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# ENERGY, INFLATION AND MARKET POWER: EXCESS PASS-THROUGH IN FRANCE

Axelle Arquié[1], Malte Thie[2]

## 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 February 2023). Our work provides some empirical evidence in favor of a role for firms' market power in explaining inflation, and in favor of the "sellers' inflation" hypothesis (Weber and Wasner (2023): in less competitive sectors, firms could use the energy price hike to increase their prices more than warranted by actual changes in costs. 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 up to 110% of the energy shock, implying an excess pass-through of 10 percentage points. In addition, we find that the association between markup and pass-through is even higher when markup dispersion is low, consistent with the argument that firms engage in price hikes when they expect their competitors to do the same.

1 Axelle Arquié, CEPII: axelle.arquie@cepii.fr
2 Malte Thie, CEPII and Université Paris Dauphine: malte.thie@dauphine.psl.eu

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

Axelle Arquié[a] and Malte Thie[a,b]

[a] *CEPII*†

[b] *Université Paris Dauphine–PSL*

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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 February 2023). Our work provides some empirical evidence in favor of a role for firms' market power in explaining inflation, and in favor of the "sellers' inflation" hypothesis (Weber and Wasner (2023)): in less competitive sectors, firms could use the energy price hike to increase their prices *more* than warranted by actual changes in costs. 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 up to 110% of the energy shock, implying an excess pass-through of 10 percentage points. In addition, we find that the association between markup and pass-through is even higher when markup dispersion is low, consistent with the argument that firms engage in price hikes when they expect their competitors to do the same.

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†20 avenue de Segur 75007 Paris, France. Contact the authors at axelle.arquie@cepii.fr and malte.thie@dauphine.psl.eu.

# 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, combined with an 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, 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.

While there is no doubt that energy prices are among the main causes of the increase in inflation, questions have arisen about the role of market power in the transmission of these shocks. Weber and Wasner (2023) 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, pointing 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. According to their argumentation, the most powerful firms were not only able to pass through the entirety of the cost shock onto prices in order to shield profits, but hiked their prices more than the initial price shock as they gained temporary monopoly power thanks to bottlenecks. US inflation can thus be seen as a "sellers' inflation". 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.

However, these findings are in contrast with standard models that would predict that sectors 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 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. These theoretical and empirical papers fall short of explaining the dynamics exposed by Weber and Wasner (2023) and Bräuning et al. (2022).

For the French context, which is the one that we study in this paper, Lafrogne-Joussier et al. (2023) use fine-grained 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. They 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.

In this paper, we similarly investigate the reaction of French manufacturing prices to energy price shocks, but we conduct our analysis 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.[1] 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 45 and 104%, an interaction with average markups reveals considerable heterogeneities. We find that within 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 almost 10 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. In addition, we find that the association between markup and pass-through is even higher when markup dispersion is low.

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 argumentation introduced by Weber and Wasner (2023).[2] Our results suggest that firms in less competitive sectors were able to pass through a significantly higher share of the cost shock onto prices. This dynamic is further exacerbated when markup dispersion is low, consistent with the argument that firms engage in price hikes when they expect their competitors to do the same. Intuitively, this could be the case because firms were seeking to shield their profit margins from decreasing. While firms in more competitive

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

[2]We study the impact on producer prices and not consumer prices. Therefore, 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.

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.

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; section 5 concludes.

# 2 Data

## 2.1 Goods’ prices

As a measure of goods’ prices we use the Producer Price Index (PPI) for different manufacturing sectors.[3] 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:

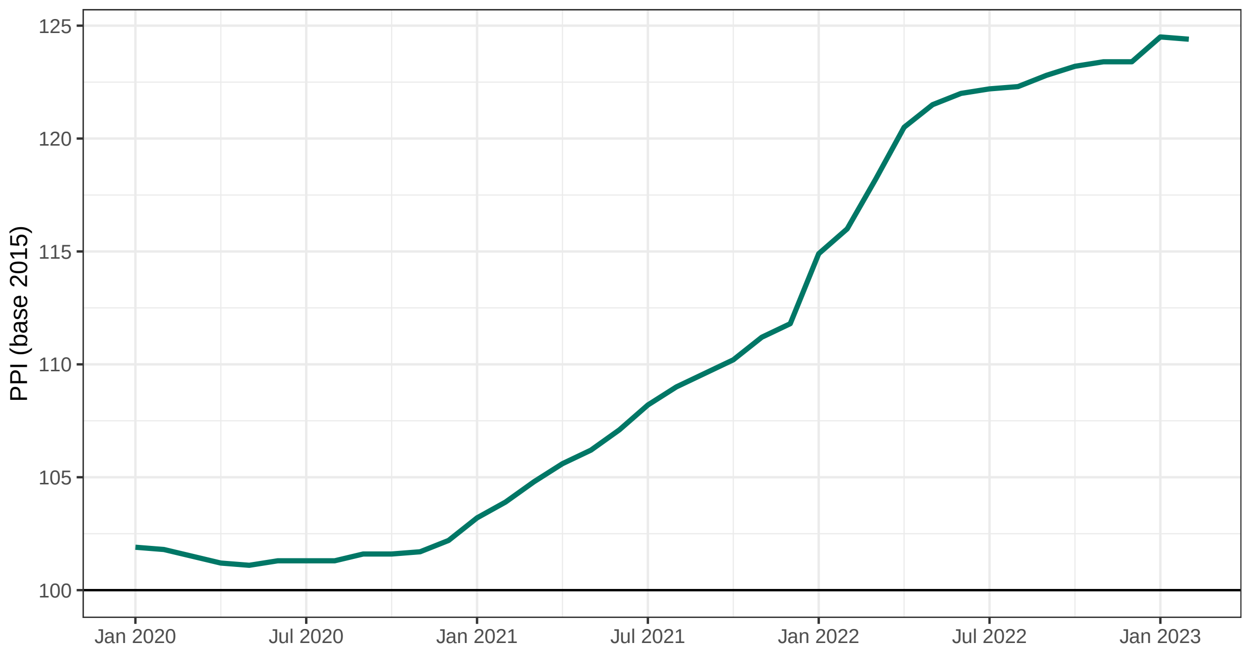
$$\Pi_{j,t,t-1} = \frac{P_{j,t} - P_{j,t-1}}{P_{j,t-1}},$$

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

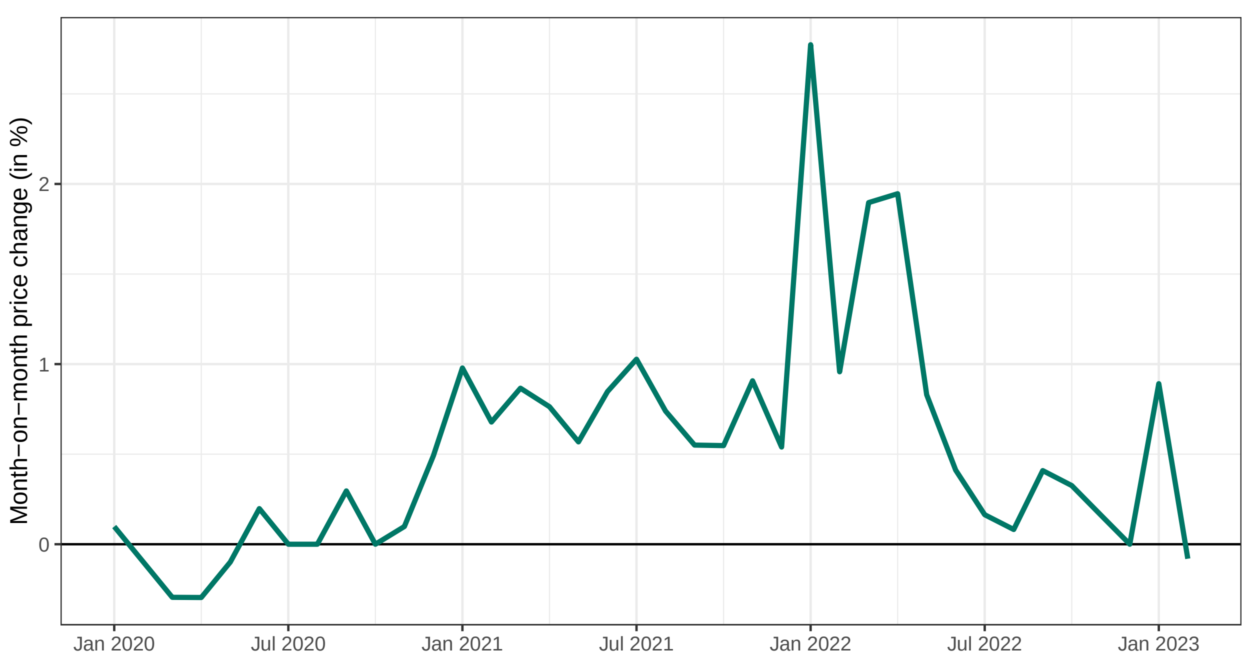
[3] See Appendix Table 6 for the full list of sectors.

