Markups and the Asymmetric Pass-Through of Cost Push Shocks*

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Abstract

This paper studies how prices and markups respond to cost push shocks, taking the example of global oil supply shocks. Using sector-level data for the US, we first document a weaker pass-through of global oil shocks to PPI inflation in sectors where firms charge higher markups. However, high markups mainly reduce the pass-through of dis-inflationary oil shocks, while they barely affect that of inflationary oil shocks. Second, using firm-level data, we show that following a dis-inflationary oil shock, high-markup firms are more likely to raise their markup. In addition, they are also more likely to increase their revenues, and hence their profits. Conversely, we find no difference in the response of high- and low-markup firms to inflationary oil shocks. Taken together, these results suggest that high-markup firms draw significant benefits from dis-inflationary oil shocks, as they are able to raise their markups *and* expand their revenues. They also suggest that high markups provide little cushion against prices pressures stemming from inflationary oil shocks.

Keywords: Markup, PPI inflation, oil shock, pass-through, profits.
JEL Classification codes: E31, D22, L13

*The views expressed in this paper are those of the authors and do not necessarily reflect the official views of the Bank for International Settlements. Deniz Igan, Enisse Kharroubi, Koji Takahashi and Egon Zakrajšek are at the BIS. Renée Spigt is a Ph.D. fellow visiting the BIS from the Erasmus University in Rotterdam. Corresponding author: Enisse Kharroubi (enisse.kharroubi@bis.org)

"Increasingly dominant corporations are taking the opportunity to jack up prices [...] squeezing consumers and supercharging inflation. Or "greedflation," as the hypothesis has come to be known."

— New York Times, June 3, 2022.

1 Introduction

Many countries around the world have witnessed a large rise in firm market power over the last decades, as reflected in the secular increase in markups (De Loecker et al. (2020)). Between the early 80's and the mid-2010's, markups increased by about 50% at the global level, and by about 75% in Advanced Economies (AEs).[1] Against this background, and following the global resurgence of inflation, markups have become one of the focal points of policy discussions questioning their role in the current inflation surge, or examining policies to address inflationary pressures. On the one hand, there was hope that high markups could act as a shock absorber and help cushion inflationary pressures. Indeed, contrary to firms pricing at their marginal cost, firms charging large markups can afford, when faced with a cost increase, to pass-on only some of it to their costumers, absorbing the other part through markup cuts.[2] On the other hand, the worry was and still is, that high markups could just act as oil on fire and contribute to the inflationary dynamics as firms holding large market power could more easily impose their price conditions and therefore pass-on cost increases to their customers.

Likewise, another, albeit more recent, worry has been that firms, especially those charging high markups, could retain some of the benefits of falling input cost. These concerns find their sources in the asymmetric relationship between input and output

[1]Figures on markup changes are from De Loecker and Eeckhout (2018). See also Kouvavas et al. (2021) for markup estimates for the Euro area, Aquilante et al. (2019) for the United Kingdom, Ciapanna et al. (2022) for Italy, Nakamura and Ohashi (2020) for Japan and Hambur (2021) for Australia. Díez et al. (2018) provides an international comparison, showing that in advanced economies, there has been a significant increase in markups, which is broad-based across industries and countries, and driven by the firms with the highest markups in each economic sector. For emerging markets and developing economies, the authors find less support for an upward trend in markups.

[2]The negative relationship between cost pass-through and market power typically holds when firms produce a homogeneous good, compete à la Cournot and the elasticity of the inverse demand function is not too low (above -1). Amiti et al. (2019) provide firm-level evidence consistent with this mechanism.

prices. In the US for instance, when input price are increasing, i.e. when the diffusion index is above the historical median, the relationship between to output prices is relatively tight, and higher input prices are associated with higher output prices (left-hand panel, Figure 1). By contrast, when input price are falling, i.e. the diffusion index is below the median, the relationship between input and output prices is much looser and a drop in input prices is not associated with any clear trend in output prices, especially in the short run (right-hand panel, Figure 1).[3]

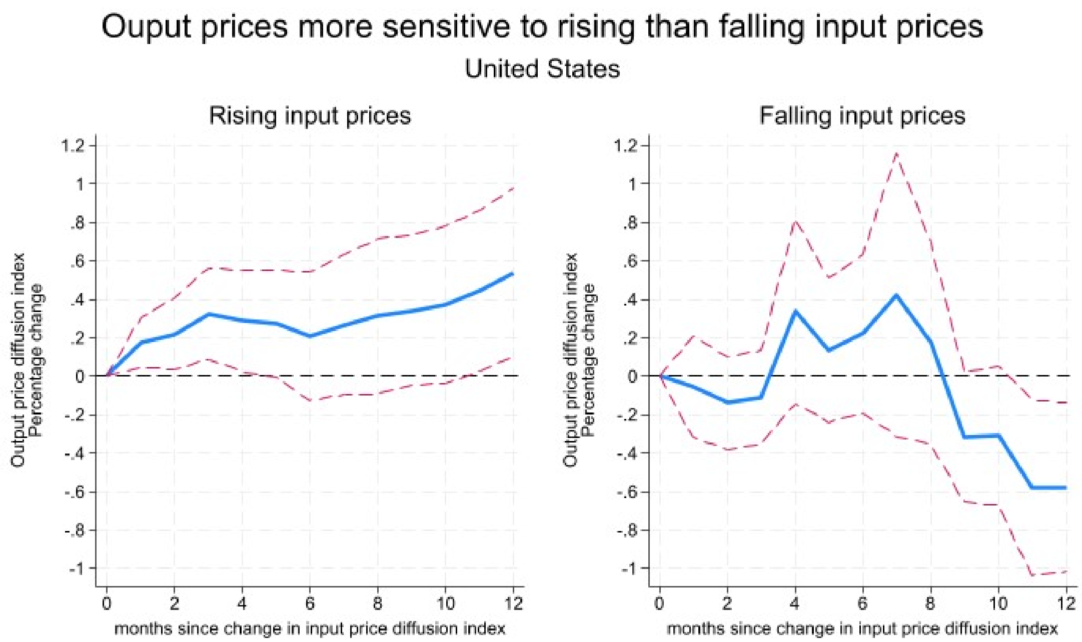

Figure 1: Output price sensitivity to input price. The blue line in each panel represents the percentage change in the PMI diffusion index for output prices following a one percentage point increase in the PMI diffusion index for input prices, for a horizon running from zero to 12 months, controlling for the current level of the PMI diffusion index for output prices. The left-hand panel (right-hand panel) estimates this relationship when the input price variable is above (below) the median. Dashed red lines display the 90% confidence interval around the mean estimate (in blue). Sample period = 2010m1-2023m4.

In this paper, we try to make sense of these differences and understand how markups affect the pass-through of cost shocks, taking the example of global oil supply shocks. Specifically, we use data for US sectors and firms over a 20-year period and explore two questions. First, considering sectoral producer price index (PPI) inflation, we test whether the data supports the view that high markups can act as shock absorbers, i.e. that oil price shocks have a smaller price impact in sectors where firms charge higher markups. In

[3]Figure A.1 in Appendix A provides similar evidence for the Euro Area.

addition, given that the role of markups as shock absorbers is particularly relevant in the case of inflationary "cost push" shocks, we go one step further and investigate if markups affect the pass-through of positive and negative oil shocks to PPI inflation differently. In a nutshell, we do find evidence that markups can act as shock absorbers: the pass-through of oil price shocks to sectoral PPI inflation effectively tends to be lower in sectors where firms charge higher markups. However, we also find that markups reduce the pass-through of dis-inflationary oil price shocks (i.e. positive oil supply shocks), but not that of inflationary ones (i.e. negative oil supply shocks). Put differently, high markups act as shock absorbers on the way down, not on the way up.

Second we go to firm-level data, to understand the mechanisms behind the asymmetric impact of markups on the pass-through of oil shocks. For this, we explore how firms react to oil shocks, considering both prices and quantities. Specifically, we first investigate the dynamics of markups at the firm-level, i.e. how firms change their markups following a given oil shock. There, consistent with sector-level evidence, we find that high-markup firms are more likely to *raise* their markup following a dis-inflationary oil shock than low-markup firms, suggesting that firms holding market power take opportunity of cost-reducing shocks to increase profits, instead of lowering prices. Quantification however shows that the increase in markups —the intensive margin effect— , while statistically significant, is not economically large. We therefore go one step further and look into firm growth —the extensive margin effect— and estimate how revenues (and profits) at the firm-level change following an oil price shock. Here, we find that firms charging higher markups tend to increase their revenues and earn larger profits following a dis-inflationary oil shock relative to firms with lower markups, consistent with sector-level evidence.

The firm-level analysis therefore suggests that the asymmetric impact of markups on the pass-through of oil price shocks reflects a combination of intensive and extensive margin effects, even if quantitatively the latter seems more important. Following a dis-inflationary oil shock, high-markup firms are more likely to raise their markup (intensive margin effect) and to grow disproportionately faster (extensive margin effect). As high-markup firms raise their markup *and* become larger, the sector-wide markup increases, which dampens the impact of dis-inflationary oil shocks.

1.1 Literature review

This paper relates to three different strands of literature. First, this paper builds on the production function approach to estimate firm-level markups as proposed by De Loecker and Warzynski (2012). Following seminal contributions by Hall (1988) and Roeger (1995), which provide country-level estimates for markups by estimating an extended expression for the Solow residual, a growing number of papers investigating markups has shifted to the production function approach, in part because of the flexibility in the estimation assumptions)[4], and despite some limitations, including substantial variation in markup estimates or some implausible implications (Syverson (2019) and Basu (2019)). Based on this approach, a number of studies have investigated the macroeconomic implications of increasing market power and markups (De Loecker et al., 2020).

Second, this paper contributes to the literature on the real effects of firm market power. Feenstra et al. (1996), Nakamura and Zerom (2010), Koujianou Goldberg and Hellerstein (2013) and Amiti et al. (2019) all provide empirical estimates of pass-through and markup variability. Focusing on the estimation of strategic complementarities at the firm-level, Amiti et al. (2019) show that prices of large firms display lower elasticity to own cost shocks. Conversely, small firms show higher elasticity, with complete pass-through. We differ from these papers in that we investigate the extent to which differences in markups —across firms or sectors— can account for differences in pass-through. Duval et al. (2021) show using firm-level data that higher markups dampen the response of output to monetary policy shocks. Kouvavas et al. (2021) run a similar exercise for Euro Area countries, providing suggestive evidence that inflation is less volatile in sectors where firms charge higher markups. In these countries, not only the pass-through of monetary policy shocks to inflation appears to be weaker for high-markup sectors but also the pass-through of oil supply and global demand shocks. That said, they do not look, as we do, into possible asymmetric effect of markups.[5] Nor do they complement their sector-level analysis with an investigation of the evolution of markups at the firm-level as we do

[4] Bond et al. (2021) and Raval (2023) propose some modification of the production function approach.

