, to maximize coverage.
[14] Gas may also be subject to contracts, but we do not detect seasonality in the gas price series.
[15] We use the average ratio over 2014-2017 to maximize coverage.

heterogeneity across firms, with a standard deviation of 3.7% and 80% of the dispersion across firms within the same 4-digit industry.

3.2. Estimating cost pass-through

Armed with these firm-level measures of cost shocks, we follow Burstein and Gopinath (2014) and estimate the pass-through of cost shocks conditional on a price adjustment:

$$\Delta_{t,\tau} p_{fpt} = \alpha \Delta_{t,\tau} z_{ft} + \beta X_{fpt} + FE + \epsilon_{fpt}$$

where $\Delta_{t,\tau} p_{fpt}$ is the price adjustment in period t for product p of a firm f that had not adjusted its price since period τ. $\Delta_{t,\tau} z_{ft}$ is the corresponding cost shock (imported input or energy) that cumulates all price adjustments between τ and t. X_{fpt} stands for a set of controls: the growth in labor costs and output between τ and t, measured at the 2-digit industry level. FE denotes a set of fixed effects. α is a parameter indicating the extent to which firms when resetting their prices, pass through cost changes that have occurred since the last revision.

We discard items whose prices remain constant in the sample. We also remove censored spells; that is, we work on products for which at least two new prices were observed in the sample. Both conditional price adjustments and cost shock variables are positive on average (see Appendix Table A4). They are also significantly dispersed, easing the identification of the α coefficient. Last, starting periods and duration of price spells vary across firms, as opposed to a setting where year-to-year changes in prices are studied. However, the dispersion in the duration of price spells is rather small: the median number of periods between τ and t is one month, and the average duration is 1.14 months (Nakamura and Steinsson, 2008).

Our preferred specification has product×period fixed effects, i.e. we identify pass-through rates solely from the cross-section of firms within a product market. Such a demanding identification strategy exploits heterogeneity across firms within the same sector in the magnitude of cost shocks since the last price adjustment. The fixed effects absorb the share of the variance that comes from the common component of cost shocks across firms within a product market. For energy cost shocks, as we use nationwide price level, fixed effects imply that identification comes from heterogeneity in both energy mixes across firms and the timing of price adjustments. We also present the results of a less demanding specification that combines period and firm×product fixed effects and thus further uses heterogeneity across firms from different sectors.

Imported input cost shocks

The results of the estimation of equation (2) for the transmission of imported input cost shocks are presented in Table 3, columns (1) to (4). We start with a simple specification in which we estimate the pass-through of input cost shocks into producer prices, unconditional on the weight of imported inputs in firms' costs. The unconditional pass-through is estimated between 7.4% and 9% depending on the structure of fixed effects (columns (1) and (3)). We however expect that this pass-through rate varies widely across firms because their exposure (the weight of imported inputs in total costs) is heterogeneous. We thus estimate the pass-through in specifications in which we normalize each shock by the contribution of the corresponding imported inputs to the firm's overall costs (columns (2) and (4)). We find that the pass-through of import input cost shocks into prices lies between 30 and 33% and is precisely estimated. The imported input cost share for the average importing firm in our sample is 32.2%, which implies that for the average importing firm an increase in imported input costs by 10% leads to an increase in prices between .98% and 1.07%.[16]

Energy cost shocks

We present the pass-through of energy cost shocks into producer prices in columns (5)-(8) of Table 3.[17] The unconditional pass-through of energy cost shocks into producer prices is estimated at 7.3%, and 4.7% in the less demanding specification with firm×product and period fixed effects. Unconditional pass-through rates are thus in the same ballpark

[16] The figures are obtained by multiplying the coefficients estimated in columns (2) and (4) by 32.2%.
[17] In the Appendix, Table A5, we also report results obtained with energy cost shocks computed from raw electricity price series. The comparison confirms the importance of controlling for the seasonality of electricity prices.

as those recovered from imported input cost shocks, despite the smaller exposure of firms to energy (Figure A1). The reason is that conditional pass-through rates are significantly larger for energy cost shocks (Columns (6) and (8)). We cannot reject full pass-through of energy cost shocks to producer prices. For the average firm in the data, full pass-through implies that a 10% increase in the cost of energy leads to a .26% price adjustment.

Table 3: Pass-through of imported input and energy cost shocks

	Imports				Energy			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Cost	0.074***		0.090***		0.073***		0.047***	
	(0.025)		(0.020)		(0.007)		(0.006)	
Δ Cost × Share		0.304***		0.333***		1.075***		0.913***
		(0.070)		(0.058)		(0.147)		(0.111)
Fixed effects	pt	pt	t + i	t + i	pt	pt	t + i	t + i
Controls			X	X			X	X
# Items	993	993	993	993	3,884	3,884	3,884	3,884
Obs.	22,611	22,611	22,611	22,611	93,535	93,535	93,535	93,535

Notes: This table reports the results of the estimation of equation (2) on imported input cost shocks (Columns (1) to (4)) and energy price shocks (Columns (5) to (8)). Controls are changes in labor costs and in output at the 2-digit industry level. Share is the firm-level ratio of imported inputs or energy consumption to total variable costs. pt, t and i stand for product×period, period, and item fixed effects, respectively. Robust standard errors in parenthesis. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Differences in imported inputs and energy pass-through

Conditional pass-through rates of imported inputs and energy prices differ markedly. The result may arise from a difference in the nature of the shock, as energy cost shocks have a stronger common component across firms within a product market, and might thus be easier to pass onto producer prices without significant competitiveness consequences. Similarly, if idiosyncratic imported input cost shocks are detrimental to competitiveness, firms may delay the pass-through of these shocks.

However, two methodological issues force us to take the difference in estimated pass-through with caution. First, import prices are more subject to endogeneity concerns than energy cost shocks. Idiosyncratic demand shocks may for instance trigger a simultaneous rise in producer and import prices, without the latter causing the former. Second, import price adjustments combine intra-firm and third-party price variations that we cannot separate in the data. Martin (2011) shows that the pass-through of import price shocks onto producer prices is close to zero in intra-firm trade. As both the endogeneity bias and the measurement issue are expected to push the estimated pass-through towards zero, we cannot exclude that the difference in pass-through rates estimated on imported input and energy cost shocks is in part driven by econometric considerations.

3.3. Extensive adjustments

Whereas the previous section focuses on pass-through rates conditional on a price adjustment, we also examine the impact of cost shocks on the *probability* of adjusting prices, using an ordered probit model on monthly price changes (Loupias and Sevestre, 2013):

$$\mathbb{1}_{fpt}(\Delta_{t,\tau}p_{fpt} >=< 0) = \alpha\Delta_{t,\tau}z_{ft} + \beta X_{fpt} + FE + \epsilon_{fpt}$$

The notations and controls are the same as in equation (2) but the left-hand side variable is now a dummy equal to -1 if the firm adjusts its price downwards, 1 if it adjusts the price up, and 0 if the price is left unchanged. Unfortunately, the model does not handle a large number of fixed effects as the linear model in equation (2) does. As a consequence, we use (2-digit) product and period fixed effects and augment the list of controls with a proxy for competitor prices that absorbs the common component of shocks at the product×period level.