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




Source: *INSEE*.

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




Source: *INSEE*, authors' calculations.

## 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 February 2023. 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 ($\pi^{avg_n}_{e,t,t-n}$). 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.[4] Hence, our estimates should be seen as reflecting the theoretical lower bound where all firms act under perfectly flexible energy contracts.[5]

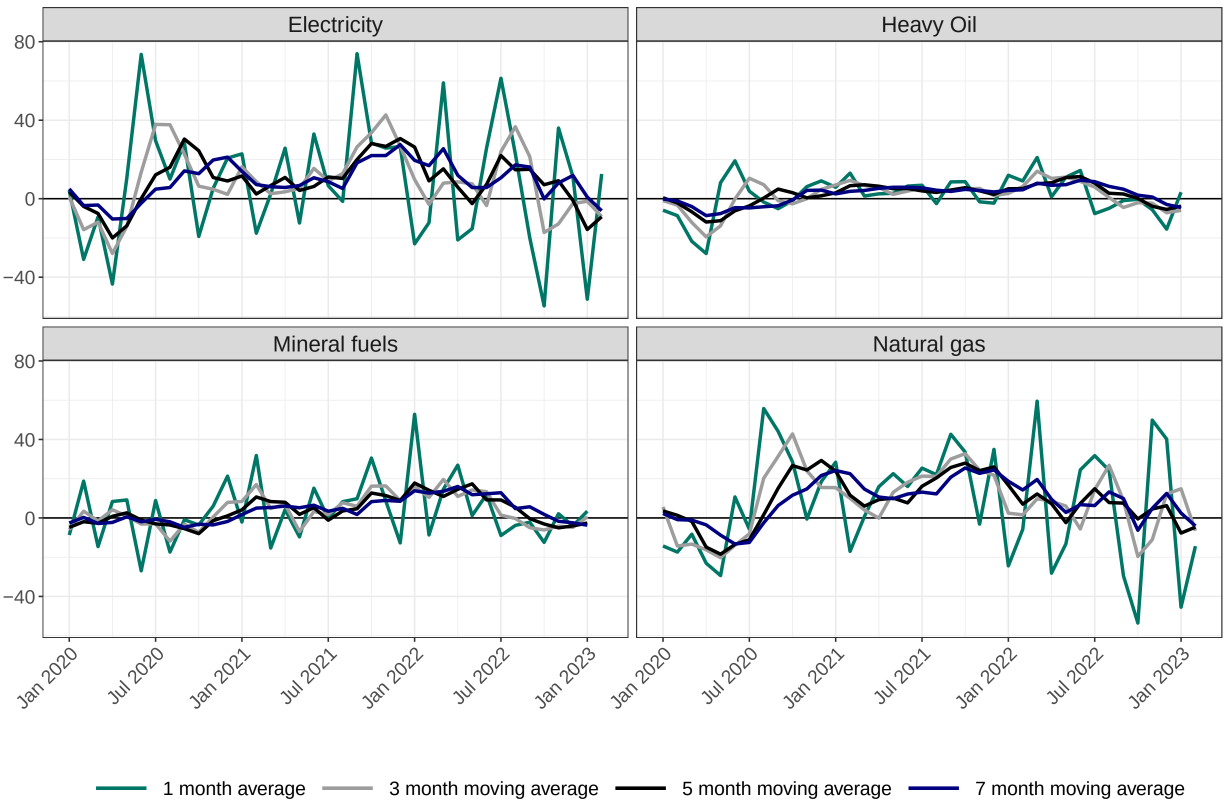
Figure 3 shows the price evolution for the different kinds of energy. As we can see, the simple monthly energy price inflation rates are highly volatile, especially for electricity and natural gas. In order to smooth the evolution of prices, we include three-month, five-month or seven-month moving averages. 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. Moreover, taking averages over $n-1$ months before the shock is in line with empirical evidence on sticky prices: given that firms can only adjust their prices in certain intervals, they will incorporate all the changes in costs that occurred since their last price-adjustment.

