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Markups as a Hedge for Input Price Uncertainty: Evidence from Sweden

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In this paper, we study a new channel to explain firms' price setting behavior. We propose that uncertainty about factor prices has a positive effect on markups. We show theoretically that firms with higher shares of inputs with volatile prices set higher markups. We use the Bartik shift-share approach to empirically test whether firms which use more oil relative to other inputs set higher markups when oil prices are more volatile. Our estimates imply that a one standard deviation increase in oil price volatility leads to a 0.38 percent increase in the markup of firms with average oil exposure.

JEL classification: D21, D22, D24, D42, D80, E31, E32, L11, L60.

Keywords: price setting, markups, input price volatility, precautionary pricing.

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1 Introduction

Markups are at the center of attention for their connection to rising profits, the decline in the labor share, and the increase in inequality between capital owners and workers. In this paper, we propose a new channel to explain firms' price setting behavior. We argue that uncertainty about factor prices has a positive effect on markups. By examining this new channel, our paper contributes to understanding the way in which firms set markups and the reasons why markups differ across firms.

First, we build a model to formalize the argument that uncertainty about factor prices leads to higher markups. We augment a simple version of the Dixit and Stiglitz (1977) model of competition with a stochastic marginal cost of production. The new mechanism we include in our model posits that firms set higher markups to hedge against negative profits that could result if firms' variable costs turn out to be high. In our model, firms are averse to negative profits because they are required to pay an additional penalty that is proportional to the amount by which dividends fall short of a threshold value. This threshold value can be interpreted as the cost of raising equity to finance negative values of dividends (Gilchrist, Schoenle, Sim and Zakrajšek, 2017) or the high cost of debt issuance via borrowing covenants (Lian and Ma, 2020). Our model shows that the exposure of firms to the price volatility of major inputs matters for the determination of firm-level markups. In particular, we find that firms with higher shares of inputs with volatile prices in their total variable costs set higher markups.

Then, we test the implications of our model empirically. Our hypothesis is that firm-level markups increase with the volatility of input prices faced by firms. We use a Bartik shift-share approach for our empirical strategy. Specifically, we measure the exposure of firms to oil price volatility and we test whether firms with higher exposures set higher markups when oil prices are more volatile.

We construct markups using current methods developed by De Loecker and Warzynski (2012) and Ackerberg, Caves and Frazer (2015). We measure firms' exposure to input price volatility by their industry's cost for oil relative to their industry's variable cost. To measure uncertainty in oil prices, we construct a forward-looking measure of expected volatility using firms' available information set at the time when they make their pricing decisions. We consider a simple GARCH model to construct an annual measure of the expected standard deviation of monthly Brent oil price changes.[1]

For identification with the Bartik shift-share approach, we follow Goldsmith-Pinkham, Sorkin and Swift (2020) and argue for the exogeneity of the oil shares. The crucial identifying assumption we make is that changes in demand that correlate with oil price volatility do not differentially affect firms in industries with higher oil shares, given the control variables. By having the markup rather than the price as the dependent variable, we eliminate the direct effect of cost shocks on prices and we isolate the effect of input price volatility on markups.

We find that a one standard deviation increase in volatility leads to a 0.38 percent increase in the markup of firms with average oil exposure. The effect is stronger for firms with high oil exposure. A one standard deviation increase in volatility leads to a 1.98 percent increase of the markup of firms with industry oil exposure in the 95th percentile versus only 0.05 percent for firms with industry oil exposure in the 5th percentile. A number of robustness checks also yield coefficients around 0.4 percent. The average within-industry change in markups is about 4 percent, suggesting that our proposed channel explains one tenth of the average markup variation.

Our paper is most related to the literature that studies the relation between input costs, markups and prices. De Loecker, Goldberg, Khandelwal and Pavcnik (2016) analyze how an increase in input costs affects markups. Born and Pfeifer (2021) show that an increase in uncertainty about the aggregate price level induces a rise in markups. In terms of price dispersion, Klepacz (2020) shows that higher oil price volatility leads to higher industry-level price dispersion. The novelty of our paper is that we look at the effect of input price volatility on levels of markups.

Our analysis intersects with three strands of literature. Much recent research has focused on the impact of uncertainty on firms' choices of quantities of inputs, output and investment. This research goes back to papers on uncertainty and investment by Oi (1961), Abel (1983), Hartman (1972) and more recently by Bloom (2009) and Bai, Kehoe and Arellano (2011). We depart from this strand of papers since we look at the impact of uncertainty on markups and prices, not the quantity choice.

Another strand of research has studied markups, often finding large and rising markups (De Loecker, Eeckhout and Unger, 2020) and a decline in the labor share (Karabarbou-

[1] We use uncertainty and volatility about input prices interchangeably when referring to the mechanism. In the data, volatility is measured by the expected standard deviation.

nis and Neiman, 2014). This literature has focused on the measurement of markups and their economic interpretations (De Loecker and Warzynski, 2012; Nakamura and Zerom, 2010; Gutierrez and Philippon, 2017; Karabarbounis and Neiman, 2018; De Loecker et al., 2020). Similarly to these papers, we construct markups from data, but we aim to investigate the impact of input price volatility on markups.

We also intersect with the literature on precautionary behavior and relate to the papers on borrowing covenants by Lian and Ma (2020) and Gilchrist et al. (2017) who consider implicit costs of external financing for firms. Our model includes a reduced form version of costly external financing which can be rationalized using the arguments in Lian and Ma (2020) and Gilchrist et al. (2017).

This paper is structured as follows. Section 2 describes the theoretical framework. Section 3 explains the method and data used for our empirical analysis. Section 4 explains the main results and section 5 presents the robustness checks. Section 6 concludes the paper.

2 Theory

To develop the argument for increasing markups from higher volatility of major inputs, we consider a simple version of the Dixit and Stiglitz (1977) model of competition with a stochastic marginal cost of production. The economy consists of a representative household and representative firms in j industries.

2.1 Household Preferences

The household consumes a variety of consumption goods from industry j and these goods are indexed by $i \in \{1, 2, ..., N\}$. Utility depends on a CES consumption aggregator over units consumed of the different varieties

$$y_j = \left\{ \sum_{i=1}^{N} (x_i)^{1-\frac{1}{\epsilon}} \right\}^{\frac{1}{1-\frac{1}{\epsilon}}}, \qquad \epsilon > 0, \tag{1}$$

where x_i denotes product variety i. Equation (1) shows the consumer's love for variety. The dual problem of cost-minimization in this setup gives rise to a good-specific demand,

$$(2) \qquad x_i(p_i) = y_j \left(\frac{q_j}{p_i}\right)^{\epsilon}, \quad \text{where} \quad q_j = \left\{\sum_{i=1}^{N} (p_i)^{1-\epsilon}\right\}^{\frac{1}{1-\epsilon}},$$

where q_j is the price index for the consumption aggregate y_j.

2.2 Firm Price Setting

The supply side of this economy consists of N firms producing varieties of goods indexed by $i \in \{1, 2, ..., N\}$. Firms face idiosyncratic stochastic marginal costs c_i of producing good i. We assume that

$$log(c_i) \sim N(\mu_i = -0.5\sigma_i^2, \sigma_i^2)$$

and we make a crucial timing assumption that the firm sets the price for each period knowing the distribution of potential marginal costs but not its actual realization. After setting the price, the marginal cost is realized and firms learn their realized profits as well as dividends.[2]

Firm i wants to maximize its expected dividend (d_i) subject to the flow of funds constraint

$$(3) \qquad d_i = (p_i - c_i)x_i(p_i) - \Lambda \max\{\hat{\pi} - d_i, 0\}$$

where $\Lambda > 0$. Producers are required to pay an additional penalty Λ which is proportional to the amount by which dividends fall short of a threshold value $\hat{\pi}$. This threshold value $\hat{\pi}$ can be interpreted as the cost of raising equity to finance negative values of dividends as in Gilchrist et al. (2017). Another interpretation of the penalty could be the high cost of debt issuance via borrowing covenants when the firm profits become too low, below a threshold (Lian and Ma, 2020).[3]

[2] Notice that we have have normalized the expected value of the marginal cost $\mathbb{E}(c_i) \equiv c_0 = \exp(-0.5\sigma_i^2 + \sigma_i^2) = 1$. Further, $Var(c_i) = \sigma_i^2 = exp(\sigma_i^2) - 1$

[3] A slightly different formulation would be to denote $\hat{\pi}$ as 'promised dividends' and assume that the firm's manager is penalized every time she fails to deliver on her promised dividends. This way of setting up the firm's problem would yield almost identical expressions.