We estimate the impact of cost shocks on the probability of price adjustment in four different specifications: using either imported inputs or energy cost shocks or cost shocks conditional on the firm's exposure. Table 4 summarizes our results. For each specification, the first two columns present the estimated coefficients and the associated Z-statistics whereas the last two columns correspond to the marginal impact of the shock on the probability of a negative and a positive price adjustment. We compute marginal effects for each observation and report the (simple) average. All coefficients are positive and significant, although estimates are less precise for energy cost shocks. The positive coefficient implies that larger cost shocks are associated with a significantly larger probability of the firm adjusting its price. In quantitative terms, a 1% increase in costs due to imported input costs (resp. energy costs) leads to a 1.56 p.p. increase (resp. 1.8 p.p. increase) in the probability that the firm adjusts its price up. As the average probability that a given firm adjusts its price upwards is around 30%, a 1% increase in imported input costs (resp. energy costs) increases the probability that the firm adjusts its price upwards by 5.2% (6%). The model constrains positive and negative cost shocks to have the same marginal effect on price adjustment probabilities. Hence, the marginal effects of negative cost shocks are identical. We question this assumption in Appendix Table A6, where we estimate different coefficients for positive and negative cost shocks. We find that a 1% increase in costs due to imported inputs increases the probability of upwards price adjustments by 1.9 p.p., while the same but negative shock increases the probability of downward price adjustments by 1 p.p. The same positive shock but originating in energy costs has a marginal effect of 0.93 p.p. on the probability of a price increase and a 1% negative energy cost shock increases the probability of a price decrease by 3 p.p. These results reinforce those recovered from the pass-through conditional on a price adjustment: In periods of upward pressures on external costs, firms adjust their prices more frequently and with larger upward adjustments. Both margins can contribute to explaining the upward trend in producer prices observed in Figure 3 from mid-2021 onwards.

Table 4: Impact of external cost shocks on adjustment probabilities

				Marginal Effects (p.p.) on a Price	
	X	Coefficient	Z-stat	Decrease	Increase
Imported inputs	Δ Cost Δ Cost × Share	1.24 4.38	7.07 9.17	-.4 -1.42	.44 1.56
Energy	Δ Cost Δ Cost × Share	.35 5.23	3.24 2.82	-.1 -1.55	.12 1.8

Notes: This table shows results of the estimation of the ordered probit model (Equation 3), using either imported input or energy costs shocks as right-hand side variables, either normalized by the corresponding cost shares or not. The first column reports the estimated coefficient, the second column shows the associated Z-statistic. The marginal effects give the probability change associated with the occurrence of a 1 percent increase in X, setting the other covariates at their sample mean. All models control for period and 2-digit product fixed effects and changes in competitors prices, 2-digit industry level labor costs, and 2-digit industry output.

4. Heterogeneity in pass-through rates

We now examine the heterogeneous response of firms to imported input and energy cost shocks. Results are reported in Tables 5 and 6. In columns (2) and (5) of Table 5, we test for asymmetries in pass-through rates of negative and positive cost shocks. We find that firms adjust their prices more on positive than negative cost shocks. Firms transmit 50% of positive shocks on their imported inputs but do not adjust their prices when imported inputs decrease. Positive energy cost shocks are more than fully passed into prices, whereas only 60% of energy cost drops are passed into prices.[18] The more-than-full pass-through rate of positive energy cost shocks is not statistically different from a 100% pass-through. In periods of high inflation, if firms, in addition to current cost shocks, expect additional energy cost shocks in the near future, they might decide to smooth their output price changes by passing-through more today. Moreover, as energy cost shocks have a macroeconomic component, energy cost shocks and other inputs cost shocks may be correlated, as suppliers also face the energy shock. In that case, the pass-through rate we estimate compounds both the direct effect from energy costs and the

[18] In both cases we can reject the equality of coefficients on positive and negative cost shocks (t-statistics at 8.79 and 5.67).

indirect effect from other material costs and may be larger than 100%. Overall, these findings are in line with the early results of Peltzman (2000) on the asymmetric response of US consumer and producer prices to positive and negative shocks.

In columns (3) and (6), we further test for non-linearities by adding an interaction of the cost shock variable with a dummy for large positive shocks. Large positive shocks are those falling into the last decile of the distribution of (positive) cost shocks. Even though the coefficient describing the supplementary pass-through associated with large positive shocks is imprecisely estimated, it is positive and relatively high, which suggests that large positive cost shocks may be passed into prices at a higher rate.

In Table 6, we test for heterogeneity across firms of different sizes.[19] The pass-through literature has long recognized that optimal pass-through rates vary depending on the firm's perceived demand elasticity. Under oligopolistic competition, large firms are willing to absorb a larger share of cost shocks through mark-up adjustments (see Atkeson and Burstein, 2008, Amiti, Itskhoki and Konings, 2019, among others). Our sample is not best suited to test for such asymmetries as the survey is restricted to relatively large firms and the number of firms within a product market is low. In columns (1) and (5), we try to check that superstar firms do not behave differently than their peers in the same sector. However, our sample is biased toward large firms and the superstar definition is demanding.[20] The absence of significant differences in the pricing of the largest firms in our sample should thus not be interpreted as a definitive finding on the heterogeneity in pass-through between large and small firms. In columns (2) and (6), we thus propose an alternative in which cost shocks are interacted with a measure of the firm's market share in the product market. Whereas the specification is more comparable to the literature on the topic, it comes with the caveat that market shares are measured on surveyed firms. Heterogeneous coverages across product markets complicate the interpretation.

Table 5: Pass-through: Heterogeneity along the distribution of shocks

	Imports			Energy		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Cost × Share	0.304***			1.075***		
	(0.070)			(0.0147)		
Max(– × – ,0)		0.469***	0.302**		1.273***	1.017***
Max() × High positive change			0.189			0.300
Min(– × – ,0)		0.060	0.067		0.578**	0.585***
Fixed effects	pt	pt	pt	pt	pt	pt
# Items	993	993	993	3,884	3,884	3,884
Int. Obs			1,010			5,712
Obs.	22,611	22,611	22,611	93,535	93,535	93,535

Notes: This table reports the results of the estimation of equation (2) with interactions of the cost shock variable with dummies for the sign and size of the shock. In columns (2) and (5) we estimate different coefficients on positive and negative cost shocks. In columns (3) and (6) we interact positive cost shocks with a high positive cost shock dummy that identifies the shock in the last decile of the distribution. pt stands for a product×period fixed effect. Robust standard errors in parenthesis. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Overall, we do not find significant heterogeneity in pass-through rates along the distribution of (relatively large) firms in our sample. In all but one specification, the coefficient on the interaction is negative but not significantly different from zero.[21]

