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Energy, Inflation and Market Power: Excess Pass-Through in France

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Highlights

- We first estimate firm-level markups, applying the methodology from De Loecker et al. (2012) on French manufacturing firms balance sheet data, and aggregate them at the sectoral level.
- We then study the response of the producer price index (PPI) to a change in spot energy prices, depending on average market power within sectors.
- We show that in the least competitive sector, firms pass through up to 115% of the energy shock.

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Abstract

We explore how, in the French manufacturing sector, producer prices vary with market power during a severe episode of energy price hikes (between January 2020 and December 2022). Our work provides micro-level empirical evidence in favor of a role for firms' market power in explaining inflation. Using a rich dataset on French manufacturing firms' balance sheets, we first estimate markups at the firm-level, and aggregate them at the sectoral level. We then study the response of the producer price index (PPI) to a change in spot energy prices, depending on average market power within sectors. We show that in sectors with higher markups, prices increase relatively more: in the least competitive sector, firms pass through over 115% of the energy shock, implying an excess pass-through of more than 15 percentage points. In addition, we analyze in greater detail the mechanisms that might be behind our results: we discard the possibility that the pricing behavior might be driven by a "liquidity buffer rationale", implying that the excess pass-through we identify is detrimental to consumers.

Keywords

Inflation, Markups.

JEL

E31, F4, L11.

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1 Introduction

After years of low inflation, high-income countries have faced a rapid increase in price levels since the beginning of 2021. In October 2022, the Euro area on average recorded a year-on-year inflation rate of 10.6%. As of March 2023, inflation has remained high, reaching 6.9%. There are various potential reasons for the price hikes that started during the pandemic. Bottlenecks in global value chains, linked to Covid-19 policies in China, have put pressure on the supply side (Santacreu and LaBelle, 2022). Another potential cause is linked to Covid-19 restrictions which have shifted demand away from services and towards manufactured goods, along with the imperfect response of supply, while, for the US, fiscal packages have also been pointed out as a source of inflation (Blanchard and Bernanke, 2023). However, in Europe, the most prominently discussed cause relates to the increase in energy prices following the war in Ukraine. Rising tensions between Russia and the European Union have decreased supply of natural gas which has increased energy prices.

Recently, questions have arisen about the role of firms' behavior in the transmission of the energy shock. There is mounting evidence for the contribution of profits to inflation at the aggregate level. Recent reports by the IMF (Hansen et al., 2023), the OECD (2023) and the ECB (2023) suggest that a considerable part of increasing prices can be attributed to larger profits in the private sector. The role of firms' pricing strategies has first been pointed out by Weber and Wasner (2023), who consider increasing profits of US industrial sectors during the period that began with the onset of the Covid-19 pandemic and analyze earning calls of major US firms. They point out the importance of competitive structures in inflationary dynamics. They rationalize their findings as a different potential of firms to set prices depending on their market power. Their results are corroborated by Bräuning et al. (2022), who find that more concentrated US industries displayed a 25% higher pass-through than other industries, suggesting that competition dynamics play a significant role in the transmission of shocks into prices, thus influencing inflation.

For France, the country we analyze in this paper, Lafrogne-Joussier et al. (2023) use firm-level data to assess the pass-through of a price shock on both intermediate imports and energy. They show that the pass-through was importantly different when looking separately at intermediate imports and at energy: only 30% of price increases in intermediate inputs were passed onto prices, while pass-through rates for energy were around 100%. The authors also analyze a potential heterogeneity with respect to pass-through depending on firms' size, however finding no difference: firms are heterogeneous in their exposure but not in their response to a cost shock.[1] Fontagné et al. (2023) analyze the adjustment of French firms to energy shocks over the period 1996-2019, also finding large pass-through rates, possibly even exceeding 100% of the initial cost shock.

Our paper makes two main contributions to the literature on pass-through following energy cost shocks. We first contribute by showing that, following an energy price hike, final prices increase relatively more in sectors in which firms have a higher market power. In the least competitive sectors, firms on average pass through over 115% of the energy shock.[2] A second contribution lies in our analysis of a possible mechanism: we discard the possibility that sectors with higher market power are increasing prices relatively more as a means to smooth profits under uncertainty. Sectors that are expecting greater shocks in the future could amass the necessary liquidity in order to face these shocks, which would inverse the long-run welfare implications of contemporary price hikes. We find that such a precautionary saving mechanism is unlikely to be driving our results: higher pass-through rates in sectors with higher market power *cannot* be explained by the hoarding of liquidity in order to insure against future shocks. As a consequence, the excess pass-through we identify is likely to be welfare reducing for consumers.

Compared to Lafrogne-Joussier et al. (2023) and Fontagné et al. (2023), we analyze the

[1]The authors caution that this might be due to a lack of identification power, as their data is restricted to the largest firms in a given product market.

[2]This is consistent with Pless and van Benthem (2019) which show that under some conditions pass-through can serve as a test to detect market power. While under perfect competition and when supply is upward-sloping and demand downward-sloping, pass-through should range between 0 and 100%, theory predicts that pass-through can exceed 100% under imperfect competition and when demand is sufficiently convex.

reaction of French manufacturing prices to energy price shocks at the *sectoral* level. We construct a shift-share measure of exposure to cost shocks, using the energy price as the shift element, common to all sectors, and the energy usage rates per sector as the share element.[3] Further, employing the methodology introduced by De Loecker and Warzynski (2012), we estimate firm-level markups based on confidential micro-level data of French firms' balance sheets. We aggregate firm-level markups at the industry-level to obtain a sectoral indicator of average market power.

We then first regress energy cost-shocks onto producer price indices (PPI). While simple regressions suggest a pass-through between 40 and 100%, an interaction with aggregate markups reveals considerable heterogeneities. We find that for industries that have higher sales-weighted average markups (and that are, thus, characterized by lower competition), the reaction of prices to the energy shock was significantly higher: the least competitive sectors pass on more than the energy price increase, with an excess pass-through of over 15 percentage points, i.e. an increase in prices not warranted by a rise in energy prices. Hence, not only are industries differently exposed to the energy shock, but their reaction to a given change in energy prices varies depending on the sectoral level of market power. One should note that due to data issues, these results should be seen as a lower bound. We then rule out the possibility that results are simply due to negative expectations about future shocks (on demand, investment costs or energy prices), which could have lead to dynamics driven by a liquidity buffer rationale in order to face future shocks.

Overall, we interpret our results as indicating that inflation was importantly influenced by the differential pass-through rates of sectors with less competition, and therefore as supporting evidence for the view that recent inflation was significantly influenced by the pricing power of firms.[4] Our results suggest that firms in less competitive sectors were able to pass

[3] We retain the following types of energy: coal, electricity, natural gas and heavy oil, as explained in subsection 2.2.

[4] We study the impact on producer prices and not consumer prices. To assess the overall impact on consumers, the whole supply chain should be considered. In particular the pricing behavior of retailers needs to be taken into account, as they might either amplify inflation or dampen it by partially shielding consumers from PPI increases.

through a significantly higher share of the cost shock onto prices. Intuitively, this could be the case because firms were seeking to shield their profit margins from decreasing. While firms in more competitive sectors were forced to increase their prices significantly less and thus decrease their profit margins, firms in less competitive industries used their market power to increase their prices more than the initial energy shock would have warranted, leading to what we coin "excess pass-through". Such pass-through rates above 100% suggest that profit-seeking by firms has contributed to inflation over the recent period of large energy price increases.

Importantly, our findings are in contrast with standard models that would predict that firms with higher markups should absorb a higher share of energy price variation by reducing their markups in order to gain market shares—encompassing both models with oligopolistic competition (Atkeson and Burstein, 2008) and models with monopolistic competition and non-CES demand (Mrázová and Neary, 2017). These results are not in line with other empirical results on cost pass-through either. For instance, Amiti et al. (2019) find that, following a currency depreciation (which increases marginal costs), Belgian firms' own-cost elasticity of prices is around 0.6. They find a large heterogeneity between large and small firms, with small firms having a pass-through close to 1. Their results suggest that large firms absorb some of the positive cost shocks in order to gain market shares by reducing their markups. However, these theoretical and empirical papers fall short of explaining the recent dynamics of high inflation.

The rest of the paper is organized as follows: section 2 describes the data we use and their treatment; section 3 introduces the methodology implemented to analyze the data; section 4 presents the results on heterogeneous pass-through rates; section 5 analyzes in more detail the liquidity buffer rationale mechanism that could potentially be driving our results; section 6 concludes.

2 Data

2.1 Goods' prices

As a measure of goods' prices we use the Producer Price Index (PPI) for different manufacturing sectors.[5] The data is freely provided by the *INSEE* and is available on a monthly basis. We transform the index into monthly inflation rates using the following, classic transformation:

$$\Pi_{j,t,t-1} = \frac{P_{j,t} - P_{j,t-1}}{P_{j,t-1}},$$

where $\Pi_{j,t,t-1}$ is the inflation rate between months t and $t-1$ in sector j, and $P_{j,t}$ indicates j's PPI in month t.

As we can see from Figure 1 and Figure 2, the increase in the PPI was quite substantial since the onset of 2020. Inflation started to rise significantly at the beginning of 2021, picking up considerable speed during the first quarter of 2022. The evolution has been slower towards the end of 2022.