The firm's problem is

$$\max \mathbb{E}^c\,[d_i] \qquad \text{subject to}$$

$$d_i = (p_i - c_i)x_i(p_i) - \Lambda \max\{\hat{\pi} - d_i, 0\}$$

$$x_i = y\left(\frac{q}{p_i}\right)^{\epsilon}$$

The Lagrangian associated with the firm's problem is given by

$$\begin{aligned} \mathcal{L} = \max_{p_i, x_i} \mathbb{E}^c \max_{d_i} \Big[& d_i + \xi_i \big\{ (p_i - c_i)x_i(p_i) - d_i - \Lambda \max\{\hat{\pi} - d_i, 0\} \big\} \\ & + \lambda_i \left\{ A p_i^{-\epsilon} - x_i \right\} \Big], \end{aligned} \tag{4}$$

where ξ_i and λ_i are the Lagrange multipliers on the flow of funds constraint and the demand function, respectively; and $A \equiv yq^{\epsilon}$. Note that the choice over p_i, x_i is made ex ante the realization of the actual costs, whereas dividends are trivially chosen after the firm learns its costs.

The first-order conditions yield

$$\{d_i\}: \quad 0 = \begin{cases} 1 + \xi_i(-1+\Lambda) & \text{if } \; d_i < \hat{\pi} \\ 1 + \xi_i(-1) & \text{if } \; d_i \geq \hat{\pi} \end{cases} \implies \xi_i = \begin{cases} \frac{1}{1-\Lambda} & \text{if } \; d_i < \hat{\pi} \\ 1 & \text{if } \; d_i \geq \hat{\pi} \end{cases} \tag{5}$$

$$\{p_i\}: \quad \mathbb{E}^c\left[\xi_i x_i + \lambda_i A(-\epsilon)p_i^{-1-\epsilon}\right] = 0 \implies \mathbb{E}^c(\xi_i) = \epsilon \frac{\mathbb{E}^c(\lambda_i)}{p_i} \tag{6}$$

$$\{x_i\}: \quad \mathbb{E}^c\left[(p_i - c_i)\xi_i - \lambda_i\right] = 0 \implies \mathbb{E}_t(\xi_i)p_i - \mathbb{E}^c(\xi_i c_i) = \mathbb{E}^c(\lambda_i) \tag{7}$$

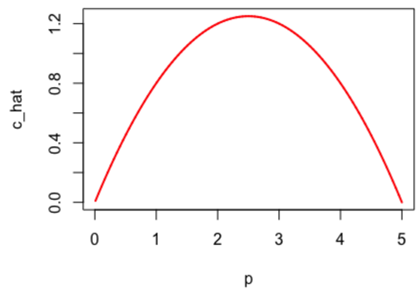
Note that the condition in equation (5) implies that the cost of external financing is higher if the firm's dividends fall short of the threshold value $\hat{\pi}$, relative to normal times when the firm has sufficient profits. Combining the last two first-order conditions yields the following pricing equation

$$p_i = \frac{\epsilon}{\epsilon - 1} \frac{\mathbb{E}(\xi_i c_i)}{\mathbb{E}(\xi_i)}. \tag{8}$$

Compared to the standard equation where $P = \frac{\epsilon}{\epsilon-1}\mathbb{E}(c)$, we find a more general equation in which both the first and second moment of the marginal cost affect the markup. The case with $\Lambda = 0$ is the special case which implies the standard markup equation. It is easier to understand the underlying workings of this model in the (p, c) plane instead of the (π, p) plane. Hence, we shall reformulate the problem in order to solve it analytically in a more tractable manner.

Let $\hat{c}$ be the idiosyncratic cost level such that, at $\hat{c}$, the firm's flow of funds constraint is binding with dividends equal to $\hat{\pi}$. Then,

$$\hat{c}_i(p_i) = p_i - \frac{\hat{\pi}}{x_i(p_i)}$$



Then, we get the equivalence that $c_{it} \lesseqgtr \hat{c}_i(p_i) \iff d_i(p_i) \lesseqgtr \hat{\pi}$, so we can simplify the expressions in the price equation above to get that

$$\begin{aligned}\mathbb{E}(\xi_i) &= \int_0^{\hat{c}(p_i)} dF(c_i) + \int_{\hat{c}_i(p_i)}^{\infty} \frac{1}{1-\Lambda} dF(c_i) \\ &= 1 + \frac{\Lambda}{1-\Lambda}\left(1 - \Phi(\hat{z}(p_i))\right),\end{aligned}$$

where $\hat{z}(p_i) \equiv (\log \hat{c}(p_i) - \mu_i)\frac{1}{\sigma_i}$ and Φ is the cumulative distribution function for the normally distributed variable $\hat{z}(p_i)$. Then, it is possible to re-write $\mathbb{E}^c(\xi_i c_i)$ as

$$\begin{aligned}\mathbb{E}^c(\xi_i c_i) &= \int_0^{\hat{c}(p_i)} c_i dF(c_i) + \int_{\hat{c}_i(p_i)}^{\infty} \frac{1}{1-\Lambda} c_i dF(c_i) \\ &= c_0 + \frac{\Lambda}{1-\Lambda}\mathbb{E}\left(c_i | c_i \geq \hat{c}(p_i)\right)\left(1 - \Phi(\hat{z}(p_i))\right), \qquad (9)\end{aligned}$$

where the second term on the right-hand side is the probability of having a cost realization larger than the threshold cost $\hat{c}$ times the expected cost. Given a positive penalty $\Lambda > 0$, the firm puts extra weight on the high-cost states. Together, this implies the following pricing equation

$$p_i = \frac{\epsilon}{\epsilon - 1} \frac{c_0 + \frac{\Lambda}{1-\Lambda}\mathbb{E}\left(c_i | c_i \geq \hat{c}(p_i)\right)\left(1 - \Phi(\hat{z}(p_i)\right)}{1 + \frac{\Lambda}{1-\Lambda}\left(1 - \Phi(\hat{z}(p_i)\right)}. \tag{10}$$

The solution to this fixed point problem yields the optimal price p_i^* charged by the firm as

$$p_i^* = \frac{\epsilon}{\epsilon - 1} \frac{c_0 + \frac{\Lambda}{1-\Lambda}\mathbb{E}\left(c_i | c_i \geq \hat{c}(p_{it}^*)\right)\left(1 - \Phi(\hat{z}(p_i^*)\right)}{1 + \frac{\Lambda}{1-\Lambda}\left(1 - \Phi(\hat{z}(p_i^*)\right)}. \tag{11}$$

Next, we can use the formula for conditional expectation of a log normally distributed variable[4]

$$\begin{aligned} \mathbb{E}_c\{c_i | c_i \geq \hat{c}(p_i)\} &= \exp\left(\mu + \frac{\sigma^2}{2}\right) \frac{\Phi\left(\frac{\mu+\sigma^2-\log(\hat{c}(p_i))}{\sigma}\right)}{1 - \Phi\left(\frac{\log \hat{c}(p_i)-\mu}{\sigma}\right)} \\ &= \frac{\Phi(-\hat{z}(p_i) + \sigma)}{1 - \Phi(\hat{z}(p_i))} = \frac{1 - \Phi(\hat{z}(p_i) - \sigma)}{1 - \Phi(\hat{z}(p_i))}, \end{aligned} \tag{12}$$

where σ is the standard deviation of the log normally distributed variable c_i and μ is its mean. We substitute (12) in equation (11) to find that the denominator in (12) cancels out with the RHS term of the numerator in (11) and obtain that

$$p_i^* = \frac{\epsilon}{\epsilon - 1} \frac{1 + \frac{\Lambda}{1-\Lambda}\left(1 - \Phi\left(\hat{z}(p_{it}^*) - \sigma\right)\right)}{1 + \frac{\Lambda}{1-\Lambda}\left(1 - \Phi\left(\hat{z}(p_{it}^*)\right)\right)} c_0. \tag{13}$$

In equation (13), the difference between the numerator and the denominator is the presence of σ in the numerator. Since Φ is a decreasing function of σ, an increase in σ tends to increase the right-hand side value, and as a result it also increases the fixed point.