However, the absence of significant heterogeneity in pass-through rates does not rule out strategic complementarities between firms. In columns (3) and (6), we add a measure of changes in firms' competitor prices.[22,23] The associated

[19] In this table, we do not normalize the shock by the corresponding cost shares as the shares are themselves correlated with the interaction terms.
[20] 28 and 44 firms are superstars in the importers and the energy sample respectively.
[21] The coefficient on the interaction in column (1) is positive and significant. However, it is identified on very few firms and sectors. Moreover, endogeneity concerns regarding import prices are particularly acute at the very top of the distribution.
[22] The variable is constructed from price changes observed since the firm's last price adjustment in the sample of firms active in the same product market. The variable is thus collinear with product×period fixed effects which explains that we need to change the structure of fixed effects. As a consequence, the variable also absorbs part of the common component of shocks, affecting in turn the level of the pass-through coefficient.
[23] This variable does not take into account the prices of foreign competitors.

coefficient is positive and significant, consistent with the view that large firms react to changes in their competitors' prices in oligopolistic markets.[24]

Table 6: Pass-through: Heterogeneity across firms

	Imports				Energy			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Cost	0.053*	0.074			0.075***	0.096***		
	(0.027)	(0.058)			(0.007)	(0.015)		
Δ Cost × Superstar	0.147***				-0.013			
	(0.053)				(0.018)			
Δ Cost × Market Share		-0.014				-0.030*		
		(0.088)				(0.017)		
Δ Cost× Share			0.294***	0.294***			0.722***	0.726***
			(0.060)	(0.060)			(0.123)	(0.122)
Competitors price change			0.315***	0.304***			0.404***	0.411***
			(0.026)	(0.030)			(0.017)	(0.022)
– × HHI				0.089				-0.064
				(0.187)				(0.137)
Fixed effects	pt	pt	t + i	t + i	pt	pt	t + i	t + i
Controls			X	X			X	X
# Items	970	970	970	970	3,791	3,791	3,791	3,791
Int. Obs	3,681				5,894			
Obs.	22,111	22,111	22,111	22,111	91,156	91,156	91,157	91,157

Notes: The definition of Superstar firms is based on employment size and market shares. Market Share corresponds to the weight of the firm in the product market, see the text. HHI is the Herfindahl-Hirschman index of the 4digit industry of the firm. Specifications include the interacted variable – Superstar, Market Share, or HHI – in levels. Controls are changes in labor costs and in output at the 2-digit industry level. pt, t and i stand for branche, product×period, period and item fixed effects, respectively. Robust standard errors in parenthesis. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

5. Contribution of cost shocks to inflation across firms and sectors

In this section, we use the pass-through estimates to examine the impact of imported inputs and energy cost shocks on producer price inflation. We limit the analysis to the industries on which we estimated pass-through rates, that is all manufacturing industries except energy sectors, tobacco, and extraction. Due to variations in the intensity and mix of inputs across firms and sectors, even homogeneous conditional pass-through rates can generate significant dispersion in predicted price adjustments. To illustrate this heterogeneity, we build expected price changes induced by the cumulated changes in imported input or energy costs between the first quarter of 2021 (2021Q1) and the second quarter of 2022 (2022Q2). We do so conditional on price changes – that is we do not predict the extensive margin – and use the asymmetric pass-through rates estimated in columns (2) and (5) of Table 5: 47% and 6% for positive and negative imported cost shocks, and 127% for energy cost shocks (which are all positive). We focus on the direct transmission of these changes and do not estimate further transmission through the production network. As such, our estimates can

[24] In columns (4) and (8), we further interact the variable with the sectoral Herfindahl index, a proxy for market concentration. Results suggest that the strength of the competition within sectors does not affect strategic complementarities.

be viewed as lower bounds of the overall increase in producer prices due to a given shock to imported costs and energy prices.[25]

Whereas 80% of firms are importers according to Customs data, not all of them are surveyed on their import prices. The reason is that the import price index is itself constructed from a representative sample of importers in the manufacturing sector. Omitting the pass-through of import prices to output prices for firms that import but are not surveyed would tend to under-evaluate the role of foreign inflation in PPI movements. To circumvent this issue we assign them the average import price change in their 2-digit industry, computed from firms for which we do observe import prices. The prediction of output price changes from energy cost shocks suffers from the same issue, if not more, as virtually each manufacturing firm in the PPI sample uses energy whereas data on energy consumption are recovered from a survey. Here as well, we extrapolate our results for firms that are not covered by the energy consumption survey, assuming they display the average energy intensity of firms in the same 2-digit industry and face their average energy cost shock.[26]

Imported input cost shocks

Although the last two years have been characterized by overall rising import prices, some firms experienced a decrease in import prices. There is indeed significant variation across firms in the size and sign of import price changes over the period. This heterogeneity translates into a distribution of predicted price changes, which is described in the first line of Table 7. At the median of the distribution, the firm-level price change that our model attributes to imported input cost shocks is positive and equal to 0.93%. This number however hides strong heterogeneity, as 10% of firms experience an increase above 7.8%. and 1% above 14.7%. We estimate that imported cost shocks can explain around 11.5% of the variance of the observed output price increase across those firms.

We then aggregate firm-level predicted price changes at the 2-digit industry level using PPI weights at the firm level, normalized to one in each 2-digit industry.[27] Importantly, we include non-importing firms, for which the model predicts a zero output price change. As illustrated in Figure 5, firms in the pharmaceutical and apparel industries are somewhat insulated from imported inputs cost shocks in the post-pandemic period. On the other side of the distribution, some industries have been hurt particularly strongly by imported inflation, most notably producers of chemicals and metals. In the metal industry, the rise in producer prices solely attributed to imported input cost increase is 6.2%.[28] Overall, we estimate that imported cost shocks contributed to increase the PPI in the manufacturing sector by 1.90% over the period (Figure 5), which is 11% of the observed inflation in the corresponding sectors. Moreover, there is substantial heterogeneity across firms within the same 2-digit industry in predicted price increases. In Figure A2, Panel A, we display the 10th and 90th percentiles of the predicted price increase distribution within 2-digit industries. The span of the predicted price changes is large and in most industries, the 10th percentile is close to or equal to zero. In the metal and the chemical industry, the 10% most impacted firms experience a price increase larger than 12%. Overall, around 73% of the dispersion in predicted prices is across firms within the same 2-digit industry. This confirms the importance of digging into micro-level data.

Energy cost shocks

We also observe substantial heterogeneity in predicted price changes from energy prices. Here, the heterogeneity comes from differences across firms in their dependence on energy and their energy mix. For the median firm in our sample, the 2021-2022 energy cost shock leads to a .81% increase in prices. The predicted impact of energy cost shocks rises to 12.4% for firms in the top percentile. We estimate that the energy price shock can explain around 6.4% of the variance of the observed output price increase across those firms. Overall, we estimate that energy cost shocks contributed to increase the PPI in the manufacturing sector by 1.62% over the period (Figure 5).

