State-Dependent Pass-Through with Heterogeneous Exposure to Common Shocks

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Abstract

We study state-dependent pass-through using the recent surge in energy cost as a natural experiment. The empirical analysis exploits data on firms' exposure to energy-driven cost shocks, matched with firm and product-level output prices from the French Producer Price Index (PPI). Pass-through of energy cost shocks increased from 70% before the energy crisis to full pass-through in 2021-2022. The pass-through of energy shocks is also found higher among the most exposed firms. A state-dependent model *à la* Cavallo et al. (2024) augmented with heterogeneous exposure to energy price shocks can replicate these patterns. The model is used to show how heterogeneity in firms' exposure to common shocks affects the aggregate response of the economy to a macro supply shock.

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1 Introduction

A series of large supply shocks triggered by the COVID-19 pandemic and the war in Ukraine hit Europe and the United States in 2021–2022, coinciding with a sharp surge in inflation. A growing literature has used state-dependent pricing models to explain price dynamics during these high-inflation episodes.[1] In these models, the short-run pass-through of supply shocks into prices rises when the economy is hit by large shocks, contributing to the acceleration of inflation. An important feature of the data, however, has received much less attention: firms' exposure to these supply shocks is highly heterogeneous. We exploit the 2021–2022 surge in energy prices as a natural experiment to test the predictions of state-dependent pricing models and to study how heterogeneity in exposure shapes the transmission of large supply shocks to aggregate inflation. Understanding how heterogeneous exposure interacts with firm size is essential to explain both firm-level price adjustments and aggregate inflation dynamics.

The first part of the paper provides empirical evidence consistent with state-dependent pricing models. Using detailed firm-level data for the French manufacturing sector, we estimate that the pass-through of energy price shocks to domestic producer prices increased from about 70 percent before 2021 to full pass-through during 2021–2022. We also document substantial cross-sectional heterogeneity: firms more exposed to the energy crisis—either because of higher energy intensity or a production structure more reliant on gas and oil—exhibit significantly higher pass-through rates.

The second part of the paper evaluates whether a state-dependent pricing model à la Cavallo et al. (2024), augmented with heterogeneous exposure to macro supply shocks, can account for these patterns. We estimate the model using a simulated method of moments and micro-level data. When fed with energy price shocks calibrated to match developments in 2021–2022, the model reproduces both the surge in aggregate pass-through and the observed cross-sectional heterogeneity across the distribution of energy exposure. Crucially, we show that the interaction between firms' exposure to energy shocks and their size is central to understanding the fast transmission of the energy crisis to output prices. This joint role of firm size and heterogeneous exposure to supply shocks is largely absent from the existing literature on state-dependent pricing. .

The empirical analysis relies on micro-level data underlying the French Producer Price Index (PPI). We focus on the manufacturing sector over the period from January 2018 to December 2022.[2] We merge the PPI data with firm-level information on energy consumption by type of energy, as well as balance-sheet data. The resulting dataset covers 1,117 manufacturing firms, representing approximately one tenth of total manufacturing output in France. Our

[1] See, for instance, Cavallo et al. (2024), Antonova (2025), Harding et al. (2023), and Gagliardone et al. (2025).

[2] Starting in January 2023, large public policies aimed at limiting the transmission of the energy crisis to firms introduce an important confounding factor into the analysis. Prior to 2023, only households and very small firms (not in our sample) were covered by public subsidies on energy prices.

baseline analysis uses around 4,500 monthly price series, disaggregated at a fine product level and covering prices charged in the domestic market.

In the estimation sample, energy expenditures account for around 2 percent of the average firm's variable costs. Energy intensity, however, displays substantial cross-sectional heterogeneity, both across and within industries. Across firms, we observe a positive correlation between energy intensity and market shares of over 30 percent. Firms also differ markedly in their energy mix: the average share of gas in total energy expenditures varies between 14 and 31 percent across sectors. As a result, firms' exposure to energy price shocks is highly heterogeneous. Based on this insight, we propose a strategy to measure firm-level energy cost shocks using detailed data on firms' energy consumption and observed fluctuations in electricity, gas, and oil prices over the sample period.[3] Heterogeneity in both energy usage and energy mix provides valuable sources of identification to measure the transmission of energy cost shocks into individual prices.

Over the full sample period, our analysis shows that energy-driven cost shocks are fully transmitted to domestic producer prices. We confirm this result using three complementary specifications: (i) a dynamic specification that allows for delayed transmission of energy cost shocks to monthly prices; (ii) a static specification that relates monthly price changes—conditional on a price adjustment—to the cumulative change in energy costs since the last price update; and (iii) a static specification based on quarterly data. In all specifications, we include sector-by-time fixed effects to control for common shocks affecting all firms within a sector at a given point in time, thereby absorbing the potential influence of demand shocks or sector-wide wage adjustments. In the context of the energy crisis, these fixed effects also capture the common drift in marginal costs, allowing the pass-through coefficient to be identified from heterogeneity in firms' exposure to energy price fluctuations.

The results indicate that energy-driven price adjustments occur rapidly, with most of the pass-through materializing within one quarter. Controlling for two potential confounders, changes in competitors' prices and in input suppliers' prices, slightly reduces the estimated pass-through rate, which nonetheless remains statistically indistinguishable from full pass-through. Given the average share of energy expenditures in total costs of manufacturing firms, our estimates imply that a 10 percent increase in energy prices leads to a 0.22 percent increase in producer prices.

We document a marked increase in firms' responses to energy price shocks over the final two years of the estimation sample. While the pass-through of energy shocks is estimated at about 70 percent over 2018–2020, it rises to 127 percent (not statistically different from full pass-through) during 2021–2022, a period characterized by high inflation and sharply increasing

[3]Together, electricity, gas, and oil account for 99.5 percent of total energy expenditures in our sample. Our approach exploits heterogeneity in firms' energy mix to approximate their exposure to common energy price increases. In practice, the specific contractual arrangements between firms and energy suppliers may also affect the timing of their exposure to energy price shocks. We discuss this additional source of heterogeneity in Section 3, using survey data on energy contracts.

energy prices. We further investigate heterogeneity in pass-through across firms with different levels of exposure to energy price shocks. Energy cost pass-through is significantly higher among more exposed firms. The magnitude of this heterogeneity is substantial: firms in the top 10 percent (respectively, top 5 percent) of the energy-intensity distribution exhibit pass-through rates that are 42 (respectively, 48) percentage points higher. Finally, we confirm the rise in average pass-through during the energy crisis using alternative identification strategies. Specifically, we go beyond a reduced-form shock by instrumenting firm-level energy prices either with the shift-share measure employed in the baseline specification or with an alternative instrument constructed from other firms' energy prices. In both cases, we confirm a higher degree of pass-through during the energy crisis.

Inspired by the empirical evidence, we examine whether a simple state-dependent pricing model à la Cavallo et al. (2024), augmented with heterogeneous exposure to macro supply shocks, can replicate these findings. In the model, firms incur a fixed cost to increase the probability of receiving a price adjustment opportunity. This feature generates a time-dependent hazard function that is increasing in the firm's price gap, defined as the percentage deviation between the firm's current and optimal price. When firms in this economy are hit by a common energy price shock, their hazard functions shift upward on impact, with a larger shift for energy-intensive firms. As a result, the model reproduces our two main empirical facts. First, the average pass-through of energy price shocks rises during episodes of sharply increasing energy prices, as firms intensify their price adjustment efforts. Second, pass-through is higher among energy-intensive firms, whose price gaps are more strongly affected by energy price shocks.

We estimate the model using a simulated method of moments and pre-crisis micro-level data. Heterogeneity is disciplined using firms' observed exposure to energy prices and its correlation with firm size. The remaining parameters are identified using moments of the distribution of price changes and the pass-through rate in the pre-crisis period. The estimated model closely replicates both the distribution of price changes and their elasticity with respect to energy price shocks prior to the crisis. We then assess the model's ability to match non-targeted moments during the energy crisis by simulating a one-time permanent energy price shock calibrated to replicate observed price dynamics over 2021–2022. We assess the fit of our model against two benchmarks: the average pass-through estimated in the data and the heterogeneity in pass-through across firms with different energy exposures. In the estimated model, average pass-through increases from 0.69 to 0.76, whereas the data suggest a rise from 0.69 to full pass-through. The model therefore accounts for about one quarter of the estimated increase in pass-through over the period. Turning to heterogeneity, for firms in the bottom 90 percent of the energy-intensity distribution, the model predicts a pass-through rate of 73 percent, compared with 82 percent in the data. Among firms in the top 10 percent of the exposure distribution, the predicted pass-through exceeds 95 percent and is not statistically different from that observed in the micro-level data. Despite its parsimonious structure, the model delivers a close quantitative fit to the observed heterogeneity.[4]

We use the model to investigate how heterogeneity in firms' exposure to energy price shocks affects their diffusion to the aggregate economy. We show that models that neglect heterogeneity in energy intensities cannot replicate the dynamics generated by the heterogeneous-firm model, whether they are calibrated using a simple average or a sales-weighted average of observed energy intensities. There are two main reasons for the discrepancies between homogeneous- and heterogeneous-firm models.

First, the heterogeneous model features stronger time variation in the hazard rate along the transition to the new steady state. These variations arise from the feedback effect of the shock on the aggregate price index, which temporarily deviates from its steady-state value. Cavallo et al. (2024) argue that such deviations are quantitatively small in their framework, which abstracts from firm-level heterogeneity. In our setting, these deviations are mechanically larger, because the systematic correlation between firms' exposure to the shock and their market shares pushes the aggregate price index further away from its steady state. Despite this amplification mechanism, we find that time variation in the hazard rate remains quantitatively negligible in the environment we study.

Second, homogeneous models neglect the correlation in the joint distribution of energy intensities and market shares observed in the data. We show that this correlation has substantial implications for the diffusion of the shock to aggregate prices. We define aggregate pass-through as the weighted average of individual pass-through rates. When the correlation between energy intensity and firm size is calibrated from the data, aggregate pass-through reaches 84% after one quarter. If this correlation is zero or negative, one-quarter aggregate pass-through falls below 80 percent. The underlying mechanism is that large firms tend to be more energy-intensive in the data; their costs therefore rise sharply during the energy crisis, which increases their incentives to adjust prices immediately. While the correlation is positive in the context of the energy crisis, it may be zero or negative in other settings, such as following a monetary shock. Overall, these results highlight that accounting for heterogeneity in exposure is crucial for understanding the transmission of aggregate supply shocks within state-dependent pricing models.

Related literature. Our article contributes to recent efforts to understand the drivers behind the surge in inflation over the 2021-2022 period. In their survey of UK firms, Bunn et al. (2022) find that energy prices, labor and material shortages account for a substantial share of the inflationary pressure observed during and after the pandemic. di Giovanni et al. (2022) show that in the Eurozone, foreign shocks and supply chain disruptions played a greater role than demand shocks, and Gagliardone and Gertler (2023) find that oil price shocks and easy

[4] Note that, in the presence of heterogeneity, the average pass-through estimated in the data may be upward biased, which could explain part of the discrepancy between the model's predictions and the empirical estimates. Additional discrepancies may also reflect mechanisms absent from the model. For instance, heightened attention and changes in expectations during 2021–2022 may have contributed to higher pass-through rates (Pfauti, 2023).

monetary policy are the main factors driving the inflation surge, whereas Giannone and Primiceri (2024) find a stronger role of demand shocks. We focus on the role of energy in the inflation surge and examine how heterogeneous exposure to energy shocks shapes their transmission to inflation.

We also contribute to the literature that studies the differences in price setting behavior in low- and high-inflation environments (Nakamura et al., 2018, Harding et al., 2023, Taylor, 2000, Cavallo et al., 2024, Weber et al., 2023, Pfauti, 2023). Cavallo et al. (2024) use a New Keynesian model with state-dependent price setting to study the impact of a significant cost shock, comparable in scale to the 2021-2022 energy price surge. They find that large positive shocks are transmitted to prices at a faster rate than small positive shocks or large negative shocks. We provide micro-level evidence consistent with state-dependence, using the energy crisis as a natural experiment. We further extend their model to account for the heterogeneous exposure of firms to energy cost shocks which we observe in our data. In this setting, the response of aggregate prices to the shock is systematically shaped by the correlation between firms' energy intensities and their size because more energy-intensive firms pass the cost shock to their price faster. We provide micro-level evidence consistent with the model's prediction.

Our work also contributes to the literature on cost pass-through.[5] Previous studies using micro-price data have examined cost pass-through in specific sectors such as the coffee or beer industries (Nakamura and Zerom, 2010, Goldberg and Hellerstein, 2013). Closer to our research, Ganapati et al. (2020) study the impact of energy cost shocks and estimate a pass-through rate of 70% on manufacturing prices, which is the level of pass-through we estimate before 2021-2022. Our study uses a different methodology, drawing on direct information on firms' energy use and energy mix. We further show that the level of pass-through varies over time. Another relevant study by Fontagné et al. (2018) uses electricity prices as a cost shifter to identify the price elasticity of exports. Although they use different data, namely annual export unit values and average electricity costs, their first-stage estimates are consistent with our findings concerning the high degree of price pass-through of energy cost shocks. Dedola et al. (2022) explore the extensive and intensive margins of price adjustments to oil and import price shocks using Danish PPI price data over 1993-2017. They find that selection issues have minimal impact on estimated pass-through. Our analysis in the French context covers a more recent period, enabling us to examine the role of energy cost shocks (including gas and electricity) in the 2021-2022 inflationary surge.