Second, we use data provided by the *INSEE* on the energy used by industrial sectors in

[4]See INSEE (2022).

[5]Multiplying our measure of energy prices with the share of flexible contracts within a sector would increase the measured effect of our baseline estimation, see the discussion in section 3.

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




Source: *Ministère de la Transition Écologique.*

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 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.

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

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

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:

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

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

## 2.3 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.1).

First, we rely on the *FICUS-FARE* dataset, which provides confidential data on French firms' balance sheets.[7] We extract information on revenue, labor expenses, material purchases and tangible capital stock.[8] 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. 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

[7]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/.

[8]See Appendix Table 5 for a full list of the variables used.

output elasticities at the three-digit industry level. The final dataset contains 22 sectors.[9] 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 based on the following specification:

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

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.1. Finally, $\eta_t$ denotes period fixed effects.

We are interested in particular in $\beta$ 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 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 February 2023.

**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 $\alpha$ (and $\beta$) is, thus, that the energy mix might actually vary in response to the change in energy prices in a way that

[9] See Appendix Table 6 for the full list of sectors.

is correlated with the change in producer prices (PPI). Such a correlation could be due to common unobserved characteristics of the sector or an unobserved shock affecting both producer prices and the strength of the energy shock through the energy mix.[10] 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.[11] 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.[12]

Regarding the estimate $\beta$ alone, another possible concern is that some unobservable both impacts PPI change and markups. To reduce this endogeneity concern, we use the markup

[10]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 1 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.

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

[12]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 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.

level of the sector in 2019, i.e. previous to the pandemic and the energy crisis.

# 4 Results

**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 effect increases once we smooth the energy shock over the three, five or seven prior months, suggesting that producer prices display some stickiness relative to the high frequency of changes in energy prices. This first rough measure of pass-through thus suggests that firms pass between 45 and 104% of their cost increases into prices, as shown in columns 3 to 8 of Table 1. Hence, except for column (8), simple regressions suggest that firms functioned as a "light cushion" to soften the impact of energy prices on inflation by reducing their profit margins.

**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 1, 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.[13]

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 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

[13] As our markups are at the industry-level, including industry fixed effects would eliminate all the variation with respect to our interaction.

**Table 1:** Energy price pass-through on PPI

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| $EP_{j,t,t-n}$ | 0.170* | 0.090 | | | | | | |
| | (0.095) | (0.098) | | | | | | |
| $EP^{avg_3}_{j,t,t-n}$ | | | 0.582*** | 0.448*** | | | | |
| | | | (0.121) | (0.143) | | | | |
| $EP^{avg_5}_{j,t,t-n}$ | | | | | 0.835*** | 0.759*** | | |
| | | | | | (0.158) | (0.224) | | |
| $EP^{avg_7}_{j,t,t-n}$ | | | | | | | 0.988*** | 1.043*** |
| | | | | | | | (0.176) | (0.251) |
| Per. FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Ind. FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Obs. | 760 | 760 | 760 | 760 | 760 | 760 | 760 | 760 |
| $R^2$ | 0.224 | 0.266 | 0.248 | 0.278 | 0.263 | 0.289 | 0.270 | 0.295 |
| Adj. $R^2$ | 0.183 | 0.206 | 0.209 | 0.220 | 0.225 | 0.231 | 0.231 | 0.238 |

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

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.

A way to make sense of this fading significance of the markup channel relies on the notion of sticky prices (Nakamura and Steinsson (2008)). While the contemporaneous shock of energy costs (line 1 of the table) has on average no effect on prices as they are sticky, only firms in the least competitive sectors were able to adjust their prices upwards, as shown by the significant interaction term. Once we enlarge the shock to take into account the shocks