Industries vary greatly in their exposure to the energy crisis, with some of the sectors that are most vulnerable to imported input shocks also being among the most affected. For instance, in the chemical industry, a cumulative increase in energy and imported input prices from 2021 to 2022 could have raised the price index by up to 14%. The predicted price changes also show significant heterogeneity within industries, with around 72% of the variance being within an

[25] In unreported results, we however quantified the possible amplification of the shocks through production networks. Given the estimated effect of imported input and energy price shocks on each industry, one can use the Leontief inverse calculated from French input-output tables to estimate the overall impact of these shocks, once we take into account the additional cost inflation attributable to upstream suppliers being themselves exposed to external shocks. We find that production networks amplify the shocks by about 25%.
[26] See Appendix B for more details.
[27] The PPI weights are formally defined at the item level. We add up these weights to the firm level, before normalizing the sum across firms within an industry.
[28] Although large in absolute value, this number needs to be put in perspective with the industry's PPI increase over the same period, equal to 46.5%.

industry, across firms with varying levels of exposure to energy cost shocks. In the chemical industry, this heterogeneity is particularly pronounced, with 90% of firms experiencing moderate cost shocks leading to price increases below 0.29%, while a few large and highly exposed firms are greatly impacted by the rise in energy costs, resulting in a 5.7% increase in the average sectoral price.

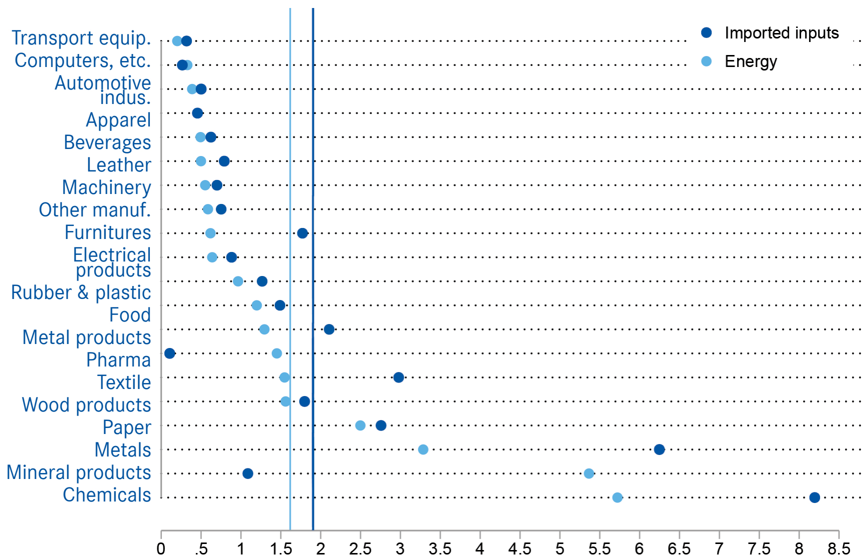
Table 7: Distribution of predicted price changes attributable to imported input and energy cost shocks

	Percentile						
	10	25	50	75	90	95	99
Imported inputs	.01	.3	.93	2.4	5.2	7.8	14.7
Energy	.24	.44	.81	1.5	4.7	5.3	12.4
Observed increase	0	3.2	9.4	22.6	43.2	60.5	101.5

Notes: This table reports the percentiles of the predicted and observed price changes (in %) for firms our sample between 2021Q1 and 2022Q2. Predicted price changes are based on asymmetric pass-through rates of 47% (6) and 127% for positive (negative) imported input and energy cost shocks respectively.

The heterogeneity of firms in their energy dependence and energy mix has significant implications for the insights we can glean from microdata, as opposed to industry-level data. As discussed in Appendix B, these sources of heterogeneity and their correlation with firms' size can lead to systematic discrepancies between sector-level predictions obtained from the microdata and those obtained from industry-level data. We estimate that the surge in energy prices has led to a 1.62% increase in prices across industries, 9% of the observed PPI inflation. Ignoring heterogeneity in firms' energy dependence and their energy mix leads to underestimating the aggregate impact of the energy price surge, by .26 percentage points. The difference is mostly explained by a composition effect, as large firms use gas more intensively in their energy mix (see Appendix Figure A3), and the price of gas has increased relatively more during the period of observations. If electricity prices surge, the direction of the bias will reverse since relatively small firms are more reliant on this source of energy. The effect of large firms' exposure to gas prices is partially offset by the fact that these firms are typically less dependent on energy overall.

Figure 5: Sectoral impact of imported input and energy price shocks



Notes: The figure shows the predicted rise in sectoral PPI attributed by the model to imported input shocks (green circles) and energy costs shocks (blue circles), in percent. We first use the model to predict the impact of the cumulated shocks observed between 2021Q1 and 2022Q2. We then build each point as the sales-weighted average of firm-level predicted price increases. Vertical lines represent aggregate predicted increases. Predictions are based on asymmetric pass-through rates: 47% (6) and 127% for positive (negative) imported inputs and energy costs shocks respectively. Details on the method in Appendix B.

6. Conclusion

We exploit micro-level data on French manufacturing firms' prices and their exposure to foreign shocks to study the pass-through of imported input and energy costs shocks and their role in the 2021 inflation surge. Following the first wave of the Covid pandemic, producer prices have started to rise in France, due to both more frequent and larger price increases, conditional on prices being adjusted. We quantify the role of imported input and energy cost shocks. First, we estimate the pass-through of these two categories of shocks on firms' prices using unique data on firm-level import prices and their dependence on various types of energy. Firms in our samples pass through 30% of imported input prices and 100% of energy costs onto their own prices, conditional on their exposure to these cost shocks. Firms' adjustment to these shocks is asymmetric, with positive cost shocks inducing significantly more pass-through than negative shocks. Heterogeneity in exposure to external shocks, across firms and sectors, drives important differences in the dynamics of inflation across firms. In the chemical and metal industry, imported and energy cost shocks have contributed to an increase in the producer price index by at least 9.5 and 13.9%.

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Appendix

A. Data

Opise is a survey of French firms ("unités légales"). However, some firms do not report directly to the pollster, and a "fournisseur" supplies the data for them. The unit in Opise is thus a "fournisseur", identified by a unique identifier called IDFOUR. IDFOUR is different from the SIREN identifier, which corresponds to legal units and is used in other firm-level datasets. In this paper, we choose to restrict to units for which there is a one-to-one matching between IDFOUR and SIREN, which is the case for 94.5% IDFOUR.
When selecting products that will enter the survey, the pollster tries to select a specific transaction of a specific product, rather than an average price of a product mix, to limit statistical biases.

B. Quantification exercise

B.1 Methodology

In this section, we describe our procedure to predict firm- and industry-level output price changes using pass-through estimates. We use asymmetric pass-through rates.