Last, we contribute to the literature on heterogeneous adjustment to macro shocks. Davis et al. (2024) show how differences in exposure to macro shocks across firms leads to heterogeneous adjustments in terms of equity returns, sales, and employment growth. Here we show that heterogeneous exposure to supply shocks leads to heterogeneous price adjustments. In a related work, Alvarez-Blaser et al. (2025) decompose individual prices and inflation into common

[5] Our paper is more broadly related to the literature on exchange rate pass-through (see, e.g., Gopinath and Itskhoki, 2010, Burstein and Gopinath, 2014).

shocks, idiosyncratic shocks, and idiosyncratic responses to common shocks. We provide direct evidence of heterogeneous adjustments to macro shocks driven by heterogeneous exposure.

The rest of the paper is organized as follows. In section 2, we describe the data and provide stylized facts on firms' exposure to energy cost shocks and their price behaviors before and during the energy crisis. Section 3 discusses the empirical results recovered from the pass-through regressions. Section 4 interprets the evidence within a model of state-dependent pricing by firms that are heterogeneous in their size and exposure to energy cost shocks. In Section 5, we investigate the quantitative implications of the model, based on a structural estimation of its parameters. Finally, Section 6 concludes.

2 Data and Stylized Facts

Individual price data. We use individual price data collected through the OPISE survey (Observation des Prix dans l'Industrie et les Services) conducted by the French Statistical Institute.[6] The data spans from January 2018 to December 2022, and we focus on manufactured products.

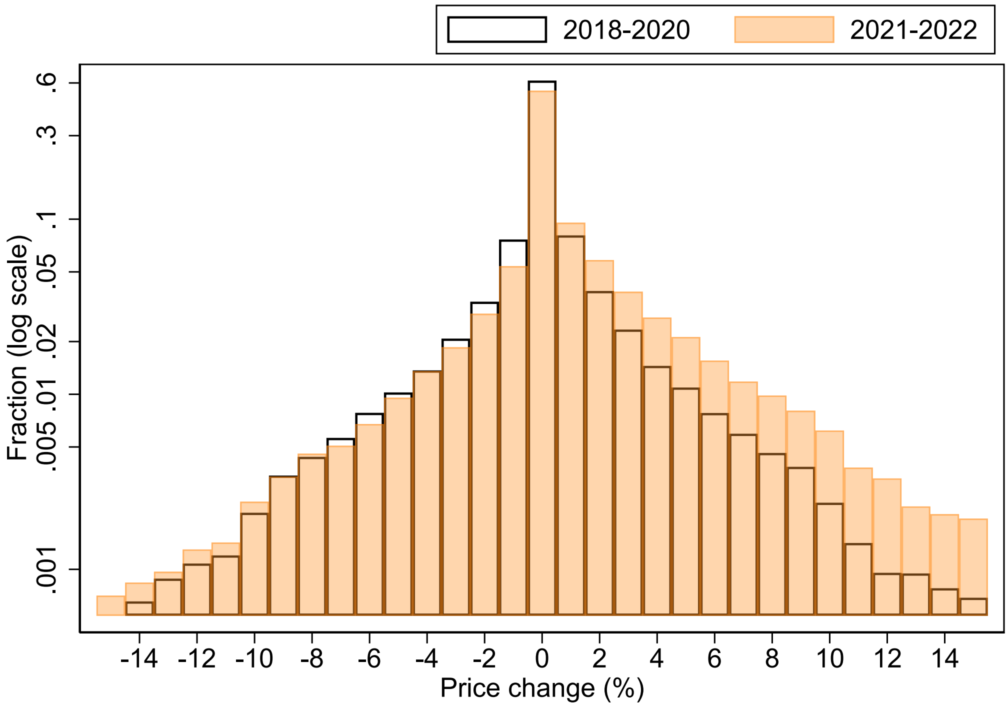
The OPISE survey covers the largest firms (by sales) within each 4-digit category. This selection ensures coverage of at least 40% of each product market, despite the limited sample of about 5,000 manufacturing firms. Once selected, a firm remains in the survey until the next sample renewal in its market, which typically occurs every five years. Each firm reports a list of its core products that best reflect the evolution of its prices. The raw data from these products are then used to construct monthly price indices for each firm–product combination. Several adjustments account for non-response, quality changes, product substitution, and atypical price movements. In 2022, the survey produced 13,803 domestic price series, each associated with a weight for the construction of the PPI. From these series, we compute monthly and quarterly price changes at the firm–product level. Following Gautier (2008), any monthly price change below 0.1% in absolute value is set to zero to mitigate potential accuracy issues.

Figure 1 presents the distribution of monthly price changes for two subperiods, 2018–2020 and 2021–2022, which we refer to as the pre-crisis and crisis periods throughout the paper. The figure reveals a clear rightward shift in the distribution of price changes in the last two years of the sample. We also observe a smaller mass around zero in 2021–2022, indicating that the frequency of price changes increased during the high-inflation episode. The shift in the distribution of price adjustments thus reflects both a higher frequency of (positive) price changes and larger magnitudes of these changes.[7] The average size of monthly price changes

[6] Earlier vintages of this dataset have been used in Gautier (2008), Martin (2011) and Vermeulen et al. (2012).

[7] Inflation dynamics have been a subject of debate in the literature, particularly about the role of the extensive and intensive margins (Gagnon, 2006, Nakamura and Steinsson, 2008, Klenow and Kryvtsov, 2008, Nakamura et al., 2018, Alvarez et al., 2019). We find that both margins are at play during the recent surge in inflation. In 2018-2020, 40% to 45% of price changed every month. The frequency increases by 6 percentage points on average, over 2021-2022. These frequencies are in the high range of the literature, similar to the frequency measured in the US PPI data by Goldberg and Hellerstein (2009), but higher than in EU countries (Vermeulen

Figure 1: Distribution of monthly price changes



Notes: This figure shows the distribution of monthly price changes over the 2018-2020 and 2021-2022 periods. The y-axis is in log scale.

increased from .11% between 2018 and 2020 to .94% during the high-inflation episode.

In Section 3, we explore the potential role of energy as a source of these dynamics. To do this, we first calculate measures of exposure to energy cost shocks at the firm level.

Energy cost shocks. To create a firm-level measure of energy price changes, we use information on each firm's energy consumption by energy type, combined with observed changes in nationwide energy prices. For each firm f, we calculate the change in the price of purchased energy using the following formula:

$$\Delta p_{ft}^{E} = \sum_{e} w_{f0}^{e} \Delta p_{t}^{e} \tag{1}$$

Δp_t^e represents the growth in the price of energy type e, calculated at a monthly or quarterly level depending on the specification. The corresponding price series are sourced from INSEE.[8] They correspond to the actual average prices set by energy providers to firms not covered by

et al., 2012). The difference might be due to the complexity of collecting producer prices (see Gautier, 2008, for a discussion).

[8] To account for the seasonal nature of electricity prices on European markets, we remove the seasonal component from the electricity price series. This adjustment allows us to isolate the underlying price changes faced by manufacturing firms. We observe no significant seasonal trend in gas and oil prices, so no further adjustment is required for these series.

regulated prices.[9]

Individual energy price series are then aggregated across energy sources within a firm, using information on the firm's energy mix measured in the pre-sample period. The shock Δp^E_{ft} is a weighted average of price variations of electricity, natural gas, and petroleum products, with weights w^e_{f0} representing the share of energy e in firm f total energy consumption, measured in tons of oil equivalent. We calculate this weight using data from the INSEE-EACEI survey ("Enquête Annuelle sur les Consommations d'Energie dans l'Industrie"), which provides comprehensive information on energy consumption at the plant level, classified by energy type. To maximize coverage while using pre-sample data, we calculate w^e_{f0} weights for each firm over the period 2014-2017. This approach allows us to capture the relative importance of each energy type in a firm's overall energy consumption. As a result, Δp^E_{ft} can be seen as a shift-share measure of exposure to energy price shocks by individual firms. This measure varies over time due to common fluctuations in energy prices, and between firms due to disparities in their energy mix.[10]

We further adjust the energy shock in equation (1) by the share S^E_{f0} of energy in variable costs, averaged over 2014-2017. This adjustment allows us to express the shock as an energy-driven marginal cost shock, simplifying the interpretation of pass-through coefficients. Nominal energy consumption in the numerator is obtained from the EACEI survey. Total variable costs are recovered from firms' balance-sheet data (Insee-FARE dataset) and include the firm's wage bill and intermediate consumption (including expenditure on raw materials, goods, and services).

Merging individual observations from the EACEI survey with price data yields a dataset of 1,635 firms. Table 1 provides an overview of firms' exposure to energy price variations. The first three columns report the share of energy in firms' overall costs, by industry. On average, energy accounts for 2% of total variable costs for the average firm in our sample. Across industries, paper products, chemicals, and mineral products exhibit the highest average energy shares, at about 4% of total variable costs. Within these sectors, however, variation is substantial: around 10% of chemical firms spend more than 12.4% of their costs on energy.

Interestingly enough, we observe a positive correlation between a firm's energy intensity and its market share.[11] In the cross-section of all firms, the correlation is sizable at 30.6%. While

[9]The distinction is important because the price cap was applied to French regulated prices, which are accessible only to households and small firms. Instead, the firms in our sample were not covered by any price cap. From January 2023, energy-intensive firms could be eligible to a financial support on their energy bill, we thus stop the analysis at the end of 2022. See details in the Online Appendix.

[10]In the shift-share, exposure to energy prices varies, but the variation in the price of each source of energy is common across firms. In practice, firms have different contracts and pay different prices. In Online Appendix A, we provide statistics on energy contracts for a subset of firms in our estimation sample. We discuss the implications for our estimates in Section 3.1.

[11]Our measure of market share combines two sources of information. First, we use the survey weight of each price serie as a measure of the firm's share in total product-level sales in the survey. We then normalize these shares by outside information from INSEE, on the coverage of each product market. The share of each firm in the market times the share of the market covered by the survey leaves us with a proxy for the share of the firm in product-level sales.

this correlation may be specific to the sample under study, it is quantitatively important, as it implies that firms' heterogeneous exposure to energy cost shocks is systematically correlated with their contribution to the PPI.

Beyond exposure, the variation in energy costs across firms and sectors can be attributed to their different energy mixes, described in the next three columns of Table 1. Around 71% of energy costs are associated with electricity consumption, while gas and oil respectively account for 23 and 5% of energy consumption, but the mix varies across firms and industries. This heterogeneity in energy mixes participates to the dispersion in the change in energy costs between 2021Q1 and 2022Q4 given the different dynamics of energy prices during this period.[12] The price of electricity rose by 38% while the price of gas and oil prices rose by 163% and 112% respectively, inducing heterogeneous energy price shocks across industries – see the last column of Table 1). Appendix Figure S2 further illustrates the high heterogeneity in exposure to energy price shocks and displays histograms of energy cost shares and of implied marginal cost shocks.

3 Estimation of pass-through rates

In this section, we study the pass-through of energy cost shocks on producer prices.

3.1 Baseline results

Model and specifications. We estimate a simple equation of pass-through of energy cost shocks into producer prices.

$$\Delta p_{fkt} = \sum_{j=0}^{L} \alpha_j \Delta p^E_{ft-j} \times S^E_{f0} + \beta X_{fkt} + FE_{st} + \epsilon_{fkt} \tag{2}$$

where Δp_{fkt} is the price adjustment in period t for product k of a firm f. Δp^E_{ft} is the corresponding cost shock, measured at the firm level and adjusted for the firm's energy cost ratio S^E_{f0}. In some specifications, we allow for a delayed transmission of the shock, and therefore introduce L energy cost lags. X_{fpt} is a set of controls, which we discuss later. FE_{st} is a set of 2-digit sector-by-period fixed effects. These fixed effects absorb any sector-specific trend to inflation, demand, labor costs, etc. Given the structure of fixed effects, we identify pass-through rates from the cross-section of firms within a sector, exploiting heterogeneity in exposure to the energy cost shock. As shown in Appendix Table S1 and Figure S2 panel (b), cost shocks are positive on average but have a wide dispersion, which helps achieve identification.

Estimating pass-through rates from monthly price data is hampered by the presence of zeros, as firms may not adjust their prices every month, particularly in sectors with higher price rigidity. Burstein and Gopinath (2014) propose a strategy for calculating the pass-through of

[12] Appendix Figure S1 shows the series of energy prices we use, over time.