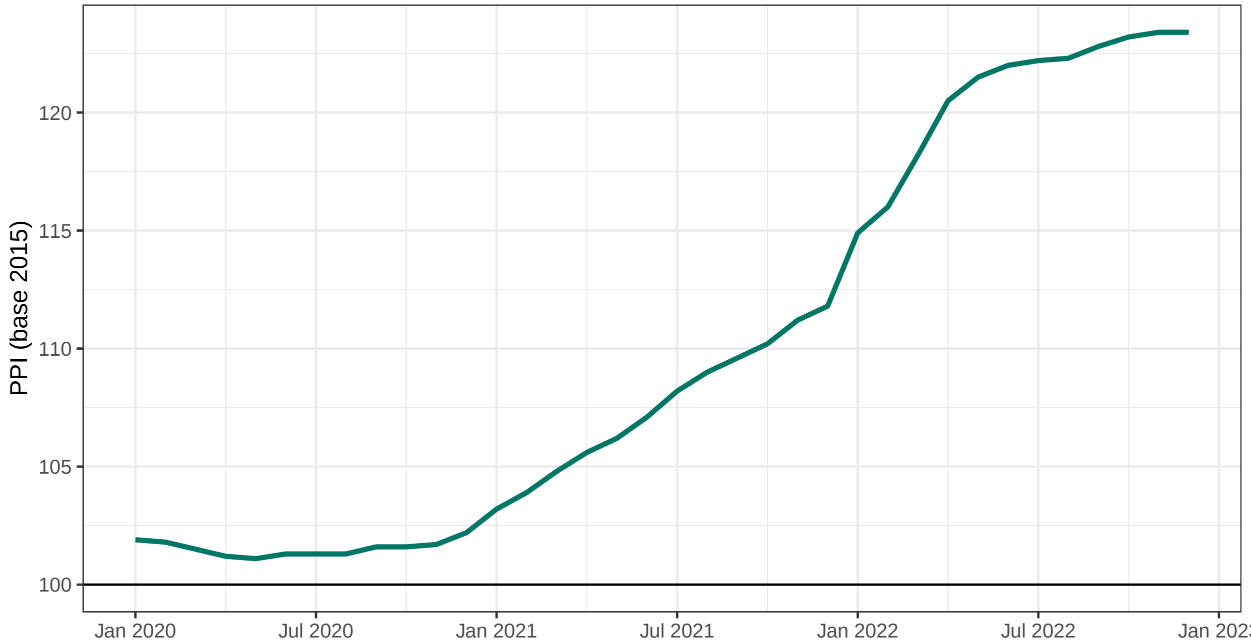
2.2 Energy prices

In order to grasp the impact of energy prices for the manufacturing sector, we rely on three distinct data sets. First, we use data provided by the *Ministère de la Transition Écologique* on prices for different types of energy over the period January 2020 until December 2022. The dataset provides us with monthly spot prices for different sources of energy. We retain the following four types of energy: coal, electricity, natural gas and heavy oil. Coal is the average price of imported coal (€/t). Heavy oil is the price of imported refined petroleum products (€/t). Electricity is the average *Epex* spot price in France (€/Mwh). Gaz is the spot price in France (€/Mwh). Analog to our procedure for the PPI, we calculate monthly inflation rates for each type of energy ($\pi^{avg_n}_{e,t,t-n}$).

Figure 3 shows the price evolution for the different kinds of energy. As we can see, the

[5] See Appendix Table A.13 for the full list of sectors.

Figure 1: PPI in manufacturing sector (excl. energy)



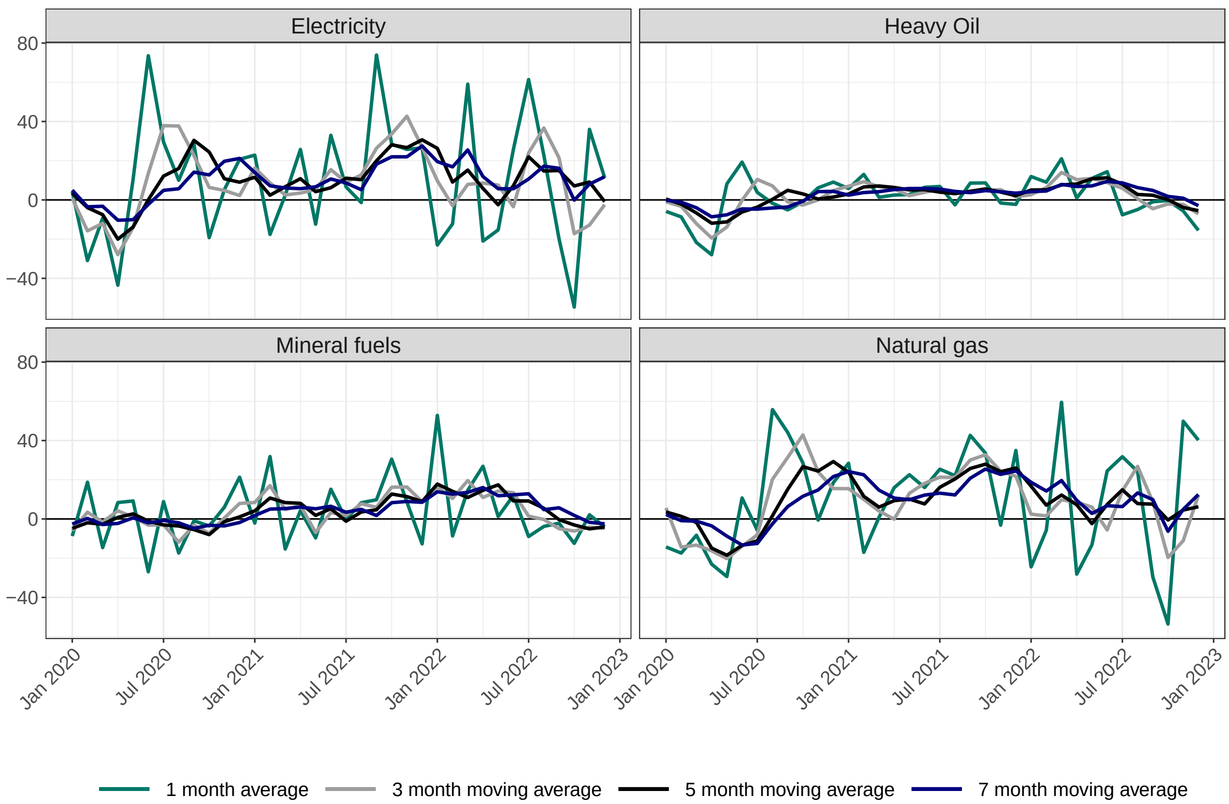
Source: *INSEE*.

Figure 2: Monthly inflation in manufacturing sector (excl. energy)

Source: *INSEE*, authors' calculations.

simple monthly energy price inflation rates are highly volatile, especially for electricity and natural gas. In order to smooth the evolution of prices, we include three-month, five-month or seven-month moving averages. For all specifications, we calculate the average up to $n-1$ months prior to the month in question. That is, to compute for example the three-month moving average for March 2022, we calculate the average for the months of January, February and March 2022.

Figure 3: Monthly energy price inflation by types of energy (in %)



Source: *Ministère de la Transition Écologique.*

Second, we use data provided by the *INSEE* on the energy used by industrial sectors in production in 2019. Sectors are specified at the two-digit NAF Rev. 2 level. We use this information to construct weights in total energy expenditure for the four types of energy for which we have extracted price evolutions (coal,[6] oil, gas and electricity). We calculate

[6]The INSEE dataset includes coal under the heading solid mineral fuels (*Combustibles minéraux solides*).

the weight of each type of energy (w_{ej}) as this energy's share in overall energy expenditures within a given sector j:

$$w_{e,j} = \frac{EXP_{e,j}}{\sum_e EXP_{e,j}},$$

where $EXP_{e,j}$ are expenditures on the type of energy e in sector j in 2019.[7]

Finally, to calibrate the aggregated shock in energy prices, we use information contained in the OECD's ICIO database in order to calculate the share of energy goods in total intermediate input use of industry j (s_j). To capture the energy content of production, we use the share of the ISIC sectors 19 ("Manufacture of coke and refined petroleum products") and 35 ("Electricity, gas, steam and air conditioning supply") in total intermediate use per two-digit sector. We use information for 2018, the last year available in the database.

We aggregate the information contained in these three datasets in order to construct a shift-share variable that reflects the energy price shock, where the energy price is the shift element—common to all sectors—and the energy usage rates per sector are the share element. Hence, our variable for the energy-price shock takes the following form:

$$EP^{avg_n}_{j,t,t-n} = s_j \sum_e w_{j,e} \pi^{avg_n}_{e,t,t-n} \tag{1}$$

where $\pi^{avg_n}_{e,t,t-n}$ reflects either three-month, five-month or seven-month moving averages.

It is important to stress at this point that our measure of the energy shock *overestimates* the actual shock. Due to limited data availability, we are constrained to use spot prices, ignoring the importance of fixed energy contracts. Spot prices do not perfectly reflect the actual costs incurred by firms as some companies have long-term fixed-price contracts with energy providers—some of which at a regulated price—shielding them from price hikes.[8] Our measure of the energy shock, therefore, reflects the hypothetical case where all energy contracts within a sector are completely flexible and subject to the changes in spot prices.