Firm-level predicted price changes from imported input cost shocks We predict output price changes using specification (2) of Table 5 and set the estimated pass-through rates to $\hat{\alpha}^M = 0.47$ for positive shocks and $\hat{\alpha}^M = 0.06$ for negative shocks. For firms for which we have import price data, we compute:

$$\Delta \hat{p}_f^M = \hat{\alpha}^M \times \Delta p_f^M \times S_f^M$$

For firms for which we do not have import price data, we compute:

$$\Delta \hat{p}_f^M = \hat{\alpha}^M \times \Delta p_s^M \times S_s^M$$

where S_f^M is the firm-level share of imported inputs in overall costs, which we recover from customs and balance-sheet data. The ratio is equal to 0 for firms that source all of their inputs domestically. Δp_f^M is the firm-level imported input cost shock, which we observe over the sub-sample of firms surveyed in OPISE. Δp_s^M is the 2-digit industry average change in import prices, defined as $\Delta p_s^M = \sum_{f \in s} w_f^M \Delta p_f^M$, where w_f^M is the weight of firm f in the import price index, normalized so that $\sum_{f \in s} w_f^M = 1$.[29]

Firm-level predicted price changes from energy cost shocks We predict output price changes using specification (5) of Table 5 and set the estimated pass-through rate to that of positive energy cost shocks, as energy prices only rose over the period: $\hat{\alpha}^E = 1.27$. We use the same notations as for imported inputs. For firms for which we have energy data, we compute:

$$\Delta \hat{p}_f^E = \hat{\alpha}^E \times \Delta p_f^E \times S_f^E$$

[29] The original weights are defined at the item level. We add up these weights to the firm level, before normalizing by the sectoral share.

For firms for which we do not have energy data, we compute:

$$\Delta\hat{p}_f^E = \hat{\alpha}^E \times \Delta p_s^E \times S_s^E$$

where Δp_s^E is the 2-digit industry average change in energy prices. More specifically, we compute $\Delta p_s^E = w_s^{elec} \times \Delta p^{elec} + w_s^{gas} \times \Delta p^{gas} + w_s^{oil} \times \Delta p^{oil}$, where $w_s^{elec} + w_s^{gas} + w_s^{oil} = 1$ are the shares of the cost of energy e in total energy costs among firms for which we have energy data. Every firm in our Opise sample is given an energy consumption level, via S_f^E. S_s^E is the 2-digit industry average share of energy costs in total variable costs. It is computed as the ratio between total energy bill and total variable costs among firms for which we have energy data.

Sectoral predicted price changes Based on the distribution of firm-level predicted price changes, we can compute the sectoral inflation which the model attributes to either imported input or energy cost shocks. Namely:

$$\Delta\hat{p}_s^t = \sum_{f\in s} w_f^{ppi} \Delta\hat{p}_f^t, \quad t = M, E \tag{4}$$

where w_f^{ppi} is the weight of firm f in the OPISE survey, normalized so that weights sum to one within a sector.

B.2.From micro to macro

For energy cost shocks, we can compare the sectoral predictions recovered from equation (4) with the counterpart obtained from sectoral data. The difference is informative about the additional information one can gather from micro-level sources.
The industry-level prediction recovered from micro data writes as follows:

$$\Delta\hat{p}_s^{micro} = \hat{\alpha}^E \sum_{f\in s} w_f^{ppi} \times \Delta p_f^E \times S_f^E \tag{5}$$

The prediction of output price change recovered from sectoral data is computed from the following formula:

$$\Delta\hat{p}_s^{Macro} = \hat{\alpha}^E \times \Delta p_s^E \times S_s^E$$

with:

$$\begin{aligned} S_s^E &= \frac{EnergyBill_s}{Costs_s} \\ \Delta p_s^E &= \sum_e w_s^e \Delta p^e, \text{ with } e = \text{ elec, gas, oil} \end{aligned}$$

Differences between $\Delta\hat{p}_s^{micro}$ and $\Delta\hat{p}_s^{Macro}$ arise from heterogeneity in the energy mix (w_f^e for all f, e) and from different expositions to energy costs (S_f^E for all f). This can be seen from the following decomposition:[30]

$$
\begin{aligned}
\Delta\hat{p}_s^{micro} &= \hat{\alpha}^E \sum_{f\in s} w_f^{ppi} \times (\Delta p_f^E - \Delta p_s^E) \times S_s^E \\
&+ \hat{\alpha}^E \sum_{f\in s} w_f^{ppi} \times (S_f^E - S_s^E) \times \Delta p_s^E \\
&+ \hat{\alpha}^E \sum_{f\in s} w_f^{ppi} \times (\Delta p_f^E - \Delta p_s^E) \times (S_f^E - S_s^E) \\
&+ \Delta\hat{p}_s^{Macro} \\
&= (a) + (b) + (c) + \Delta\hat{p}_s^{Macro} \qquad (6)
\end{aligned}
$$

The difference between the predicted micro-based and industry-based price predictions comes from heterogeneity in the energy mix (a),[31] heterogeneity in the energy cost share (b), and the correlation between the two. To get insights about the size of these sources of heterogeneity, and their impact at the sector level, we proceed as follows:

- (a) is the difference between micro and macro predictions when there is no heterogeneity in energy cost shares. Then
$$(a) = \Delta\hat{p}_s^m(S_f^E = S_s^E) - \Delta\hat{p}_s^{Macro},$$
where $\Delta\hat{p}_s^m(S_f^E = S_s^E)$ is the industry-level prediction recovered from micro data ignoring heterogeneity in cost shares.
- Similarly, (b) is the difference between micro and macro predictions when there is no heterogeneity in energy mixes. Then
$$(b) = \Delta\hat{p}_s^m(w_f^e = w_s^e) - \Delta\hat{p}_s^{Macro}.$$
- Armed with these two counterfactuals, we can compute
$$(c) = \Delta\hat{p}_s^{micro} + \Delta\hat{p}_s^{Macro} - \Delta\hat{p}_s^m(w_f^e = w_s^e) - \Delta\hat{p}_s^m(S_f^E = S_s^E)$$

Table A7 displays $\Delta\hat{p}_s^{Macro}$, $\Delta\hat{p}_s^{micro}$, (a), and (b) for each industry and at the aggregate level. In the overall manufacturing sector, heterogeneity in the energy mix contributes to inflating the aggregate predicted price increase (+0.36 p.p.), whereas differences in energy cost shares across firms have a small dampening effect (-.11 p.p.). The large role played by the energy mix has to do with the nature of the shock: The surge in energy prices between 2021Q1 and 2022Q2 largely comes from gas and oil prices (+110% and 148% from our price data, respectively). In our sample, relatively large firms (with a large w_f^{ppi}) rely relatively more on gas and have thus been exposed to a larger energy cost shock over the period. By ignoring the heterogeneity, industry-based predictions underestimate the overall impact of the shock. By contrast, large firms display relatively low energy cost shares which pushes the sector-level prediction down, in comparison with the industry-based counterpart that ignores the heterogeneity. Finally, the residual term (c) is small in the aggregate, around 0.01 p.p. In some industries, it contributes to increasing micro-level predictions.