Table 1: Energy consumption statistics by industry

	Energy costs (S^E_{f0}, %)			Share of... (%)			$\Delta_{22,21}\bar{p}^E_f$
	P10	P90	Avg.	Elec.	Gas	Oil	(%)
Food	.27	2.9	1.61	68.8	27.2	3.75	36.4
Beverages	.14	2.91	1.1	67.3	29.4	3.39	38.8
Textile	.33	6.54	2.73	64.2	31	4.61	39.6
Apparel	0	1.11	.5	68.1	23.9	8.05	30.8
Leather	0	1.62	.67	70.9	22.1	7	30.7
Wood products	.19	4.07	1.69	81.5	7.65	10.8	24
Paper	.74	9.94	4.13	69.8	26.5	3.25	36.2
Printing	.13	4.74	2.16	79.9	18.8	1.34	26.5
Chemicals	.33	11.8	4.1	63.8	28.6	6.42	39.7
Pharma	.36	5.79	2.53	72.1	27.2	.48	35.1
Rubber and plastic	.44	3.68	1.91	82	14.8	3.18	25.8
Mineral products	.46	12.9	4.87	57.3	31.5	9.17	42.8
Metals	.5	6.97	3.9	68.9	24	5.14	34.3
Metal products	.27	3.64	1.55	72.7	22	4.95	32.3
Computers, etc.	.08	1.97	.77	83.5	14.5	2.04	23.1
Electrical products	.18	2.3	1.41	71.6	22.8	4.83	32.4
Machinery	.14	1.51	.73	65.6	28.6	5.81	38.7
Automotive indus.	.12	2.3	1.02	72.8	22.3	4.89	32.7
Transport equip.	.11	1.05	.51	70.2	26.4	3.28	35.6
Furnitures	0	2.34	1.13	73.3	22.3	4.41	28.9
Other manuf.	.08	2.43	1	76.3	20.9	2.77	28.8
All	.16	4.46	2	70.7	23.8	5.07	33.7

Notes: "Energy costs" refers to the ratio of the energy bill to total variable costs (percentage). Total variable costs include the firm's wage bill and intermediate consumption, which consists of raw materials, merchandises, and services. The energy bill is averaged over the pre-sample years (2014-2017). The values reported as P10, P90, and Avg represent the 10th percentile, 90th percentile, and simple average, respectively, of the distribution of the energy costs ratio within each 2-digit industry. "Share of..." refers to the proportion of each type of energy (electricity, gas, and oil products) in the total energy bill (percentage). To calculate the shares, the annual bill of each energy type is averaged over the pre-sample years, and then divided by the average total energy bill. "$\Delta_{22,21}\bar{p}^E_f$" represents the average change in energy costs within each 2-digit industry between 2021Q1 and 2022Q4. It is computed by first calculating the firm-level change in energy prices, which is a weighted average of the changes in electricity, gas, and oil price indices. The weights used are based on the firm-level shares of energy types. Finally, the average change in energy costs is calculated by averaging the firm-level changes within each 2-digit industry.

cumulative changes in costs, *conditional* upon the price being adjusted. One of the limitations of this approach is that energy shocks can also affect the *probability* of price adjustments (Dedola et al., 2022).[13] Cavallo et al. (2021) propose instead to keep the zeros but include lags in their regression of the pass-through of tariffs to border prices. In Table 2, we pursue both strategies. Column (1) uses a balanced panel of monthly price data, while Column (2) is restricted to non-zero price changes. In the latter case, the shock is cumulated over all periods since the last price adjustment. Finally, we aggregate the data at the quarterly level, in Columns (3)-(6).

Table 2: Pass-through of energy cost shocks

	Monthly		Quarterly			
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta p^E_{ft} \times S^E_{f0}$	0.802***		1.786***	1.104***	1.299***	1.152***
	(0.082)		(0.125)	(0.117)	(0.220)	(0.289)
$\Delta p^E_{ft-1} \times S^E_{f0}$	0.306***					
	(0.075)					
$\Delta p^E_{ft-2} \times S^E_{f0}$	0.289***					
	(0.075)					
$\Delta p^E_{ft-3} \times S^E_{f0}$	0.211***					
	(0.076)					
$\Delta p^E_{ft-4} \times S^E_{f0}$	-0.004					
	(0.068)					
$\Delta p^E_{ft-\tau} \times S^E_{f0}$		0.979***				
		(0.081)				
Δp^H_{kt}				0.614***	0.641***	0.610***
				(0.014)	(0.034)	(0.037)
$\Delta p^{H,imp}_{kt}$				0.046**	0.118***	0.106***
				(0.013)	(0.026)	(0.030)
Δp^V_{ft}				0.585***	0.920***	0.906***
				(0.083)	(0.224)	(0.255)
Long-run PT	1.604	0.979	1.786	1.104	1.299	1.152
S.E.	0.169	0.081	0.125	0.117	0.220	0.289
Obs.	366,470	230,053	130,589	130,589	22,865	19,403

Notes: This table reports the results of the estimation of equation (2). All specifications include 2-digit industry by period fixed effects. In Columns (1)-(2), the period is a month. In Column (1), the left-hand side variable is a first difference in logs, and we keep the zeros when prices do not change from a period to the next. In Column (2), the regression is conditional on output price changes and the explanatory variable is the cumulative change in energy costs since the last price change. In Columns (3)-(6), data is aggregated at the quarterly level. In Columns (5)-(6), we run the regression on firms for which we have information on energy contracts. In Column (6), we exclude firms whose contracts is indexed on wholesale prices. Δp^H_{kt} and Δp^V_{kt} respectively denote the "horizontal" and "vertical" shocks. Robust standard errors in parenthesis. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

[13]We estimated an ordered probit model to evaluate the impact of energy cost shocks on the probability that firms adjust prices, following Loupias and Sevestre (2013). The result is a positive but small impact of energy cost shocks on the probability of price adjustment (see Table S3).

Baseline pass-through estimates. The estimated pass-through of energy shocks on producer prices is equal to 80% on impact (Column (1)). Moreover, the coefficients for the first three lags are statistically significant, indicating a smooth adjustment process. When we consider the cumulative impact of 4 months of energy changes, the pass-through rate reaches 160%. In this specification, we cannot reject more than full pass-through of energy cost shocks into producer prices. For a firm with the average exposure to energy cost shocks in our data (2.1%), this pass-through rate implies that a 10% increase in energy costs leads to a price increase of 0.34% (three times higher than the average size of price changes in our pre-crisis period). In Column (2), we exclude zero price changes and estimate the pass-through of energy cost shocks conditional on a price adjustment (Burstein and Gopinath, 2014). The estimated pass-through rate remains high at 98% and is not significantly different from full pass-through. The results in Column (1) indicate that most of the pass-through of energy cost shocks to producer prices occurs within a quarter. For this reason, we then aggregate the data at the quarterly level and reproduce the specification of Column (1) in Column (3). The corresponding pass-through rate is around 179%, which is remarkably similar to the long-term pass-through rate estimated from the monthly data. In unreported results, we verified that introducing a lag in this quarterly specification does not change the results as the entirety of the shock is passed within the next quarter. Based on these results, we will use the static quarterly specification for the remainder of the analysis.

Confounding factors. The reduced form evidence indicates that the pass-through of energy-related cost shocks is high, consistent with full or even more than full pass-through. Our estimates are notably higher than pass-through rates found in the rest of the literature, notably the 70% pass-through rate estimated in Ganapati et al. (2020). In Column (4), we test whether this high pass-through rate is triggered by commonality factors. Energy cost shocks have a strong commonality component since energy prices are mainly determined on global markets. As a result, firms tend to adjust their prices when their competitors and input suppliers are also likely to do so. To account for this common component, we add three control variables to the reduced-form equation: the change in the PPI at the product level, which represents domestic "horizontal" shocks, a measure of foreign "horizontal" shocks calculated from product-specific import price indices and a proxy for changes in input prices, called a "vertical" shock.[14] All three

[14]The "vertical" shock is computed as follows: $\Delta p^V_{ft} = S^I_{f0} \times \sum_{s'} w^{s'}_{f0} \Delta p_{s't}$, where $w^{s'}_{f0}$ denotes the share of sector s' in firm f intermediate consumption and $\Delta p_{s't}$ represents the change in output prices for sector s'. Since we do not have access to individual data on input-output relationships, we assume that the weights $w^{s'}_{f0}$ are sector-specific and use weights obtained from I-O tables. S^I_{f0} represents the firm's exposure to these shocks, which is calculated as the ratio of domestic intermediate consumption (variable costs minus the wage bill and imported intermediate consumption) over variable costs. The "horizontal" shock represents the average price adjustment in the product market. This variable serves as a proxy for how the firm's competitors adjust their prices. The reason why this variable is not multicolinear with fixed effects is that sectors are more aggregated than products in our data. Finally, imported inflation is calculated at product-level using import price indices, also collected through the OPISE survey. Import prices serve as a control for price adjustments from foreign competitors.

control variables are positively correlated with price adjustments at the firm level. Firms adjust their prices in response to their competitors' and also pass on a substantial proportion (69%) of price shocks affecting other input purchases. As expected, the estimated pass-through of the firm-specific energy shock is reduced in this specification, to 110%. But the pass-through rate remains high and not statistically different from full pass-through. In unreported regressions, we find that most of the reduction in pass-through is due to the inclusion of the horizontal price index. This means that the fact that all firms in a product market face the same shocks, albeit with different intensities, partly explains the high level of pass-through we estimate.[15] We will systematically control for these three confounding factors in the rest of the analysis.

The role of energy contracts. In columns (5) and (6) of Table 2, we take advantage of firm-level information on energy contracts, which we observe for a small sub-sample of firms in our dataset using the *Enquête Conjoncture* produced by INSEE. In doing so, we want to test the robustness of our results to one potential source of measurement error, induced by firms facing different energy prices, conditional on their energy mix.[16] As discussed in Section A of the Online Appendix, a significant proportion of the firms in the manufacturing sector benefit from fixed price contracts while roughly 10% of the respondents are instead exposed to more volatile wholesale prices. Fixed price contracts do not insulate firms from exposure to energy price shocks, although the actual intra-year volatility of their costs is reduced. This likely explains that the seasonally-adjusted electricity price serie that we use, which is reproduced in Figure S1, is relatively stable throughout 2021 and displays a significant jump in December 2021-January 2022, when most energy contracts are renewed. Whereas fixed price contracts tend to smooth the impact of volatile energy prices, contracts indexed on wholesale prices instead expose firms to extreme volatility, which the empirical setting neglects.

In Column (5), we reproduce our baseline estimate on the sub-sample of firms which have been surveyed on their energy contract in 2022. In this subsample, the pass-through rate is found higher, at 130%, but not statistically different from the 110% estimated on the full sample (Column (4)). In Column (6), we exclude firms whose contracts is indexed on wholesale prices. Excluding the sub-sample of firms that are systematically exposed to more volatile energy prices tends to lower the pass-through. The pass-through remains high however (115%). Because the patterns do not differ substantially between the two groups, and to preserve sufficient statistical power, we retain all firms, regardless of their contract type, in the rest of the analysis.

Taken together, the evidence in Table 2 thus suggest an almost full pass-through of energy shocks into producer prices over 2018-2022.

[15] See Auer and Schoenle (2016), Muehlegger and Sweeney (2022) for a formal discussion of the bias affecting the estimation of own-cost pass-through when firms' adjustment to competitor prices are not controlled for.

[16] It has to be noted that the direction of a potential bias induced by deviations from our assumption of common price shocks across firms is not clear. While measurement errors tend to drive estimated coefficients down, one may also bias the coefficient up (resp. down) if we systematically underestimate (resp. overestimate) the actual price variations that firms are exposed to.

3.2 Evidence of state-dependent pass-through

In models featuring state-dependent pricing, the average degree of pass-through varies with the size of shocks. As argued by Cavallo et al. (2024), this may have induced an increase in the pass-through of energy shocks during the recent energy crisis, when the distribution of these shocks has been shifted to the right (Figure S2 panel (b)). Table 3, column (1), confirms the theoretical prediction. The pass-through estimated on the pre-crisis period (2018-2020) is incomplete, at 70%, while jumping to 127% during the 2021-2022 energy crisis. The pre-crisis energy pass-through of 70% is similar to the estimate of Ganapati et al. (2020) using U.S. data. In unreported results, we checked that the pre- and post-crisis periods do not significantly differ in terms of the transmission speed: In both cases, the lagged variable is non-significant, indicating that the price effect of the shock is observed in the data within the following quarter.

In the theoretical model developed in Section 4, the state-dependence in prices is driven by firms most exposed to energy cost shocks increasing their effort to adjust prices when hit by a large energy price shock. We provide direct evidence for the mechanism in Columns (2)-(5) of Table 3. Here, we test for heterogeneity in pass-through rates among firms more or less exposed to energy shocks, as defined by their position in the distribution of energy intensities. We consider that the exposure is large if firms belong to the top 5% of firms in terms of energy share (columns 2 and 3) or in the top 10% (columns 4 and 5). Columns (2) and (4) show that firms with a large exposure have a higher pass-through. This result holds in columns (3) and (5) where we further control for heterogeneous pass-through rates in the pre- and post-crisis periods.

Asymmetric pass-through. Results thus confirm significant differences in pass-through rates in normal and crisis times, and a higher pass-through of shocks for more exposed firms. These findings are consistent with state-dependence in firms' price adjustments to energy cost shocks. In Section 4, we thus dig further into the heterogeneity, using the guidance of a theoretical model. Before this, we investigate another interpretation of the observed patterns, associated with asymmetric pass-through. A number of papers in the literature (Peltzman, 2000, Benzarti et al., 2020, e.g.) indeed argue that firms tend to pass positive shocks more quickly than negative cost adjustments. Since the 2021-2022 period is characterized by an almost complete shift of the distribution towards positive energy shocks, the larger pass-through estimated on 2021-2022 may be attributable to composition effects. Although ruling out this possibility is tricky, results in Table S2 suggests that asymmetries in pass-through rates is not the sole explanation of evidence in Table 3. Column (2) indeed confirm that the pass-through rate is on average larger after positive than negative shocks though the effect is imprecisely measured (see the positive coefficient on the interaction of the shock with a dummy for positive shocks). Importantly, column (3) shows that the interaction between the shock and the 2021-2022 dummy remains positive and significant while controlling for asymmetric pass-through.