[7] The dataset contains a variable that reflects the total expenditure on energy costs, which is the denominator in our energy share. For the clothing industry, this variable is missing, so we reconstruct the total expenditure from the expenditures on individual energy sources that are available for that sector.

[8] See INSEE (2022).

Multiplying our measure by the share of non-fixed contracts within a sector would considerably decrease the energy shock variable and, thus, *increase* the point estimates in section 4. Hence, we see our results as a lower bound of average pass-through.

2.3 Other input prices

We construct a measure of the imported intermediate input price shock similar to our measure of the energy shock. We use monthly EU customs data (COMEXT) to construct monthly changes in unit-costs for ISIC 2-digit sectors. We merge HS6 product codes to ISIC 2-digit industries using the concordance table provided by the OECD. We then allocate these country-level changes to French sectors using the OECD's ICIO tables. We use the same tables to scale the shock, using the share of intermediates for which we have price information in overall expenditure for each French sector considered. We include this measure as a control in all our specifications.

2.4 Sectoral markups

In order to compute sectoral markups, we begin by estimating firm-level markups, following the state-of-the-art methodology initially introduced by De Loecker and Warzynski (2012). In this section, we only lay out the most important features with regard to our estimations, leaving the detailed description of the method to the appendix (subsection A.3).

First, we rely on the *FICUS-FARE* dataset, which provides confidential data on French firms' balance sheets.[9] We extract information on revenue, labor expenses, material purchases and tangible capital stock.[10] All values are deflated using two-digit industry deflators from *EU-KLEMS*. Moreover, we rely on the insight from De Ridder et al. (2021) and estimate markups using a translog production function, and more specifically a third-order polynom.

[9] This dataset is provided by *INSEE* and made available to researchers through the *CASD* after approval of the project by the Statistical Secrecy Committee. See https://www.casd.eu/en/your-project/procedures-dhabilitation/.

[10] See Appendix Table A.12 for a full list of the variables used.

Using a translog function instead of a Cobb-Douglas allows for output elasticity to depend on input use intensity and therefore allows for heterogeneity across firms and time. Finally, in order to control for outliers, we trim all relevant variables at the 1% level. We then estimate output elasticities at the three-digit industry level. The final dataset contains 22 sectors.[11] Following De Loecker et al. (2020), we aggregate firm-level markups at the sectoral level using market shares as weights.

3 Methodology

Specification We estimate by OLS the pass-through from energy prices to producer prices (PPI) at the sectoral level, for the period from January 2020 to December 2022, based on the following specification:

$$\Pi_{j,t,t-1} = \alpha EP^{avg_n}_{j,t,t-n} + \gamma \mathcal{M}_{j,2019} + \beta EP^{avg_n}_{j,t,t-n} * \mathcal{M}_{j,2019} + \zeta_{j,t,t-n} + \eta_t + \epsilon_{j,t}, \tag{2}$$

where, for a given sector j, $\Pi_{j,t,t-1}$ is the PPI price change between month t and month $t-1$, as detailed in subsection 2.1, $EP^{avg_n}_{j,t,t-n}$ is the sector j-specific measure of the energy price shock whose construction is described in subsection 2.2, and $\mathcal{M}_{j,2019}$ is the sales-weighted average markup of sector j in 2019, estimated following the methodology laid out in appendix subsection A.3. We also control for the sector-specific price shock that is due to the change in imported intermediate input prices other than energy, denoted by $\zeta_{j,t,t-n}$. Finally, η_t denotes period fixed effects.

We are interested in particular in β which is interpreted as the additional pass-through that is associated with higher market power (measured by markups): a positive coefficient means that firms in a sector with a higher sales-weighted average markup pass on a larger share of energy price increases to consumers. This is the hypothesis that we aim to test for French manufacturing sectors between January 2020 and December 2022.

[11] See Appendix Table A.13 for the full list of sectors.

Endogeneity concerns This specification could suffer from the usual bias: energy prices and PPI respond simultaneously to supply and demand shocks, blurring the impact of energy shocks on goods' prices only. However, in our specific case, energy prices vary at the national level and are allocated to sectors according to their energy mix and the share of energy in intermediate expenditure. The main concern for estimating α (and β) is, thus, that the energy mix might actually vary in response to the change in energy prices in a way that is correlated with the change in producer prices (PPI). Such a correlation could be due to unobserved characteristics of the sector or an unobserved shock affecting both producer prices and the strength of the energy shock through the energy mix.[12] To mitigate these concerns, we hold the energy mix and its share in total intermediates fixed at pre-crisis levels. Further, due to the short period considered, major changes in the energy mix are not very likely.

A second potential bias in our results is linked to the fact that we do not observe the share of fixed-price contracts for the energy consumption of each sector.[13] The size of the energy shock we capture, $EP^{avg_n}_{j,t,t-n}$, is higher than the true shock impacting the sector, if we were able to account for the heterogeneity in contracts. In that case, we would indeed multiply $EP^{avg_n}_{j,t,t-n}$ by a factor between 0 and 1. As a consequence, we are, on average, overestimating the size of the shock, i.e. the size of price variation affecting prices. Consequently we are underestimating on average the elasticity and our estimate represents a lower bound of the true pass-through.[14]

[12]For instance, imagine a sector where a positive productivity shock affects both its energy use, making it less dependent on energy, and its prices, which decrease due to efficiency gains. In that case, the effect we are capturing by estimating Equation 2 would be a lower bound of the true effect, as we would be overestimating the size of the true energy shock (by discarding the change in the energy mix that made the sector actually less vulnerable) and as we would ignore the fact that prices have decreased due to the unobserved change in technology. Most worrying would be a shock that would both increase the reliance of the sector on energy while increasing goods' prices, such as a negative productivity shock.

[13]See INSEE (2022) for an analysis of the varying importance of fixed-price contracts for French firms.

[14]A related concern is that the share of fixed-price contracts might vary across sectors in a way that is correlated with the level of market power, therefore biasing our results on the additional effect of markups on pass-through. For instance, there might be a significantly lower portion of fixed-price contracts in high markup sectors. In that case, our interaction of markups with the energy shock would in fact simply reflect the heterogeneity with respect to the nature of contracts: sectors with a lower part of long-term contracts will pass-through more of the energy price, simply because they are more exposed to the shock (due to the lower share of fixed-price contracts). To get a sense of the magnitude of this issue, consider the following idea: sectors that have energy as a larger fraction of their production process likely have a greater incentive

Regarding the estimate β alone, another possible concern is that some unobservable both impacts PPI change and markups. To reduce this endogeneity concern, we use the markup level of the sector in 2019, i.e. previous to the pandemic and the energy crisis.

4 Heterogeneous Pass-Through

Average energy pass-through We first look at the average effect of changes in energy prices on the PPI. We include specifications with either only period (month-year) or with both period and industry fixed effects. The results are shown in Table 1. As we can see, changes in producer prices seem weakly associated with changes in energy prices in the same period ($EP_{j,t,t-1}$). This first rough measure of pass-through thus suggests that firms pass between 40 and 100% of their cost increases into prices, as shown in columns 3 to 8 of Table 1. Hence, except for column (7), simple regressions suggest that firms functioned as a "light cushion" to soften the impact of energy prices on inflation by reducing their profit margins.

to adopt fixed-price contracts. Hence, for our estimation to be affected by the omitted variable bias that markups simply reflect a lower share of fixed contracts, we would need to find a strong negative correlation between the share of energy in the production process and our markup measure. Taking the correlation of our TiVA measure of the share of energy in production and our measure of markup, we find a weakly negative correlation of -0.149. Hence, our concerns cannot be completely alleviated, but seem to be of relatively little importance.

Table 1: Average energy price pass-through

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EP_{j,t,t-n}$	0.208**	0.095						
	(0.093)	(0.093)						
$EP^{avg_3}_{j,t,t-n}$			0.589***	0.405***				
			(0.121)	(0.144)				
$EP^{avg_5}_{j,t,t-n}$					0.876***	0.769***		
					(0.157)	(0.214)		
$EP^{avg_7}_{j,t,t-n}$							1.007***	0.990***
							(0.177)	(0.244)
Per. FE	✓	✓	✓	✓	✓	✓	✓	✓
Ind. FE		✓		✓		✓		✓
Obs	756	756	756	756	756	756	756	756
R^2	0.226	0.291	0.250	0.302	0.269	0.314	0.274	0.319

* p<0.1, ** p<0.05, *** p<0.01

Robust standard errors in parentheses. The dependent variable is the monthly PPI inflation rate at the 2-digit sectoral level. $EP^{avg_n}_{j,t,t-n}$ corresponds to the average energy shock of the current month and the $n-1$ months before. Period fixed effects indicate fixed effects for a given month-year. Industry fixed effects are at the 2-digit sector level. The estimation is conducted on the period from January 2020 to December 2022.

Interaction with markups We now analyze the heterogeneity in pass-through depending on the competition within sectors, as measured by markups. We employ our baseline estimation from Equation 2, where we interact the sales-weighted average markup at the 2-digit industry level ($\mathcal{M}_j$) with our measure of energy prices ($EP^{avg_n}_{j,t,t-n}$). We include period fixed effects in every specification and use again the contemporaneous measure of energy prices, as well as the three-month, five-month and seven-month moving averages.