Equation (13) implies that $p_i^* = f(\sigma)\ c_0$, i.e. the optimal price is a function of σ and the expected cost c_0. Then, the log markup can be written as $ln(\mu_i) = ln(p_i^*) - ln(c_i)$ so that

$$ln(\mu_i) = ln(f(\sigma)) + ln(c_0) - ln(c_i). \tag{14}$$

Equation (14) shows that the markup is an increasing function of the standard deviation

[4] The formula says that the conditional expectation of a log-normal variable is its partial expectation divided by the cumulative probability of being in the range above some threshold variable k.

of the volatile input.

2.3 Micro-founding marginal costs and volatility

We assume that the firm produces using Cobb-Douglas technology with oil m_o and another variable input m_w. We also assume that firms within industry j use the same oil input mix in their production so that if firm i belongs to industry j, then good x_i is produced according to

$$x_i = z m_o^{\alpha_j} m_w^{1-\alpha_j},$$

where z denotes the firm's productivity and α_j is the share of oil in the firm's production that **only** differs across industries. The firm minimizes its costs subject to its technology.

$$min_{m_o,m_w} V m_o + W m_w + \eta_j (x_i - z m_o^{\alpha_j} m_w^{1-\alpha_j}) \tag{15}$$

where η_j is the Lagrange multiplier on the production function, the price of oil is V and the price of the other variable input is W. The first-order conditions are

$$V = \alpha_j \eta_j \frac{x_i}{m_o}, \quad \text{and} \quad W = (1-\alpha_j)\eta_j \frac{x}{m_w}. \tag{16}$$

Using these first-order conditions, we find that the total cost is the product of the marginal cost η_j and the quantity produced

$$V m_o + W m_w = \eta_j x_i \tag{17}$$

Raising each first-order condition to the respective share and multiplying yields the marginal cost

$$\eta_j = \frac{1}{z}\left(\frac{V}{\alpha_j}\right)^{\alpha_j}\left(\frac{W}{1-\alpha_j}\right)^{1-\alpha_j}. \tag{18}$$

This implies that the standard deviation of the log marginal cost caused by variations in oil prices is

$$\sigma_\eta = \alpha_j \ \sigma_v, \tag{19}$$

where σ_v is the standard deviation of the log of the oil price. To find a suitable measure of volatility, we can use a local linear approximation to Φ in equation (13) which yields the numerator to be

$$-\Phi\Big(\frac{ln(\hat{c}-\mu)}{\sigma}\Big) \approx \Phi'\Big(\sigma - \frac{ln(\hat{c}-\mu)}{\sigma} - C\Big), \tag{20}$$

where C is a constant. The first term in expression (20) increases linearly in σ and the second term increases in σ at a decreasing rate, indicating a concave function. Expression (20) suggests that a suitable measure of volatility implied by equation (13) is the standard deviation. Therefore, we are interested in estimating the regression

$$ln(\mu_{it}) = C + \beta(\alpha_j \times \sigma_{v_t}) + \varepsilon_{it} \tag{21}$$

where C is a constant, α_j is the industry share of oil relative to the industry's total variable costs and σ_{v_t} is a measure of the expected standard deviation of oil prices.

2.4 Numerical Solution in Partial Equilibrium

To show numerically how the markup increases if firms face different levels of exposure to a volatile input, we solve equation (13) numerically.[5] The solid line in Figure (1) shows the relationship between α_j and markups for a given level of standard deviation of costs σ. Note that firms with an increasing degree of marginal cost volatility $\alpha_j\sigma$ are on the x-axis. The solid line depicts that the firm-level markup increases in exposure α_j for a given standard deviation of the input price. Figure (1) suggests that the distribution of firms across α_j matters for the determination of the average markup in the economy.

Further, we consider an increase in the volatility σ from σ to 2σ and to 3σ. The solid line corresponds to the baseline σ and dotted lines represent higher values of σ.

[5] We take $\epsilon = 3, c_0 = 1, \Lambda = 0.6$, $\sigma = 3$.

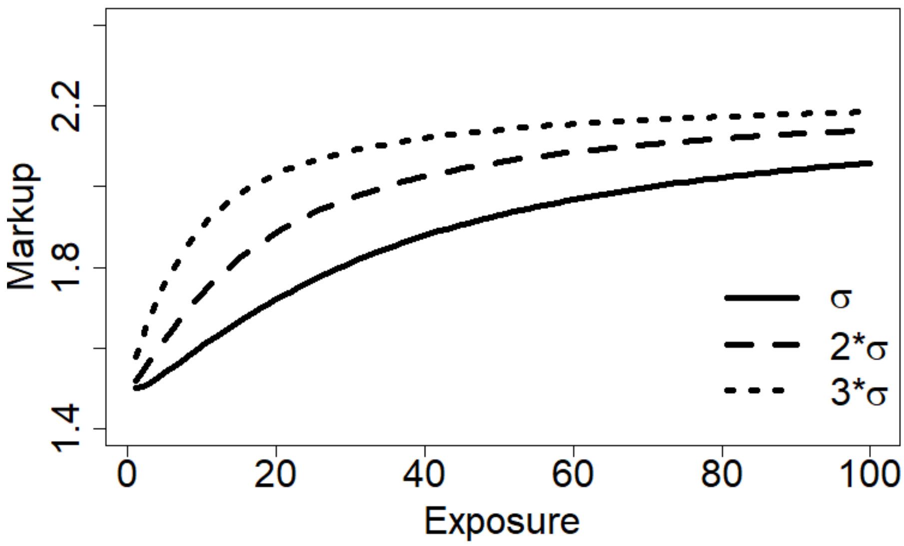


Figure 1: Markups as a function of oil shares α_j and input cost volatility σ.

The increase in the dashed lines relative to the solid line in Figure 1 shows that firms with extremely low or high exposure respond less to increases in volatility than firms with moderate exposure. In addition, firms with the lowest exposures are affected the most when their exposure increases as compared to firms at the highest end. This effect is due to the concavity of markups in exposure.

3 Method and Data

3.1 Empirical Regression

Our main regression specification is

$$ln(\mu_{i,t}) = \beta \left(\frac{Oil_j}{TVC_j} \times \mathbb{E}[SD_t] \right) + \delta_j + \gamma_t + \varepsilon_{i,t}, \tag{22}$$

where $\frac{Oil_j}{TVC_j}$ is a two-digit manufacturing industry j's nominal oil consumption over the industry's nominal variable cost. In the baseline estimation, we use the industry's oil consumption to variable cost ratio in 2008, i.e. in the first year of the sample. As a robustness check, we use the industry time-average variable defined as $\frac{1}{T}\sum_{t=2008}^{T=2016} \frac{Oil_{j,t}}{TVC_{j,t}}$ as a measure of exposure in an alternative specification.

$\mathbb{E}[SD_t]$ is the annual expected volatility of monthly Brent oil price changes derived from a GARCH model. A detailed description of these variables follows below.

In (22), industry fixed effects δ_j control for time-invariant industry-specific unobserved confounding variables and year fixed effects γ_t take care of variation in general economic conditions over time.

3.2 Firm population and industries

In the Swedish business registry, some firms may be inactive or serve purely legal purposes, for example companies that manage savings and investments of individuals. In order to focus on economically active firms and eliminate companies that do not participate in production, we consider firms with more than ten employees and positive sales. As a robustness check, we include firms with more than two employees. We focus on an unbalanced panel of firms in the manufacturing industry between 2008-2016.