[5] Importantly, this paper concludes that high markups have contributed to low inflation by shielded Euro Area countries from the fall out of inflationary shocks. Conversely, the evidence presented in this paper for the United States rather shows that high markups barely provide any hedge against such shocks.

in this paper. Bräuning et al. (2022) are close to this paper in that they investigate the differential effect of concentration on the pass-through of both positive as well as negative cost shocks. They find however no impact of concentration on the pass-through of negative cost shocks. Conversely, they show that the pass-through of positive cost shocks is larger in more concentrated industries. While these results differ from ours, it is important to note that concentration, while useful to proxy for market power, also suffer a number of drawbacks, that can make it a poor approximation for market power (Berry et al., 2019). Finally, Conlon et al. (2023) measure the correlation between the change in firm-level markups and the change in industry-level prices as measured by the PPI and find little to no relationship. One explanation is that markups could have risen more quickly than prices in the aggregate, which could indicate that firms have not fully passed on declines in marginal costs to consumers. In this respect, our paper provide empirical evidence consistent with this view: following positive oil supply shocks, high-markup firms do not seem to pass on fully the reduction in the marginal cost of production. Instead, they benefit from their pricing power after dis-inflationary oil supply shocks by increasing their markups, sales and profits. Also, we do not find any evidence that firms with higher markups cushion inflationary price pressures. The fact that firms with pricing power can benefit from supply side developments, relates somewhat to the findings of Franzoni et al. (2023). However, the origins of their shocks are not directly related to input costs but to supply chain shortages. They find that "superstar" firms benefit from supply chain shortages through higher markups and profitability.

Third, our paper adds to the specific literature on the pass-through of energy cost shocks. Using data on French manufacturing firms' prices, Lafrogne-Joussier et al. (2023) show that firms pass on 100% of energy cost shocks (and 30% of non-energy imported input price shocks), conditional on their exposure to these shocks. They also find evidence of asymmetric pass-through, with positive cost shocks inducing significantly higher pass-through than to negative shocks. In our paper, we find a similar asymmetric effect. However, we go one step further in that we find that the asymmetry is driven by sector- and firm-level markups. In addition, we exploit the full universe of sectors, and a longer time span from 1997 to 2019, allowing us to examine not only many positive cost shocks but also a substantial number of negative cost shocks.

The rest of the paper proceeds as follows. Section 2 presents our estimation methodology of markups and the estimates as well as the firm-level datasets. Section 3 describes the oil supply shock and sectoral PPI inflation data. Section 4 estimates the pass-through of oil shocks to inflation at the sectoral level. Section 5 explores the mechanism behind the difference in the sectoral pass-through using firm-level markups and revenues. Finally, concluding remarks are given in Section 6.

2 Markup estimation

In this section, we review the methodology used to estimate markups as well as the data used in this estimation. We then briefly discuss our markup estimates and benchmark them against those existing in the literature.

2.1 Methodology

To estimate markups, we follow the production function approach pioneered by De Loecker and Warzynski (2012). Let us denote μ_{it} the markup for firm i at time t as the ratio of its price P_{it} to its marginal cost of production MC_{it}, i.e. $\mu_{it} = \frac{P_{it}}{MC_{it}}$. Then, let us assume firm i's technology is summarised by a production function F which depends on a set of variable inputs $V_{it}^{1}, ..., V_{it}^{v}$, —-eg. labour, material, energy, etc.—, a state variable K_{it} —typically the capital stock— and total factor productivity ω_{it}:

$$Y_{it} = F(V_{it}^{1}, ..., V_{it}^{v}, K_{it}, \omega_{it}) \tag{1}$$

Then, solving the cost minimization problem, the expression for the markup of firm i at time t simplifies as:

$$\mu_{it} = \beta_{it}^{v} \left[\frac{P_{it} Y_{it}}{P_{it}^{v} V_{it}} \right] \tag{2}$$

where β_{it}^{v} is the elasticity of firm i's output at time t to the variable input v and $\frac{P_{it}Y_{it}}{P_{it}^{v}V_{it}}$ is the ratio of output to the variable input v for firm i at time t.

Obtaining (one of) the elasticities β of output to the variable inputs requires estimating the production function, which in turn requires making three choices: one about the specific functional form for F, one about the panel of firms you use to estimate the production function on, and finally one about productivity shocks and in particular how to address related simultaneity issues. First, we assume a Cobb-Douglas production function, so that the production function can be estimated using linear regressions on the log-transformed variables. In addition, we assume that firms' output (revenues) depends on capital (net property plant and equipment) and a composite variable input (cost of goods sold) that bundles labour and intermediary inputs together.

Second, in line with De Loecker et al. (2020), we estimate the production functions for a panel of firms within the same industry, which in our case is defined by the 3-digit NAICS industry. In the time dimension, we consider a three-year (backward-looking) rolling window, to account for technology and productivity changes over time.

Third, productivity shocks can induce a simultaneity bias in the production function estimation as firms facing positive productivity shocks are likely to increase their demand for inputs and expand output at the same time, thereby affecting the estimates for the $\beta_{s,t}$ elasticity. Here, we follow Olley and Pakes (1996), and use log-capital expenditures to proxy for firm-level productivity shocks, the idea being that capital expenditures and productivity shocks should be positively correlated.[6] Hence, letting lower-case letters represent logs of upper-case variables, the Cobb-Douglas production function writes as:

$$y_{i,t} = \alpha + v_{i,t}\beta_{s,t} + k_{i,t}\gamma_{s,t} + \omega_{i,t} + \varepsilon_{i,t} \tag{3}$$

where i refers to firm, s refers to sector and t refers to the time dimension. y is the log of output, v is the log of the cost of goods sold, k is the log of net property, plant and equipment, the state variable, ω is the unobservable productivity efficiency and ε is a white noise idiosyncratic shock. Then assuming firm-level investment increases

[6]This approach is valid when the idiosyncratic productivity shock is not correlated with the current and lagged values of the state variable, here capital.

monotonically and is invertible in firm-level productivity, i.e. $i_{it} = f(k_{i,t}; \omega_{i,t})$, we can write firm-level productivity ω as a function of capital and investment.[7] Formally, inverting their investment policy function, and denoting $h(.)$ the invert of $f(.)$, the production function (3) can be written as

$$y_{i,t} = \alpha + v_{i,t}\beta_{s,t} + k_{i,t}\gamma_{s,t} + h(i_{it}; k_{i,t}) + \varepsilon_{i,t} = \alpha + v_{i,t}\beta_{s,t} + \Phi_{s,t}(i_{it}; k_{i,t}) + \varepsilon_{i,t} \tag{4}$$

The estimation procedure then goes into two steps. The first stage is about approximating the $\Phi_{s,t}$ function. For this, we use a third degree polynomial. Second, denoting $\widehat{\Phi_{s,t}}$ the estimate for $\Phi_{s,t}$, one can get a consistent estimate of $\beta_{s,t}$ by estimating the regression:

$$y_{i,t} = \alpha + v_{i,t}\beta_{s,t} + \widehat{\Phi_{s,t}}(i_{it}; k_{i,t}) + \varepsilon_{i,t} \tag{5}$$

Denoting $\widehat{\beta_{s,t}}$ the estimate for $\beta_{s,t}$, the estimated markup for firm i at time t then writes as

$$\mu_{i,t} = \widehat{\beta_{s,t}} \left[\frac{P^v_{i,t} V_{i,t}}{P_{i,t} Y_{i,t}} \right]^{-1} \tag{6}$$

where $P_{i,t}Y_{i,t}$ and $P^V_{i,t}V_{i,t}$ are respectively the values for firm i output and variable input at time t.

2.2 Data

This paper focuses on firms from the United States. To estimate their markups, we use firm-level data from Standards and Poor's Capital IQ. This source provides standard balance sheet and income statement data for listed and large private firms. This includes data on total revenues, cost of goods sold (COGS), net property plant and equipment, and capital expenditures, which we use to measure respectively gross output, the variable input, capital and investment.[8] The data sample runs from 1998 to 2019 and covers all

[7] There are two additional requirements. One is that the state variable evolves according to the investment policy function. Another is that the variable input v is non-dynamic, i.e. it does not affect subsequent profits.

[8] We deflate all variables used to estimate the markups with the corresponding price index. Revenues and cost of goods sold are deflated with the gross output price index, capital expenditures with the gross fixed capital formation price index and net property plant and equipment with the capital goods price

sectors in the US economy, with more than 15,000 individual firms over the full sample period. We perform several cleaning steps before running the estimation of markups.[9] This shrinks our sample to about 7,000 public and private firms.[10]

We construct markups by estimating sector-specific elasticities of output to COGS, lumping together all firms that operate in a given sector, following the 3-digit NAICS industrial classification, spanning about 75 sectors covering all sectors in the economy, but "Agriculture, Forestry, Fishing and Hunting", "Finance and Insurance", "Government and Non-Profit Firms", "Oil and Gas Extraction", and "Utilities". We exclude these industries from the sector-level analysis either because there is no corresponding PPI data (Agriculture or Government Firms), because estimated markups are likely unreliable measures of market power (Finance and Insurance or Utilities), or because oil supply shocks are unlikely to be a good proxy for cost push shocks (Oil and Gas Extraction).[11] Moreover we estimate time-varying elasticities by estimating production functions over three-year backward-looking rolling windows. This way, we can allow for changes — cyclical or structural— in the production function parameters. Finally, markups being estimated at the firm-level, we construct sector-level markup aggregates using quantiles of the within sector-time distribution of firm markups, where firm-level observations are weighted by revenues. Specifically, denoting $F_{s,t}$ the cumulative distribution of firm markups in sector s at time t, and considering the n^{th}-percentile of the firm revenue distribution in sector s at time t, the markup for sector s at time t for the n^{th}-percentile, which we denote $\text{mkup}_{s,t}^{n}$, is defined as $F_{s,t}\left(\text{mkup}_{s,t}^{n}\right) = \frac{n}{100}$.

index. Moreover, we winsorise the growth rates of revenues, capital expenditures, net property plant and equipment and cost of goods at the 1^{st} and 99^{th} percentile to exclude outliers. In the firm-level analysis, we limit the range of markup to 0.5-2.5 and exclude any observation with a markup estimate outside this range.