Table 2: Energy price pass-through and market power

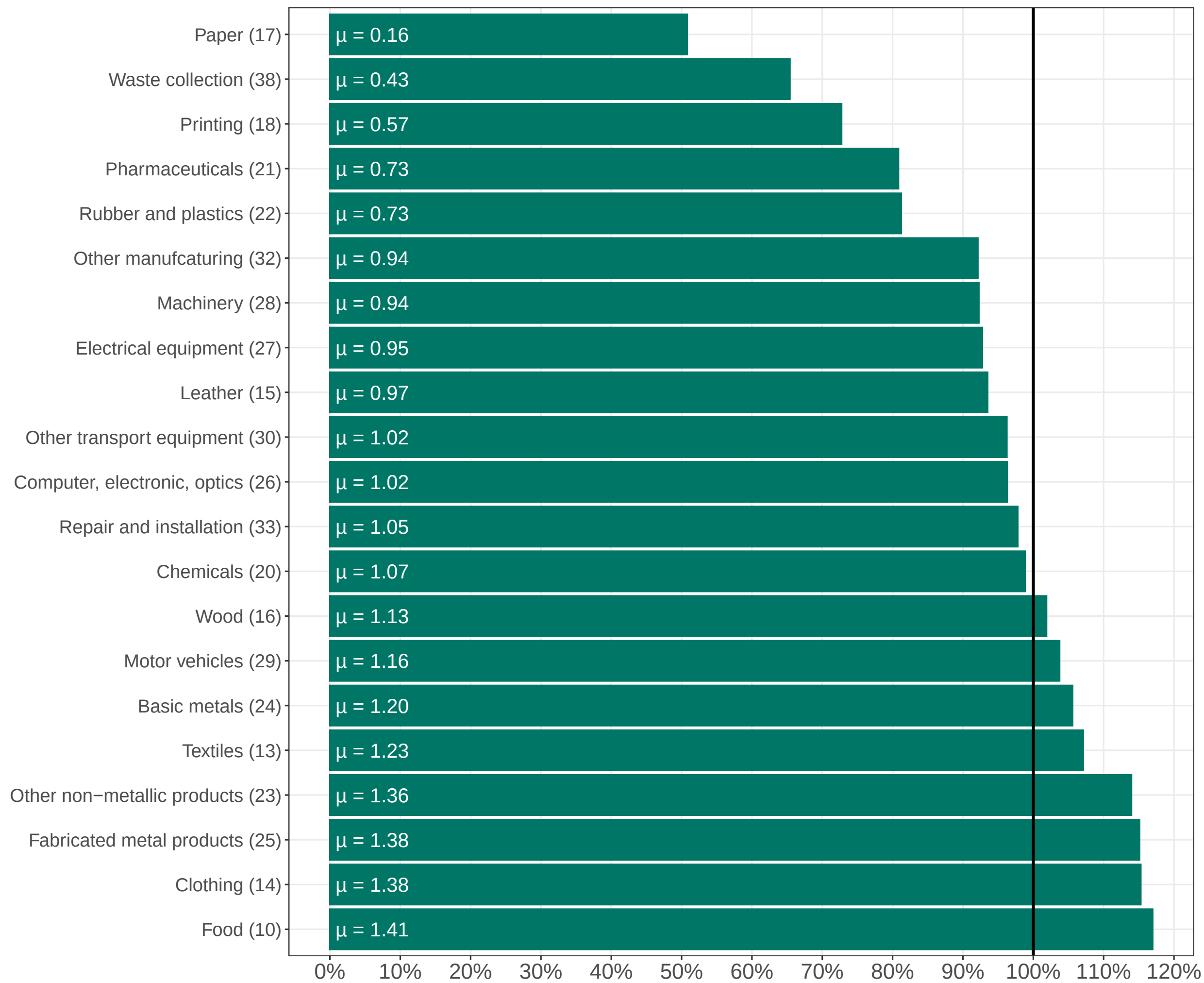
	(1)	(2)	(3)	(4)
$EP_{j,t,t-n}$	-0.051			
	(0.116)			
$EP^{avg3}_{j,t,t-n}$		0.157		
		(0.175)		
$EP^{avg5}_{j,t,t-n}$			0.427^{*}	
			(0.225)	
$EP^{avg7}_{j,t,t-n}$				0.566^{**}
				(0.245)
$\mathcal{M}_j$	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
$EP_{j,t,t-n} \times \mathcal{M}_j$	0.329^{**}			
	(0.130)			
$EP^{avg3}_{j,t,t-n} \times \mathcal{M}_j$		0.526^{***}		
		(0.185)		
$EP^{avg5}_{j,t,t-n} \times \mathcal{M}_j$			0.527^{**}	
			(0.246)	
$EP^{avg7}_{j,t,t-n} \times \mathcal{M}_j$				0.508^{*}
				(0.278)
Per. FE	✓	✓	✓	✓
Obs.	756	756	756	756
R^2	0.237	0.259	0.274	0.278

* p<0.1, ** p<0.05, *** p<0.01

Robust standard errors in parentheses. The dependent variable is the monthly PPI inflation rate at the 2-digit sectoral level. $EP^{avg_n}_{j,t,t-n}$ corresponds to the average energy shock of the current month and the $n-1$ months before. $\mathcal{M}_j$ denotes the sales-weighted average markup at the 2-digit industry level in 2019. Period fixed effects indicate fixed effects for a given month-year. The estimation is conducted on the period from January 2020 to December 2022.

Table 2 shows the results of this exercise. Our estimations reveal important heterogeneities with respect to the reaction of producer prices to energy cost shocks. While it still appears

Figure 4: Estimated pass-through by sector, in %



Note: The black line corresponds to a pass-through of 100%: 8 sectors exhibit an excess pass-through with bars beyond this line. The sales-weighted average sectoral markup (μ) is specified inside each bar. Sectors are at the 2-digit level with NAF/ISIC classification codes between parentheses. See subsection A.4 for a more detailed description of sectors. Source: Authors' estimations based on Equation 2, using estimates from the third specification in Table 2.

that the contemporaneous cost shock has no effect on prices, there are significant differences across sectors when interacting the shock with the sales-weighted average markup. Sectors that display a higher average markup saw a significantly higher increase in their PPI given a certain energy cost shock. This suggests that firms in less competitive sectors exploited their market power to pass through a higher percentage of the increases in energy prices. This effect is exacerbated using three and five month averages. While the priorly discussed general effect of energy costs on producer prices (see Table 1) now becomes visible for all sectors on average, firms in less competitive sectors still display a significantly higher pass-through as shown by the interaction term. This significant effect only disappears once we take the average price shock over the seven prior months.

Considering that our maximum value of $\mathcal{M}_j$ is around 1.41, a back of the envelope calculation suggests that pass-through reached a maximum of 117% for the least competitive sectors, implying an excess pass-through—i.e. a pass through not warranted by the energy price hike itself—of 17 percentage points.[15] There are eight sectors for which there is more than 100% pass-through according to our regression: (i) food products, (ii) clothing, (iii) fabricated metal products (except machinery), (iv) other non-metallic products, (v) textiles, (vi) basic metals, (vii) motor vehicles, and (viii) wood as shown in Figure 4. Interestingly, the food industry not only displays the highest rate of pass-through, but also has the second highest annual inflation rate after the energy sector (excluded in our sample): +12.1% in December 2022 (*INSEE*).

Robustness using HHI Now, to check the robustness of our result, we replace the measure of markup in Equation 2 by the Herfindahl-Hirschman Index (HHI).[16] The results are shown in Table 3. We again find a positive and significant estimate on the interaction between the HHI and the energy shock, meaning that more concentrated industries are more likely to have an excess pass-through (corroborating the results by Bräuning et al. (2022)). Note that results are not directly comparable to our specification using average markups as the HHI is an imperfect measure of market power (see Syverson (2019) for a discussion).

[15] The calculation takes the coefficients from column (3) of Table 2 and inserts the maximum 1.413 for $\mathcal{M}_j$, and applies the following equation: $\Delta PPI = 0.427 + 1.413 * 0.527 - 0.002 * 1.413 = 1.120$.

[16] The HHI is computed either at the 3-digit sector level and then aggregated at the 2-digit level using sectoral sales weights or is directly computed at the two-digit level. We use the following standard definition for the HHI: $HHI_j = \sum_f \left(\frac{Sales_{f,j,2019}}{\sum_f Sales_{f,j,2019}}\right)^2$. We then multiply the HHI by 100. In our specification in Table 3 we use the direct 2-digit level HHI, but results are robust to using the alternative aggregated 3-digit measure.