3.3 Markups

Firm-level markups are constructed following De Loecker and Warzynski (2012) based on estimating a value added production function as in Ackerberg, Caves and Frazer (2015). The theoretical foundation for defining markups is the cost minimization problem of the firm. We closely follow the steps described by De Loecker and Warzynski (2012) and Ackerberg et al. (2015) to construct markups and we include a description of our procedures in Appendix A.1.

In the regression, we consider two sets of markups that we construct using (i) the Cobb-Douglas and (ii) the translog production functions.[6] Table 1 presents the summary statistics for firm-level markups. While the average markup is similar across the Cobb-Douglas and the translog specifications, the range of estimated markups is much wider when **the** markups are based on the translog production function.

[6]Note that constructing markups as the labor share over sales would not be appropriate for the regressions since sales are price times quantity where prices vary endogenously with costs.

Table 1: Summary statistics: markups

	Mean	SD	p5	p50	p95
Markup of firms with > 2 employees					
markupCD	1.63	0.32	1.29	1.58	2.17
markupTL	1.83	1.16	0.68	1.31	3.98
Markup of firms with > 10 employees					
markupCD	1.66	0.34	1.29	1.61	2.25
markupTL	1.92	1.26	0.58	1.37	4.25

It is important to note that the markups based on the Cobb-Douglas production function are only slightly different from the firm's labor share relative to the firm's value added output by an industry-specific constant θ_j, i.e. the industry-specific output elasticity. This feature of the Cobb-Douglas markups implies that the variation used in estimating (22) is simply the variation in the firm-level labor share relative to the firm's value added output over time and differences across industries due to the elasticity of output to inputs are soaked up by the industry fixed effects.

On the other hand, translog markups have a time-firm specific elasticity of output component,[7] which is why regression (22) with translog markups can utilize further variation in the dependent variable that is not soaked up by the industry fixed effects.

3.4 Volatility of oil prices

The annual volatility of oil prices is measured by the expected standard deviation of monthly Brent oil price changes from a GARCH model. We use the data on monthly crude oil spot prices for Brent in Europe because it is used as a reference for pricing a number of oil products used by the Swedish firms as input. We collect the monthly price series for dollars per barrel from FRED data. It can be argued that changes in Brent oil price volatility are plausibly exogenous to Swedish firms. The oil price series are deflated using finished goods US PPI to get the real oil prices

$$P^{\text{oil}} = \frac{\text{Brent Spot price}_t}{PPI_t}.$$

We want to consider the volatility in input prices that the firms expect when making

[7]The output elasticity based on the translog production function takes the form of expression (30) in appendix A.1.

output pricing decisions. Therefore, it is important to consider a forward-looking measure of expected volatility using the information set available to firms at the time when they make their pricing decisions. To model expected volatility in oil prices, we use a simple GARCH model on oil price returns.

Let us define the monthly return on the Brent oil spot price for time period t as

$$r_t^{\text{oil}} = \log P_t^{\text{oil}} - \log P_{t-1}^{\text{oil}}.$$

Figure 2 depicts the monthly Brent oil spot prices and returns.

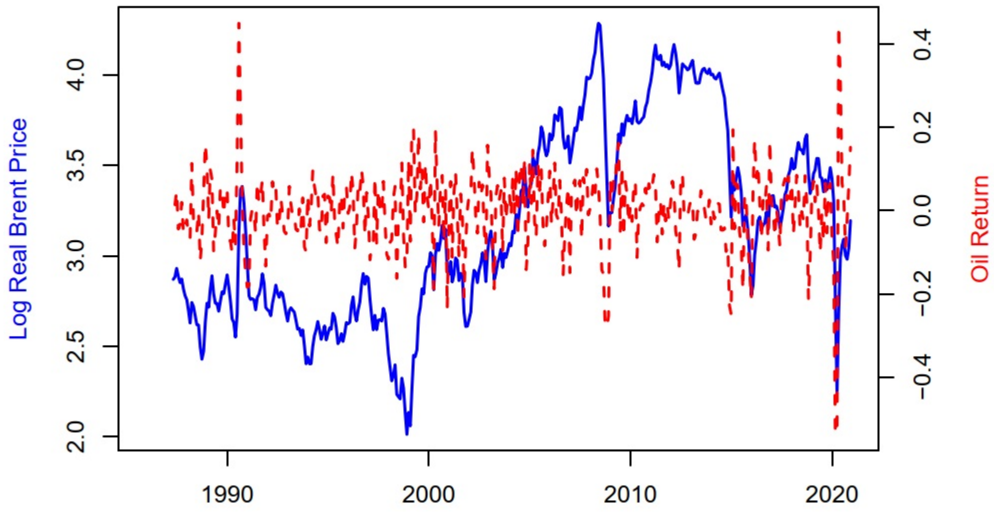


Figure 2: Monthly Brent oil spot prices and returns

We consider a GARCH model of oil price volatility, assuming a stationary oil price return series. The estimated GARCH(1,1) process is

$$\begin{aligned} r_t^{\text{oil}} &= \mu + \rho r_{t-1}^{\text{oil}} + \epsilon_t, \qquad \text{where} \qquad \epsilon_t = \sigma_t z_t, \quad z_t \sim N(0,1) \\ \sigma_t^2 &= \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2. \end{aligned}$$

The conditional heteroskedasticity of oil prices in the estimated GARCH(1,1) model of oil prices has both significant autoregressive and moving average components. The GARCH(1,1) model can then be used to form expectations of the input price variance over the next 12 month horizon for each time period.

The expected volatility is calculated as the expected standard deviation

$$\mathbb{E}[SD_t] = \sqrt{\sum_{i=1}^{12} \mathbb{E}_t \sigma_{t+i}^2}, \tag{23}$$

which is the square root of the sum of the time t expectation of the Brent price variance over the next 12 months.

By using an annual measure for the expected standard deviation, we implicitly assume that firms set prices every year; and when they do, they consider volatility for the coming year during which they will be stuck with the price they set. The annual expected standard deviation is depicted in Figure 3.

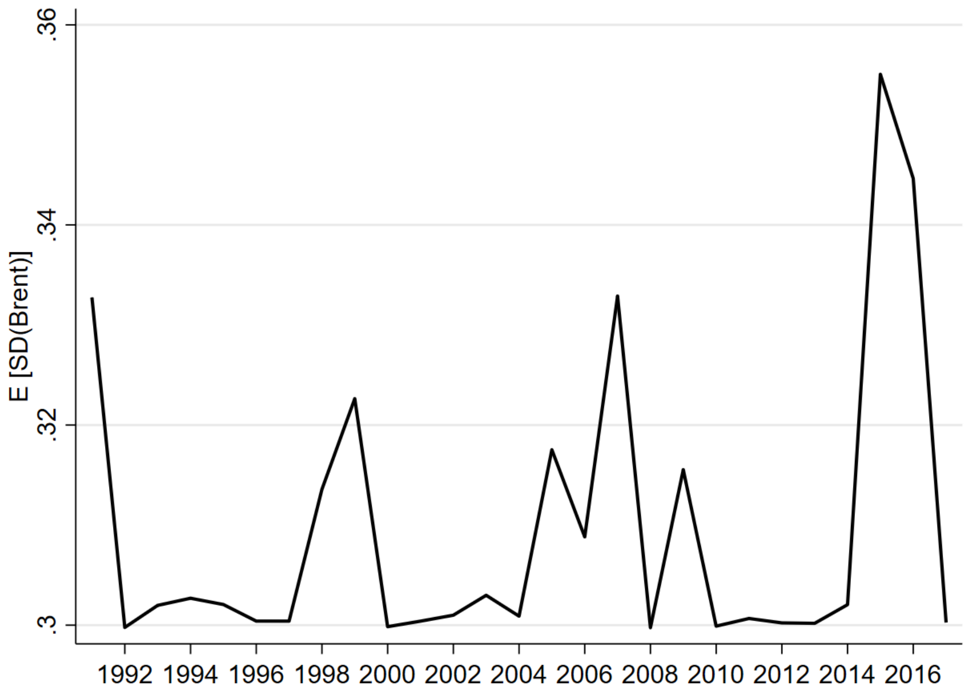


Figure 3: Annual expected standard deviation

The summary statistics for the annual expected standard deviation is presented in Table 2. The mean of expected volatility is 0.3 and its standard deviation is 0.02.