[30] The decomposition ignores that industry-based predictions imp itly liaggregate the shadow firm-level price predictions using cost-based rather than sales-based weights ($S_s^E = \sum_{f\in s} \frac{Costs_f}{Costs_s} S_f^E$). Whereas the difference in the aggregation weights could in theory drive both predictions further away from each other, the difference is small in the aggregate in the aggregate (lower than 0.01%) because sales and cost shares are strongly correlated.

[31] $(a) = \hat{\alpha} \quad \sum_{f\in s} w_f^{ppi} \times \sum_e \Delta p^e (w_f^e - w_s^e) \times S_s^E$

Figure A3 illustrates the correlation between firms' size and their exposure to energy cost shocks, in the overall dataset. The figure shows the strong correlation between a firm's size and its exposure to gas prices and the negative correlation with its overall energy dependence that triggers the results just mentioned. Note however that the strength and direction of these correlations are not uniform across sectors. The correlation between a firm's size and its energy exposure through the firm's energy mix is particularly pronounced in chemicals, as a consequence of large chemical producers being highly dependent on oil. In this sector, heterogeneity in energy cost shares instead has a strong dampening effect, because large chemical producers display relatively low energy dependence. In a few industries such as wood products, printing, or pharmaceuticals, both sources of heterogeneity reinforce each other because relatively large firms are more exposed to the crisis through their energy mix *and* more dependent on energy on average.

C. Additional Tables

Table A1: Energy consumption statistics

	Variables	# Firms	10 pctl	Mean	Median	90 pctl	St.dev.
	Energy share	1,130	.3	2.7	1.5	10	4.1
Share of energy consumption	Elec.+Gas+Oil	1,130	99.2	99.4	100	100	5.4
	Elec.	1,130	18.6	61.2	61.8	100	26
	Gas	870	0	31.8	29.2	79.1	27.5
	Oil	645	0	6.4	.1	38.3	15.1

Notes: This table reports energy usage statistics among firms in our sample. Energy Share is the cost of energy over variable costs (in percentage points). The next 4 rows report statistics on the share of each type of energy in firms' real consumption (in toe).

Table A2: Size of the sample of firms

	Share of...			
	PPI (%)	Production (%)	Imports (%)	Exports (%)
Sample	36	22.66	22.73	25.15
Importers	6	5	7.02	7.22
Energy	16	9.48	10.48	11.18
Superstar	7	4.17	3.99	4.48

Notes: This table reports the share of PPI weights, of production (Source: FARE), imports and exports (Source: French Customs) that firms in the sample account for. 2018.

Table A3: Within-industry and between-industry variation in monthly price changes

	Period	Product× Period	Product (2D)× Period	Industry× Period	Industry (2D)× Period
Variance explained (%)	1.19	5.53	2.12	5.06	2.12

Notes: This table reports the adjusted R-squared of five regressions of monthly item (log) price changes on various fixed effects: period (calendar time), 4-digit product × period, 2-digit product × period, 4-digit industry × period, 2-digit industry × period. The regressions use domestic prices over Jan. 2018 - July 2022.

Table A4: Distributions of shocks and price changes

		5 pctl	Mean	Median	95 pctl	St.dev.
Importers	Δ Cost	-3.91	.49	0	6.13	4.24
	Δ Cost × Share	-1.2	.15	0	2.01	1.59
	Δ Price	-6.6	.34	.26	7.67	5.61
Energy	Δ Cost	-5.7	1.37	.85	9.68	5.59
	Δ Cost × Share	-.12	.03	.01	.25	.26
	Δ Price	-6	.54	.31	7.73	5.46

Notes: This table reports statistics on the conditional changes in output prices and cost shocks in our two estimation samples. In %.

Table A5: Pass-through of energy costs shocks, by type of energy

	Baseline		Raw Electricity Price	
	(1)	(2)	(3)	(4)
Δ Energy cost × Energy Share	1.075***		0.745***	
	(0.147)		(0.118)	
Δ Electricity cost × Electricity Share		1.334***		0.070
		(0.380)		(0.172)
Δ Gas cost × Gas Share		1.290***		1.398***
		(0.272)		(0.269)
Δ Oil cost × Oil Share		0.938***		0.953***
		(0.246)		(0.248)
Fixed Effects	pt	pt	pt	pt
# Items Obs.	3,884	3,884	3,884	3,884
	93,535	93,535	93,535	93,535

Notes: The table reports the results of the estimation of equation (2) using our measure of energy cost shocks as right-hand side variable. Columns (2) and (4) decompose energy cost shocks into the sum of electricity, gas, and oil cost shocks. Columns (3) and (4) report pass-through estimates when electricity prices are not adjusted for seasonality. pt stands for product×period fixed effects. Robust standard errors in parenthesis. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table A6: Impact of external cost shocks on adjustment probabilities: Asymmetric shocks

				Marginal Effects (pp) on a Price	
	X	Coefficient	Z-stat	Decrease	Increase
Imported inputs	Δ Cost ≥ 0	2.08	8.54	-.68	.74
	Δ Cost ≤ 0	-.07	-.25	.02	-.03
	Δ Cost ≥ 0× Share Δ	5.29	8.12	-1.71	1.88
	Cost ≤ 0× Share	-3.05	-3.84	.99	-1.09
Energy	Δ Cost ≥ 0	.28	1.6	-.08	.1
	Δ Cost ≤ 0	-.41	-2.56	.12	-.14
	Δ Cost ≥ 0× Share Δ	2.72	1.17	-.81	.93
	Cost ≤ 0× Share	-10	-3.05	2.97	-3.43

Notes: This table shows results of the estimation of the ordered probit model (Equation 3), using either positive or negative imported input or energy costs shocks as right-hand side variables, either normalized by the corresponding cost shares or not. Negative cost shocks are in absolute value. The first column reports the estimated coefficient, the second column shows the associated Z-statistic. The marginal effects give the probability change associated with the occurence of a 1 percent increase in X, setting the other covariates at