[9] In particular, we drop firms with missing or below zero values for total revenues, net property plant and equipment, cost of goods sold and capital expenditures, total debt or total assets. In addition, we exclude firms with less than five years of data and sector-year pairs with less than five firms.

[10] In Figure A.2 we show that the growth rate in aggregated revenues of our sample of firms follows simlar trends over time as the total gross output as published by the US BEA.

[11] Another issue is that some firms report more than one sector of activity. In the absence of a sectoral break-down of revenues and costs, we duplicate the data so that these firms are represented in each sector they operate in. Note that for the firm-level regressions, we make sure that there only exists one observation for a given firm-year.

2.3 Markup estimates

The left-hand panel of Figure 2 plots the distribution of estimated markups, when sectoral markups are aggregated at the one-digit level. First, our estimates of median markups tend to overlap quite well with those provided by De Loecker et al. (2020), which are estimated based on Compustat data. As is the case with our estimates, De Loecker et al. (2020) finds "Wholesale Trade" and "Transportation & Warehousing" to be amongst the sectors with the lowest sectoral markups, and "Information", "Manufacturing" and "Other Services" to be amongst sectors with the highest markups. Also, the markups of sectors as "Construction", "Retail Trade" and "Accommodation & Food Services" are close to each other in magnitude with a median markup of around 1.1. For some sectors, the ranking slightly differs. According to our estimates "Mining" is for example at the lower end of the sectoral markup spectrum, whereas De Loecker et al. (2020) estimate the "Mining" sectoral markup to be in the middle. Such differences could arise, because of differences in sub-sector composition of the 2-digit NAICS code. As discussed in Section 2.2, we exclude the 3-digit NAICS sectors that are related to oil and gas extraction, which are part of the 2-digit NAICS "Mining, Quarrying, and Oil and Gas Extraction" sector. Furthermore, in contrast to De Loecker et al. (2020), we not only cover public firms but also large private firms and we extend our sample period to 2019 instead of 2016.

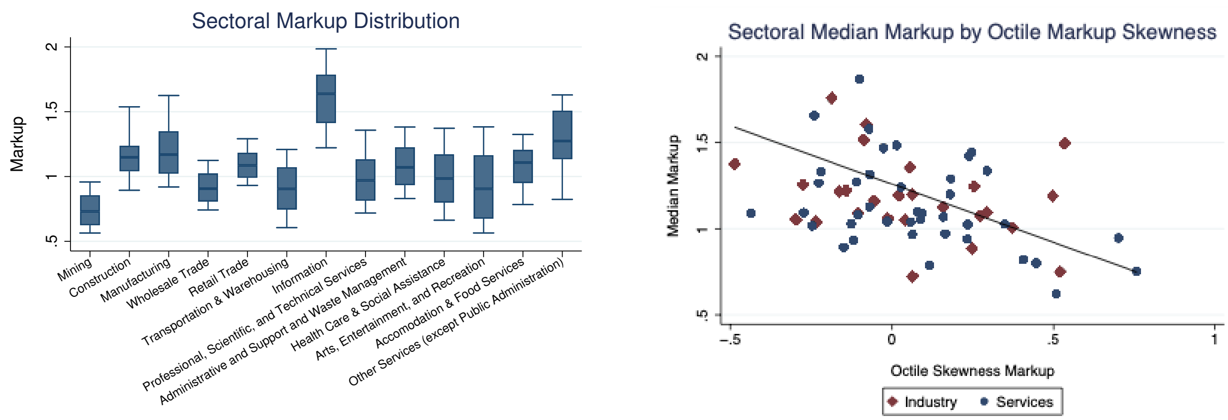

Figure 2: The distribution of sectoral markup. The left-hand figure shows the distribution of markups for 2-digit NAICS sectors, and with revenue-weighted percentiles. The box shows the interquartile range together with the median sectoral markup. The whiskers use the 10^{th} and 90^{th} percentile as the lower and upper extremes. The right-hand panel shows the 3-digit NAICS revenue-weighted sectoral median markups plotted against the revenue-weighted octile skewness, with the octile skewness computed by $\frac{(Q_{0.875}-Q_{0.5})-(Q_{0.5}-Q_{0.125})}{Q_{0.875}-Q_{0.125}}$. All dots represent 3-digit NAICS sectors, with in red the industry-related sectors and in blue the services-related sectors. Both panels are estimated using firm-level data, and cover our full sample period.

Second, turning to the within-sector distribution of markups, dispersion within 2-digit sectors also turns out to be quite significant. It is largest in "Manufacturing", "Arts, Entertainment & Recreation" and "Other Services", with a revenue-weighted standard deviation of 0.32 against a weighted average of 1.2, 0.9 and 1.3, respectively. Conversely, sectors like "Mining" or "Wholesale Trade" and "Retail Trade", display much lower markup dispersion.[12,13]

Third, our markup estimates show a strong negative cross-sectoral correlation between median markups and markup skewness (Figure 2, right-hand panel). We compute the markup skewness using the octile skewness measure, which is robust to outliers and is bounded between -1 and 1 (Hinkley, 1975). Sectors where the median markup is higher display a stronger left tail asymmetry, suggesting that the mass of the high sectoral median markup distribution is concentrated on the right, as opposed to uniformly higher markups over the whole distribution. This relationship holds for both industry-related sectors as well as for services-related sectors.

[12]For "Mining", "Wholesale Trade" and "Retail Trade" the revenue-weighted standard deviations are equal to 0.17, 0.15 and 0.16, and the revenue-weighted averages to 0.8, 0.9 and 1.1, respectively.

[13]It is important to note that having aggregated markup distributions at the 2-digit level, our dispersion measures capture, not only the within-sector dispersion at the 3-digit level but also differences in average markups across 3-digit sectors that belong to a single sectoral aggregate, which are also likely to be significant.

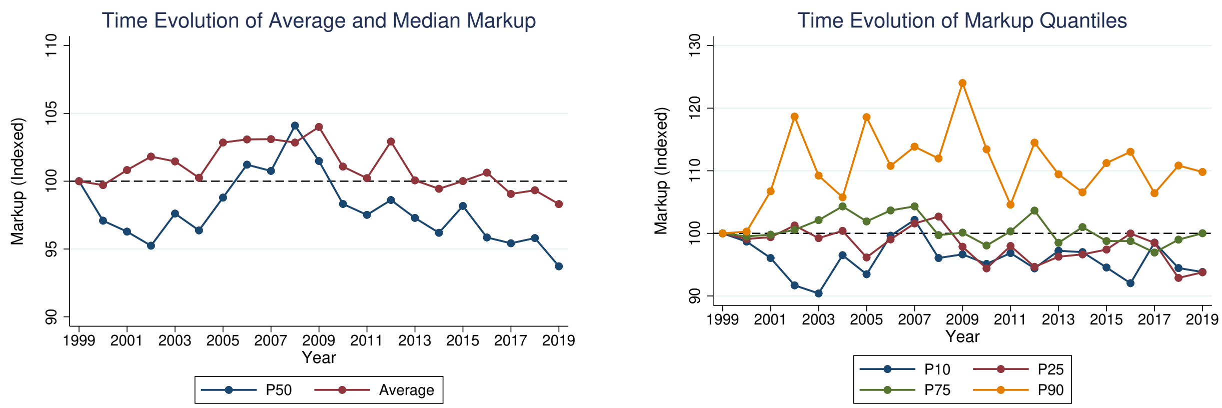

Figure 3: The distribution of markups over time. The left-hand panel of the Figure shows the time evolution of the revenue-weighted median and mean firm-level markup. The right-hand panel shows the time evolution of the P–10, P–25, P–75 and P–90 markup quantiles. Markup quantiles are computed weighing firm-level markups using firm-level revenues. All quantiles are rebased at 100 in 1998.

Finally, we examine in Figure 3 the evolution of the distribution of the estimated markups over time. In the left-hand panel, we show that both the average as well as the median markup have stayed relatively constant from 1999 up until 2019. There has been a slight upward trend in the average and median markup from 2003 to roughly 2008 after which the trend reversed, but all within the bandwidth of 5% relative to the base. However, upon examining the full distribution displayed in the right-hand panel, distinct patterns emerge for the upper and lower tails, pointing to diverging trends. The most upper tail of the distribution, i.e. the 90$^{\text{th}}$ percentile, has been on the rise, whereas the two lower tails, the 25$^{\text{th}}$ and the 10$^{\text{th}}$ percentile, have been falling somewhat over time. In other words, the dispersion in the distribution of markups has increased since 1999.

In Figure A.3 we provide a similar time series, but this time unweighted. Also in this series, we observe that the 90$^{\text{th}}$ percentile has been following an upward trend although less pronounced than in the revenue-weighted series. This implies that especially the larger firms have gained in markup in the 90$^{\text{th}}$ percentile. The observation that the 90$^{\text{th}}$ percentile has been the main driver of a markup increase is in line with previous literature, including De Loecker et al. (2020).

3 Oil shocks and PPI inflation

To estimate how prices at the sector-level respond to cost shocks and how this response depends (if at all) on markups charged by firms in different sectors, we use empirically identified structural shocks and estimate a set of cross-sector panel local projections à la Jorda (2005). Following the literature[14], we rely on identified global oil supply shocks from Baumeister and Hamilton (2019), available on a monthly frequency. Such oil supply shocks are defined as unpredictable interruptions / expansions to global oil production, whose cause could be related to the start or the end of wars, the occurrence of bad weather conditions or the imposition or relaxation of export limits by large oil producing countries.[15,16]

Figure A.4 provides some descriptive statistics as well as the density plot for the monthly oil supply shock series. As one would expect, the mean and median of the oil supply shocks are about zero, while the inter-quartile range and the standard deviation are comparable (1.07 vs. 1.05). In addition, oil supply shocks are roughly symmetrically distributed, even if the skewness is slightly positive, as reflected by the relatively large number of mid-sized positive oil supply shock in the right-hand panel of Figure A.4.