Actually, in this specification, the coefficient on the interaction with the dummy for positive shocks turns negative, and the coefficient on the post-crisis interaction is doubled compared to the specification in column (1). Although these specifications are characterized by a large degree of collinearity, they seem to suggest that asymmetry does not explain the rise in the pass-through rate during the energy crisis.

Beyond a reduced-form shock. The analysis so far relies on regressions of prices on a reduced-form shock, constructed from firms' observed exposure to shocks and energy price fluctuations measured through the PPI survey. However, the state dependence we measure may be driven by the fact that the reduced-form shock correlates more strongly with firms' actual energy costs in some periods than in others. To move beyond this reduced-form approach, we can leverage the EACEI dataset described earlier. These data allow us to directly measure firms' unit energy costs.[17] The main limitation is that these costs are observed at annual frequency. Another caveat is that the unit energy costs paid by firms may be endogenous, implying that a proper estimation of pass-through requires a 2SLS approach with a credible identification strategy.

Table S4 displays the results of our examination of state-dependent pass-through in yearly data. Columns (1) and (2) reproduce our state-dependent analysis at a yearly frequency using the reduced-form shock. We find consistent evidence of state-dependence pass-through, with coefficients that are remarkably similar to the ones estimated using quarterly data. In columns (3) to (6), we instead regress the change in producer prices on the change in energy unit costs paid by the firm. In columns (3) and (4), the energy unit cost is instrumented by the reduced form cost used in columns (1) and (2). In columns (5) and (6), the energy unit cost shock of each firm is instrumented by a variable that uses energy price shocks incurred by all firms in the sample, excluding the firm' own shock. Both strategies estimate an average pass-through rate that is not significantly different from the coefficient recovered from the reduced-form equation in column (1). Moreover, results in columns (4) and (6) confirm that the pass-through rate is higher in 2021-2022, compared to the pre-crisis period, although the effect in column (4) is imprecisely measured. While running a comparable IV specification in quarterly data is not possible, these results thus confirm that the state-dependence observed in earlier results is not an artefact of the use of a reduced-form equation interpreted in terms of firm-level pass-through behaviors.

[17] Specifically, we measure changes in energy costs at firm-level as a quantity weighted average of the growth rates of unit values on the firm's purchases of electricity, oil and gas. The shock is the product of changes in energy costs and the share of energy in firms variable costs.

$$\Delta s^E_{ft} = S^E_{f,t-1} \times \sum_e w^e_{f,t-1} \Delta p^e_{ft}$$

where $S^E_{f,t-1}$ is the share of energy expenditures in firms total variable costs, $w^e_{f,t-1}$ is the share of energy e in the total energy consumption of the firm in the year before and Δp^e_{ft} is the (log) change in the unit value of purchases of energy e, as defined by the ratio of the value over the quantity of energy consumption.

Table 3: Pass-through of energy cost shocks: State-Dependence

		Exposure			
	(1)	(2)	(3)	(4)	(5)
$\Delta p_t \times S_0^E$	0.694***	0.697***	0.325	0.682***	0.240
	(0.133)	(0.217)	(0.239)	(0.172)	(0.214)
$- \times (Y \geq 2021)$	0.573***		0.564***		0.587***
	(0.198)		(0.198)		(0.200)
$\Delta p_t \times S_0^E \times large$		0.415*	0.381*	0.460**	0.484**
		(0.217)	(0.216)	(0.188)	(0.188)
Δp_{kt}^H	0.614***	0.614***	0.614***	0.614***	0.614***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
$\Delta p_{kt}^{H,imp}$	0.046***	0.046***	0.046***	0.046***	0.046***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Δp_{ft}^V	0.594***	0.578***	0.587***	0.582***	0.591***
	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)
Observations	130,589	130,589	130,589	130,589	130,589
Period	2018-2022	2018-2022	2018-2022	2018-2022	2018-2022
Percentile Threshold		0.0462	0.0462	0.0796	0.0796

Notes: Quarterly data. *large* is a dummy equal to one if the firm / shock falls in the top 5th percentile (columns (2)-(3)) / 10th percentile ((columns (4)-(5)) of the corresponding distribution. Percentiles are computed along the distribution of exposure. Estimates with robust standard errors in parenthesis. It includes 2-digit industry x time fixed effects.

4 A model of state-dependent pricing

In this Section, we develop a tractable model of state-dependent pricing to rationalize the stylized facts just described. The model is based on Cavallo et al. (2024) who model state-dependence in firms' pricing decisions through a generalized hazard function *à la* Caballero and Engel (2007). The model is used to analyze the transmission of energy price shocks to aggregate prices, in normal time and in a crisis period characterized by large energy cost shocks. Compared to Cavallo et al. (2024), we extend the theoretical framework to take into account heterogeneity across firms in their size and exposure to aggregate energy cost shocks. This heterogeneity is indeed a striking feature of the data, as discussed in Section 2.

4.1 Model assumptions

Households. Time is continuous and the representative household maximizes the following discounted present value:

$$\int_0^\infty e^{-\rho t}\left[\frac{C_t^{1-\epsilon}}{1-\epsilon}-\alpha H_t+\log\left(\frac{M_t}{P_t}\right)\right]dt$$

where ρ is the discount rate, H_t is the aggregate labor supply and M_t/P_t is the real value of money holdings. The representative household consumes a CES aggregate C_t of imperfectly substitutable varieties, each produced by a firm f, associated with an ideal price index P_t:

$$C_t=\left[\int_0^1 (A_{ft}c_{ft})^{\frac{\eta}{\eta-1}}\,df\right]^{\frac{\eta-1}{\eta}},\quad P_t=\left[\int_0^1\left(\frac{p_{ft}}{A_{ft}}\right)^{1-\eta}df\right]^{\frac{1}{1-\eta}}$$

η is the elasticity of substitution between varieties. A_{ft} denotes a preference parameter which we will use to match the observed heterogeneity across firms in terms of their market shares.

Households choose consumption, labor supply and money demand to maximize their intertemporal utility under the following budget constraint:

$$M_0+\int_0^\infty Q_t\left(W_t(1+\tau_\ell)H_t+\Pi_t+\tau_t-R_tM_t-\int_0^1 p_{ft}c_{ft}df\right)dt=0$$

with M_0 the initial stock of money holdings, $Q_t=exp(-\int_0^t R_s ds)$ the real discount factor, R_t the nominal interest rate, W_t the nominal wage rate, Π_t firms' residual profits, τ_t a lump-sum transfer, τ_ℓ a labor income tax. Following Cavallo et al. (2024), a distortionary labor tax is introduced to insure that the flexible price equilibrium is efficient: $(1+\tau_\ell)=\frac{\eta}{\eta-1}$.

In Appendix B, we solve the problem of the household and discuss the equilibrium conditions. In particular, we derive the demand addressed to final good producers:

$$c_{ft} = C_t A_{ft}^{\eta-1} \left(\frac{p_{ft}}{P_t} \right)^{-\eta} \tag{3}$$

Firms. Firms compete under monopolistic competition, given the following CRS technology:

$$y_{ft} = Z_f \left(\frac{h_{ft}}{Z_{ft}} \right)^{1-\xi_f} m_{ft}^{\xi_f}$$

In this equation, h_{ft} is the firm's labor demand, Z_{ft} denotes the productivity of labor, Z_f is total factor productivity, and m_{ft} is energy consumption. Compared to Cavallo et al. (2024), we allow for heterogeneity in firms' energy intensity ξ_f. As a consequence, firms' exposure to energy price shocks is also heterogeneous, as evident from the form of their marginal cost:

$$mc_{ft} = Z_f (W_t Z_{ft})^{1-\xi_f} \; E_t{}^{\xi_f} \; B_f \tag{4}$$

where $B_f \equiv \xi_f^{-\xi_f}(1-\xi_f)^{\xi_f - 1}$ is a firm-specific technological constant, W_t is the wage rate and E_t is the price of energy. Consistent with the empirical analysis, the assumption is that the price of energy is homogeneous across firms but energy price shocks have heterogeneous marginal cost consequences due to heterogeneity in the production function. In the rest of the analysis, we interpret the S^E_{f0} cost share observed in the data as the empirical counterpart of ξ_f.

Following Cavallo et al. (2024), we assume that the time-varying component of firms' labor productivity is stochastic so that $Z_{ft} = e^{\sigma z_{ft}}$ where each z_{ft} follows a Brownian motion independent from other firms'. In this setting, σ^2 is a measure of the volatility of idiosyncratic productivity shocks, that we will later calibrate using the distribution of price changes observed in the data prior to the energy crisis. We will also impose $Z_{ft}^{1-\xi_f}/A_{ft} = 1$ so that both optimal prices and market shares are deterministic. In this setting, the baseline productivity Z_f, together with the technological constant B_f, shape the baseline distribution of market shares. These parameters are homogeneous across firms in Cavallo et al. (2024) and are instead calibrated based on the data in Section 5.

4.2 The price-setting problem

In the absence of price rigidities, the firm would set prices as a constant markup over its marginal cost:

$$p^*_{ft} = \frac{\eta}{\eta - 1} mc_{ft}$$

The (log) price gap between the firm's current and optimal price is

$$x_{ft} = \log(p_{ft}) - \log(p^*_{ft})$$

The firm's profit function, in real terms, is given by

$$
\begin{aligned}
\frac{\Pi(x_{ft}, ms^*_{ft}, t)}{P_t} &= \frac{(p_{ft} - mc_{ft})c_{ft}}{P_t} \\
&= e^{-\eta x_{ft}} \left(e^{x_{ft}} - \frac{\eta - 1}{\eta} \right) ms^*_{ft} C_t \left(\frac{P_t}{P^*_t} \right)^{\eta - 1}
\end{aligned}
$$

where ms^*_{ft} is the firm's (deterministic) market share in the flexible price equilibrium. As in Cavallo et al. (2024), the firm's real profit is decreasing in the price gap x_{ft}, i.e. firms incur a profit loss from not adjusting their price continuously. Compared to Cavallo et al. (2024), the profit function also involves the firm's flexible price market share ms^*_{ft}, and its distribution across firms (through the aggregate flexible price level, P^*_t), as well as aggregate consumption C_t. In Cavallo et al. (2024), firms have homogeneous market shares, and face a combination of purely idiosyncratic and pure macro shocks, which implies that neither P_t nor any other aggregate variable deviate significantly from their flexible-price values in equilibrium. In our case, the heterogeneous exposure of firms to energy cost shocks, combined with heterogeneous market shares, generates potential deviations of aggregate variables from their flexible-price counterparts.

We now introduce nominal rigidities, by letting firms choose the probability of a price adjustment in each period, which is denoted ℓ_t. The firm's problem consists in choosing a path of ℓ_t to minimize the flow cost of deviating from the flexible-price mark-up:

$$
\nu(x, 0) = \min_{\ell_s, x^*} \mathbb{E} \left[\int_t^\infty e^{-\rho s} \left[F(x_{fs}, s) + (\kappa \ell_s)^\gamma \right] ds \middle| x_{f,0} = x \right], \tag{5}
$$

where ℓ_s is the hazard rate of adjusting prices at time s, $(\kappa\ell_s)^\gamma$ is the cost of adjusting with probability ℓ_s, and x^* is the firm's optimal price gap.[18] In equation (5), $F(x_{fs}, s)$ measures forgone real profits associated with deviations from the optimal price, expressed in relative terms with respect to no price gap in the steady state:[19]

$$
\begin{aligned}
F(x_{fs}, s) &= 1 - \frac{\Pi(x_{fs}, ms^*_{fs}, s)/P_s}{\Pi_{ss}(0, ms^*_{fs}, s)/P_{s,SS}} \\
&= 1 - \eta e^{-\eta x_{ft}} \left(e^{x_{ft}} - \frac{\eta - 1}{\eta} \right) \left(\frac{P_s}{P_{s,SS}} \right)^{-\frac{1}{\varepsilon} + \eta - 1}
\end{aligned} \tag{6}
$$

where $P_{s,SS}$ stands for the price index in a steady state. The flow cost function is identical across firms. The cost evolves over time only through the aggregate price level, which summarizes

[18] In this model, firms do not choose the flexible price when adjusting their price because their marginal cost is stochastic and they realize that the flexible price may not be optimal in the future. As a consequence, x^* is not equal to zero in equilibrium.

[19] Note that simplifications leading to the formula hold in steady state and along a transition after a permanent shock. Instead, if energy shocks are stochastic, the trajectories of flexible price market shares and of the aggregate price level have no reason to coincide with their steady-state values.

the joint distribution of price gaps and market shares. Compared to Cavallo et al. (2024), this dependence makes the value function time-dependent. In steady state however, the ratio of P_s over $P_{s,SS}$ is equal to one by definition and we are back to the model solved in Cavallo et al. (2024).