Table A7: Predictions of output price change

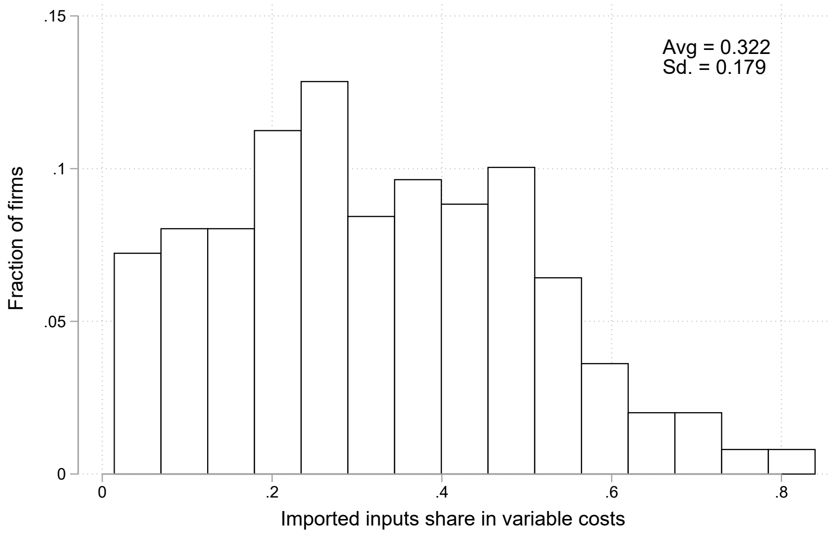
Industry	NAF2	(1) $\Delta\hat{p}_s^{Macro}$	(2) $\Delta\hat{p}_s^{Micro}$	(3) (a)	(4) (b)	(5) (c)	(6) PPI
10	Food	1.23	1.20	0.08	-0.15	0.04	16.7
11	Beverages	0.55	0.50	-0.03	-0.01	-0.01	4.28
13	Textile	1.47	1.55	0.16	-0.10	0.02	19.21
14	Apparel	0.19	0.46	0.29	-0.01	-0.01	1.97
15	Leather	0.22	0.50	0.24	0.00	0.04	2.46
16	Wood products	0.82	1.57	0.53	0.04	0.18	27.88
17	Paper	3.12	2.51	-0.11	-0.59	0.08	26.72
18	Printing	0.71	1.73	0.70	0.12	0.21	6.87
20	Chemicals	5.27	5.75	1.96	-1.64	0.16	56.47
21	Pharma.	0.46	1.46	0.70	0.12	0.18	5.00
22	Rubber and plastic	0.80	0.97	0.09	0.05	0.03	18.2
23	Mineral products	4.50	5.39	1.03	-0.48	0.35	15.79
24	Metals	3.01	3.31	-0.47	0.36	0.41	46.44
25	Metal products	0.74	1.30	0.46	0.01	0.09	14.66
26	Computers. etc.	0.21	0.33	0.15	-0.02	-0.02	2.68
27	Electrical products	0.46	0.64	0.15	0.01	0.02	9.79
28	Machinery	0.39	0.55	0.14	0.03	0.00	9.61
29	Automotive indus.	0.80	0.40	-0.40	-0.01	0.00	7.39
30	Transport equip.	0.17	0.20	0.03	0.00	0.00	2.02
31	Furnitures	0.48	0.62	0.26	-0.07	-0.05	13.58
32	Other manuf.	0.31	0.59	0.21	0.04	0.03	3.92
	All	1.36	1.62	0.36	-0.11	0.01	17.46

Notes: This table reports the industry level predicted output price change from energy cost changes and factors of the decomposition in Equation (6). Column (1) uses industry-level energy costs. Columns (2) uses firms' cost share and energy mix. Column (3) reports the contribution of heterogeneity in energy mix across firms within industries to the difference between (1) and (2). Column (4) reports the contribution of heterogeneity in energy cost shares across firms within industries to the difference between (1) and (2). Column (5) reports the contribution of the correlation between heterogeneity in energy cost shares and heterogeneity in energy mix across firms within industries to the difference between (1) and (2). Column (6) reports the observed increase in output prices at the industry level. The last row ("All") is the aggregate from all the industries above. All