The time series of the oil supply shock is displayed in Figure 4, left-hand panel. The grey highlighted area represents the global financial crisis (GFC) and the yellow highlighted areas denote other notable events for oil markets. At the start of the sample period, oil prices were heavily affected by the Asian financial crisis. A combination of stagnating demand and excess supply caused oil prices to drop significantly. During 1998 and 1999, the Organization of the Petroleum Exporting Countries (OPEC) announced various supply cuts, leading to multiple negative supply shocks. In September 2001, the period of relative price stabilization came to an end with the 9/11 attacks. The turmoil in the oil market

[14] See for instance Kouvavas et al. (2021).

[15] The oil shocks are estimated using a 4-variable Bayesian Structural Vector Autoregression (SVAR) model which provides a flexible empirical framework that nests frequentist identification strategies as a special case. The four variables are global oil production, real oil prices, global real economic activity and oil inventories, the oil supply shock being the residual to the first equation. As is clear, these shocks do not embed any sector- or firm-level information, which could otherwise invalidate our identification strategy.

[16] We choose to focus on global oil supply shocks and abstract from global oil demand shocks, which Baumeister and Hamilton (2019) also provide, as the latter are likely to pick up global demand shocks, and could hence affect prices independently of the cost channel.

continued at the end of 2002 with the Venezuelan oil field strikes, as reflected by the strong negative supply shock, and lasted up until 2003 with the onset of the Iraq war.

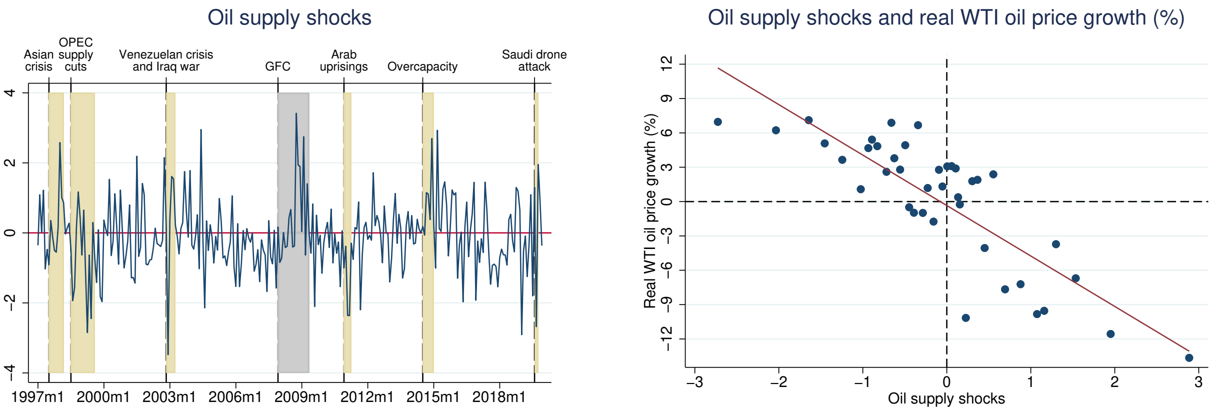

Figure 4: Oil supply shocks and oil prices. The left-hand panel plots the time series of the monthly oil supply shocks. The grey highlighted area denotes the global financial crisis. The yellow highlighted areas indicate other notable events which have strongly affected the oil price development, all of which are listed at the top of the graph. The right-hand panel shows the relationship between the monthly oil supply shocks and the monthly growth rate of the West Texas Intermediate (WTI) oil price – deflated using US CPI. It makes use of the binscatter command, with the monthly oil supply shocks divided into 40 equal-sized bins.

The 2007 to 2008 time frame was characterized by a longer period of negative oil supply shocks. During this period, global oil production was mostly flat, while global oil demand was particularly strong, sending oil prices up to almost 150 US $ a barrel. The price run-up came to an end in mid-2008, when the global economy entered in recession, and Brent crude oil price plummeted all the way down to 40 US $ per barrel at the turn of 2009. The next geopolitical event hitting the oil market came a few years later with the Arab uprisings in 2011. The growing unrest caused uncertainty about the oil supply development, pushing the oil supply shocks in negative territory.

The next episode of positive oil supply shocks came only in 2014, when global oil supply was particularly strong while global oil demand was rather weak. Baumeister and Hamilton (2019) show that both supply and demand developments played a significant role in the oil price collapse during 2014-2016. The final major oil supply disruption in our sample period was caused by the Saudi oil attack in September 2019, as shown by the large negative spike in the left-hand panel of Figure 4.

The right-hand panel of Figure A.4 plots the relationship between the oil supply shock and the monthly growth rate of the West Texas Intermediate (WTI) oil price — deflated using US CPI.[17] The negative correlation displayed in the panel confirms that positive oil supply shock are associated with lower growth in the real WTI oil price. Quantitatively, a unitary —approximately one standard deviation— monthly oil supply shock is on average associated with a 4.4 percentage points decrease in the growth rate of the real price of oil over the same period.

Last to investigate the link between cost shocks, markups and prices, we rely on sectoral inflation, defined as the growth rate of the seasonally-adjusted monthly series of the Producer Price Index (PPI) for the years 1998 to 2019. We do so for all sectors at the 3-digit NAICS level, which yields us in the end a total of 46 industries after merging the PPI data with the sectoral markup data. The summary statistics of the annual PPI growth rate per sector can be found in Table A.1. On average, sectors have a PPI growth rate of 0.2%. Sectors with significant price fluctuations are ”Petroleum and Coal Products Manufacturing”, ”Electronics and Applicance Stores” and ”Gasoline Stations”.

[17]The right-hand panel of Figure A.4 makes use of the binscatter command, with the monthly oil supply shocks divided into 40 equal-sized bins.

4 Markups and the sectoral pass-through of oil shocks

In this section, we estimate the pass-through at the sector-level of oil shocks to PPI inflation, allowing it to depend on the initial markup in the sector.

4.1 Empirical specification

To test for the possibility that high markups can cushion cost-push shocks, we run a set of regressions where the dependent variable is inflation in sector s between t and $t+h$, denoted $p_{s,t+h} - p_{s,t}$, in what follows. On the right-hand side, we use as explanatory variables, the oil shock at month t denoted OIL_t, and a measure of the revenue-weighted median markup in sector s, which we lag one year and denote $\mu_{s,t-1}$[18]. In addition, to test for the cushioning hypothesis, we include the interaction between the monthly oil shock OIL_t and the measure of the sectoral markup μ_{st-1} to allow the sensitivity of sectoral inflation to the oil shock to change with the sectoral markup. Finally, we also include in our specification lagged PPI inflation as a control variable, with lags going from 1 to 12 months.

To estimate our baseline regression, we follow two alternative approaches. In the first, we rely on a standard linear interaction term between the oil shock and the sectoral markup itself. Our second approach creates indicator variables for low, medium and high sectoral median markups. For example, the dummy variable for the low (high) sectoral markup is equal to one for sectors whose markup on a given year belongs to the lower (upper) tercile of the distribution of sectoral markups on that year. In each of these different specifications, we include sector fixed effects θ_s and run specifications with and without time dummies λ_t. The year-month dummies help us to control for any aggregate developments, such as overall inflation of GDP growth.

With $\mu_{s,t-1}$ denoting the yearly sectoral median markup at time $t-1$, the first variant of the baseline empirical specification with the standard linear interaction term writes as:

[18] As the markup frequency is annual, $t-1$ represents the previous year for sectoral markups and not the previous month. To be precise, if an oil shock hits in July 2011, then we take the pre-determined sectoral markup of 2010, estimated based on a three-year backward-looking rolling window as described in the 2.2 Data section.

$$p_{s,t+h} - p_{s,t} = \sum_{j=0}^{12} \rho_{j,h} \Delta p_{s,t-j} + \beta_{1,h}\mu_{s,t-1} + \beta_{2,h}\text{OIL}_t + \beta_{3,h}\text{OIL}_t\mu_{s,t-1} + \theta_{s,h} + \lambda_{t,h} + \epsilon_{s,t+h} \tag{7}$$

In the second specification, we use the interaction term between the oil supply shock and the indicator variables for the markup terciles. In particular, the variable $\mathbf{1}_{\mu_{s,t-1} \in (\mu_{t-1}^X, \mu_{t-1}^Y)}$ represents an indicator that takes the value one when the sectoral markup μ_{st-1} lies between the x^{th} and the y^{th} percentiles of the yearly distribution of sectoral markups:

$$\begin{aligned} p_{s,t+h} - p_{s,t} = \sum_{j=0}^{12} \rho_{j,h} \Delta p_{s,t-j} + \beta_{1,h}^{low} + \beta_{2,h}^{low}\text{OIL}_t + [\beta_{3,h}^{med} + \beta_{4,h}^{med}\text{OIL}_t]\mathbf{1}_{\mu_{s,t-1} \in (\mu_{t-1}^{33}, \mu_{t-1}^{67})} \\ +[\beta_{5,h}^{high} + \beta_{6,h}^{high}\text{OIL}_t]\mathbf{1}_{\mu_{s,t-1} \in (\mu_{t-1}^{67}, \mu_{t-1}^{100})} + \theta_{s,h} + \lambda_{t,h} + \epsilon_{s,t+h} \end{aligned} \tag{8}$$

We first run regressions using as a dependent variable one-year ahead PPI inflation, i.e. for $h = 12$. Thereafter, we investigate the full time dynamics, considering PPI inflation from 1 to 36 months ahead.[19]

4.2 Estimation results

We first discuss the empirical results based on estimations of regressions (7) and (8) using the oil supply shock and the median sectoral markup.

Columns (1) and (2) of Table 1 show that positive oil supply shocks are associated with significant lower PPI inflation at a 12 month horizon, but less so in sectors where the median markup is higher. To illustrate, we can take a high and a low median markup sector, defined at the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentile of our sectoral markup distribution, and with markups of 0.8 and 1.6 respectively. Column (1) shows that for the high-markup sector, the PPI inflation is reduced by -1 percentage points following a 10 percentage points decrease in real oil price growth[20], and by -2.4 percentage points for the low-markup sector, reflecting a 1.4

[19] As is clear from specifications (7) and (8), the oil shock variable OIL_t and the time dummies $\lambda_{t,h}$ are perfectly colinear. Hence the oil shock variable OIL_t matters only insofar as the time dummies are not included in the regression.

[20] In Figure A.4 we show that a one-unit increase in an oil supply shock is on average associated with a

percentage points difference. Differences in sectoral markups therefore make a significant difference as to how much of the oil shock is passed onto sectoral inflation. This result is robust to including time dummies (column (2)).