Table 3: Energy price pass-through and concentration

	(1)	(2)	(3)	(4)
$EP_{j,t,t-n}$	0.144			
	(0.090)			
$EP^{avg_3}_{j,t,t-n}$		0.473***		
		(0.122)		
$EP^{avg_5}_{j,t,t-n}$			0.681***	
			(0.162)	
$EP^{avg_7}_{j,t,t-1}$				0.734***
				(0.186)
HHI_j	-0.000***	-0.000**	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$EP_{j,t,t-n} \times HHI_j$	0.081***			
	(0.030)			
$EP^{avg_3}_{j,t,t-n} \times HHI_j$		0.118**		
		(0.047)		
$EP^{avg_5}_{j,t,t-n} \times HHI_j$			0.175**	
			(0.072)	
$EP^{avg_7}_{j,t,t-n} \times HHI_j$				0.225***
				(0.082)
Per. FE	✓	✓	✓	✓
Obs.	756	756	756	756
R^2	0.241	0.260	0.282	0.291

* p<0.1, ** p<0.05, *** p<0.01

Robust standard errors in parentheses. The dependent variable is the monthly PPI inflation rate at the 2-digit sectoral level. $EP^{avg_n}_{j,t,t-n}$ corresponds to the average energy shock of the current month and the $n-1$ months before. HHI_j denotes the Herfindahl-Hirschman index at the 2-digit sector level. Period fixed effects indicate fixed effects for a given month-year. The estimation is conducted on the period from January 2020 to December 2022.

5 Liquidity Buffer Rationale

The finding that pass-through rates differ from sector to sector depending on the aggregate markup raises the question of the mechanism that underlies these results. In this section, we analyze whether our results can be explained by a "liquidity buffer" rationale, showing that this is *not* the case. According to this argument, firms exposed to a higher uncertainty with respect to future shocks might raise prices more than warranted by the current cost increases in order to ensure sufficient liquidity to face these future shocks, potentially occurring at times when price increases might not be possible anymore.

Hence, higher pass-through rates might simply reflect negative expectations as to future shocks in certain sectors. Firms in these industries might see price hikes as a "necessary bad" in order to hoard sufficient liquidity to absorb negative shocks in the future where price hikes might be impossible. In this sense, while the aggressive price setting in these sectors might drive inflation up in the short term, these price increases assure their viability in the long run. Therefore, if this mechanism were to prevail, future welfare considerations might outweigh short-term welfare losses in terms of higher inflation.

Econometrically speaking, our specifications would be affected by an omitted variable bias if the sales-weighted average markups in 2019—used in our interaction term as shown in equation 2—are determined by expectations formed by firms on future cost shocks. To test the existence of such an omitted variable bias, we construct three different proxies for future expectations of shocks, each based on dynamics prior to the period of analysis (i.e. up to 2019), implicitly making the assumption that firms form expectations in a Bayesian way, relying on past information. Our three types of shocks include potential motives for firms to amass liquidity when possible: fluctuations in demand, in energy prices or in investment costs. A higher volatility of either of these factors might indeed incentivize firms to increase prices relatively more than warranted by the current shock, in order to be in a position to sustain higher shocks in the future—where price hikes might not be possible anymore.

To check whether this "liquidity buffer" mechanism could be driving our results, we propose two different approaches. The first approach consists in introducing the three measures of shock volatility as controls in our baseline regression (see Table 2) in order to check whether the interaction becomes indistinguishable from zero, as would be the case if this liquidity buffer rationale were at play. The second approach is akin to a two-stage least squares design. In a first step, we purge sectoral markups from the effect of prior shocks, which allows us to test whether markups are significantly determined by prior evolutions and therefore by expectations of future shocks. In a second step, we use the residual from this first stage instead of our baseline measure of markups, in order to check whether the effect of market power remains when purged from the liquidity buffer rationale.

We construct three different industry-level volatility measures: volatility in energy prices, in investment expenditures and in sales (as a proxy for demand). First, to construct the energy price volatility we employ the formula in Equation 1 to each year from 2013 until 2019.[17] Compared to our baseline measure of the energy shock, we here take the average annual price of the different types of energy to generate year-to-year price changes. We then construct the energy price volatility as the sectoral standard deviation of the change in yearly energy expenditures from 2013 until 2019.[18] The interpretation of this measure is that a higher value depicts a relatively greater ability of the sector to adjust energy expenditures in the past and therefore a *lower* effective price volatility. Indeed, energy price variations are common at the national level so that differences between sectors reflect a different share of energy expenditures in total cost and a different energy mix. Hence, this measure proxies expectations on the severity of future energy price volatility for the sector in the following way: the lower this measure, the lower the adjustment potential of the sector's cost structure and, therefore, the higher its exposition to energy price variations.

Second, we construct a measure of volatility in investment from the firm-level information

[17] For the year 2019, we scale the shock using information on energy use by sector from TiVA 2018, the last year available in the database.

[18] There is no particular reason to assume that expectations are based on the 6 prior years. We choose 6 years to allow for more observations in the first stage below and in order to properly capture a variability over time. In Appendix subsection A.1 we include other specifications, where we construct volatility on 7, 5, 4 or 3 prior years. All of our results are virtually unaffected by the temporal specification.

contained in *FICUS-FARE*. We define investment as the change of tangible capital between years t and $t+1$.[19] To account for differences in size, we normalize investment by aggregate sales of an industry. We then calculate the standard deviation for individual firms and aggregate these standard deviations at the industry level using sales in 2019 as weights. The idea here is that firms in sectors that experienced a higher volatility in investment foresee higher volatility in the future and therefore use price hikes to create the necessary financial reserves to face these potential additional expenditures.

Finally, we similarly generate a measure of the firm-level volatility in sales, again using *FICUS-FARE*. We first calculate the year-on-year changes in revenue at the firm level and then take their standard deviation at the firm level over the period 2013-2019. We then aggregate these at the industry level using again 2019-sales as weights. As before, the idea is that sectors that experience a greater variability in sales prior to the period of crisis expect a larger variability in the future and therefore aim to make liquidity buffers.

Controls As a first test of whether the heterogeneous pass-through uncovered before can be explained by liquidity buffer dynamics, we introduce each of the prior shocks as controls in our baseline specification. If only past trends were to explain the pricing strategy of firms, our interaction term should now be insignificant. We first introduce each control one by one and then all of them together. To save space, we only present the specification with three- and five-month moving averages.[20]

The results are shown in Table 4. Introducing the controls does not significantly change our baseline results.The interaction term stays significant across all specifications. Interestingly, it seems as though prior volatility shocks in energy and investment have a significant effect on the average change in producer prices over the period of crisis for the three-month specification. Investment also seems to have an effect in the five-month specification. However, neither of the two coefficients display the expected sign. As our energy variable reflects

[19] We use the variable *immo_ corp* in *FICUS-FARE*

[20] Table A.10 in the Appendix shows the results for all specifications when including all three shocks as controls.

a greater ability to adjust to energy prices, we would expect a negative sign on our variable $s.d._j^E$ if firms were hoarding liquidity. Here, the coefficient indicates that sectors that adjusted their energy expenditure more easily to past shocks displayed a greater increase in their prices than other sectors. Further, the results suggest that firms that experienced a greater volatility in their investment rate, experienced significantly *lower* price increases. We leave it to further research to explain these results.

Table 4: Energy price pass-through, controlling for prior shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EP^{avg_3}_{j,t,t-n}$	0.047	0.129	0.142	0.027				
	(0.172)	(0.174)	(0.176)	(0.172)				
$EP^{avg_3}_{j,t,t-n} \times \mathcal{M}_j$	0.433**	0.532***	0.535***	0.449**				
	(0.185)	(0.185)	(0.185)	(0.185)				
$EP^{avg_5}_{j,t,t-n}$					0.335	0.389*	0.405*	0.299
					(0.232)	(0.225)	(0.227)	(0.232)
$EP^{avg_5}_{j,t,t-n} \times \mathcal{M}_j$					0.464*	0.540**	0.542**	0.491**
					(0.248)	(0.245)	(0.245)	(0.248)
$s.d._j^E$	0.287***			0.269**	0.149			0.134
	(0.111)			(0.113)	(0.122)			(0.124)
$s.d._j^I$		-0.128**		-0.077		-0.100*		-0.074
		(0.060)		(0.063)		(0.057)		(0.060)
$s.d._j^S$			-0.000	-0.000			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)
Per. FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	756	756	756	756	756	756	756	756
R^2	0.269	0.262	0.260	0.271	0.276	0.276	0.275	0.278

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Robust standard errors in parentheses. The dependent variable is the monthly PPI inflation rate at the 2-digit sectoral level. $EP^{avg_n}_{j,t,t-n}$ corresponds to the average energy shock of the current month and the $n-1$ months before. $\mathcal{M}_j$ denotes the sales-weighted average markup of sector j. $s.d._j^X$ denotes the variability of other shocks in sector j, with X being j's prior volatility with respect to either energy (E), investment (I), or sales (S). Period fixed effects indicate fixed effects for a given month-year. The estimation is conducted on the period from January 2020 to December 2022.

Purging Markups Second, we now employ a strategy that is close in spirit to an instrumental variable approach. We first regress the prior shocks on markups to see whether sales-weighted average markups might be explained by past trends. In our first stage, we thus estimate the following equation:

$$\mathcal{M}_{j,t} = \alpha + \beta_1 s.d._{j,t}^{E} + \beta_2 s.d._{j,t}^{I} + \beta_3 s.d._{j,t}^{S} + \eta_t + \varepsilon_{j,t}, \tag{3}$$

where $\mathcal{M}_{j,t}$ denotes the sales-weighted average markup in industry j in year t (2018 or 2019) and where η_t denote year fixed effects.[21] From this specification we extract the industry-specific error term $\varepsilon_{j,t}$ for the year 2019 and define this as the markup purged from expectations of future volatility ($\widetilde{\mathcal{M}}_j$). We differentiate between the different first stages by adding a superscript X to $\widetilde{\mathcal{M}}_j$, where X can take the values E (energy-price volatility), I (investment volatility), S (sales volatility) or EIS (all shocks together).