Table 2: Summary statistic: volatility

	Mean	SD	p5	p50	p95
$\mathbb{E}[SD_t]$	0.31	0.02	0.30	0.30	0.36

3.5 Bartik shift-shares

The firm's exposure to oil price volatility is measured by its industry's nominal oil consumption as a share of its industry's total nominal variable costs. The regressions use the variation in these industry-level variables. In particular, we compare the markup of firms that are in industries with low oil exposures to the markup of firms that are in industries with high oil exposure. The 24 manufacturing industries with their 2-digit industry codes corresponding to the NACE (in Swedish SNI) classification are listed in Table 3. Table 3 includes statistics about the number of firms operating in the industry and the industries' oil shares.

Table 3: List of 2-digit industries, number of firms and their oil shares

NACE	Industry name	Firms	Ind2008Oil/TVC	IndAvgOil/TVC
10	food products	823	0.0032	0.0022
11	beverages	27	0.0255	0.0203
13	textiles	116	0.0044	0.0027
14	wearing apparel	40	0.0129	0.0110
15	leather and related products	21	0.0282	0.0174
16	wood and of products of wood and cork, except furniture	644	0.0012	0.0009
17	paper and paper products	204	0.0136	0.0099
18	printing and reproduction of recorded media	395	0.0002	0.0001
19	coke and refined petroleum products	9	0.0022	0.0011
20	chemicals and chemical products	217	0.0026	0.0027
21	basic pharmaceutical products and pharmaceutical preparations	41	0.0056	0.0051
22	rubber and plastic products	430	0.0019	0.0013
23	other non-metallic mineral products	229	0.0127	0.0073
24	basic metals	208	0.0053	0.0029
25	fabricated metal products, except machinery and equipment	2029	0.0011	0.0008
26	computer, electronic and optical products	343	0.0007	0.0004
27	electrical equipment	269	0.0032	0.0021
28	machinery and equipment n.e.c.	903	0.0005	0.0003
29	motor vehicles, trailers and semi-trailers	101	0.0003	0.0002
30	other transport equipment	105	0.0025	0.0014
31	furniture	321	0.0017	0.0011
32	other manufacturing	199	0.0018	0.0011
33	repair and installation of machinery and equipment	442	0.0015	0.0011
	Total number of firms	8116		

Figure 4 shows the variation over time in the oil shares for industries with the highest oil shares relative to the industry's total variable cost. Figure 4 depicts the oil shares of the industries with the lowest ratios.

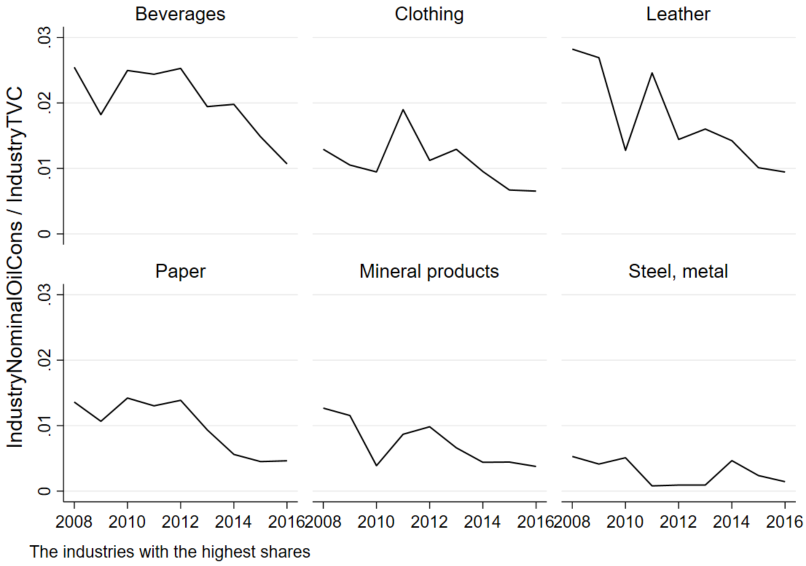


Figure 4: High oil industries

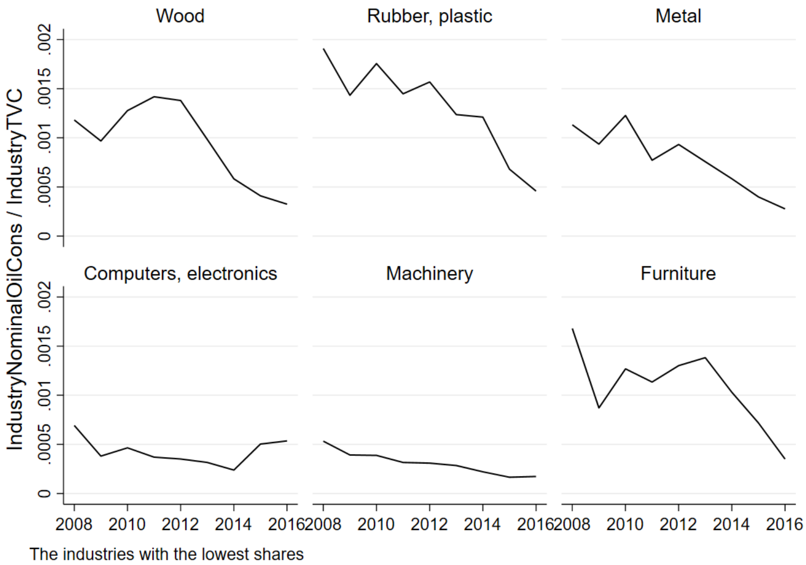


Figure 5: Low oil industries

The summary statistics for the two measures of oil exposure are presented in Table 4. The baseline regression uses the 2008 share and, as a robustness check, we use the time-average share.

Table 4: Summary statistics: exposures

	Mean	SD	p5	p50	p95
Ind2008(Oil/TVC)	0.0025	0.0035	0.0003	0.0012	0.0127
IndAvg(Oil/TVC)	0.0017	0.0024	0.0002	0.0009	0.0073

Figure 6 depicts the correlation between firms' oil shares and markups. In particular, Figure 6 shows that firms with higher industry oil shares set higher markups, whereas firms with lower industry oil shares set lower markups. This wedge is persistent over time. Figure 6 suggests that firms that use more oil also have higher markups; however, this difference may be due to other systematic differences between firms, for example, volatility in the prices of other inputs. Thus, a more careful investigation is warranted.

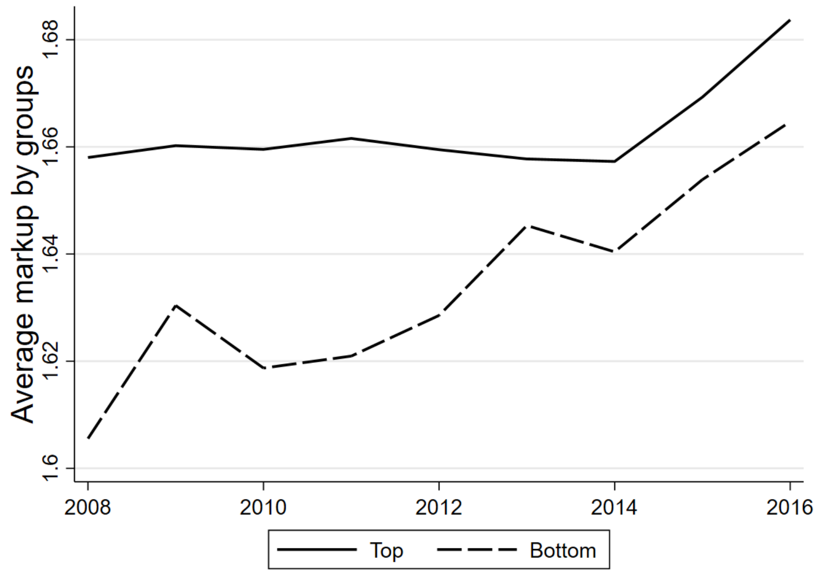


Figure 6: Average markup in the top and bottom quartile of firms by their industry oil shares based on IndAvg(Oil/TVC)

3.6 Identification

The identification strategy is based on the Bartik shift-share approach. In particular, our empirical strategy is an exposure research design where the industry shares measure the differential exposure to common shocks. We use the result of Goldsmith-Pinkham, Sorkin and Swift (2020) who show that the Bartik identifying assumption requires the exogeneity of industry shares conditional on observables and industry fixed effects.