Dependent variable: 1-year PPI inflation				
	(1)	(2)	(3)	(4)
Oil supply shock	-1.630***		-1.078***	
	(0.473)		*(0.298)*	
Oil supply shock × Sectoral markup	0.739***	0.806***		
	(0.263)	*(0.267)*		
Oil supply shock × Medium sectoral markup			0.449*	0.458*
			(0.242)	*(0.245)*
Oil supply shock × High sectoral markup			0.524**	0.532**
			(0.211)	*(0.213)*
Observations	8,185	8,185	8,185	8,185
R-squared	0.073	0.190	0.076	0.193
Number of industries	46	46	46	46
Industry FE	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	No	Yes

Table 1: The dampening effect of markups on the pass-through of oil shocks. This table presents estimation results from specification (7). The unit of observation is sector s, month t. The dependent variable is $\Delta PPI\, 1y$ which is defined as the log change in PPI from t to $t + h$ with h equal to 12. *Oil supply shock* is an oil supply shock in month t. *Sectoral markup* is the sectoral revenue-weighted median markup the year before the oil supply shock. *Med* and *high median sectoral markup* denote the dummy variables for the medium and the high terciles for sectoral median markups the year before the oil supply shock. The uninteracted *Sectoral markup* and *Med and high median sectoral markup* terms and the lagged sectoral inflation terms are included in the estimation but not reported for brevity. Driscoll-Kraay standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Similarly, estimation results based on the empirical specification including the tercile dummies confirm the main result (columns (3) and (4)). Columns (3) and (4) of Table 1 show that sectoral inflation responds negatively to positive oil supply shocks (first row), but that the sensitivity of PPI inflation to oil supply shocks is lower when the sectoral markup is higher, i.e. when it belongs to the higher terciles of the cross-sectoral distribution (third and fourth row). To give an order of magnitude, the pass-through of oil supply shocks to 1-year ahead PPI inflation is roughly cut by half for sectors whose median markup is in the third tercile of the cross-sectoral distribution of markups, relative sectors whose median markup is in the first tercile of the cross-sectoral distribution. The results in column (3) indicate that when an oil supply shock hits the economy which represents a 10 percentage

4.4 percentage point decrease in the oil price growth. Thus, a 10 percentage points decrease in real oil price, translates into an additional positive oil supply shock of roughly 2.27.

points cut in real oil price growth, the PPI inflation is reduced by -2.4 percentage points for sectors whose median markup is in the first tercile of the cross-sectoral distribution of markups, whereas the PPI inflation is reduced by -1.3 percentage points for sectors in the third tercile.[21] Column (4) again shows that this effect is robust to the inclusion of year-month fixed effects and thus to macro-economic shocks at time t.

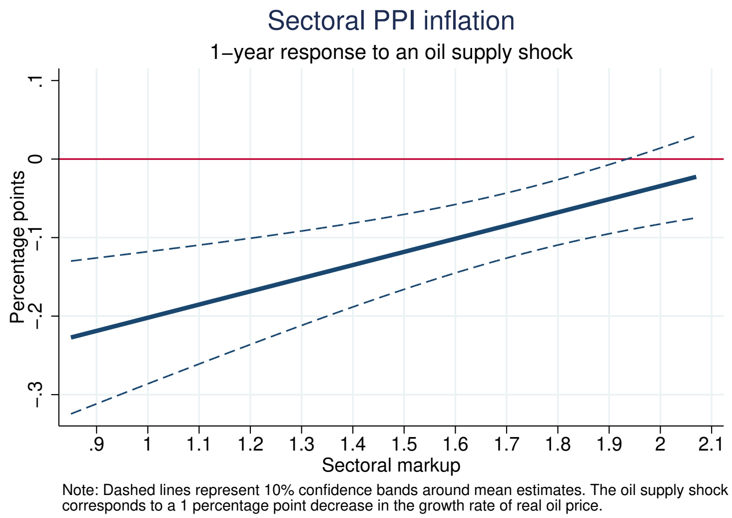

Figure 5: High markups reduce the pass-through of oil supply shocks to sectoral inflation. The figure shows the oil supply shock pass-through to 1-year ahead sectoral inflation across the sectoral median markup distribution. The oil supply shock corresponds to a 1 percentage point decrease in the growth rate of real oil prices.

Our regression results from the specification using the linear interaction allow us to examine the dampening effect in pass-through for the full sectoral markup distribution. Using Figure 5, we can gain several additional insights. First, using as a benchmark the case of a sector whose markup is 1, and using the rule of thumb linking the growth rate of the real WTI oil price and oil supply shock, an oil supply shock amounting to a 1 percentage point reduction in the real WTI price of oil typically translates into a -0.2 percentage point reduction in sectoral inflation one year later, an arguably large pass-through. Since our median markup is about 1.1, this means that, at the aggregate level, the pass-through from oil supply shocks to PPI inflation is close to 20%. Second, we learn that in sectors where the median markup is relatively high, i.e. about 1.9 and above, oil supply shocks do not have

[21]These magnitudes thus reflect a 1.1 percentage points difference in the effect of a 10 percentage points decrease in real oil prices for high-markup sectors relative to low-markup sectors.

any significant impact on 1-year ahead sectoral inflation, as the estimated pass-through then shrinks to zero.

4.2.1 How persistent is the impact of oil shocks on PPI inflation?

Up to now, we have focused on the impact of oil shocks on inflation over the subsequent 12 months. We extend the analysis by examining the effect at different time horizons within the 12-month period and by going beyond that. Table 2 reports the response of PPI inflation to oil supply shocks for 3 to 24-months ahead.

Dependent variable: Sectoral PPI Inflation h-months ahead

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time horizon h in months	3	6	12	24	3	6	12	24
Oil supply shock	-0.670***	-1.137***	-1.630***	-1.437**				
	(0.226)	*(0.364)*	*(0.473)*	*(0.642)*				
Oil supply shock × Sectoral markup	0.280**	0.525***	0.739***	0.638*	0.344**	0.617***	0.806***	0.700**
	(0.141)	*(0.199)*	*(0.263)*	*(0.372)*	*(0.154)*	*(0.221)*	*(0.267)*	*(0.339)*
Observations	8,608	8,467	8,185	7,621	8,608	8,467	8,185	7,621
R-squared	0.066	0.057	0.073	0.116	0.137	0.156	0.190	0.252
Number of industries	46	46	46	46	46	46	46	46
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	No	No	No	Yes	Yes	Yes	Yes

Table 2: Markups and pass-through dynamics. This table presents estimation results from specification (8). The unit of observation is sector s, month t. The dependent variable is $\Delta PPI\, t+h$ which is defined as the log change in PPI from t to $t+h$ with h ranging from 3 to 24. *Oil supply shock* is an oil supply shock in month t. *Sectoral markup* is the revenue-weighted sectoral median markup the year before the oil supply shock. The uninteracted *Sectoral markup* term and the lagged sectoral inflation terms are included in the estimation but not reported for brevity. Driscoll-Kraay standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

From columns (1)-(4), we can get two main results. On the one hand, oil supply shocks have a significant impact on sectoral inflation up to two years ahead. However, as would be expected, the magnitude of the effect first gradually increases and then diminishes over time. On the other hand, sectors where firms charge higher markups typically display a lower pass-through of oil shocks to PPI up to two years ahead, the dampening effect of markups relative to the oil supply shocks being fairly constant over this three-year horizon. Quantitatively, the results in column (4) imply that for an oil supply shock that cuts the growth rate of WTI real oil prices by 10 percentage points, the PPI inflation pass-through 2-years ahead is attenuated by roughly 1.2 percentage points for a high-markup sector relative to a low-markup sector.[22] In addition, introducing time effects, and focusing on the difference-in-difference effect, columns (5)-(8) show that sectors where firms charge higher markups typically tend to respond significantly less to oil shocks than sectors where firms charge lower markups, this being true up to two years ahead.

Figure 6 shows the full time dynamics of the pass-through of oil shocks to PPI inflation up to 36 months ahead, again considering two sectors, one with a markup at the 90^{th} percentile of the cross-sectoral distribution of markups and one with a markup at the 10^{th} percentile of the cross-sectoral distribution of markups. In addition, we consider this time a positive oil supply shock corresponding to a one percentage point decrease in the real WTI oil price. The left-hand panel shows that the overall pass-through of oil shocks gradually increases with time and peaks after about 15 months for both high and low-markup sectors. 15 months is also the horizon over which the pass-through of oil shocks to PPI inflation in high- and low-markup sectors are significantly different.[23]

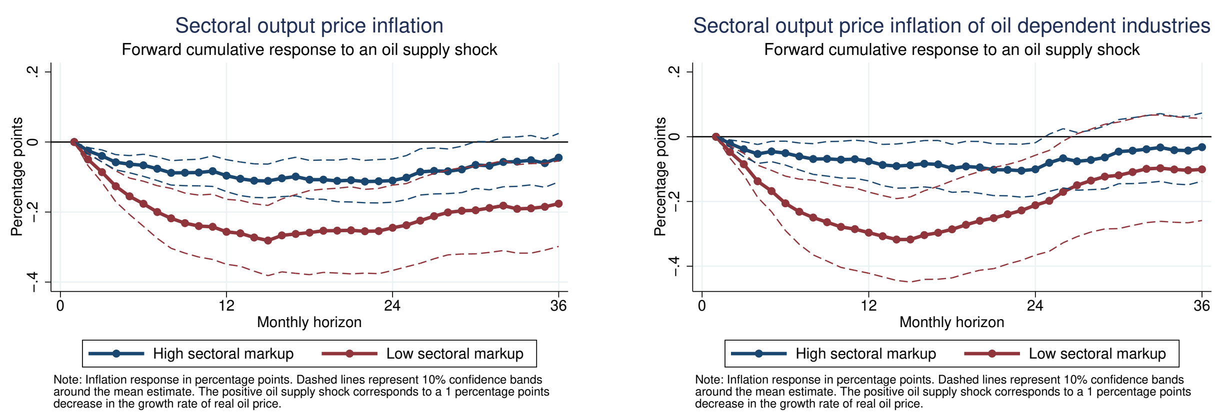

Figure 6: Markups and tynamics of oil shocks pass-through to sectoral inflation The left-hand panel shows the 1-year ahead pass-through of oil supply shocks for high and low-markup sectors defined at the 90^{th} and 10^{th} percentile. The right-hand panel provides a similar graph but only based on a sub-sample of oil dependent industries, including mining, manufacturing and transportation. The oil supply shock corresponds to a 1 percentage point decrease in the growth rate of real oil prices.