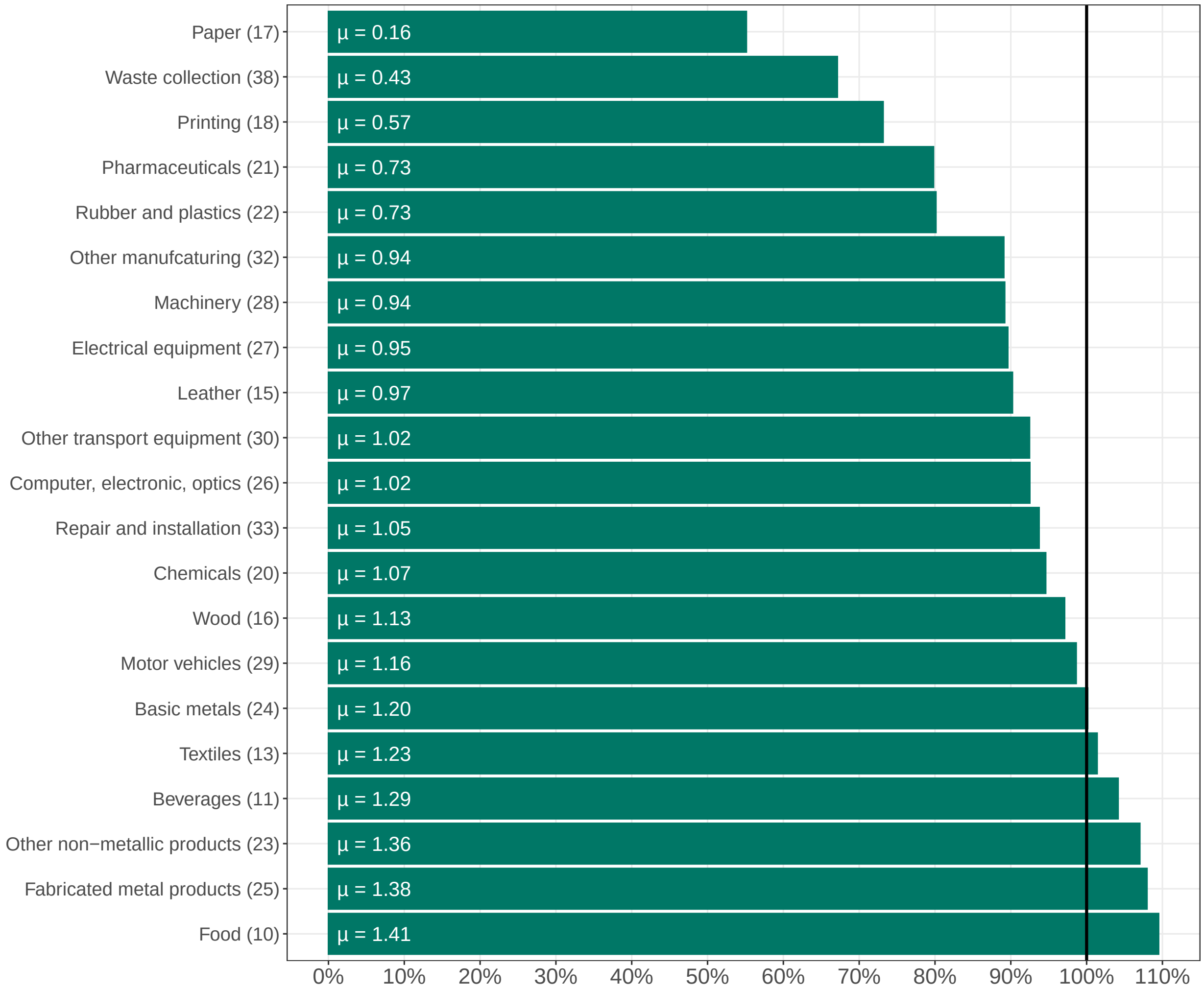
**Table 2:** Energy price pass-through and market power

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $EP_{j,t,t-n}$ | -0.048 | | | |
| | (0.121) | | | |
| $EP^{avg_3}_{j,t,t-n}$ | | 0.198 | | |
| | | (0.175) | | |
| $EP^{avg_5}_{j,t,t-n}$ | | | 0.483** | |
| | | | (0.235) | |
| $EP^{avg_7}_{j,t,t-n}$ | | | | 0.681*** |
| | | | | (0.246) |
| $\mathcal{M}_j$ | -0.001 | -0.001 | -0.000 | 0.000 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| $EP_{j,t,t-n} \times \mathcal{M}_j$ | 0.282** | | | |
| | (0.140) | | | |
| $EP^{avg_3}_{j,t,t-n} \times \mathcal{M}_j$ | | 0.481** | | |
| | | (0.187) | | |
| $EP^{avg_5}_{j,t,t-n} \times \mathcal{M}_j$ | | | 0.433* | |
| | | | (0.258) | |
| $EP^{avg_7}_{j,t,t-n} \times \mathcal{M}_j$ | | | | 0.376 |
| | | | | (0.279) |
| Period FE | Yes | Yes | Yes | Yes |
| Obs. | 760 | 760 | 760 | 760 |
| R squared | 0.232 | 0.256 | 0.268 | 0.273 |
| Adjusted R-squared | 0.189 | 0.215 | 0.227 | 0.233 |