The identifying assumption based on the exogeneity of shares requires that industry oil shares are not correlated with confounding variables which may affect markups. The exogeneity of shares assumption implies that a higher oil exposure of one industry as compared to another is associated with a higher level of markup only because oil prices are volatile and not because the shares are correlated with unobservables. The central identification concern under the shares assumption is that the industry's exposure to oil may be correlated with demand or some other factor that affects the markup. In order to address concerns about a plausible permanent relation between demand, markups and oil shares, we include industry fixed effects as controls.

In addition, we fix industries' oil share at their first year value in 2008. Using time-invariant shares eliminates the possibility that industry-specific variation in demand causes variation in markups through variation in industry oil shares. A remaining threat to identification may be if the initial oil shares in 2008 are correlated with the variation in demand and the variation in markups overtime. It is difficult to construct a plausible scenario where this would occur because it would require a stochastic trend in industry demand that is correlated with the industry oil shares in 2008.

We include year fixed effects in our estimation to control for unobserved confounding variables that are correlated with the general business cycle. Year fixed effects account for the average annual effect of the business cycle on markups. In particular, year fixed effects eliminate the concern that oil price volatility and levels of oil prices may be correlated with levels of demand and therefore affect markups.

In summary, our identifying assumption is that changes in demand that correlate with oil price volatility do not differentially affect firms in industries with higher oil shares given controls and the use of initial industry oil shares as exposure.

4 Results

Table 5 presents the main results. To interpret the coefficient in the first column in Table 5, we can multiply one standard deviation in volatility (0.02) with the average 2008 Oil/TVC ratio (0.0025) and the coefficient of 76.17. This estimate implies that a one standard deviation increase in volatility leads to a 0.38 percent increase in the markup of firms with average oil exposure. For example, a volatility increase from the average 0.31 to 0.33 leads to an increase in the average markup from 1.63 to 1.636. The effect is stronger for firms with high oil exposure. A one standard deviation increase in volatility leads to a 1.98 percent increase in the markup of firms with industry oil exposure in the 95th percentile versus only 0.05 percent for firms with industry oil exposure in the 5th percentile.

Table 5: Main regression

	(1) lnmarkupCD	(2) lnmarkupTL
Ind2008(Oil/TVC) $\times$ $\mathbb{E}[SD_t]$	76.17***	81.87***
	(20.06)	(22.60)
Year FE	X	X
Industry FE	X	X
Observations	46122	46122
Adjusted R^2	0.612	0.749

Notes: Standard errors are two-way clustered at the industry $\times$ year level. Regressions are sales-weighted. Ind2008(Oil/TVC) is the two-digit industry's oil to TVC ratio in 2008 and $\mathbb{E}[SD_t]$ is expected volatility in year t given by equation (23). Stars +10% *5% **1% and ***0.1%.

Table 6 shows that the within-industry average percentage change in markups is about 4 percent, thus implying that about one tenth of the average within-industry variation in markups is explained by this channel.

Table 6: Within industry summary statistics of markup changes

	Mean	SD	p5	p50	p95
$\lvert\Delta\text{MarkupCD}_t\rvert$	.0395846	.0325462	.0206375	.0306612	.0835094
$\lvert\Delta\text{MarkupCD}_{t+1}\rvert$	.0502538	.029709	.0270304	.0404458	.112743
$\lvert\Delta\text{MarkupTL}_t\rvert$	.0395846	.0325462	.0206375	.0306612	.0835094
$\lvert\Delta\text{MarkupTL}_{t+1}\rvert$	.0502538	.029709	.0270304	.0404458	.112743

5 Robustness

5.1 Time-average industry exposure

Table 7 presents the results using the time-average industry oil to TVC variable as exposure. The results remain positive, significant and they are similar in magnitude.

Table 7: Robustness with IndAvg(Oil/TVC) as a regressor

	(1) lnmarkupCD	(2) lnmarkupTL
IndAvg(Oil/TVC) $\times$ $\mathbb{E}[SD_t]$	76.55**	85.29**
	(25.23)	(28.46)
Year FE	X	X
Industry FE	X	X
Observations	46122	46122
Adjusted R^2	0.612	0.749

Notes: Standard errors are two-way clustered at the industry $\times$ year level. Regressions are sales-weighted. IndAvg(Oil/TVC) is the time average of the two-digit industry's oil to TVC ratio and $\mathbb{E}[SD_t]$ is expected volatility in year t given by equation (23). Stars +10% *5% **1% and ***0.1%.

5.2 Including smaller firms

Table 8 presents the results using a more complete sample of firms that include small firms. The results remain significant and similar in magnitude even when using a larger sample.

Table 8: Robustness with small firms

	(1) lnmarkupCD	(2) lnmarkupTL
Ind2008(Oil/TVC) $\times$ $\mathbb{E}[SD_t]$	74.64***	78.85***
	(19.83)	(22.53)
Year FE	X	X
Industry FE	X	X
Observations	106490	106490
Adjusted R^2	0.604	0.733

Notes: Standard errors are two-way clustered at the industry $\times$ year level. Regressions are sales-weighted. Ind2008(Oil/TVC) is the two-digit industry's oil to TVC ratio in 2008 and $\mathbb{E}[SD_t]$ is expected volatility in year t given by equation (23). Stars +10% *5% **1% and ***0.1%.

Table 9: Robustness with small firms and IndAvg(Oil/TVC) as a regressor

	(1) lnmarkupCD	(2) lnmarkupTL
IndAvg(Oil/TVC) $\times$ $\mathbb{E}[SD_t]$	75.31**	81.95**
	(25.13)	(28.52)
Year FE	X	X
Industry FE	X	X
Observations	106490	106490
Adjusted R^2	0.604	0.733

Notes: Standard errors are two-way clustered at the industry $\times$ year level. Regressions are sales-weighted. Ind2008(Oil/TVC) is the two-digit industry's oil to TVC ratio in 2008 and $\mathbb{E}[SD_t]$ is expected volatility in year t given by equation (23). Stars +10% *5% **1% and ***0.1%.

5.3 Control for demand

To check whether demand is a confounding variable for markups and oil shares, we include the industry's real value added as a control variable. We may be concerned that oil prices in levels are correlated with the oil shares chosen by industries and with the industry level of demand, which in turn is correlated with markups. Table 10 shows that the coefficients remain positive and significant, but they are reduced in magnitude.

Table 10: Robustness: controlling for industry demand

	(1) lnmarkupCD	(2) lnmarkupTL
Ind2008(Oil/TVC) $\times$ $\mathbb{E}[SD_t]$	21.61**	24.12**
	(7.756)	(8.433)
IndLn(RealVA)	-0.0682	-0.0571
	(0.100)	(0.101)
Year FE	X	X
Industry FE	X	X
Observations	46122	46122
Adjusted R^2	0.613	0.749

Notes: Standard errors are two-way clustered at the industry $\times$ year level. Regressions are sales-weighted. Ind2008(Oil/TVC) is the two-digit industry's oil to TVC ratio in 2008 and $\mathbb{E}[SD_t]$ is expected volatility in year t given by equation (23). Stars +10% *5% **1% and ***0.1%.