The right-hand panel in Figure 6 displays the pass-through of oil supply shocks to PPI inflation, focusing on oil dependent industries, i.e. mining, manufacturing and trans-

[22] As in the previous section, the high and low-markup sectors are defined at the 90^{th} and 10^{th} percentile of the sectoral markup distribution, with a sectoral markup of 1.6 and 0.8 respectively. These definitions are used throughout the text, unless stated differently.

[23] Note that the difference-in-difference is still significant up to 36 months ahead. The shorter horizon over which the pass-throughs displayed in Figure 6 are significantly different from each other simply reflects the standard error on the coefficient on the oil shock variable.

portation sectors. Pass-through estimates are qualitatively similar to those displayed in the left-hand panel which includes all sectors, confirming that sectors with little exposure to oil shocks play a relatively minor role in our results.

4.2.2 Markups or energy intensity?

Firms from different sectors charge different markups, but firms from different sectors also differ in how much they rely on energy as an input. So if firms charging high markups happen to be operating in sectors with barely any reliance on energy, the dampening effect of high markups on the pass-through of oil shocks could simply reflect that sectors relying less on energy naturally display a lower pass-through of oil shocks. To ensure that high sectoral markups, not low energy intensity drive the dampening effect of oil supply shocks on PPI inflation, we augment our data set with input data from the U.S. Bureau of Economic Analysis (BEA), which describes the intermediate inputs that are used by industries in their production of goods and service. We construct the variable $\textit{Energy intensity}_{s,t}$ by taking an industry's energy input as a proportion of the total intermediate inputs that an industry consumes in a year. Using this variable and the interaction term with the oil supply shock variable, we revisit specification (8) and run a horse race against the interacted markup $\mu_{s,t-1}$ and oil supply shock in the specification below:

$$p_{s,t+h} - p_{s,t} = \sum_{j=0}^{12} \rho_{j,h} \Delta p_{s,t-j} + \beta_{1,h}\mu_{s,t-1} + \beta_{2,h}\mathrm{OIL}_t + \beta_{3,h}\textit{Energy intensity}_{s,t} \tag{9}$$

$$+\beta_{4,h}\mathrm{OIL}_t\mu_{s,t-1} + \beta_{5,h}\mathrm{OIL}_t\,\textit{Energy intensity}_{s,t} + \theta_{s,h} + \lambda_{t,h} + \epsilon_{s,t+h}$$

Table 3 provides estimation results when we allow both markups and energy intensity to affect the pass-through of oil supply shocks to PPI inflation. Columns (1) and (2) show that the dampening effect of high markups on the pass-through of oil shocks to PPI inflation is robust to controlling for sectoral energy intensity. Regression results in column (1) —based on a specification without time effects— show that energy intensity does not have any significant impact on the pass-through of oil shocks to PPI inflation. Conversely, with time effects —the regression then estimates difference-in-difference effects—, both the sectoral markup and the sectoral energy intensity affect significantly the pass-through of oil shocks to PPI inflation (column (2)).

Dependent variable: 1-year ahead PPI inflation	(1)	(2)	(3)	(4)
Oil supply shock	-1.333***		-0.946*	
	(0.482)		*(0.536)*	
Oil supply shock × Sectoral markup	0.583**	0.660**	0.222	0.423
	(0.270)	*(0.269)*	*(0.333)*	*(0.331)*
Oil supply shock × Sectoral energy intensity	-0.013	-0.014*	-0.085**	-0.062*
	(0.009)	*(0.008)*	*(0.040)*	*(0.034)*
Oil supply shock × Sectoral energy intensity × Sectoral markup			0.071**	0.046*
			(0.033)	*(0.027)*
Observations	8,185	8,185	8,185	8,185
R-squared	0.079	0.191	0.080	0.191
Number of industries	46	46	46	46
Industry FE	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	No	Yes

Table 3: Markups vs. energy intensity as drivers of oil shocks pass-through. This table presents estimation results from the adjusted specification (8). The unit of observation is sector s, month t. The dependent variable is $\Delta PPI\,1y$ which is defined as the log change in PPI from t to $t+h$ with h equal to 12. *Oil supply shock* is an oil supply shock in month t. *Sectoral markup* is the sectoral revenue-weighted median markup the year before the oil supply shock. *Energy intensity* is the sectoral energy input divided by the total inputs in the year of the oil supply shock and is expressed as a percentage. The uninteracted *Sectoral markup* and *Energy intensity* term, as well as the various interactions and the lagged sectoral inflation terms are included in the estimation but not reported for brevity. Driscoll-Kraay standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The magnitudes of the coefficients on the interaction terms between oil shocks on the one hand and the sectoral median markup and the sectoral energy intensity are comparable across the two specifications but are opposite in sign. Using the results of column (1), an oil supply shock that cuts the growth rate of WTI real oil prices by 10 percentage points dampens the PPI inflation pass-through in a high-markup sector by roughly 1.1 percentage points relative to a low-markup sector.[24][25] Conversely, columns (1) and (2) shows that the same shock hitting a high energy intensity sector would increase the PPI inflation pass-through by 0.5 percentage points relative to a sector whose energy intensity is low.

In Columns (3) and (4) we go one step further and introduce a triple interaction term to Specification (9), interacting the oil supply shock with the sectoral energy input and the sectoral median markup. The augmented specification writes as follows:

[24] As for high and low-markup sectors, we define a high (low) energy intensive sector as a sector whose energy intensity is at the 90% (10%) percentile of the cross-sectoral distribution of energy intensity. The energy intensity of a high (low) energy intensive sector is equal to 17.7% (1.2%).

[25] The differential effect has a standard error of 0.49 and is significant at the 5% level.

$$p_{s,t+h} - p_{s,t} = \sum_{j=0}^{12} \rho_{j,h} \Delta p_{s,t-j} + \beta_{1,h} \mu_{s,t-1} + \beta_{2,h} \mathrm{OIL}_t + \beta_{3,h} \textit{Energy intensity}_{s,t} \tag{10}$$

$$+ \beta_{4,h} \mu_{s,t-1} \textit{ Energy intensity}_{s,t} + \beta_{5,h} \mathrm{OIL}_t \mu_{s,t-1} + \beta_{6,h} \mathrm{OIL}_t \textit{ Energy intensity}_{s,t}$$

$$+ \beta_{7,h} \mathrm{OIL}_t \, \mu_{s,t-1} \textit{ Energy intensity}_{s,t} + \theta_{s,h} + \lambda_{t,h} + \epsilon_{s,t+h}$$

The results support our previous findings: for a given oil supply shock, a higher sectoral energy intensity increases the pass-through to sectoral PPI inflation, but less so when the sectoral markup is higher. Put differently, high markups mitigate the impact of oil supply shocks, especially in energy intensive sectors. Quantitatively, using our results from column (3), it means that when you consider an oil supply shock that cuts the growth rate of WTI real oil prices by 10 percentage points, PPI inflation is cut by 2.9 percentage points for a high energy intensity, low-markup sector. In contrast, a high energy intensity, high-markup sector experiences a cut of only 0.2 percentage points, which is even statistically indistinguishable from zero. This further confirms our findings that markups mitigate the pass-through of real WTI oil price reductions and that our results are driven by the high energy intensive sectors.

4.3 The pass-through of positive and negative oil supply shocks

Thus far, we have shown that the pass-through of oil shocks to PPI inflation tends to be smaller in sectors where firms charge higher markups. The question that naturally follows is whether high markups uniformly reduce the pass-through of oil shocks or whether they affect the pass-through of positive or negative oil shocks differently? To test for the possibility that markups have asymmetric effects on the pass-through of oil shocks, we split oil shocks into positive and negative, and allow markups to affect their respective pass-through differently. Denoting OIL^p positive (dis inflationary) oil supply shocks, and OIL^n, negative (inflationary) supply shocks, the extended empirical specification writes as:

$$p_{s,t+h} - p_{s,t} = \sum_{j=0}^{12} \rho_{j,h} \Delta p_{s,t-j} + \sum_{i=p,n} [\beta^i_{h,1} + \beta^i_{h,2} \mu_{s,t-1}] \mathrm{OIL}^i_t + \beta_{h,3} \mu_{s,t-1} + \theta_{s,h} + \lambda_{t,h} + \epsilon_{s,t+h} \tag{11}$$

As previously, $p_{s,t+h} - p_{s,t}$ is the log-change in PPI index in sector s from t to $t+h$, μ^s_{t-1} is the sectoral median markup, OIL^p_t and OIL^n_t are respectively positive and negative oil supply shock at time t, positive oil supply shocks being defined as the oil supply shock when it is positive and zero otherwise. Conversely, the negative oil supply shock is the opposite of the oil supply shock when the oil supply shock is negative and zero otherwise. This is to ease the interpretation of estimated coefficient in what follows. Finally, θ_s are sector-level fixed effects and λ_t are year-month fixed effects.

Dependent variable: Sectoral PPI Inflation h-months ahead

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time horizon h in months	3	6	12	24	3	6	12	24
Positive oil supply shock	-1.397***	-1.817***	-2.202***	-1.634*				
	(0.295)	*(0.495)*	*(0.560)*	*(0.974)*				
Positive oil supply shock × Sectoral markup	0.650***	0.889***	1.008***	0.804	0.690***	1.002***	1.069***	0.835*
	(0.186)	*(0.266)*	*(0.311)*	*(0.553)*	*(0.195)*	*(0.283)*	*(0.312)*	*(0.488)*
Negative oil supply shock	0.021	0.482	1.032*	1.222				
	(0.176)	*(0.298)*	*(0.553)*	*(1.011)*				
Negative oil supply shock × Sectoral markup	0.029	-0.189	-0.476	-0.456	0.002	-0.211	-0.512	-0.551
	(0.123)	*(0.177)*	*(0.313)*	*(0.551)*	*(0.121)*	*(0.173)*	*(0.331)*	*(0.522)*
Observations	8,608	8,467	8,185	7,621	8,608	8,467	8,185	7,621
R-squared	0.071	0.059	0.074	0.116	0.137	0.156	0.190	0.252
Number of industries	46	46	46	46	46	46	46	46
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	No	No	No	Yes	Yes	Yes	Yes

Table 4: The asymmetric effect of markups on the pass-through of oil shocks This table presents estimation results from specification (11). The unit of observation is sector s, month t. The dependent variable is $\Delta PPI\, t+h$ which is defined as the log change in PPI from t to $t+h$ with h ranging from 3 to 24. *Positive oil supply shock* is a positive oil supply shock in month t and is set to zero in case of negative oil supply shocks. *Negative oil supply shock* is a negative oil supply shock in month t and is set to zero in case of positive oil supply shocks. *Sectoral markup* is the sectoral median markup the year before the oil supply shock. The uninteracted *Sectoral markup* term and the lagged sectoral inflation terms are included in the estimation but not reported for brevity. Driscoll-Kraay standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 reports the estimation results when we allow the pass-through of oil supply shocks to be asymmetric, considering the impact of oil shocks on 3- to 24-months ahead sectoral PPI inflation. Empirical estimates show that positive oil supply shocks are associated with lower PPI inflation (first row), with the peak impact observed at a one-year horizon. In addition, the interaction term between the *positive* oil supply shock and the sectoral markup is positive significant (up to 12 months ahead), implying that high markups tend to dampen the pass-through of (dis-inflationary) positive oil supply shocks (second row). In contrast however, the interaction term between the *negative* oil supply shock and the sectoral markup is close to zero (fourth row), indicating that high markups do not have a significant impact on the pass-through of (inflationary) negative oil supply shocks. The results therefore suggest that following a positive oil supply shock, the PPI of sectors where firms charge low markups tends to fall more strongly than the PPI of sectors where firms charge high markups. In other words, firms in low-markup sectors seem eager to pass on the benefit of lower costs induced by a drop in oil prices. Conversely, firms in high-markup sectors seem rather reluctant to pass-on the benefit of lower costs.