Reassuringly, the results of the first stage, shown in Table 5, all depict the expected sign. Moreover, column (3) reveals that markups seem to be significantly linked to volatility in sales: higher volatility in sales is positively correlated with markups.[22] However, this effect disappears once we regress markups on all the shocks together. Of course, we only have a very small sample here, as we only have two observations by each sector.[23]

In the second stage, we then plug markups purged from expectations of future volatility ($\varepsilon_j \equiv \widetilde{\mathcal{M}}_j$, retrieved from Equation 3) into our baseline specification from Equation 2. We first regress all prior shocks individually and then all together. As before, we concentrate on the three- and five-month moving average specifications.[24] All standard errors in the second

[21] Intuitively, we cannot include industry-fixed effects as this would capture all of the baseline difference between industries with regard to competition. Thus, including industry fixed effects would purge our competition measure of competition, amounting to conceptual non-sense.

[22] The standard deviation is calculated on nominal sales, hence the variable has large values which drastically lowers the coefficient.

[23] To increase the precision of the first stage, we also include the beverages sector, for which we have markups and past volatility shocks. However, for this sector we do not possess the series of PPI prices, such that we need to exclude it from all baseline estimations. Results are virtually unchanged when excluding beverages from the first stage.

[24] Table A.11 in the Appendix shows the results when purging aggregate markups from all three shocks and when including all specifications.

Table 5: Correlation between markups and controls

	(1)	(2)	(3)	(4)
$s.d._j^E$	-9.721			-9.643
	(11.306)			(11.521)
$s.d._j^I$		2.026		-4.901
		(3.149)		(4.995)
$s.d._j^S$			0.000**	0.000
			(0.000)	(0.000)
Per. FE	✓	✓	✓	✓
Obs.	46	46	46	46
R^2	0.092	0.079	0.084	0.100

* p<0.1, ** p<0.05, *** p<0.01

Robust standard errors in parentheses. The dependent variable is the sales-weighted average markup at the 2-digit sectoral level ($\mathcal{M}_j$). $s.d._j^X$ denotes the variability of other shocks in sector j, with X being j's prior volatility with respect to either energy (E), investment (I), or sales (S). The estimation is conducted on the period from January 2020 to December 2022.

stage are bootstrapped.

Table 6 shows the results of this exercise. Before commenting our findings, note here that point estimates are not comparable to our baseline specification. Our measure of the purged markup $\widetilde{\mathcal{M}}_j$ in fact is the deviation from the markup predicted through our first stage. With this in mind, we can see that our findings of heterogeneous pass-through rates depending on the competitive structure are still present, even after purging for the expectations of volatility. If anything, the results seem to be even stronger. We see this as a further indication that during the most recent crisis inflation was considerably driven by firms in sectors where competition was lacking, and without this firm behavior being linked to any liquidity buffer motive.

Table 6: Energy price pass-through, purging $\mathcal{M}$ from prior shocks

	$\widetilde{\mathcal{M}}_j^E$	$\widetilde{\mathcal{M}}_j^I$	$\widetilde{\mathcal{M}}_j^S$	$\widetilde{\mathcal{M}}_j^{EIS}$	$\widetilde{\mathcal{M}}_j^E$	$\widetilde{\mathcal{M}}_j^I$	$\widetilde{\mathcal{M}}_j^S$	$\widetilde{\mathcal{M}}_j^{EIS}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EP^{avg_3}_{j,t,t-n}$	0.649***	0.693***	0.695***	0.654***				
	(0.121)	(0.130)	(0.130)	(0.122)				
$EP^{avg_3}_{j,t,t-n} \times \widetilde{\mathcal{M}}_j^X$	0.495***	0.518***	0.520***	0.502***				
	(0.189)	(0.190)	(0.190)	(0.189)				
$EP^{avg_5}_{j,t,t-n}$					0.924***	0.965***	0.966***	0.928***
					(0.160)	(0.171)	(0.171)	(0.161)
$EP^{avg_5}_{j,t,t-n} \times \widetilde{\mathcal{M}}_j^X$					0.503**	0.517**	0.519**	0.510**
					(0.253)	(0.250)	(0.251)	(0.253)
$\widetilde{\mathcal{M}}_j^X$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Per. FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	756	756	756	756	756	756	756	756
R^2	0.258	0.259	0.259	0.258	0.274	0.274	0.274	0.274

* p<0.1, ** p<0.05, *** p<0.01

Bootstrapped standard errors in parentheses. The dependent variable is the monthly PPI inflation rate at the 2-digit sectoral level. $EP^{avg_n}_{j,t,t-n}$ corresponds to the average energy shock of the current month and the $n-1$ months before. $\widetilde{\mathcal{M}}_j^X$ denotes the aggregate markup, purged from the effect of X, with X being j's prior volatility with respect to either energy (E), investment (I), sales (S) or all three together (EIS). Period fixed effects indicate fixed effects for a given month-year. The estimation is conducted on the period from January 2020 to December 2022.

6 Conclusion

The recent spectacular return of inflation in the Euro Area calls for analyses of its root causes. In this paper, we empirically test the hypothesis that recent inflation has been significantly influenced by the aggressive pricing behavior of firms. We construct a sector-specific shift-share measure of the energy cost shock, relying on pre-crisis energy mix and pre-crisis share of energy in total expenditure as the share element and energy price evolution from January 2020 until December 2022 as the shift element.

We first regress this measure of the cost shock on the Producer Price Index (PPI), finding that on average firms passed through 40 to 100% of the cost shock into goods' prices. We then use the state-of-the-art methodology introduced by De Loecker and Warzynski (2012) to measure firm-level markups, which we—in line with De Loecker et al. (2020)—aggregate at the sectoral level using market shares as weights. Interacting these average markups with our energy cost shock, we find that sectors with higher markups (less competition) passed through a significantly *higher* amount of the cost shock into prices. A back-of-the-envelope calculation suggests that pass-through for the least competitive sector was over 115%, meaning that prices increased more than the initial energy shock would have warranted. Our baseline results are further corroborated by an interaction with the more classical measure of competition, the HHI index.

We also look more deeply into the potential mechanism that might underly our results. Specifically, we show that results are *not* driven by a "liquidity buffer rationale". One could suspect those sectors that expect bigger shocks in the future to amass liquidity in order to face these potential negative shocks. Such a dynamic would considerably change the implications of heterogeneous pass-through rates, as financial cushions might soften future blows. However, using past volatility with regard to inputs and demand in order to proxy for expectations on future shocks, we still find a significant heterogeneity along the lines of aggregate market power. Thus, our results should be interpreted as indicating that in certain sectors firms' pricing strategies have been detrimental to the welfare of consumers during the recent energy crisis.

In summary, our results provide evidence in favor of the argument that recent inflation was driven by the pricing behavior of firms in some sectors. We reveal the necessity of accounting for the differential competitive structures within sectors when assessing the response of prices to the energy cost shocks: sectors with more market power have passed through a higher amount of the cost shock and, hence, have contributed significantly to the recent evolution of inflation. Once available, further research should use more fine-grained data to explore at the firm level the sectoral dynamics we have highlighted in this paper. Moreover, modeling this recent pricing behavior might be a fruitful research agenda for the future in order to better analyze the underlying dynamics at play and to formulate relevant policy recommendation.

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A Appendix

A.1 Liquidity Buffer Rationale – Other specifications

To test the robustness of our results, we include other specifications, for which we construct volatility on 7, 5, 4 or 3 prior years. All of our results are virtually unaffected.

A.1.1 3 years volatility

Table A.1: Energy price pass-through, controlling for prior shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EP^{avg_3}_{j,t,t-n}$	0.046	0.153	0.141	0.017				
	(0.172)	(0.175)	(0.176)	(0.171)				
$EP^{avg_3}_{j,t,t-n} \times \mathcal{M}_j$	0.445**	0.507***	0.535***	0.477***				
	(0.185)	(0.190)	(0.185)	(0.184)				
$EP^{avg_5}_{j,t,t-n}$					0.344	0.430*	0.404*	0.289
					(0.233)	(0.227)	(0.227)	(0.234)
$EP^{avg_5}_{j,t,t-n} \times \mathcal{M}_j$					0.480*	0.543**	0.542**	0.538**
					(0.249)	(0.258)	(0.245)	(0.251)
$s.d._j^E$	0.203**			0.246**	0.094			0.137
	(0.081)			(0.115)	(0.090)			(0.119)
$s.d._j^I$		0.004		-0.008		-0.002		-0.008
		(0.006)		(0.009)		(0.007)		(0.009)
$s.d._j^S$			-0.000	-0.000			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)
Per. FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	756	756	756	756	756	756	756	756
R^2	0.268	0.260	0.260	0.270	0.276	0.274	0.275	0.278
Adj. R^2	0.227	0.218	0.219	0.227	0.235	0.234	0.235	0.235

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table A.2: Correlation between markups and controls