4.3 Solution to the pricing problem

Solving the firm's problem involves minimizing the flow cost in equation (5) accounting for the fact x_{ft} evolves according to a stochastic process:

$$dx_{ft} = -\mu dt + \sigma dz_{ft}$$

where μ is the growth rate of money supply.[20] Hence, $\nu(.,.)$ solves the following Hamilton-Jacobian-Bellman (HJB) equation:

$$\rho\nu(x_{ft},t) = F(x_{ft},t) + \nu_t(x_{ft},t) - \mu\nu'(x_{ft},t) + \tfrac{1}{2}\sigma^2\nu''(x_{ft},t) + \min_{\ell_{ft}\geq 0}\{\ell_{ft}\left[\nu(x_t^*,t) - \nu(x_{ft},t)\right] + (\kappa\ell_{ft})^\gamma\}$$

with x_t^* satisfying $\nu_t'(x_t^*,t) = 0$. Note that both the value function and the optimal price gap are identical across firms, as they share the same $F(.,.)$ function. The solution to this equation is a time-dependent hazard function:

$$\ell_{ft}^* = \Lambda(x_{ft},t) = \frac{1}{\kappa}\left(\frac{\nu(x_{ft},t) - \nu(x_t^*,t)}{\kappa\gamma}\right)^{\frac{1}{\gamma-1}} \tag{7}$$

The decision rule for firms results in a generalized hazard function as in Caballero and Engel (2007). This setup embeds a large class of sticky-price models, including the time-dependent model in Calvo (1983) ($\gamma \to \infty$) and state-dependent models in Golosov and Lucas (2007) and Nakamura and Steinsson (2010) ($1 < \gamma < \infty$).

The price gap evolves according to a stochastic differential equation and thus its distribution verifies a Kolmogorov Forward Equation (KFE), that is given by

$$m_t(x,t) = -\Lambda(x,t)m(x,t) + \mu m(x,t) + \frac{1}{2}\sigma^2 m''(x,t), \quad x \neq x_t^* \tag{8}$$

A notable difference with Cavallo et al. (2024) is that the optimal price gap is not time-invariant. This is due to feedback effects from the joint distribution of price gaps and market shares to the aggregate price index, which is negligible in the homogeneous-firm model of Cavallo et al. (2024). Hence, the equilibrium is a fixed point problem, in which the HJB and the KFE equations are verified with a consistent path for P_t.

[20] See details in Appendix B. Outside energy crises, the assumption is that the price of energy evolves at the same rate as wages, which is also the growth rate of money supply.

4.4 Energy cost shocks and state-dependent pass-through

We now consider the response of firms and the economy to a permanent energy cost shock. At some time 0, the price of energy jumps so that $d\ln E_0 = e^{\delta}+\mu$ (given $d\ln E_s = \mu$, $\forall s \neq 0$). Since the shock is permanent, the aggregate price level increases in the steady state, in proportion to the average energy intensity of firms in the economy, times the size of the shock. The dynamics of prices in the steady state is however left unchanged.

On impact, the distribution of price gaps shifts to $\hat{m}$ such that:

$$\hat{m}(x,0) = \int \mathbb{1}(\tilde{x} - \xi_f \delta = x) m_{SS}(\tilde{x}) G(\xi_f) d\tilde{x} d\xi_f$$

where $\hat{m}(x,0)$ denotes the post-shock distribution, evaluated at time 0, and $\mathbb{1}(\tilde{x} - \xi_f \delta = x)$ is a dummy variable that is equal to one for all firms with pre-shock price gap $\tilde{x}$ and energy intensity ξ_f such that $\tilde{x} - \xi_f \delta = x$. Starting from this new distribution of price gaps, the transition to the new steady state is described by the time-dependent hazard function described in Eq. (7) and the distribution of price gaps verifies a Kolmogorov Forward Equation as in Eq. (8).

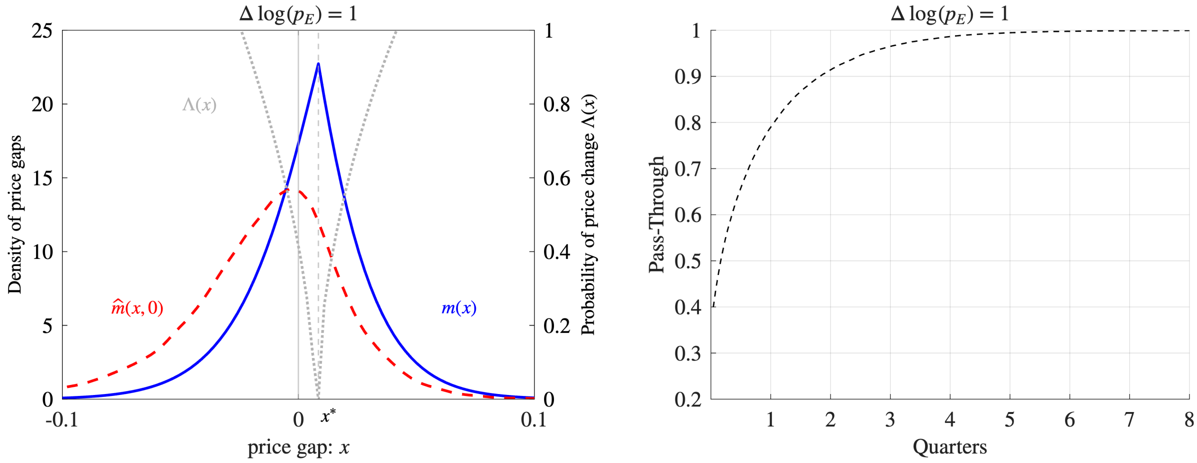
The instantaneous impact of the energy price shock on the distribution of price gaps is illustrated in panel (a) of Figure 2. In Cavallo et al. (2024), the shock shifts the whole distribution of price gaps to the left, leaving the shape of the distribution unchanged. When firms' exposure to energy price shocks is heterogeneous, the shock further affects the shape of the distribution. In the calibration used in Figure 2, the mass of firms displaying large negative price gaps increases, due to the large exposure of high-ξ_f firms to the energy cost shock. As the hazard function is increasing in (the absolute value of) price gaps (grey line in panel (a) of Figure 2), the shock increases the average effort of firms to adjust their price, thus the frequency of price adjustments.

The rise in the frequency of price adjustments ($N(t) = \int \Lambda(x,t)\hat{m}(x,t)dx$) is the fundamental force at the root of the rise in the aggregate pass-through rate. Since firms return to their optimal price gap whenever they have the opportunity to adjust, and the optimal price gap is unaffected by the permanent energy shock, the firm-level pass-through of the shock is complete after the first price adjustment. As a consequence, the aggregate pass-through only depends on the (time-varying) share of firms that have adjusted their price at least once after the shock. This pass-through rate is illustrated in panel (b) of Figure 2. On impact, the frequency of price adjustments increases, thus the pass-through of energy price shocks. In the baseline calibration, the pass-through is equal to 40% on impact. This corresponds to the share of firms that immediately get an opportunity to adjust their price, and pass the energy shock entirely as a consequence. Over time, the pass-through smoothly converges towards 100% while more and more firms adjust their price.

We can now confront the model's predictions with the empirical evidence discussed in Section 3. Panel (a) of Figure 3 illustrates how the model replicates changes in the degree of instantaneous pass-through in normal times and during episodes of soaring energy prices. Be-

Figure 2: Consequences of a permanent energy price shock

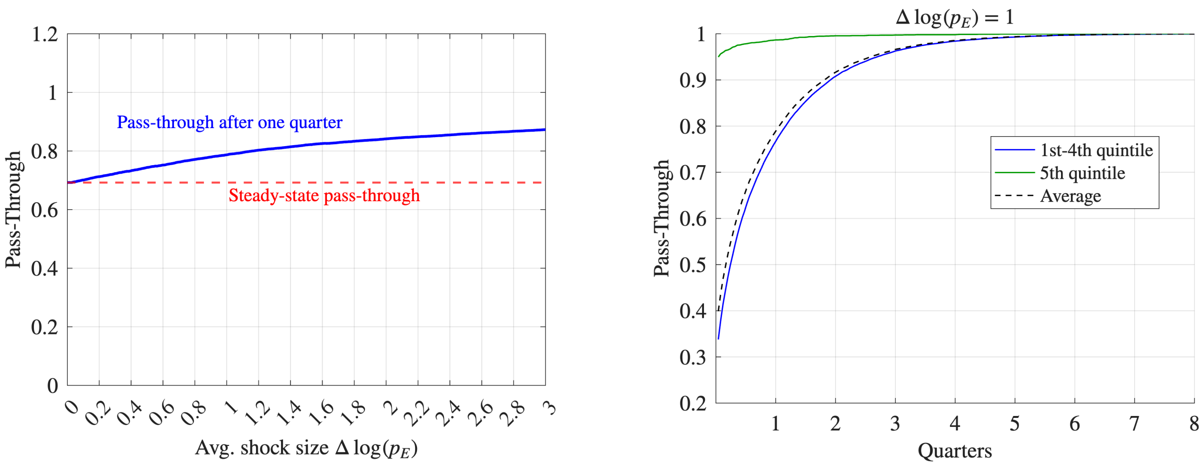
Panel (a): Price gaps and hazard function **Panel (b)**: Average pass-through



Notes: In **Panel (a)**, $m(x)$ is the steady state price gaps distribution. $\hat{m}(x, 0)$ is the distribution of price gaps just after the shock. $\Lambda(x)$ is the Generalized Hazard Function. **Panel (b)** displays the pass-through rate, over time. In both panels, parameters are taken at calibrated values from Section 5.1 and the energy price shocks is normalized to 100%.

Figure 3: State-dependent pass-through rates

Panel (a): Size of the shock **Panel (b)**: Cross-sectional heterogeneity



Notes: **Panel (a)** illustrates how the pass-through on impact varies as a function of the size of the shock. **Panel (b)** displays the pass-through rate, over time, along the distribution of firms' energy intensities. In both panels, parameters are taken at calibrated values from Section 5.1.

cause the shift in the distribution of price gaps ($\hat{m}(x,0) - m(x,0)$) depends on the size of the shock, larger energy cost shocks are associated with a faster transmission to producer prices and, consequently, higher pass-through rates. As shown in Figure 3, panel (a), the average pass-through of energy cost shocks after one quarter increases by about 10 percentage points as shocks vary from 0 to 100%. Given the low average exposure to energy shocks, this represents a sizable effect.

Likewise, the model reproduces the cross-sectional heterogeneity in pass-through behavior along the distribution of energy intensities. Panel (b) of Figure 3 contrasts the dynamics of average price adjustments between firms in the top 20% and those in the bottom 80% of the energy-intensity distribution. Because the distribution of price gaps shifts more strongly on impact for firms in the fifth quintile, their price adjustment probabilities are more responsive to the shock, resulting in a faster transmission to producer prices. When the shock is calibrated at 100%, the difference is substantial: instantaneous pass-through remains below 30% for firms in the bottom 80% of the distribution, but exceeds 80% for the most energy-intensive firms. Qualitatively, the model is therefore able to reproduce both stylized facts documented in micro-price data during the energy crisis.

5 Quantitative insights

5.1 Estimation of the model

The model features 8 parameters $(\alpha, \eta, \varepsilon, \rho, \mu, \gamma, \kappa, \sigma)$, which are calibrated and/or estimated at the quarterly frequency. We chose the parameters in two steps. In the first step, we calibrate $(\alpha, \eta, \varepsilon, \rho)$ to values taken from the literature. We set the parameters of risk aversion and labor disutility following Golosov and Lucas (2007), which implies $\alpha = 6$, $\varepsilon = 2$. The elasticity of substitution is calibrated to a value of $\eta = 6$, so that the flexible-price markup is equal to 20%. The discount rate is fixed at $\rho = 0.012$, for an annual discount factor of 0.95. We additionally set pre-crisis quarterly inflation rate to $\mu = 0.5\%$. In the second step, we use indirect inference to recover the value of the effort cost parameters (κ, γ) and of the variance of idiosyncratic productivity shocks σ. We use identification results from Cavallo et al. (2024), in which those three parameters are identified at steady state from the variance of price changes (σ), the frequency of price changes (κ) and the kurtosis of price changes (γ).

A challenge is that our data exhibit price adjustment frequencies exceeding conventional values.[21] Hence, we chose not to target the measured frequency of price changes and instead

[21] In our data, the monthly frequency of price adjustments is equal to .55, to be compared to .21 reported in Vermeulen et al. (2012) for the euro area. One possible reason is that producers may declare the price set on their average downstream partner. If this is the case and prices are not systematically reset at the same time (e.g. because of the existence of long-term contracts), the frequency of (average) price adjustments may not be measured accurately. To the extent that the problem is equally important along the distribution of firms, empirical moments calculated from the cross-sectional variance of price adjustments can still be exploited for identification.

use the level of (pre-crisis) pass-through after one period. As explained in Section 4.4, the pass-through rate is closely tied to the (true) frequency of price changes. We thus target the level of pass-through after one quarter in the pre-crisis period (0.69). The kurtosis of price changes measures by how much price changes are concentrated around their mean. In the model, it is closely tied to the curvature of the hazard function Λ as the steepness of Λ dictates by how much the probability to reset prices varies with price gaps. Last, the variance of idiosyncratic shocks σ^2 is well identified by the variance of price changes in the pre-crisis period. Targeted moments are summarized in Table 4, column (3).