5.4 Changes on changes regression

We try an additional estimation method using first differences in markups and volatility. Table 11 depicts the coefficient estimates. The results confirm a positive relationship but the magnitude is smaller. A standard deviation increase in volatility (0.02) increases the markups by 0.04 percent for the firm with average oil exposure (0.002). Since the within-industry average percentage change in markups is about 4 percent, this coefficient estimate implies that only about one percent of the average variation in markups is explained by this channel[8]

Table 11: First-difference regressions with Ind2008(Oil/TVC) as exposure

	(1) ΔMarkupCD$_t$	(2) ΔMarkupTL$_t$	(3) ΔMarkupCD$_{t+1}$	(4) ΔMarkupTL$_{t+1}$
Ind2008(Oil/TVC) $\times$ $\Delta E[SD_t]$	12.52***	12.22***	-38.45	-42.23
	(3.499)	(3.613)	(24.06)	(27.48)
Ind2008(Oil/TVC) $\times$ ΔP_t^{oil}	10.98	13.77	-119.2^{+}	-123.3
	(9.779)	(10.50)	(67.27)	(76.79)
ΔMarkupCD$_{t-1,t-2}$	0.128	0.122^{+}		
	(0.0863)	(0.0733)		
ΔMarkupCD$_{t-2,t-3}$	-0.111***	-0.0916**		
	(0.0318)	(0.0304)		
ΔMarkupCD$_{t,t-2}$			0.372***	0.427***
			(0.0499)	(0.0600)
ΔMarkupCD$_{t-1,t-3}$			-0.183***	-0.201***
			(0.0287)	(0.0600)
Observations	24140	24098	19060	18996
Adjusted R^2	0.112	0.074	0.249	0.251

Notes: Standard errors are two-way clustered at the industry $\times$ year level. Regressions are sales-weighted. All regressions control for year and industry fixed effects, as well as two lags of the dependent variable. Ind2008(Oil/TVC) is the two-digit industry's oil to TVC ratio in 2008 and $\Delta\mathbb{E}[SD_t]$ is the log change in the expected volatility from year $t-1$ to t. ΔMarkupCD$_t$ (ΔMarkupCD$_{t+1}$) is the log change in the markup between t ($t+1$) and $t-1$. Stars +10% *5% **1% and ***0.1%.

The summary statistics of markups, oil price and volatility changes are listed in Table 12. The averages refer to the means of variables in the full sample across firms and industries.

[8]A potential reason for a small coefficient estimate may be due to the Nickel bias since the time series is relatively short and the first-difference regressions include lags as control variables to remove the potential serial correlation in the error term.

Table 12: Log changes in markups, oil prices and oil price volatility

	mean	sd	p5	p50	p95
ΔMarkupCD$_t$	.0001531	.0633437	-.0627881	-.000414	.0671749
ΔMarkupCD$_{t+1}$	.0024141	.0780057	-.078599	.0002822	.0910864
ΔMarkupTL$_t$	.0017258	.1426662	-.0814184	.0007474	.083904
ΔMarkupTL$_{t+1}$	.0038752	.1741313	-.1067537	.0021562	.1144941
$\Delta E[SD_t]$	.0021748	.0693593	-.1048869	-.0001293	.161683
ΔP_t^{oil}	.0756004	.0222737	.0304227	.084684	.0977478

6 Conclusion

In this paper, we study how uncertainty about factor prices leads to higher markups. Our model predicts that the exposure of firms to the price volatility of major inputs matters for the determination of firm-level markups. In particular, we find that firms with higher shares of inputs with volatile prices in their total variable costs set higher markups.

We empirically test the implications of our model using the Bartik shift-share approach. We construct markups following the production function approach developed by De Loecker and Warzynski (2012) and Ackerberg, Caves and Frazer (2015). We measure uncertainty in input prices by estimating the annual expected standard deviation of monthly oil price changes within a simple GARCH model. The identifying assumption we make in our estimation is that changes in demand that correlate with oil price volatility do not differentially affect firms in industries with higher oil shares.

We show that a one standard deviation increase in volatility leads to a 0.38 percent increase in the markup of firms with average oil exposure. The effect is stronger for firms with high oil exposure. A one standard deviation increase in volatility leads to a 1.98 percent increase in the markup of firms with industry oil exposure in the 95th percentile versus only 0.05 percent for firms with industry oil exposure in the 5th percentile.

The average within-industry change in markups is about 4 percent, suggesting that our proposed channel explains one tenth of the average within-industry markup variation. The effect is statistically and economically significant and thus, our findings help us understand the variation in markups across firms and over time.

In terms of the economic significance, Gamber (2020) estimates large effects of markups on revenue, ranging from 21.7% to 64.4%. His findings suggest that the business cycle implications of even small changes in markups could be substantial. Future research may find it interesting to explore the output and labor implications of variation in markups due to input price volatility.

Our results also support the notion that firms are financially constrained and they want to avoid situations with low profits. This is consistent with Gilchrist, Schoenle, Sim and Zakrajšek (2017) and Lian and Ma (2020) who assume that firms are financially constrained because they face an added cost when raising equity or issuing debt.

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A Appendix

A.1 Markups

Analytical definition of the firm markup Firm-level markups are constructed following De Loecker and Warzynski (2012) (DLW). The theoretical foundation for defining markups is based on the cost minimization problem of a firm with one variable input, labor L_{it} with associated wages w_{it}. The Lagrangian function can be set up as

$$\mathcal{L}_{it} = w_{it}L_{it} + r_{it}K_{it} + \lambda_{it}(Y_{it} - F_{it}(L_{it}, K_{it}, \omega_{it})) \tag{24}$$

The first-order condition with respect to the single-variable input is

$$\frac{\partial \mathcal{L}_{it}}{\partial L_{it}} = w_{it} - \lambda_{it}\frac{\partial F_{it}(L_{it}, K_{it}, \omega_{it})}{\partial L_{it}} \tag{25}$$

Since the marginal cost of production $\frac{\partial \mathcal{L}_{it}}{\partial Y_{it}}$ is λ_{it}, markups can be defined as the price-cost margin $\mu \equiv \frac{P_{it}}{\lambda_{it}}$. Equating the first-order condition with zero and multiplying both sides of it by L_{it}/Y_{it} gives

$$\frac{\partial F_{it}(L_{it}, K_{it}, \omega_{it})}{\partial L_{it}}\frac{L_{it}}{Y_{it}} = \frac{1}{\lambda_{it}}\frac{w_{it}L_{it}}{Y_{it}} \tag{26}$$

which states that the output elasticity equals the inverse marginal cost times the labor share of output. Using the definition of the markup and defining the output elasticity θ_{it} as the left-hand side of equation (26) yields

$$\mu_{it} = \frac{\theta^L_{it}}{\alpha^L_{it}} \tag{27}$$

where θ^L_{it} is the output elasticity and α^L_{it} is the labor share of output $\frac{w_{it}L_{it}}{P_{it}Y_{it}}$.

Estimation The estimation requires specifying the functional form for the production function. Note that assuming a Cobb-Douglas production function for F_{it} introduces the implicit assumption that output elasticities are common across all firms, i.e. $\theta \equiv \beta_l$ in the linear regression of

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it} \tag{28}$$

DLW uses the value-added translog production function as their baseline specification which takes the form

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \omega_{it} + \epsilon_{it}. \tag{29}$$

The translog production function does not require the restrictive assumption of smooth substitution between production factors and it is parsimonious in terms of the data requirement. Assuming a translog production function yields firm-specific output elasticities

$$\theta_{it}^L = \beta_l + 2\beta_{ll} l_{it} + \beta_{lk} k_{it} \tag{30}$$

which can be computed directly using the estimated betas ($\hat{\beta} = \hat{\beta}_l, \hat{\beta}_k, \hat{\beta}_{kl}, \hat{\beta}_{ll}, \hat{\beta}_{kk}$).