	(1)	(2)	(3)	(4)
$s.d._j^E$	2.258			1.993
	(6.052)			(6.245)
$s.d._j^I$		-0.168		-0.168
		(0.141)		(0.144)
$s.d._j^S$			-0.000	-0.000
			(0.000)	(0.000)
Per. FE	✓	✓	✓	✓
Obs.	105	105	105	105
R^2	0.085	0.103	0.087	0.107

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table A.3: Energy price pass-through, purging $\mathcal{M}$ from prior shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EP^{avg_3}_{j,t,t-n}$	0.693***	0.667***	0.679***	0.679***				
	(0.131)	(0.126)	(0.128)	(0.128)				
$EP^{avg_3}_{j,t,t-n} \times \widetilde{\mathcal{M}}^X_j$	0.535***	0.482***	0.527***	0.491***				
	(0.190)	(0.184)	(0.190)	(0.184)				
$EP^{avg_5}_{j,t,t-n}$					0.964***	0.939***	0.950***	0.950***
					(0.172)	(0.166)	(0.168)	(0.169)
$EP^{avg_5}_{j,t,t-n} \times \widetilde{\mathcal{M}}^X_j$					0.536**	0.474*	0.529**	0.484**
					(0.250)	(0.244)	(0.251)	(0.243)
$\widetilde{\mathcal{M}}^X_j$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Per. FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	756	756	756	756	756	756	756	756
R^2	0.259	0.258	0.259	0.258	0.274	0.273	0.274	0.274
Adj. R^2	0.219	0.218	0.219	0.218	0.235	0.234	0.235	0.234

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

A.1.2 5 years volatility

Table A.4: Energy price pass-through, controlling for prior shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EP^{avg_3}_{j,t,t-n}$	0.046	0.165	0.141	0.037				
	(0.172)	(0.173)	(0.176)	(0.171)				
$EP^{avg_3}_{j,t,t-n} \times \mathcal{M}_j$	0.440**	0.488**	0.534***	0.448**				
	(0.185)	(0.195)	(0.185)	(0.187)				
$EP^{avg_5}_{j,t,t-n}$					0.340	0.437**	0.403*	0.324
					(0.233)	(0.221)	(0.227)	(0.236)
$EP^{avg_5}_{j,t,t-n} \times \mathcal{M}_j$					0.474*	0.493*	0.541**	0.484*
					(0.248)	(0.270)	(0.245)	(0.262)
$s.d._j^E$	0.269**			0.261*	0.130			0.123
	(0.106)			(0.135)	(0.117)			(0.141)
$s.d._j^I$		0.005		0.000		0.003		0.000
		(0.007)		(0.008)		(0.008)		(0.009)
$s.d._j^S$			-0.000	-0.000			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)
Per. FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	756	756	756	756	756	756	756	756
R^2	0.268	0.261	0.261	0.269	0.276	0.275	0.275	0.277
Adj. R^2	0.227	0.219	0.219	0.226	0.236	0.234	0.235	0.234

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table A.5: Correlation between markups and controls

	(1)	(2)	(3)	(4)
$s.d._j^E$	-3.273			-2.303
	(7.705)			(8.027)
$s.d._j^I$		-0.259		-0.258
		(0.180)		(0.183)
$s.d._j^S$			0.000*	0.000*
			(0.000)	(0.000)
Per. FE	✓	✓	✓	✓
Obs.	69	69	69	69
R^2	0.070	0.086	0.073	0.093

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table A.6: Energy price pass-through, purging $\mathcal{M}$ from prior shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EP_{j,t,t-n}^{avg_3}$	0.679***	0.675***	0.695***	0.664***				
	(0.127)	(0.127)	(0.130)	(0.125)				
$EP_{j,t,t-n}^{avg_3} \times \widetilde{\mathcal{M}}_j^X$	0.515***	0.446**	0.522***	0.436**				
	(0.190)	(0.179)	(0.190)	(0.179)				
$EP_{j,t,t-n}^{avg_5}$					0.952***	0.948***	0.966***	0.938***
					(0.167)	(0.167)	(0.171)	(0.165)
$EP_{j,t,t-n}^{avg_5} \times \widetilde{\mathcal{M}}_j^X$					0.518**	0.439*	0.522**	0.428*
					(0.252)	(0.239)	(0.251)	(0.239)
$\widetilde{\mathcal{M}}_j^X$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Per. FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	756	756	756	756	756	756	756	756
R^2	0.259	0.257	0.259	0.257	0.274	0.273	0.274	0.273
Adj. R^2	0.218	0.216	0.219	0.216	0.235	0.233	0.235	0.233

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

A.1.3 7 years volatility

Table A.7: Energy price pass-through, controlling for prior shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EP^{avg3}_{j,t,t-n}$	0.046	0.156	0.158	0.036				
	(0.172)	(0.175)	(0.175)	(0.172)				
$EP^{avg3}_{j,t,t-n} \times \mathcal{M}_j$	0.472**	0.536***	0.533***	0.484***				
	(0.185)	(0.186)	(0.186)	(0.186)				
$EP^{avg5}_{j,t,t-n}$					0.359	0.423*	0.429*	0.339
					(0.234)	(0.225)	(0.225)	(0.234)
$EP^{avg5}_{j,t,t-n} \times \mathcal{M}_j$					0.505**	0.546**	0.542**	0.528**
					(0.249)	(0.246)	(0.246)	(0.250)
$s.d._j^E$	0.361**			0.365**	0.133			0.134
	(0.165)			(0.177)	(0.184)			(0.195)
$s.d._j^I$		0.000		0.000		0.000*		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
$s.d._j^S$			0.000	-0.000			0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)
Per. FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	756	756	756	756	756	756	756	756
R^2	0.266	0.261	0.260	0.269	0.275	0.276	0.276	0.278
Adj. R^2	0.225	0.219	0.219	0.226	0.235	0.236	0.235	0.236

Standard errors in parentheses

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table A.8: Correlation between markups and controls

	(1)	(2)	(3)	(4)
$s.d._j^E$	-33.064			-34.415
	(20.173)			(22.044)
$s.d._j^I$		0.003*		0.021
		(0.002)		(0.025)
$s.d._j^S$			0.000	-0.000
			(0.000)	(0.000)
Per. FE	No	No	No	No
Obs.	23	23	23	23
R^2	0.131	0.007	0.007	0.140

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table A.9: Energy price pass-through, purging $\mathcal{M}$ from prior shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EP^{avg_3}_{j,t,t-n}$	0.577***	0.693***	0.692***	0.575***				
	(0.115)	(0.129)	(0.129)	(0.114)				
$EP^{avg_3}_{j,t,t-n} \times \widetilde{\mathcal{M}}^X_j$	0.436**	0.536***	0.530***	0.470**				
	(0.204)	(0.191)	(0.191)	(0.206)				
$EP^{avg_5}_{j,t,t-n}$					0.862***	0.965***	0.964***	0.860***
					(0.150)	(0.170)	(0.170)	(0.149)
$EP^{avg_5}_{j,t,t-n} \times \widetilde{\mathcal{M}}^X_j$					0.425	0.544**	0.537**	0.476*
					(0.268)	(0.252)	(0.252)	(0.271)
$\widetilde{\mathcal{M}}^X_j$	-0.001	-0.002	-0.002	-0.001	-0.001	-0.002	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Per. FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	756	756	756	756	756	756	756	756
R^2	0.256	0.259	0.259	0.257	0.272	0.275	0.274	0.273
Adj. R^2	0.216	0.219	0.219	0.216	0.233	0.235	0.235	0.233

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

A.2 Liquidity Buffer Rationale – 6 years – Additional tables

Table A.10 shows the results for all specifications when including all three shocks as controls.

Table A.10: Energy price pass-through, controlling for all prior evolutions

	(1)	(2)	(3)	(4)
$EP_{j,t,t-n}$	-0.122			
	(0.109)			
$EP^{avg_3}_{j,t,t-n}$		0.027		
		(0.172)		
$EP^{avg_5}_{j,t,t-n}$			0.299	
			(0.232)	
$EP^{avg_7}_{j,t,t-n}$				0.455*
				(0.264)
$\mathcal{M}_j$	-0.001	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
$s.d._j^E$	0.387***	0.269**	0.134	0.064
	(0.102)	(0.113)	(0.124)	(0.125)
$s.d._j^I$	-0.079	-0.077	-0.074	-0.075
	(0.064)	(0.063)	(0.060)	(0.058)
$s.d._j^S$	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$EP_{j,t,t-n} \times \mathcal{M}_j$	0.274**			
	(0.126)			
$EP^{avg_3}_{j,t,t-n} \times \mathcal{M}_j$		0.449**		
		(0.185)		
$EP^{avg_5}_{j,t,t-n} \times \mathcal{M}_j$			0.491**	
			(0.248)	
$EP^{avg_7}_{j,t,t-n} \times \mathcal{M}_j$				0.510*
				(0.285)
Per. FE	✓	✓	✓	✓
Obs.	756	756	756	756
R^2	0.263	0.271	0.278	0.280
Adj. R^2	0.219	0.228	0.236	0.238

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table A.11 shows the results when purging aggregate markups from all three shocks and when including all specifications together.