We estimate $\theta = (\gamma, \kappa, \sigma)$ using an interior-point algorithm to find the triplet θ^* that minimizes the mean square error of simulated moments, expressed as a deviation from data moments:

$$\mathcal{L}(\hat{\theta}) = \sqrt{\sum_i \left(\frac{h_i(\hat{\theta}) - h_i(\theta)}{h_i(\theta)}\right)^2} \tag{9}$$

where $h(\theta)$ is the vector of moments computed from the data and $h(\hat{\theta})$ from the model.

Results. Table 4 reports estimation results, together with a summary of the model fit, on targeted moments. The model performs well in matching the firm-level data. As the standard deviation (resp. kurtosis) of price changes is smaller (resp. larger) in our data than what is reported for the French food industry by Cavallo et al. (2024), we estimate a smaller value for σ (resp. a larger value for γ). Figure S3 in Appendix displays the loss function and the simulated moments around the estimated parameters, showing that the estimated parameters are an actual optimum.

Table 4: Moments and calibrated parameters

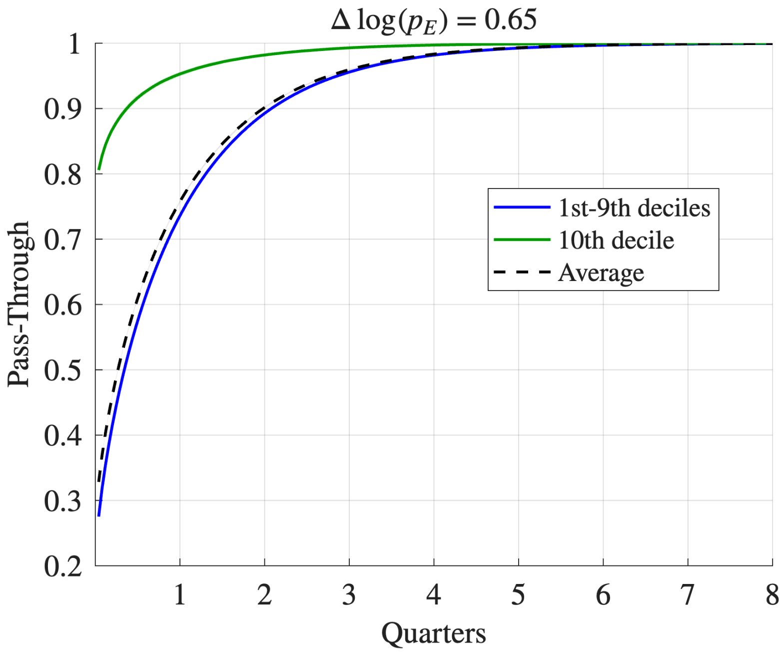
Parameter	Estimated value (1)	Targeted moment (2)	Data (3)	Model (4)
σ	0.028	Std. Dev of price changes	0.0346	0.0360
γ	4.288	Kurtosis of price changes	3.219	3.222
κ	0.265	PT after one quarter	0.694	0.695

Notes: All moments are computed on the pre-crisis period, 2018-2020. The standard deviation of price changes is computed as the average across products of the standard deviation of price changes at the product-level. Kurtosis is estimated accounting for unobserved heterogeneity, following Alvarez et al. (2022). To increase precision in computing variance and kurtosis, we remove products with less than three price spells.

5.2 Model fit during the energy crisis

Based on the estimated model, we now study the dynamics of prices following an aggregate energy price shock comparable to that observed in 2021–2022. To this end, we first introduce firm heterogeneity by jointly drawing firms' flexible-price market shares ms_f^* and energy cost

Figure 4: Price dynamics after the energy shock in the estimated model



Notes: This figure illustrates average price adjustments after an energy price shock within the estimated model, over time. The dashed line is for the average firm in the economy. The green line corresponds to firms belonging to the top decile of the simulated population, in terms of energy intensities. The blue line corresponds to the bottom nine deciles.

shares ξ_f so as to match both their marginal distributions and their correlation in the pre-crisis period. The simulated distribution of energy cost shares is a beta mixture and market shares follow a normalized Pareto distribution. From market shares and energy cost shares, we recover firms' baseline productivity Z_f,, which is required to compute the post-shock steady state. Since ms^*_{ft} is proportional to $\left(Z_f \left(\frac{E_t}{W_t}\right)^{\xi_f} K_f\right)^{1-\eta}$, conditional on an initial value of $\frac{E_0}{W_0}$, we can identify Z_f up to a constant. We then simulate an economy with 30,000 firms. During 2021–2022, quarterly energy prices increased by 6.35% on average. We therefore model the shock as a permanent 65% increase in energy prices occurring at time 0.[22]

Figure 4 illustrates the price dynamics following the energy price shock in the estimated model. The price adjustment frequency rises on impact, increasing the instantaneous pass-through rate to 33%. Although post-shock price adjustment is relatively rapid, the average pass-through after one quarter, at 76%, remains below the full pass-through estimated from micro-level data during the crisis period.

The discrepancy between the model's predictions and the empirical estimates can reflect two factors. First, the model is deliberately parsimonious and therefore omits potentially important mechanisms, such as heightened attention and changes in expectations during 2021–2022,

[22]In doing so, we follow the strategy in Cavallo et al. (2024) and model the energy price increase as a one-time permanent shock. This modeling choice simplifies the analysis by abstracting from firms' expectations about the future path of shocks. Under a sequence of repeated shocks, firms' pricing decisions would reflect both the contemporaneous impact of each shock on adjustment frequencies and forward-looking considerations about future cost increases, which would affect the size of price adjustments.

which may have contributed to higher pass-through rates (Pfauti, 2023). Second, the average pass-through estimated on the pooled sample may be overstated. In particular, neglecting heterogeneity in pass-through rates along the distribution of firms' exposure can generate a heterogeneity bias.

Consistent with the second explanation, the fit of the model improves when focusing on sub-samples of firms varying by their exposure to the energy crisis. For firms in the bottom 90 percent of the exposure distribution (the least exposed firms represented by a blue line in Figure 4) the model implies a one-quarter pass-through of 73 percent, compared with 82 percent in the data (column (5) of Table 3). By contrast, among firms in the top 10 percent of the exposure distribution (green line), the predicted pass-through exceeds 95 percent and is not statistically different from the more-than-full pass-through observed in the micro-level data. Despite its parsimonious structure, the model delivers a good quantitative fit, and reproduces the heterogeneity observed across firms.

5.3 Impact of heterogeneous exposures to common shocks

A key novelty of the model is that it accounts for firms' heterogeneous exposure to the surge in energy prices. Consistent with the empirical evidence, the model predicts that more exposed firms exhibit higher pass-through of energy cost shocks. We now assess how heterogeneous exposure shapes the aggregate price response to energy price shocks. Rather than computing the unweighted average firm-level response—which we use as the model counterpart to the pass-through rate estimated in the micro-level data—we compute a sales-weighted average of firm-level pass-through rates to recover the model-implied response of the producer price index (PPI). We then conduct two counterfactual exercises.

In the first exercise, we compare the benchmark aggregate pass-through—computed using the observed joint distribution of energy intensities and market shares—with that obtained in a counterfactual economy in which all firms face identical exposure to energy price shocks. In this counterfactual, energy cost shares are set equal across firms, either to the simple average or to the sales-weighted average observed in the data. This comparison allows us to isolate the role of heterogeneity in exposure in shaping aggregate price dynamics.

Panel (a) of Figure 5 summarizes the results.[23] Relative to the unweighted average firm-level pass-through reported in Figure 4, the aggregate price index displays a higher response to energy price shocks, reflecting the fact that larger firms—whose prices receive more weight in the PPI—are on average more exposed to energy price increases. As a result, their higher pass-through rates raise aggregate pass-through. After one quarter, the estimated model implies an 84 percent pass-through of the energy shock to the PPI.

Interestingly, neither homogeneous-firm specification exactly replicates the aggregate re-

[23]Due to the highly skewed distribution of market shares, the computed aggregate pass-through is sensitive to randomness in firm-level draws. In Figure 5, we therefore report the median across 100 simulations, together with confidence bands defined by the 25th and 75th percentiles.

sponse in the baseline model. When energy cost shares are set equal to the simple average across firms (red line in Figure 5), aggregate pass-through is almost 10 percentage points lower than in the baseline model, because this calibration understates the exposure, and thus the responsiveness, of large firms. By contrast, when energy cost shares are set equal to the sales-weighted average, the homogeneous model slightly overestimates aggregate pass-through. In this case, a large mass of firms in the lower part of the exposure distribution is predicted to exhibit pass-through rates above the 72 percent average implied by the heterogeneous-firm model, which mechanically pushes the elasticity of the aggregate price index above its baseline value.

Note that, in theory, models with homogeneous and heterogeneous exposure can differ for two distinct reasons. The first is mechanical: when more exposed firms are larger, aggregate pass-through increases because these firms receive greater weight in the aggregate price index. The second reason is more subtle. Heterogeneity in firms' exposure to shocks along the size distribution amplifies the feedback effect of price adjustments on the aggregate price index along the transition path, which in turn induces time variation in firms' optimal price gaps following the shock. In principle, this effect could be quantitatively important relative to the homogeneous-firm framework of Cavallo et al. (2024), since the systematic correlation between price deviations and market shares magnifies deviations of the aggregate price index from its steady-state value. In Appendix Figure S4, however, we show that the resulting state dependence of optimal price gaps has a negligible impact on the response of the aggregate price index to the shock.

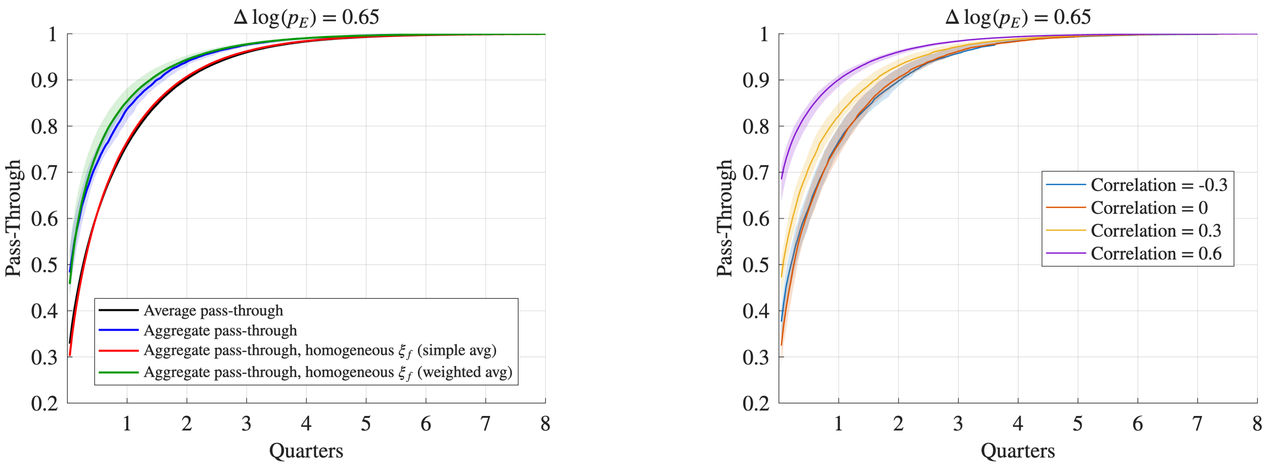
In the second exercise, we compute aggregate pass-through rates for different values of the correlation between firm size and shock exposure. Panel (b) of Figure 5 shows that a higher correlation between size and exposure leads to substantially greater aggregate pass-through. While this relationship is intuitive, the model allows us to quantify its magnitude. Increasing the correlation from 0 to 60% raises aggregate pass-through by 40 percentage points on impact (from 40% to 80%), and by 12 percentage points after one quarter.

Interestingly, aggregate pass-through is very similar when the correlation is zero or negative. The reason is that, even in the absence of a positive correlation, a sizable mass of firms adjusts prices at high frequency, sustaining a baseline level of aggregate pass-through. By contrast, increasing the correlation between energy intensities and market shares has quantitatively important effects by shifting greater weight toward firms that face larger cost shocks and thus adjust prices more frequently.

Taken together, these two exercises show that heterogeneous exposure to common shocks has quantitatively significant effects on the level of aggregate pass-through. Although we illustrate this mechanism in the context of the 2021–2022 surge in energy prices, it applies more broadly to any macroeconomic shock for which firms face non-uniform exposure, such as changes in the minimum wage, interest rates, or exchange rate fluctuations.

Figure 5: The role of firm heterogeneity for pass-through

Panel (a): Energy cost share heterogeneity **Panel (b)**: Cost shares and market shares correlation



Notes: **Panel (a)** reports the aggregate pass-through of price changes following an aggregate energy price shock, comparing an economy in which firms are homogeneous in energy cost shares (red and green lines) with the baseline economy featuring heterogeneous cost shares (blue line). The black line corresponds to the simple average pass-through already reported in Figure 4. In the homogeneous-economy counterfactuals, the red line sets energy cost shares equal to their simple average in the data, while the green line uses the sales-weighted average. Lines and bands correspond to the median, 25^{th} and 75^{th} percentiles of the values over 100 simulations. **Panel (b)** reports aggregate pass-through rates computed in counterfactual scenarios in which the correlation between market shares and exposure to energy price shocks is varied, holding all other parameters at their calibrated values. Lines and bands correspond to the median, 25^{th} and 75^{th} percentiles of the values over 100 simulations.