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

of prior months, the stickiness of prices disappears and we observe on average an adjustment of prices for all sectors, with still a significant premium in the least competitive sectors. Only once we allow for relatively large windows (7 months), there seems to be no significant difference between high- and low-competition sectors. These results suggest an interesting

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




Note: The black line corresponds to a pass-through of 100%: 5 sectors exhibit an excess pass-through with bars beyond this line. The weighted-average sectoral markup ($\mu$) is specified inside each bar. Sectors are at the 2-digit level with NAF/ISIC classification codes between parentheses. See subsection A.2 for a more detailed description of sectors. Source: Authors' estimations based on Equation 1, using estimates from the third specification in Table 2.

link between prices and competition, namely that the stickiness of prices depends on the degree of competition.

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 110% for the least competitive sectors, implying an excess pass-through—i.e. a pass through not warranted by the energy price hike itself—of 10 percentage points.[14] There are 5 sectors for which there is more than 100% pass-through according to our regression: (i) food products, (ii) beverages, (iii) textiles, (iv) other non-metallic mineral products, and (v) fabricated metal products (except machinery), as shown in Figure 4. Interestingly, the food industry not only displays the highest rate of pass-through, but also has the highest annual inflation rate: +14.4% in February 2023 (*INSEE*).

**Interaction with HHI** Now, to check the robustness of our result, we replace the measure of markup in Equation 1 by the Herfindahl-Hirschman Index (HHI).[15] 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. 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).

**Markup dispersion** We now investigate the possibility that a given sales-weighted average level of markup in a sector is associated with different pass-through rates depending on the distribution of market power between firms. Such an average could mask profoundly different competitive forces: a sector constituted of a highly productive superstar firm with a large market share and a mass of low-markup firms—thus displaying a relatively high markup dispersion—could be much more competitive than a sector dominated by a few powerful firms and characterized by low markup dispersion, even if both sectors have the same sales-weighted average markup.

We hence test whether the positive effect that average markups have on pass-through

[14]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: $\Delta PPI = 0.483 + 1.413 * 0.433 - 0.000 * 1.413 = 1.095$.

[15]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 3-digit measure.

**Table 3:** Energy price pass-through and concentration

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $EP_{j,t,t-n}$ | 0.1089 | | | |
| | (0.0914) | | | |
| $EP^{avg_3}_{j,t,t-n}$ | | 0.4706*** | | |
| | | (0.1219) | | |
| $EP^{avg_5}_{j,t,t-n}$ | | | 0.6379*** | |
| | | | (0.1642) | |
| $EP^{avg_7}_{j,t,t-1}$ | | | | 0.7230*** |
| | | | | (0.1847) |
| $HHI_j$ | -0.0002*** | -0.0002*** | -0.0002*** | -0.0003*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| $EP_{j,t,t-n} \times HHI_j$ | 0.0844*** | | | |
| | (0.0297) | | | |
| $EP^{avg_3}_{j,t,t-n} \times HHI_j$ | | 0.1106** | | |
| | | (0.0466) | | |
| $EP^{avg_5}_{j,t,t-n} \times HHI_j$ | | | 0.1805*** | |
| | | | (0.0694) | |
| $EP^{avg_7}_{j,t,t-n} \times HHI_j$ | | | | 0.2176*** |
| | | | | (0.0802) |
| Period FE | Yes | Yes | Yes | Yes |
| Obs. | 760 | 760 | 760 | 760 |
| R squared | 0.242 | 0.258 | 0.278 | 0.285 |
| Adjusted R-squared | 0.200 | 0.217 | 0.238 | 0.246 |

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

varies with markup dispersion within the sector. We employ a triple interaction specification where we interact the interaction term in Equation 1 with the industries' standard deviation of markups. A positive, significant effect of this triple interaction would indicate that the additional effect of the energy shock in less competitive sectors further increases with a larger dispersion of markups with the sector.