Table A.11: Energy price pass-through, purging $\mathcal{M}$ from prior shocks

	(1)	(2)	(3)	(4)
$EP_{j,t,t-n}$	0.256***			
	(0.098)			
$EP^{avg3}_{j,t,t-n}$		0.654***		
		(0.122)		
$EP^{avg5}_{j,t,t-n}$			0.928***	
			(0.161)	
$EP^{avg7}_{j,t,t-n}$				1.051***
				(0.181)
$\widetilde{\mathcal{M}}^{EIS}_j$	-0.001	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
$EP_{j,t,t-n} \times \widetilde{\mathcal{M}}^{EIS}_j$	0.309**			
	(0.136)			
$EP^{avg3}_{j,t,t-n} \times \widetilde{\mathcal{M}}^{EIS}_j$		0.502***		
		(0.189)		
$EP^{avg5}_{j,t,t-n} \times \widetilde{\mathcal{M}}^{EIS}_j$			0.510**	
			(0.253)	
$EP^{avg7}_{j,t,t-n} \times \widetilde{\mathcal{M}}^{EIS}_j$				0.509*
				(0.283)
Per. FE	✓	✓	✓	✓
Obs.	756	756	756	756
R^2	0.236	0.258	0.274	0.278
Adj. R^2	0.194	0.218	0.235	0.239

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

A.3 Markup Estimation

In order to compute markups, we rely on the so-called production function approach initially introduced by De Loecker and Warzynski (2012). As described in De Loecker and Warzynski (2012) and De Loecker et al. (2020), firm-level markups can be identified using the following equation within a framework similar to Hall et al. (1986):

$$\mu_{it} = \theta_{it}^{V} \frac{P_{it} Q_{it}}{P_{it}^{V} V_{it}^{V}}. \tag{4}$$

As the input share is observed, the crucial parameter that needs to be estimated is the output elasticity of the variable input of production, θ_{it}^{V}. A naive estimation of elasticity by simply regressing input on output is biased in the presence of idiosyncratic productivity shocks (observed by the firm but not by the econometrician). Therefore, De Loecker and Warzynski (2012) propose a two-stage generalized method of moments (GGM) procedure to identify the output elasticity in the presence of unobserved productivity shocks and measurement error in output. The procedure starts with the following unspecified production function:

$$y_{it} = f(v_{it}, k_{it}; \beta) + \omega_{it} + \varepsilon_{it}, \tag{5}$$

where ω_{it} denotes firm i's productivity at time t (observed by the firm before it takes its input decision, but unobserved by the econometrician) and the error term ε_{it} includes unanticipated shocks to productivity and measurement error in the output. Both ω_{it} and ε_{it} are unobserved. $f(v_{it}, k_{it}; \beta)$ represents the part of the production function that we will need to specify more concretely in the following, in which v_{it} represents variable inputs and k_{it} is capital. In our implementation of the procedure, we will assume $f(\cdot)$ to be a translog function with third order polynomials.

There is some debate around the exact form to adopt for $f(\cdot)$, with researchers either using a Cobb-Douglas or a translog function. The debate, with perks and disadvantages of each specification can be found in great detail in De Ridder et al. (2021). We rely on the insight by De Ridder et al. (2021) which investigate the suitability of different implementations of the procedure, using the same data we use. They conclude that the translog is best suited as it allows the elasticity to depend on the level of input use and ultimately allows for some heterogeneity in elasticity across firms and time. A Cobb-Douglas does not allow output elasticities to depend on input use intensity and therefore attributes variation in technology to variation in markups, introducing a bias.

Within Equation 5, one needs to account for productivity ω_{it}, unobserved by the econometrician but observed by the firm and guiding its input decision. Following Ackerberg et al. (2015), the demand for materials is used to proxy for the productivity of a given firm i at time t. This demand is written as:

$$m_{it} = m_t(k_{it}, \omega_{it}, z_{it})$$

where z_{it} denotes a vector of control variables that might affect input demand. The exact variables used for z_{it} depend on the data set and the problem analyzed in the study. In our estimation we follow the literature and use firms' sectoral market share to control for input demand shifters. Assuming monotonicity of the demand for materials, we can invert it to get:

$$\omega_{it} = h_t(k_{it}, m_{it}, z_{it}), \tag{6}$$

where $h_t = m_t^{-1}$.

Using this, we can now look at the two-stage GMM method. The objective of the first stage is to purge output from measurement error and from productivity shocks unobserved by the firm. This stage consists of an unparametrical estimation of the production function presented in Equation 5 in order to obtain the expected output, $\hat{\phi}_{it}$, and the measurement error, ε_{it}. The main challenge of this first stage is to identify productivity and measurement error separately, both of which are unobserved (De Ridder et al., 2021). In order to obtain a coherent separation between the two in a setting of imperfect competition, we will need to include coherent variables that control for productivity (the use of intermediates) and markups (the market share).

In essence, in the first stage we estimate the following equation:

$$y_{it} = \phi_t(v_{it}, k_{it}, z_{it}) + \varepsilon_{it} \tag{7}$$

where y_{it} denotes observed output (total revenue) and z_{it} represents materials-demand shifters (market share). The variable v_{it} denotes the static input, which consists in our case of direct and other inputs for production (see Table A.12). We follow the literature and estimate the expected output $\hat{\phi}_{it}$ through a non-parametric estimation of a translog production function including up to third-order polynomials (see above):

$$\hat{\phi}_{it} = \beta_v v_{it} + \beta_{v^2} v_{it}^2 + \beta_{v^3} v_{it}^3 + \beta_k k_{it} + \beta_{k^2} k_{it}^2 + \beta_{k^3} k_{it}^3 + I_{vk} + h_t(k_{it}, m_{it}, z_{it}), \tag{8}$$

where I_{vk} denotes the full set of interactions between v and k, and $h_t(\cdot)$ denotes the inverted material demand from Equation 6.

The second stage now uses the cleaned output (estimated in the first stage) and aims to identify productivity ω_{it} for any set of β's. Following Equation 8 productivity is given by:

$$\omega_{it} = \hat{\phi}_{it} - \beta_v v_{it} - \beta_{v^2} v_{it}^2 - \beta_{v^3} v_{it}^3 - \beta_k k_{it} - \beta_{k^2} k_{it}^2 - \beta_{k^3} k_{it}^3 - I_{vk}. \tag{9}$$

We now posit that the law of motion for productivity follows an AR(1) process. Productivity is hence modeled as an unparametric function of past productivity ω_{it-1} and a term ξ_{it}, the innovation to productivity:

$$\omega_{it} = g_t(\omega_{it-1}) + \xi_{it}. \tag{10}$$

Using this, we can form moments in order to obtain the estimates of the production function:

$$E\left(\xi_{it}(\beta)\begin{pmatrix} v_{it-1} \\ k_{it} \\ v_{it-1}^2 \\ k_{it}^2 \\ v_{it-1}k_{it} \end{pmatrix}\right) = 0. \tag{11}$$

The moment conditions describe the necessary condition that productivity is uncorrelated to (i) the dynamic input (capital k_{it}) which is chosen a period ahead and thus independently from changes in productivity ($\xi_{it}(\beta)$) and (ii) that the lagged static input (v_{it-1}) does not react to current-period shocks to productivity. Under the condition that these moments are satisfied, we can use lagged values of v to instrument for its current values in order to identify the output elasticities of variable inputs for each two-digit sector. We can then calculate the output elasticity of variable inputs as:

$$\hat{\theta}_{it}^V = \hat{\beta}_v + 2\hat{\beta}_{v^2}v_{it} + \hat{\beta}_{vk}, \tag{12}$$

which, after inserting $\hat{\theta}_{it}^V$ into Equation 4 and purging revenue $P_{it}Q_{it}$ from unanticipated productivity shocks and measurement error ε_{it} (Equation 5), yields firm-level markups at time t, i.e. μ_{it}.

A.3.1 Variables FARE

Table A.12: Variables used in markup estimation

Variable in model	Variable description	Variable in FARE
Revenue	Total sales, including exports	REDIR310
Employment	Full-time equivalent of the number of directly employed workers by the firm average over each accounting quarter	REDIE200
Wage bill	Sum of wage payments and social security contributions	REDIR216 + REDIR217
Direct inputs	Sum of merchandise and raw material purchases, corrected for fluctuations in inventory	REDIR210 + REDIR212 + REDIR211 + REDIR213
Other inputs	Purchases of services (includes outsourcing costs, lease payments, rental charges for equipment and furniture, maintenance expenses, insurance premiums and costs for external market research, advertising, transportation, and external consultants)	REDIR214
Operating profits	Revenue minus wage bill, expenditure on direct production inputs, other purchases, import duties and similar taxes, capital depreciation, provisions and other charges	REDIR310 - REDIR215 (taxes) - REDIR201 (rest)
Capital stock	Stock of fixed tangible assets (land, buildings, machinery and other installations)	IMMOCORP
Value added	Value added before taxes	REDIR003

A.4 Sectors

Table A.13: Manufacturing sectors

NAF/ISIC code	Description
10	Manufacture of food products
13	Manufacture of textiles
14	Manufacture of clothing
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork (exc. furniture)
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
20	Manufacture of chemicals and chemical products
21	Manufacture of pharmaceuticals medicinal chemical and botanical products
22	Manufacture of rubber and plastics products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
32	Other manufacturing
33	Repair and installation of machinery and equipment
38	Waste collection, treatment and disposal activities; materials recovery