Nothing comparable is happening following negative oil supply shocks at the three-month horizon. When oil prices increase, there is no evidence that high and low-markup sectors respond differently. Specifically, in the short-run, the coefficient of the negative oil supply shock is small and insignificant, suggesting that firms try to shield customers from price increases over short horizons. However as we consider longer period, there is some evidence that negative oil supply shocks get transmitted to PPI inflation, although sectoral differences in markups remain by and large, still irrelevant.

The second part of Table 4 (columns 5 to 8) introduces year-month fixed effects to control for (aggregate) developments, and confirms that high sectoral markups reduce the pass-through of dis-inflationary shocks, particularly in the short-run. Conversely, there is still no similar evidence on the pass-through of negative oil supply shock. The interaction terms all have near zero or negative coefficients but none is significant, confirming that markups do not matter for the pass-through of inflationary shocks.

Figure 7 displays the impact of positive and negative oil supply shocks on sectoral PPI inflation for 1 to 36-months ahead. The full dynamics confirms that markups matter for the pass-through of oil supply shocks, especially positive ones. In addition, consistent with results from regression tables, the pass-through of positive oil supply shocks peaks at about 12 months. At this horizon, the pass-through for high sectoral markups is roughly three times smaller than the pass-through for low sectoral markups. For negative oil supply shocks, consistent with estimated coefficients, the pass-through steadily increases over the estimation horizon. To give an order of magnitude, the peak pass-through for positive oil supply shocks —observed at a 12-months horizon— is comparable to the pass-through of negative oil supply shocks after 36 months.

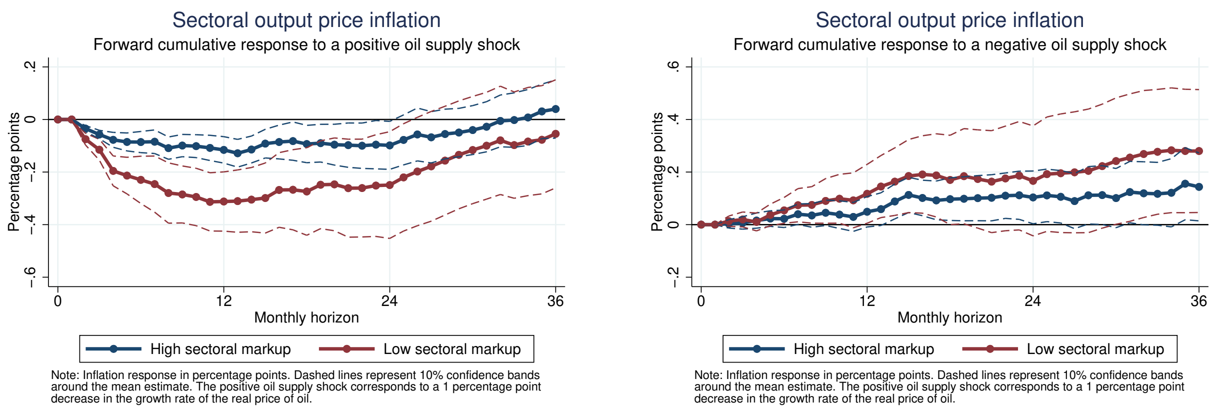

Figure 7: High markups reduce the pass-through of positive oil supply shocks. The left-hand panel shows the pass-through of positive oil supply shocks for high and low-markup sectors defined at the 90$^{\text{th}}$ and 10$^{\text{th}}$ percentile, respectively. The right-hand panel shows the pass-through for negative oil supply shocks. The oil supply shock corresponds to a 1 percentage point decrease in the growth rate of real oil prices.

5 The impact of oil shocks at the firm level

In the previous section, we showed that (i) high markups are associated with a reduced pass-through of oil shocks to sectoral PPI inflation; and (ii) that high markups particularly reduce the pass-through of positive, i.e. dis-inflationary, oil supply shocks.

These results suggest that firms with different markups respond differently to positive and negative oil supply shocks. One obvious possibility could be that high-markup firms typically raise their markups in response to positive oil supply shocks. If so, the sector-wide markup would go up and attenuate the impact of dis-inflationary shocks, like positive oil supply shocks, and the more so, in sectors with a larger number of high-markup firms. Another possibility could be that following a positive oil supply shock, firms with relatively higher markups are able to grab a larger share of the market, to the detriment of firms with lower markups. This would also contribute to raise the average sector-wide markup and therefore dampen the impact of positive, dis-inflationary, oil supply shocks on output prices. We investigate these two possibilities in the next sections.

We start with the first, namely how firms adjust their markups in response to oil supply shocks, separating as previously dis-inflationary positive supply shocks from inflationary negative supply shocks. Then, we look into firm-level growth, and examine whether high-markup firms are indeed able to outgrow their low-markup peers, in the aftermath of oil positive and negative supply shocks.

5.1 Markup and oil shocks

To uncover how firms adjust markups in the aftermath of oil shocks, we adopt the following strategy. We first note that markups being estimated, not observed, our measures include some noise reflecting the uncertainty surrounding the production function parameter estimates. With this in mind, we focus on changes in markups, that can be sufficiently large to ensure that observed changes in markups signal genuine changes, rather than noise. To this end, we define an indicator variable P that takes the value 1 for a given firm on a given year if the yearly change in the markup of that firm $\mu_{i,t} - \mu_{i,t-1}$ exceeds some threshold, which we denote e:

$$P_{i,t}(e) = \mathbf{1}[\mu_{i,t} - \mu_{i,t-1} \geq e] \tag{12}$$

Obviously the choice of the threshold e —that separates changes coded as increases vs. those classified as no change or decrease — is arbitrary. To get around this limitation, we span all threshold values from 0 to 12.5 percentage points, with 2.5 percentage point increments. This range should be evaluated against the quantiles of the distribution of firm-level yearly changes in markups, as reported in the left-hand panel of Table 5. The median for yearly changes in firm-level markups being roughly at zero, the sample if roughly cut into two equal part when the threshold e is zero: half the observations are coded as markup increases, and the other half as markup decreases. Conversely, with the 75$^{\text{th}}$ percentile of the distribution of yearly changes in markups around about 7.5 percentage points, setting the threshold value e at that value codes about 25% of the sample observations as markup increases and 75% as no change or decreases. Finally, when the threshold e is set to the maximum value of 12.5 percentage points, then only 17% of the sample observations qualify as a markup increase, the rest being coded as decreases or no changes in markup.

Descriptive statistics of $\Delta\mu_{i,t}$	
Mean	-0.001
Standard deviation	0.213
P25	-0.081
P50	-0.001
P75	0.076
Min	-2.127
Max	2.127
Skewness	0.301
Kurtosis	15.589

Fraction of sample			
Threshold e	Type of markup change using e		
	Increase	No change	Decrease
0	48%	-	52%
2.5	41%	20%	39%
5	33%	36%	31%
7.5	26%	48%	25%
10	21%	58%	20%
12.5	17%	65%	17%

Table 5: Firm-level markup changes: Some descriptive statistics. The left-hand panel shows the descriptive statistics of the annual change in markup. The right-hand panel shows the fraction of the firm-year observations, which have i) an increase in markup ii) no change in markup iii) decrease in markup, for various thresholds of e.

Using the indicator variable $P_{i,t}(e)$ as a dependent variable, we run two set of regressions. The first consists in estimating a set of linear probability models, the second relies on multinominal logit specifications.

5.1.1 Linear probability models

Starting with the linear probability model, our empirical specification writes as:

$$P_{i,t}(e) = \alpha_i + \alpha_{s,t} + \sum_{i=p,n} \left[\beta_1^i \mathrm{OIL}_{t-1}^i + \beta_2^i \mathrm{OIL}_{t-1}^i \times \mu_{i,t-1}\right] + \beta_3 \mu_{i,t-1} + \beta_4 X_{i,t-1} + \varepsilon_{i,t} \tag{13}$$

In this specification, the indicator variable $P_{i,t}(e)$ for an increase in the markup of firm i between year t and $t-1$ depends on the oil shock OIL_{t-1}^i in year $t-1$, the markup (of firm i) $\mu_{i,t-1}$ in year $t-1$ and the interaction between the oil shock and the firm markup.[26] Moreover, as is visible in specification (13), we separate positive and negative oil supply shocks and allow them to affect the likelihood of a markup increase in possibly different ways. Last the vector X wraps up control variables, which we choose according to existing

[26]The oil shock variables OIL_{t-1}^p and OIL_{t-1}^n represent respectively the average yearly positive and negative oil supply shocks, matched to the firm-level data according to each company's fiscal year end to ensure proper time alignment.

evidence on their role as determinants of markups. This includes the 1-year lagged values of: (i) the log of revenues, (ii) the leverage ratio, (iii) Tobin's Q, (iv) the cash to total asset ratio, (v) the net property plant and equipment to total asset ratio.[27] These variables are respectively proxies for firm-level size, indebtedness, growth opportunities, asset liquidity and asset tangibility, all of which are known to affect firm markups.