6 Conclusion

Using detailed micro-level data on individual prices and energy usage, we document three key facts. First, firms' exposure to energy prices is highly heterogeneous, even within narrowly defined industries. Second, the pass-through of energy prices is state-dependent: it increased from roughly 70% before 2021 to full pass-through during 2021–2022. Third, pass-through is higher among firms that are most exposed to energy price shocks.

We show that a state-dependent pricing model à la Cavallo et al. (2024), augmented with heterogeneous exposure to macroeconomic supply shocks, can replicate both the surge in pass-through following a large aggregate shock and the higher pass-through observed among more exposed firms. While the estimated model somewhat underestimates the increase in pass-through during the energy crisis, it successfully reproduces the heterogeneity in pass-through rates along the distribution of energy intensities. Other concomitant shocks, together with the heightened salience of energy price increases, may account for the remaining gap.[24]

Our quantitative exercises also shed light on the macroeconomic implications of heterogeneous exposure to common shocks. In the context of the energy crisis, we find that heterogeneity in exposure along the distribution of market shares plays a central role in accelerating the transmission of energy price shocks to producer prices.

[24]In an early version of this work (Lafrogne-Joussier et al., 2023), we showed that pass-through is higher in quarters when the energy crisis received substantial public attention. Pfauti (2023) proposes a model that rationalizes higher pass-through when shocks are more salient.

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Online Appendix

A Energy contracts

The shift-share variable used to measure energy-cost shocks at the firm-level relies on the implicit assumption that manufacturing firms are all exposed to the same fluctuations in energy prices, conditional on the type of energy. In reality, firms display different energy contracts, that determine the volatility of their energy costs.

In September 2022, INSEE has conducted a survey on firms in the manufacturing and service sectors, to evaluate their exposure to the energy crisis (INSEE, 2022). The survey included questions on the firm's consumption of energy and gas including the value of its energy bill, the nature and expiration date of its contract with the energy provider, the estimated evolution of the unit price paid on energy between 2021 and 2022, the anticipated evolution of the price between 2022 and 2023, and the expected effect of energy prices on the firm's activity in the coming months. The survey covered 1,319 firms, out of which 412 can be matched with our estimation sample.

Table A1: Descriptive statistics on energy contracts

	Electricity	Gas
Number of firms	412	302
Contract type (%)		
Regulated prices	8.5	0
Indexed on regulated prices	6.8	0
Fixed price	47.3	45.4
Indexed on wholesale prices	10.9	14.8
Other	21.4	13.1
No response	5.1	26.7
Contract renewal (Fixed price contract) (%)		
Before end of 2022	53.8	34.8
2023-S1	6.7	8.6
2023-S2	24.1	28.3
2024	8.7	15.0
2025+	6.7	10.7
Estimated price increase 2021-2022 (%)		
Fixed price contract	11.6	44.8
Contract indexed on wholesale prices	81.2	159.8
Estimated price increase 2022-2023 (%)		
Fixed price contract	53.3	28.4
Contract indexed on wholesale prices	48.9	78.1

Notes: The table gives statistics on the subsample of firms in the estimation sample which are surveyed in INSEE (2022). The top panel covers the nature of their contract with their energy provider. It has to be noted that regulated prices are restricted to firms with less than 10 employees. In our data, all firms that declare benefiting from a contract with regulated prices have more than 10 employees. The second panel is the expiration date of the contract, conditional on the firm benefiting from a fixed-price contract. The third panel is the average estimated unit price increase between 2021 and 2022. The fourth panel is the average unit price increase that firms expect to incur between 2022 and 2023. Both estimated unit price increases are computed as weighted averages using nominal energy consumptions as weights.

Table A1 summarizes the main insights from this survey, in the subsample of matched firms. As expected, firms benefit from heterogeneous contracts with their energy providers, from fixed price contracts to contracts indexed on wholesale prices. While our shift-share measure of energy cost shocks may overestimate the volatility of prices for the former, it instead underestimates it for firms which contract is indexed on wholesale prices. Benefiting from a fixed price contract does not imply that you are insulated from the energy crisis though. The reason is that prices are renegotiated when the contract is renewed, which seems to happen at least once a year (see the second panel in Table A1).

The last two panels of Table A1 provide additional insights regarding the price changes faced by firms benefiting from fixed price contracts versus contracts indexed on wholesale prices. As expected, contracts indexed on wholesale prices have been more exposed to the energy crisis in 2021-2023. On average, firms engaged into such contracts declare having suffered a 81% (resp. 160%) increase in the price of their electricity (resp. gas) between 2021 and 2022, which is substantially above the numbers reported by firms benefiting from fixed price contracts, at 12 and 45% respectively. These average price variations can be compared with what is measured in the data and used in our measure of exposure to energy price shocks (Figure S1). Over 2021-2022Q3, the average price increase of electricity (resp. of gas) is equal to 19% (resp. 79%), in the ballpark of numbers reported by firms engaged into fixed term contracts. In Table 2, we test the robustness of our results to negelecting firms engaged into contracts indexed on wholesale prices, for which exposure to energy price shocks is systematically under-estimated. As expected, discarding firms which contract is indexed on wholesale prices reduces our estimated pass-through. But the average pass-through rate remains high and not statistically different from one.

B Additional theoretical results

We provide derivations and details about the model introduced in Section 4.

B.1 Household's problem

The household maximizes intertemporal utility under the budget constraint described in the main text. Calling λ the Lagrange multiplier associated with the intertemporal budget constraint, the first order conditions write:

$$
\begin{aligned}
C_t: &\quad e^{-\rho t}C_t^{-\epsilon} - \lambda Q_t P_t = 0 \\
c_{ft}: &\quad e^{-\rho t}C_t^{-\epsilon}C_t^{\frac{1}{\eta}}c_{ft}^{\frac{1}{\eta}}A_{ft}^{\frac{\eta-1}{\eta}} - \lambda Q_t p_{ft} = 0 \\
H_t: &\quad -\alpha e^{-\rho t} + Q_t W_t(1+\tau_l)\lambda = 0 \\
M_t: &\quad e^{-\rho t}\frac{1}{M_t} - \lambda Q_t R_t = 0
\end{aligned}
$$

We now combine the FOC to obtain an expression for the nominal wage, and for the aggregate consumption level and the price level as a function of micro-level prices. To this aim, we first define the evolution of aggregate money supply:

Assumption A1 (Monetary policy) $M_t = M_0 e^{\mu t}$

The FOC wrt M_t then gives a differential equation for the interest rate R_t, $R_t - \frac{\dot{R}_t}{R_t} = \mu + \rho$ which is solved by

$$R_t = \rho + \mu.$$

Combining this result with the FOC wrt H_t, we obtain an expression for the nominal wage that only depends on parameters and time:

$$W_t = \frac{\alpha M_0(\rho+\mu)}{1+\tau_l}e^{\mu t}.$$

From this, we obtain that the growth of nominal wages is equal to the growth rate of money supply μ.

Combining the FOCs wrt C_t and H_t, implies a relationship between P_t and C_t :

$$P_t = C_t^{-\epsilon} W_t \frac{1+\tau_l}{\alpha} = C_t^{-\epsilon} e^{\mu t} M_0(\rho+\mu) \tag{10}$$

Finally, the demand addressed to individual producers is recovered from the FOCs wrt c_{ft} and C_t :

$$c_{ft} = C_t A_{ft}^{\eta-1} \left(\frac{p_{ft}}{P_t}\right)^{-\eta} \tag{11}$$

B.2 Aggregates

From Eq. 11, the definition of price gaps, and the assumption that $Z_{ft} = Z_f A_{ft}$, we have

$$\begin{aligned}
c_{ft} &= C_t A_{ft}^{\eta-1} \left(\frac{p_{ft}}{P_t}\right)^{-\eta} \\
A_{ft} c_{ft} &= C_t e^{-\eta x_{ft}} P_t^{\eta} \left(\frac{\eta}{\eta-1} W_t Z_f \left(\frac{E_t}{W_t}\right)^{\xi_f} K_f\right)^{-\eta} \\
A_{ft} c_{ft} &= C_t e^{-\eta x_{ft}} C_t^{-\varepsilon\eta} \alpha^{-\eta} \left(Z_f \left(\frac{E_t}{W_t}\right)^{\xi_f} K_f\right)^{-\eta} \\
\int (A_{ft} c_{ft})^{\frac{\eta-1}{\eta}} df &= \left(C_t^{1-\varepsilon\eta}\right)^{\frac{\eta-1}{\eta}} \alpha^{1-\eta} \int e^{(1-\eta)x_{ft}} \left(Z_f \left(\frac{E_t}{W_t}\right)^{\xi_f} K_f\right)^{1-\eta} df \\
C_t^{\varepsilon\eta} &= \alpha^{-\eta} \left[\int e^{(1-\eta)x_{ft}} \left(Z_f \left(\frac{E_t}{W_t}\right)^{\xi_f} K_f\right)^{1-\eta} df\right]^{\frac{\eta}{\eta-1}}
\end{aligned}$$

where the third line uses Eq. 10. This links aggregate consumption to the cross-sectional distribution of price gaps and market shares, as we have:

$$\begin{aligned}
ms_{ft}^* &= \left(\frac{mc_{ft}}{A_{ft}}\right)^{1-\eta} \left(P_t^* \frac{\eta}{\eta-1}\right)^{\eta-1} \\
&= \left(Z_f \left(\frac{E_t}{W_t}\right)^{\xi_f} K_f\right)^{1-\eta} \left(\frac{P_t^*}{W_t \frac{\eta}{\eta-1}}\right)^{\eta-1} = \frac{\left(Z_f \left(\frac{E_t}{W_t}\right)^{\xi_f} K_f\right)^{1-\eta}}{\int \left(Z_f \left(\frac{E_t}{W_t}\right)^{\xi_f} K_f\right)^{1-\eta} df}
\end{aligned}$$

where $P_t^* \equiv \left[\int_0^1 \left(\frac{p_{ft}^*}{A_{ft}}\right)^{1-\eta} df\right]^{\frac{1}{1-\eta}}$ is the price index in the absence of nominal rigidities and we use a common assumption (See, e.g., Cavallo et al. (2024), Woodford (2009)) that the preference shocks follow productivity shocks, i.e. $\frac{Z_{ft}^{1-\xi_f}}{A_{ft}} = 1$. This assumption implies deterministic optimal prices and market shares and reduces the dimensionality of the state-space.

B.3 Dynamics of price gaps

By definition, the price gap is equal to:

$$x_{ft} = \log p_t - \log p_t^*$$

In the absence of price adjustment, the price gap evolves according to the following dynamic equation:

$$\begin{aligned} dx_{ft} &= \log p_t^* - \log p_{t+1}^* \\ &= \log \frac{W_t}{W_{t+1}} + \log \frac{Z_{ft}}{Z_{ft+1}} + \xi_f \log \frac{p_t^E}{Z_{ft}W_t} \frac{Z_{ft+1}W_{t+1}}{p_{t+1}^E} \end{aligned}$$

In the flexible price equilibrium, all prices grow at the same rate, which is also the growth rate of the money supply. The dynamic of price gaps thus simplifies into:

$$dx_{ft} = -\mu dt + \sigma dz_{ft}$$

C Additional Tables

Table S1: Distributions of shocks and price changes, 2018-2020

	5 pctl	Mean	Median	95 pctl	St.dev.
Monthly					
$\Delta p^E_{ft} \times S^E_{f0}$	-.11	.02	.01	.2	.21
Δp_{fkt}	-4	.33	0	5.62	4.11
Quarterly					
$\Delta p^E_{ft} \times S^E_{f0}$	-.09	.06	.01	.37	.33
Δp_{fkt}	-4.8	1	0	8.98	5.38

Notes: This table reports statistics on the changes in output prices and cost shocks in our two estimation samples: monthly and quarterly data. $\Delta p^E_{ft} \times S^E_{f0}$ is the firm-level direct change in marginal costs from energy prices. Δp_{fkt} is the output price change. In %. N = 404,891 and 130,589, respectively. Period: 2018-2022

Table S2: Pass-through of energy cost shocks: Asymmetric pass-through

	(1)	(2)	(3)
$\Delta p_{ft} \times S^{E}_{f0}$	0.694***	0.933***	0.888***
	(0.133)	(0.176)	(0.172)
$- \times (Y \geq 2021)$	0.573***		1.053***
	(0.198)		(0.270)
$\Delta p_{ft} \times S^{E}_{f0}$ (Positive)		0.219	-0.688**
		(0.226)	(0.293)
Δp^{H}_{kt}	0.614***	0.614***	0.614***
	(0.014)	(0.014)	(0.014)
$\Delta p^{H,imp}_{kt}$	0.046***	0.046***	0.046***
	(0.013)	(0.013)	(0.013)
Δp^{V}_{ft}	0.594***	0.589***	0.589***
	(0.083)	(0.083)	(0.083)
Observations	130,589	130,589	130,589
Period	2018-2022	2018-2022	2018-2022

Notes: Quarterly data. Estimates with robust standard errors in parenthesis. All estimations include 2-digit industry x time fixed effects. Δp^{H}_{kt} is the average price change of competitors from the same 4-digit industry, $\Delta p^{H,imp}_{kt}$ the price change of imported products, Δp^{V}_{ft} a proxy for input price shocks, recovered from sectoral price indices combined with technical coefficients. $(Y \geq 2021)$ is a dummy that takes the values one when the observations are in the year 2021 or after. $\Delta p_{ft} \times S^{E}_{f0}$ (Positive) interacts the shock with a dummy for positive energy price adjustments.