Turning to our results displayed in Table 4, we find that a greater standard deviation of markups within a given sector is associated with a *lower* boosting effect of markups on pass-through. In other words, more dispersion in the levels of markups between firms in the sector contributes to dampen the link between average markups and pass-through.

Such a result might appear surprising in light of theory. The seminal work of Lerner (1934) even showed that it is the dispersion of market power that entails welfare losses, not the existence of market power per se: if all prices incorporated the same markup, first-best would be reached as relative prices would not be distorted. Dispersion of markups is therefore a suboptimal situation resulting in misallocations—a result also present for example in New Keynesian models. Further, recent papers such as Autor et al. (2020) and De Loecker et al. (2020) show the importance of a small number of highly productive firms ("superstar firms") in explaining trends in aggregate markups. To the extent that a higher standard deviation of markups reflects the presence of a few high markup firms, one would expect the triple interaction to have a positive sign if inflation was driven by the pass-through of superstar firms.

To interpret our result, we refer to the reasoning developed in Weber and Wasner (2023). The authors argue that firms that are price makers "*only engage in price hikes if they expect their competitors to do the same*", which "*requires an implicit agreement which can be coordinated by sector-wide shocks and supply bottlenecks*". It is precisely in sectors in which aggregate markup is high and markup dispersion is low that such a situation is likely to arise. Firms expect their competitors to engage more in price increases if these firms also have a high markup, a situation that is reflected by a higher sales-weighted average markup ($\mathcal{M}_j$) and a low standard deviation of markups ($\sigma_{\mathcal{M}_j}$) within the industry.

**Table 4:** Energy price pass-through, market power and markup dispersion

| | (1) | (2) | (3) |
|---|---|---|---|
| $EP^{avg_3}_{j,t,t-n}$ | 1.118 | | |
| | (1.622) | | |
| $EP^{avg_5}_{j,t,t-n}$ | | 0.432 | |
| | | (2.288) | |
| $EP^{avg_7}_{j,t,t-n}$ | | | 0.220 |
| | | | (2.331) |
| $\mathcal{M}_j$ | 0.006 | 0.003 | 0.001 |
| | (0.014) | (0.015) | (0.015) |
| $\sigma_{\mathcal{M}_j}$ | 0.012 | 0.012 | 0.011 |
| | (0.050) | (0.054) | (0.055) |
| $EP^{avg_3}_{j,t,t-n} \times \mathcal{M}_j$ | 2.124 | | |
| | (1.753) | | |
| $EP^{avg_5}_{j,t,t-n} \times \mathcal{M}_j$ | | 4.704* | |
| | | (2.491) | |
| $EP^{avg_7}_{j,t,t-n} \times \mathcal{M}_j$ | | | 5.643** |
| | | | (2.623) |
| $\mathcal{M}_j \times \sigma_{\mathcal{M}_j}$ | -0.025 | -0.009 | -0.000 |
| | (0.046) | (0.050) | (0.050) |
| $EP^{avg_3}_{j,t,t-n} \times \sigma_{\mathcal{M}_j}$ | -2.469 | | |
| | (5.312) | | |
| $EP^{avg_5}_{j,t,t-n} \times \sigma_{\mathcal{M}_j}$ | | 1.043 | |
| | | (7.689) | |
| $EP^{avg_7}_{j,t,t-n} \times \sigma_{\mathcal{M}_j}$ | | | 2.528 |
| | | | (7.748) |
| $EP^{avg_3}_{j,t,t-n} \times \mathcal{M}_j \times \sigma_{\mathcal{M}_j}$ | -6.620 | | |
| | (5.817) | | |
| $EP^{avg_5}_{j,t,t-n} \times \mathcal{M}_j \times \sigma_{\mathcal{M}_j}$ | | -16.041* | |
| | | (8.417) | |
| $EP^{avg_7}_{j,t,t-n} \times \mathcal{M}_j \times \sigma_{\mathcal{M}_j}$ | | | -19.599** |
| | | | (8.786) |
| Period FE | Yes | Yes | Yes |
| Obs. | 760 | 760 | 760 |
| R squared | 0.287 | 0.311 | 0.314 |
| Adjusted R-squared | 0.243 | 0.269 | 0.272 |

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. $\sigma_{\mathcal{M}_j}$ denotes the standard deviation of 2019 markups within 2-digit industries.
* p<0.1, ** p<0.05, *** p<0.01

# 5 Conclusion

The recent spectacular return of inflation in the Euro Area calls for analyses of its root causes. In this short policy paper, we empirically test the hypothesis put forward initially by Weber and Wasner (2023), which states that recent inflation should be seen as a "sellers' inflation". 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 February 2023 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 45 to 104% 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 as high as 110%, 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.