To proxy for the unobserved productivity ω_{it}, we use the control function method proposed by Levinsohn and Petrin (2003) (LP). Specifically, we assume that changes in material inputs ($m_{it} = f_t(k_{it}, l_{it}, \omega_{it})$) are perfectly correlated with productivity shocks. In practice, this assumption requires that firms adjust the level of intermediate inputs immediately after the technical efficiency shock is realized. The LP control function is corrected for functional dependence following Ackerberg et al. (2015) (ACF). ACF prescribes a two-step procedure for estimating the production function. The first step is to invert the intermediate input demand and express the unobserved productivity $\omega_{it} = f_t^{-1}(k_{it}, l_{it}, m_{it})$ as in LP and substitute it into the production function such that the first stage (Cobb-Dougles production) becomes

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + f_t^{-1}(k_{it}, l_{it}, m_{it}) + \varepsilon_{it} = \Phi_t(k_{it}, l_{it}, m_{it}) + \varepsilon_{it}. \tag{31}$$

In the first stage, f_t^{-1} is estimated non-parametrically so that $\beta = \beta_0, \beta_l, \beta_k$ are not identified separately but are estimated within the function $\Phi_t(k_{it}, l_{it}, m_{it}) = \beta_0 + \beta_l l_{it} +$

$\beta_k k_{it} + \omega_{it}$. The resulting first-stage moment condition is

$$E[\varepsilon_{it}] = E[y_{it} - \Phi_t(k_{it}, l_{it}, m_{it})] = 0. \tag{32}$$

In this way, the correction of the functional dependence is achieved by conditioning on labor within the estimation of the first stage. Since ACF cannot estimate β_l in the first stage (unline LP), β_l is estimated along with the other production function parameters in the second stage. To illustrate the exact moment conditions used in the second stage, we use ACF's example and define the functional form of the productivity process as an AR(1) $\omega_{it} = \rho\omega_{it-1} + \xi_{it}$. With this simple functional form assumption, the following second-stage moment conditions are used for the estimation

$$E\left[(\omega_{it}(\beta) - \rho\omega_{it-1}(\beta)) \otimes \begin{pmatrix} 1 \\ l_{it-1} \\ k_{it} \\ \Phi_{t-1}(k_{it-1}, l_{it-1}, m_{it-1}) \end{pmatrix}\right] = 0 \tag{33}$$

which is equivalent to

(34)

$$E\left[(y_{it} - \beta_0 - \beta_l l_{it} - \beta_k k_{it} - \rho(\Phi_{t-1} - \beta_0 - \beta_l l_{it-1} - \beta_k k_{it-1})) \otimes \begin{pmatrix} 1 \\ l_{it-1} \\ k_{it} \\ \Phi_{t-1}(k_{it-1}, l_{it-1}, m_{it-1}) \end{pmatrix}\right] = 0$$

or simply

$$E\left[\xi_{it} \otimes \begin{pmatrix} 1 \\ l_{it-1} \\ k_{it} \\ \Phi_{t-1}(k_{it-1}, l_{it-1}, m_{it-1}) \end{pmatrix}\right] = 0 \tag{35}$$

Since the second stage requires estimating an additional parameter β_l as compared to LP, an additional unconditional moment is required relative to LP. A natural set of four second-stage moment conditions to estimate the three production function parameters in β and ρ include the lagged value l_{it-1} in order to avoid that labor is chosen after time t-1 and is therefore correlated with the error term ξ_{it}.

Note that the actual estimation retains the OP/LP/ACF assumption of a general functional form for the productivity process which evolves according to a first-order Markov process according to

$$\omega_{it} = E(\omega_{it}|\omega_{it-1}) + u_{it} = g(\omega_{it-1}) + u_{it} \tag{36}$$

where $g(\omega_{it-1})$ is left unspecified and approximated by an n^{th} order polynomial. We use a 4^{th} order polynomial.

In addition, the estimation accounts for Olley and Pakes' (1996) observation of the inherent selection problem generated by the relationship between the unobserved productivity variable and the exit decision of firms. Specifically, less productive firms find it optimal to shut down, thus yielding selection into production. To be able to use an unbalanced panel, we address attrition in the data by estimating $g(\omega_{it-1}, \chi_{it})$ where χ_{it} is an indicator function for the attrition in the market. The practical implementation of the estimation follows Rovigatti and Mollisi (2018).

The final step in the markup estimation procedure is to use the first-stage residuals in (31) to correct the labor share α^l_{it}. Since the observed output y_{it} includes the error, $y^*_{it} = y_{it}exp(\varepsilon_{it})$, it is possible to use the fitted residuals in (31) to obtain the corrected markups as

$$\alpha^{l*}_{it} = \frac{w_{it}l_{it}}{p_{it}\frac{y_{it}}{exp(\hat{\varepsilon}_{it})}} = \frac{w_{it}l_{it}}{p_{it}y^*_{it}}. \tag{37}$$

This completes the markup estimation procedure.

Implicit assumptions The assumption of common factor prices is the main assumption underlying the DLW markup estimation based on OP/LP/ACF production functions. Since the intermediate input demand equation $m_{it} = f_t(k_{it}, l_{it}, \omega_{it})$ is not indexed by other factors, e.g. factor prices, it is assumed that these input prices are common across firms. For this assumption to be reasonable, the production function - and the elasticity of output derived from it - is estimated industry by industry in line with ACF and DLW.

To estimate a real production function, which is a function that maps real inputs to real output, all variables are deflated prior to the estimation. For the production function estimation, log values are used in all variables and thus, negative and zero values are eliminated in the process. All variables are annual. An itemized variable description follows.

Capital The balance sheet value of the firm's capital stock is defined as the firm's buildings, land, machines and intangible capital. The individual capital items are first deflated using the appropriate 2-digit industry deflators, namely a deflator for buildings, machines and intangible capital. Then, the deflated capital values are added together to get the firm-level capital measure.

Labor Labor costs, including social contributions, are defined as the total wages in the income statement of the firm. This variable is deflated by the wage index specific to the industry where the firm operates.

Value Added Value added is the firm's value added item calculated by the Swedish Statistics agency for each firm. Value added is a measure of the total value added produced by the enterprise (that is, its contribution to the gross domestic product) and it is defined in the Structural Business Statistics as the production value minus the cost of purchased goods and services used as inputs in the production. This does not include wages, social security contributions and the purchase cost of goods sold without processing (SCB, 2017). This variable is deflated by the value added price index specific to the industry where the firm operates.

Material Inputs Material inputs are the firm's raw material inputs and the intermediate inputs in the firm's income statement. The material inputs are calculated as the sum of the two items and deflated by the 2-digit industry-specific intermediate input deflator.

Caveats of estimating translog markups with GMM Rovigatti (2020) uses simulations to show that the Cobb-Douglas markups overlap with the baseline markups even in the presence of measurement error, whereas translog markups are much less reliable to deliver the baseline distribution when measurement error is present. In particular, moderate and high measurement errors generate a bimodal distribution for translog markups, with a noisy hump shaped tail on the right-end. The degenerate tail implies that the estimated larger translog markups are more likely to be farther from their true value.

In addition, Rovigatti and Mollisi (2018) show that the ACF methodology has limitations in empirical applications with translog markups due to the use of the GMM optimizer. Rovigatti and Mollisi (2018) report the bias and MSE estimates with different starting points for the GMM optimization routine.[9] Specifically, they show that the coefficient estimates for the production elasticity are significantly different when the optimizer's starting points are fixed at the true values as compared to when the starting points depart from the true values. The estimation error is increasingly worse for extreme values of the starting point departures. Rovigatti and Mollisi (2018) note that lower starting points lead to very noisy but not very biased results, while for larger values the bias increases and is statistically significant. This problem related to the starting points is particularly pronounced for the translog production function since it requires a selection of five starting points whereas the Cobb-Douglas production function requires only two. This difficulty implies that translog markups within the tails of the translog markup distribution are likely to be estimated with larger errors.

[9] Rovigatti and Mollisi (2018) use an optimization routine with the Newton–Raphson (NR) optimizer algorithm that they deem to perform best across different optimizers.