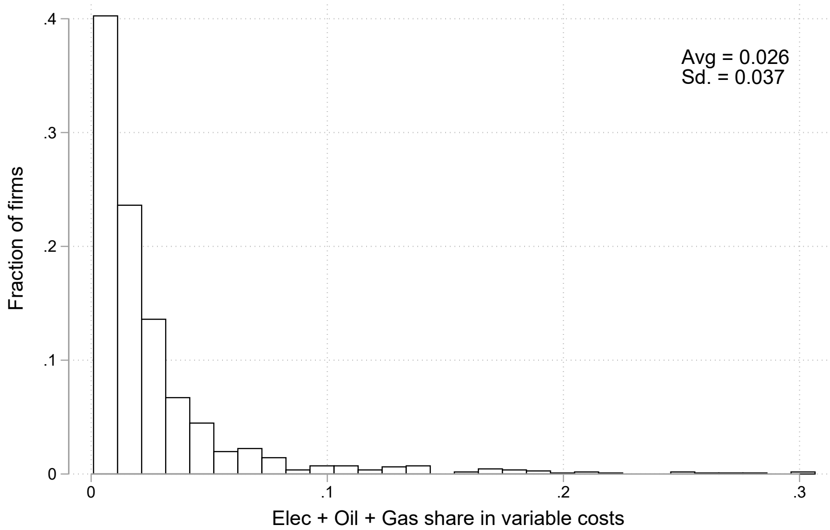
D. Additional Figures

Figure A1: Distribution of cost shares

Panel A: Import shares

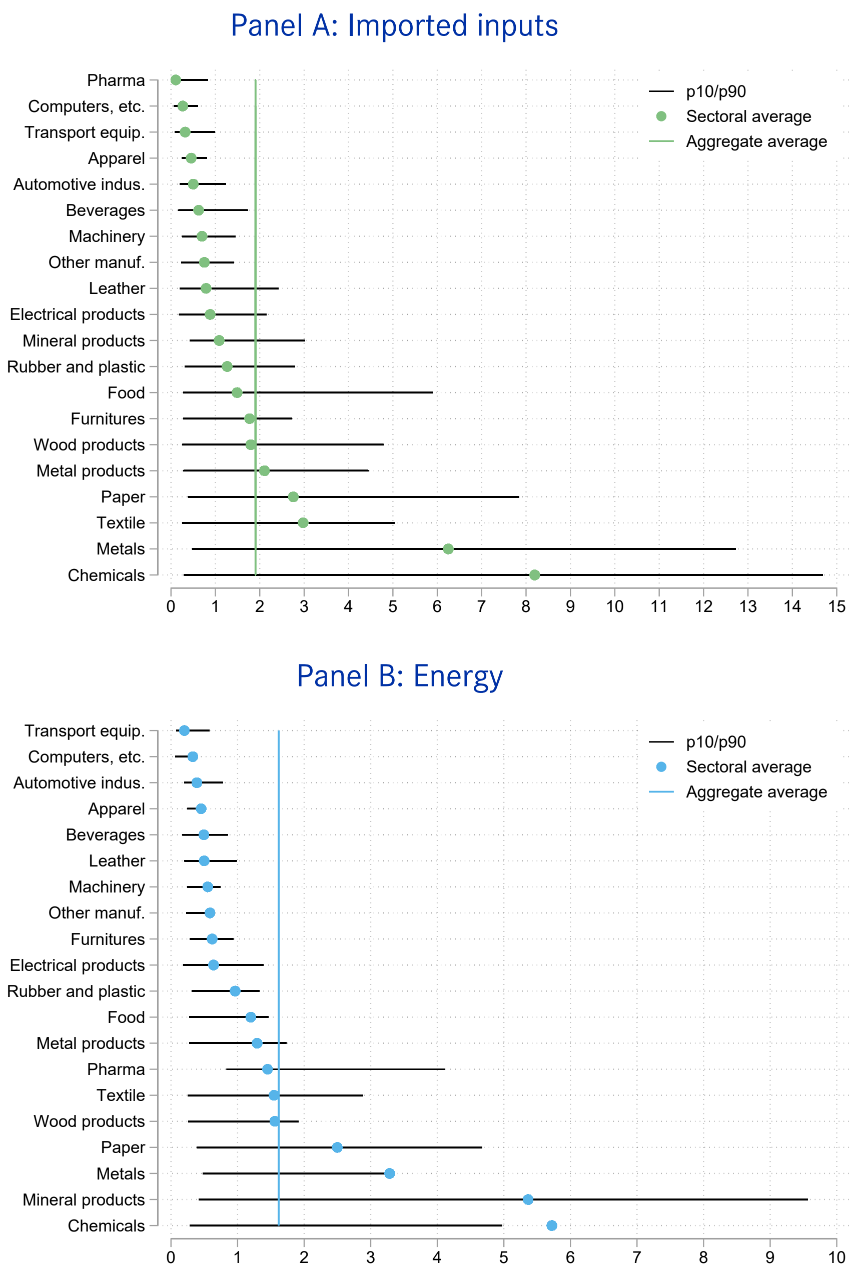


Panel B: Energy shares



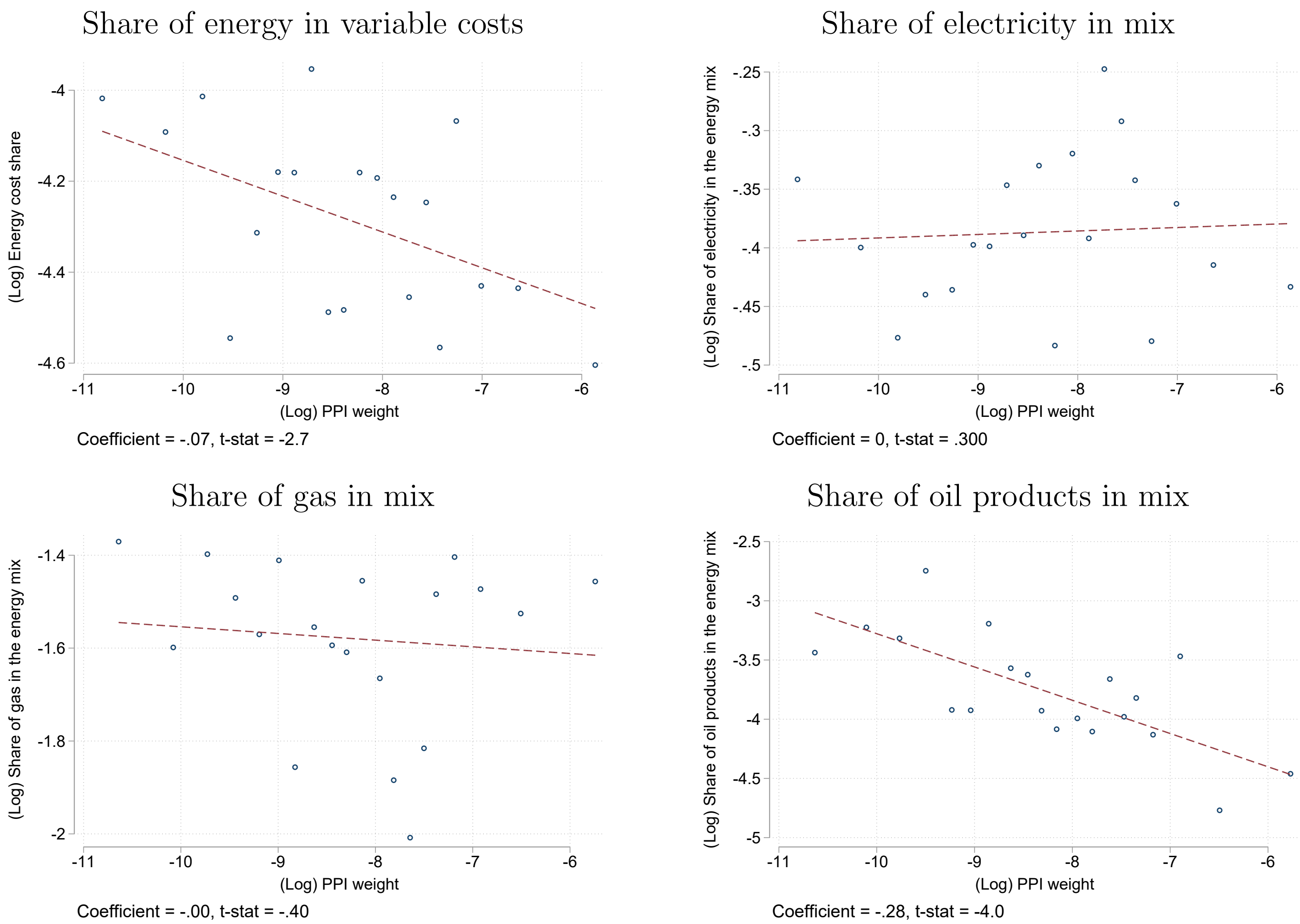
Notes: Panel A shows the distribution of imported inputs shares, defined as the ratio of imports over output using data for 2018. Panel B shows energy cost shares, defined as the ratio of (nominal) energy consumption over output, also using data from 2018. Energy consumption is restricted to electricity, gas, and oil.

Figure A2: Predicted price increases in 2-digit industries: 10th and 90th percentiles



Notes: The figure shows the predicted rise in sectoral PPI and the 10th and 90th percentiles of the firm-level predicted price increase distribution within 2-digit industries attributed by the model, from imported input shocks (Panel A) and energy costs shocks (Panel B). We first use the model to predict the impact of the cumulated shocks observed between 2021Q1 and 2022Q2. We then build each point as the sales-weighted average of firm-level predicted price increases. Vertical lines represent aggregate predicted increases. Predictions are based on asymmetric pass-through rates: 47% (6) and 127% for positive (negative) imported inputs and energy costs shocks respectively. Changes are in%. Details on the method in Appendix B.

Figure A3: Correlations between PPI weights, energy exposure, and energy mix



Notes: This figure displays binscatters of S_f^E (top left), w_f^{elec} (top right), w_f^{gas} (bottom left), w_f^{oil} (bottom right) on PPI weights. The red dashed line represents the OLS fit, which estimated coefficient is below each panel. Variables in log.