Going more deeply into the underlying dynamics in pass-through, we employ a triple interaction specification to check whether the dispersion of markups can further explain some of the heterogeneous sectoral responses to cost shocks. We find that sectors with a greater dispersion of markups passed through significantly *less* of the cost shock. We interpret these results as supporting evidence for the theoretical mechanism put forward by Weber and Wasner (2023): the pass-through was highest in sectors that displayed both a higher average level of markups and a smaller dispersion, suggesting that firms hike prices more if they expect their competitors to do the same.

In summary, our results provide suggestive evidence in favor of the existence of a "sellers' inflation” 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 less 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.

# A Appendix

## A.1 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):

$$\mu_{it} = \theta_{it}^{V} \frac{P_{it} Q_{it}}{P_{it}^{V} V_{it}^{V}}. \tag{2}$$

As the input share is observed, the crucial parameter that needs to be estimated is the output elasticity of the variable input of production, $\theta_{it}^{V}$. 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:

$$y_{it} = f(v_{it}, k_{it}; \beta) + \omega_{it} + \varepsilon_{it}, \tag{3}$$

where $\omega_{it}$ 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 $\varepsilon_{it}$ includes unanticipated shocks to productivity and measurement error in the output. Both $\omega_{it}$ and $\varepsilon_{it}$ 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 3, one needs to account for productivity $\omega_{it}$, 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:

$$\omega_{it} = h_t(k_{it}, m_{it}, z_{it}), \tag{4}$$

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 3 in order to obtain the expected output, $\hat{\phi}_{it}$, and the measurement error, $\varepsilon_{it}$. 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:

$$y_{it} = \phi_t(v_{it}, k_{it}, z_{it}) + \varepsilon_{it} \tag{5}$$

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 5). 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):

$$\hat{\phi}_{it} = \beta_v v_{it} + \beta_{v^2} v_{it}^2 + \beta_{v^3} v_{it}^3 + \beta_k k_{it} + \beta_{k^2} k_{it}^2 + \beta_{k^3} k_{it}^3 + I_{vk} + h_t(k_{it}, m_{it}, z_{it}), \tag{6}$$

where $I_{vk}$ denotes the full set of interactions between $v$ and $k$, and $h_t(\cdot)$ denotes the inverted material demand from Equation 4.

The second stage now uses the cleaned output (estimated in the first stage) and aims to identify productivity $\omega_{it}$ for any set of $\beta$'s. Following Equation 6 productivity is given by:

$$\omega_{it} = \hat{\phi}_{it} - \beta_v v_{it} - \beta_{v^2} v_{it}^2 - \beta_{v^3} v_{it}^3 - \beta_k k_{it} - \beta_{k^2} k_{it}^2 - \beta_{k^3} k_{it}^3 - I_{vk}. \tag{7}$$

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 $\omega_{it-1}$ and a term $\xi_{it}$, the innovation to productivity:

$$\omega_{it} = g_t(\omega_{it-1}) + \xi_{it}. \tag{8}$$

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

$$E\left(\xi_{it}(\beta)\begin{pmatrix} v_{it-1} \\ k_{it} \\ v_{it-1}^2 \\ k_{it}^2 \\ v_{it-1}k_{it} \end{pmatrix}\right) = 0. \tag{9}$$

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:

$$\hat{\theta}_{it}^{V} = \hat{\beta}_v + 2\hat{\beta}_{v^2} v_{it} + \hat{\beta}_{vk}, \tag{10}$$

which, after inserting $\hat{\theta}_{it}^{V}$ into Equation 2 and purging revenue $P_{it}Q_{it}$ from unanticipated productivity shocks and measurement error $\varepsilon_{it}$ (Equation 3), yields firm-level markups at time $t$, i.e. $\mu_{it}$.

### A.1.1 Variables FARE

**Table 5:** 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.2 Sectors

**Table 6:** Manufacturing sectors

| NAF/ISIC code | Description |
|---|---|
| 10 | Manufacture of food products |
| 11 | Manufacture of beverages |
| 13 | Manufacture of textiles |
| 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 |

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