Table S3: Impact of energy cost shocks on price change probabilities

			Marginal effect (pp) on a price	
X	Coefficient	Z-stat	Change	Increase
$\Delta p^{E}_{ft} \times S^{E}_{f0}$	3.14	2.97	.14	1.08
Δp^{H}_{kt}	17.48	107.69	.79	5.99
$\Delta p^{H,imp}_{kt}$	0.19	1.22	.01	.07
Δp^{V}_{ft}	15.51	7.52	.70	5.32

Notes: This table shows results of the estimation of an ordered probit model, following Loupias and Sevestre (2013). The estimated equation is: $\mathbb{1}_{fpt}(\Delta p_{fkt} >=< 0) = \alpha \Delta p^{E}_{ft-j} \times S^{E}_{f0} + \beta X_{fkt} + FE_{st} + \epsilon_{fkt}$. The first column reports the estimated coefficient α, the second column shows the associated Z-statistic. The marginal effects give the probability change associated with a 1 percent increase in the corresponding covariate, setting the other covariates at their sample mean. All specifications include 2-digit industry by period fixed effects.

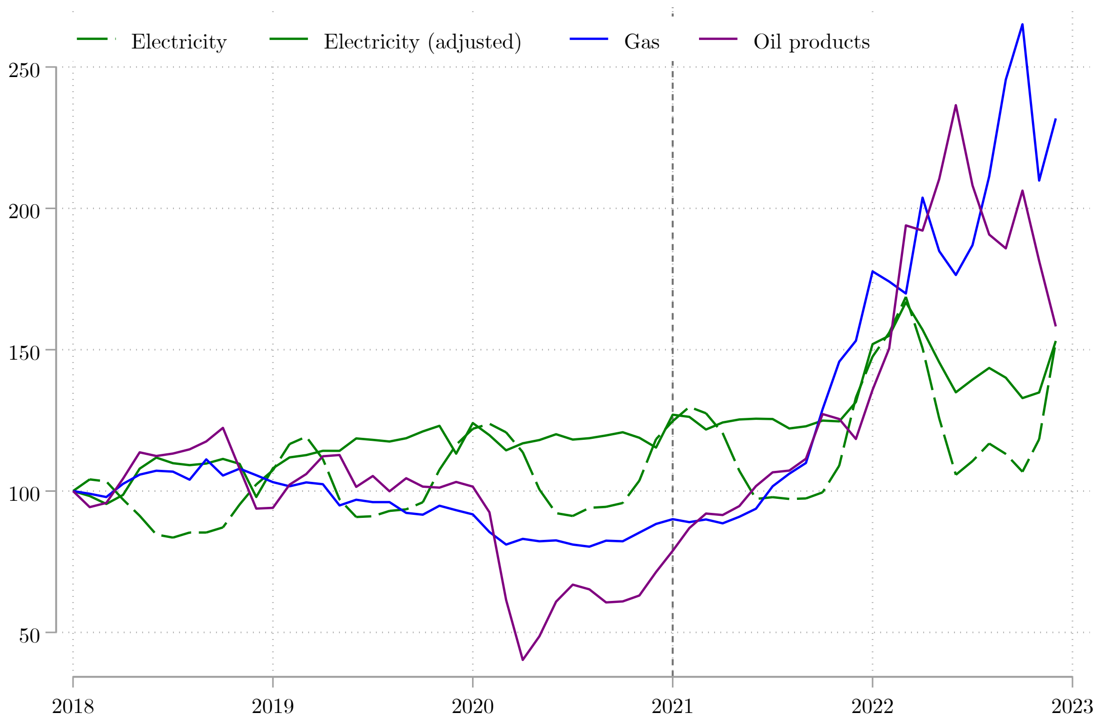
Table S4: Pass-through of energy cost shocks: 2-Stage Least Squares on Annual data

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta p^E_{ft} \times S^E_{f0}$	0.906***	0.574***				
	(0.139)	(0.174)				
$- \times (Y \geq 2021)$		0.405*				
		(0.236)				
$\Delta s^E_{ft} \times S^E_{f0}$			0.847***	0.708***	0.803***	0.396**
			(0.128)	(0.208)	(0.124)	(0.164)
$- \times (Y \geq 2021)$				0.162		0.483**
				(0.248)		(0.216)
Δp^H_{kt}	0.665***	0.665***	0.653***	0.652***	0.655***	0.653***
	(0.023)	(0.023)	(0.023)	(0.024)	(0.023)	(0.023)
$\Delta p^{H,imp}_{kt}$	0.031*	0.031*	0.030	0.031*	0.031*	0.033*
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Δp^V_{ft}	0.459***	0.469***	0.465***	0.469***	0.458***	0.472
	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)
Method	OLS	OLS	2SLS	2SLS	2SLS	2SLS
Observations	28,874	28,874	28,874	28,874	28,874	28,874
F-stat			377.2	200.2	383.4	240.4
				198.2		160.0

Notes: Yearly data. Estimates with robust standard errors in parenthesis. All estimations include 2-digit industry x time fixed effects. Δp^H_{kt} is the average price change of competitors from the same 4-digit industry, $\Delta p^{H,imp}_{kt}$ the price change of imported products, Δp^V_{ft} a proxy for input price shocks, recovered from sectoral price indices combined with technical coefficients. $(Y \geq 2021)$ is a dummy that takes the values one when the observations are in the year 2021 or after. In columns (3) and (4), the instrument for firm-level energy cost shocks is a weighted average of energy-specific price indices, weighted by the firm's energy mix in the reference period and scaled by the firm's energy intensity $(\Delta p^E_{ft} \times S^E_{f0})$. In columns (5) and (6), we also use a weighted average of energy-specific price changes but prices are measured as an average of changes in unit values incurred by all other firms in the estimation sample. As the aggregation of data at annual frequency constrains the time-dimension of the panel, we extend the dataset backwards, using price information over 2015-2017. Due to a change in the sample of surveyed firms in 2018, this implies appending the existing dataset with price variations recovered from a different set of firms. The underlying assumption is thus that the price behaviors of these firms over 2015-2017 is not significantly different from what we would have observed if the firms surveyed over 2018-2022 had been surveyed in the earlier period.

D Additional Figures

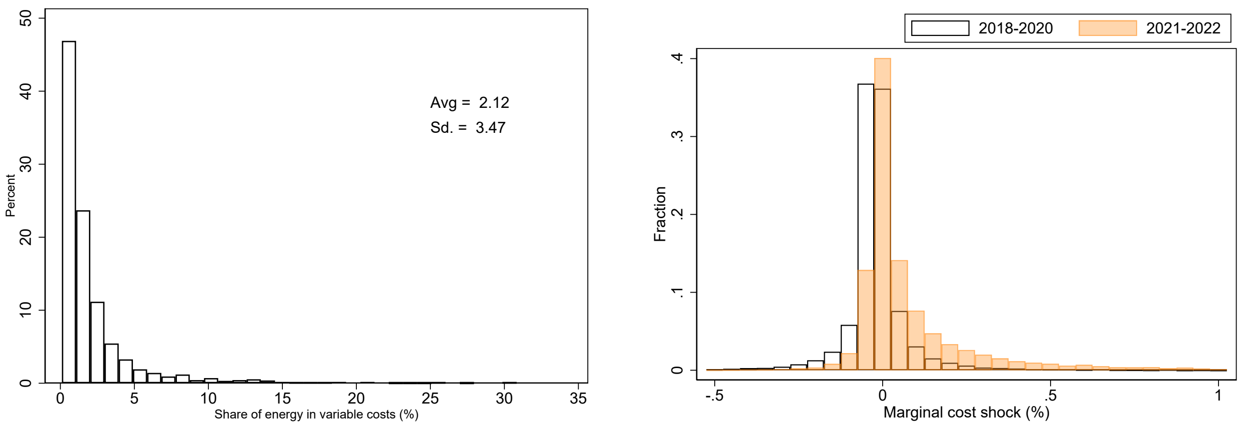
Figure S1: Evolution of energy prices



Notes: This figure shows the evolution of the PPI for electricity, gas and oil products, constructed by INSEE. For electricity and gas, the PPI is constructed from prices set by energy providers to firms for direct consumption. For oil products, the PPI is defined for all coking and refining products. For electricity, the raw data in dashed green is corrected for seasonality before being used in the analysis (green solid line). Normalized to 100 in January 2018.

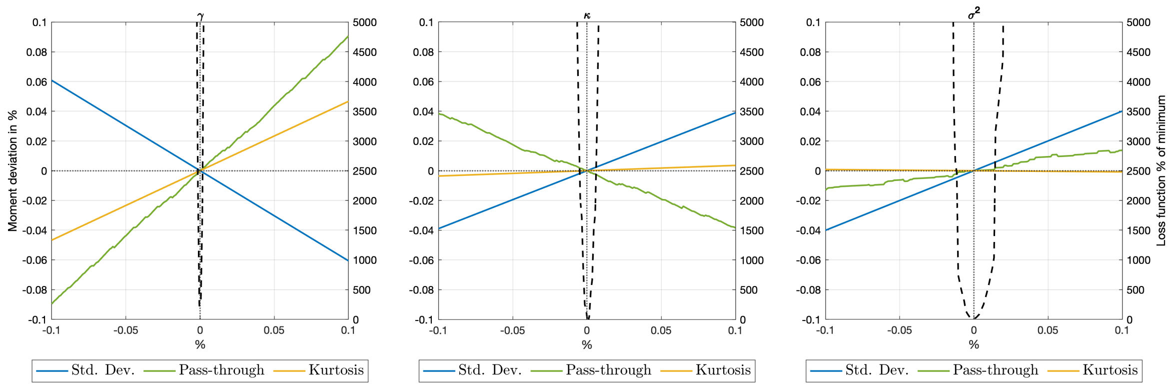
Figure S2: Firm-level distributions of energy cost shocks and cost shares

Panel (a): energy costs shares S^E_{f0} **Panel (b)**: energy costs shocks $\Delta p^E_{ft} \times S^E_{f0}$



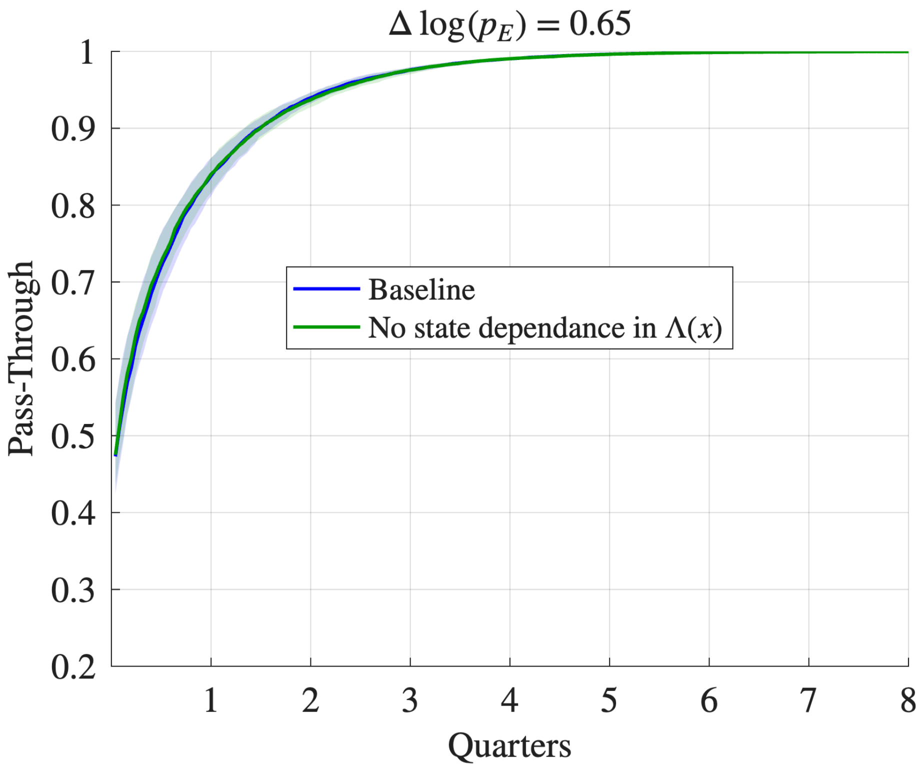
Notes: **Panel (a)** shows the distribution of energy costs share in our sample, the ratio of the energy bill to total variable costs, in percent. Total variable costs are defined as the sum of the firm's wage bill and intermediate consumption (raw materials, merchandises, and services). The ratio is calculated at the firm level by averaging the energy bill to costs ratio over pre-sample years (2014-2017). **Panel (b)** figure shows the distribution of energy-driven costs shocks $\Delta p^E_{ft} \times S^E_f$ that we use in the estimation of Equation 2, at the quarterly frequency.

Figure S3: Simulated moments and loss function around calibrated parameter values



Notes: This figure displays the deviation of the loss function (dashed black) and of the three targeted moments (plain colors) in percentage, relative to their value at calibrated parameters, as a function of the deviation of the parameters from their calibrated values.

Figure S4: Impact of time-varying optimal price gaps



Notes: This figure compares the aggregate response of prices in the full model (blue line) and a model that neglects the state-dependence of optimal price gaps arising from the feedback impact of the shock on the ideal price index, along the transition path.