Linear probability models are advantageous in that they allow for the inclusion of firm fixed effects —denoted α_i in specification (13)—, which in turn allows to focus on the determinants of the within-firm variations in markups. In addition, we also include sector-time fixed effects —denoted $\alpha_{s,t}$—, which purge the probability for a firm to raise its markup, —the left-hand side variable—, of any time varying sector-wide development such as sector-specific shock that may affect the likelihood that all firms in a given sector raise or cut their markups on a given year.[28]

Estimates in Table 6 provide three main results. First, positive oil supply shocks reduce the likelihood that a firm raises its markup when the firm starts with a relatively low markup. This is visible from the negative coefficient on the positive oil supply shock variable on the first row. Conversely, positive oil supply shocks tend to *raise* the likelihood that a firm increases its markup when the initial markup is sufficiently high, as indicated by the positive coefficient on the interaction term between positive oil supply shocks and the initial markup (on the second row). Second, negative oil supply shocks have barely any impact on the likelihood of firms changing their markups, one way or the other (third and fourth rows). Neither the negative oil supply shock variable, nor the interaction term with the firm's initial markup, have significant coefficients. Moreover, the magnitude of estimated coefficients is also much smaller relative to the case of positive oil supply shocks. Third, specifications where the threshold e defining a markup increase is set at 10% tend to provide clearer and more significant results than those where the threshold is set at zero. In particular, the estimated coefficient on the interaction term between positive oil supply shocks and firms' initial markup tends to be larger and more precisely estimated. This

[27] The leverage ratio is computed as the ratio of total debt to total assets while Tobin's Q is defined as the sum of the market value of equity and the book value of non-equity liabilities, taken as a ratio of the book value of assets.

[28] Industry-time effects are based on the 2-digit NAICS industrial classification, and set at the year-month level, as firms differ in their fiscal year end.

confirms that focusing on large changes in markups helps filter the dependent variable from uncertainty around markup estimates.[29]

	Probability of raising markup by more than e					
	$e = 0$			$e = 0.10$		
	(1)	(2)	(3)	(4)	(5)	(6)
Positive oil supply shock	-0.133			-0.160		
	(0.105)			*(0.106)*		
Positive oil supply shock × firm markup	0.123*	0.126*	0.120*	0.163**	0.168**	0.177**
	(0.072)	*(0.065)*	*(0.070)*	*(0.079)*	*(0.073)*	*(0.089)*
Negative oil supply shock	-0.033			-0.076		
	(0.070)			*(0.075)*		
Negative oil supply shock × firm markup	0.032	0.032	0.062	0.064	0.062	0.078
	(0.048)	*(0.044)*	*(0.061)*	*(0.059)*	*(0.056)*	*(0.064)*
Observations	40,002	40,002	39,282	31,169	31,169	30,412
R-squared	0.205	0.222	0.296	0.306	0.320	0.383
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	No	No	Yes	No
Industry-year-month FE	No	No	Yes	No	No	Yes

Table 6: The likelihood of firms raising their markup. This table presents estimation results from specification (13). The unit of observation is firm i, year(-month) t. The dependent variable is $P_{i,t} = 1[\mu_{i,t} > \mu_{i,t-1} + e]$, where μ denotes the firm markup. In Columns (1) to (3), we set the threshold e to zero, with $P_{i,t}$ equal to one for $\mu_{i,t} > \mu_{i,t-1}$ and $P_{i,t}$ equal to zero for $\mu_{i,t} <= \mu_{i,t-1}$. In Columns (4) to (6), we adjust the threshold e to $e = 0.10$. For Columns (4) to (6), we set $P_{i,t}$ equal to one for $\mu_{i,t} > \mu_{i,t-1} + 0.10$ and equal to zero for $\mu_{i,t} \in [\mu_{i,t-1} - 0.10, \mu_{i,t-1} + 0.10]$. *Positive oil supply shock* and *Negative oil supply shock* represent the average yearly positive and negative oil supply shocks which are matched based on a company's fiscal year end to ensure proper alignment and *firm markup* denotes the 1-year lagged firm markup. For the sake of brevity we do not report our set of lagged firm control variables including firm markup, log of revenue, leverage, Tobin's Q, cash over total assets, and net PPE over total assets. Note that the time fixed effects are measured at the year-month level to make use of the additional time variation in firms' fiscal year end. Standard errors are conservatively clustered at the NAICS 2-digit industry × year-month level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Altogether, these empirical results confirm the asymmetric impact of oil shocks on firms' markup. Moreover they also support the view that sectors where firms charge higher markup are likely to see a larger dampening effect of positive oil supply shocks as high-markup firms are more likely to raise their markup in these conditions.

Quantitatively speaking, considering a positive oil supply shock at the 75th percentile of the historical distribution, the probability of raising the markup for firms at the 25th percentile of the markup distribution (corresponding to a markup of about one) would roughly be unchanged. By contrast, following the same positive oil supply shock, the

[29]Another interesting feature of the results reported in Table 6 is that the estimated coefficients display strong stability across specifications. In particular, regressions that include year-month dummies and hence focus on the difference-in-difference effect provide remarkably similar estimates to those which abstract from such fixed effects.

likelihood of raising the markup for a firm whose initial markup is at the 75$^{\text{th}}$ percentile of the markup distribution (corresponding to a markup around 1.5) would increase by about 3 percentage points.[30]

5.1.2 Multinomial logit models

Results from the linear probability model estimations suggest that firms that start with high markups are more likely to raise their markups following positive oil supply shocks. This analysis however suffers a limitation: the dependent variable only focuses on markup increases and lumps together situations where firms keep their markups roughly stable using a threshold e. Ideally one would like to consider markup increases as well as markup decreases, against the benchmark of no change. To address this limitation, we run the analysis using a multinomial logit model. In this approach, the dependent variable, $P^m(e)$, takes three values: for a given threshold e, $P^m(e)$ is equal to 1, when the yearly change in markups is larger than e. Conversely, it is equal to -1, when the yearly change in markups is less than $-e$. Finally it is zero otherwise:

$$P^m_{i,t}(e) = \mathbf{1}[\mu_{i,t} - \mu_{i,t-1} \geq e] - \mathbf{1}[\mu_{i,t} - \mu_{i,t-1} \leq -e] \tag{14}$$

Denoting j the value of the outcome variable, the specification estimating the multinominal logit model then writes as:

$$\Pr[P^m_{i,t}(e) = j] = \alpha_{s,j} + \alpha_{t,j} + \sum_{i=p,n} \left[\beta^i_{1,j}\text{OIL}^i_{t-1} + \beta^i_{2,j}\text{OIL}^i_{t-1} \times \mu_{i,t-1}\right] + \beta_{3,j}\mu_{i,t-1} + \beta_{4,j}X_{i,t-1} + \varepsilon_{i,t} \tag{15}$$

The multinominal logit model estimates a different set of parameters for each value j of the outcome variable, taking the case $P^m_{i,t}(e) = 0$, of no markup change, as the baseline. This upside however comes at a cost: the specification only allows for sector fixed effects, as the presence firm fixed effects would trigger a dimensionality problem. For the rest,

[30]Comparing a firm with a markup at the 90% percentile of the markup distribution vs. one with a markup at the 10% percentile, the difference in the likelihood to raise the markup following the same positive oil supply shock at the 75% percentile would jump to about 7.5 percentage points, based on the specification where the threshold e defining a markup increase is set at zero. In the case where the threshold defining a markup increase is set at 10 percentage points, the same difference —in the likelihood to raise the markup— would be about 10 percentage points.

explanatory variables are the same as those of the linear probability specification. In particular, oil supply shocks are still separated in positive and negative shocks.

Empirical results reported in Table 7 Panel A show that high-markup firms are somewhat less likely to cut their markup following a dis-inflationary oil shock relative to their low-markup peers (first column, second row), this result being most visible when the threshold separating a markup increase or decrease from no change is set at relatively low levels (5 percentage points). On the contrary, at higher threshold values, i.e. when we tighten the definition of a markup increase/decrease, estimation results show that high-markup firms are significantly more likely to *raise* their markup following a positive oil supply shock than low-markup firms. By contrast, estimation results do not display any significant difference between high- and low-markup firms in the likelihood to reduce markups.[31]

Panel A. Dependent variable: indicator variable for raising / cutting markup by more than e								
	e = 0.050		e = 0.075		e = 0.100		e = 0.125	
Direction of markup change	(1) down	(2) up	(3) down	(4) up	(5) down	(6) up	(7) down	(8) up
Positive oil supply shock	0.605*	-0.365	0.119	-0.738	0.029	-1.009*	-0.046	-0.973
	(0.354)	*(0.494)*	*(0.398)*	*(0.547)*	*(0.446)*	*(0.603)*	*(0.482)*	*(0.639)*
Positive oil supply shock × firm markup	-0.401*	0.542	-0.064	0.825**	-0.040	1.072**	-0.018	1.017**
	(0.240)	*(0.380)*	*(0.268)*	*(0.411)*	*(0.286)*	*(0.459)*	*(0.302)*	*(0.496)*
Negative oil supply shock	0.147	-0.106	0.057	-0.205	0.002	-0.449	-0.184	-0.665
	(0.329)	*(0.402)*	*(0.344)*	*(0.441)*	*(0.402)*	*(0.481)*	*(0.394)*	*(0.492)*
Negative oil supply shock × firm markup	-0.108	0.102	-0.070	0.132	-0.045	0.325	0.107	0.502
	(0.213)	*(0.320)*	*(0.213)*	*(0.358)*	*(0.240)*	*(0.395)*	*(0.238)*	*(0.410)*
Observations	40,366		40,366		40,366		40,366	
Industry FE	Yes		Yes		Yes		Yes	
Year-month FE	No		No		No		No	

Table 7: The likelihood of firms raising or cutting their markup. Panel A presents the estimation results from the multinomial logit regressions (15). The unit of observation is firm i, year(-month) t and the dependent variable is defined as in (14). Positive (negative) oil supply shock is the average yearly oil supply shocks, matched to the firm-level data, based on the companies' fiscal year end, when it is positive (negative) and zero otherwise. Firm markup denotes the 1-year lagged firm markup. For the sake of brevity, we do not report estimated coefficients on firm-level control variables including the 1-year lagged values of firm markup, log of revenue, leverage, Tobin's Q, cash over total assets, and net PPE over total assets. Standard errors are clustered at the NAICS 2-digit industry × year-month level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Next, we quantify how much oil supply shocks affect the likelihood for a firm to raise or

[31]Table B.1 in Appendix provides estimation results when time fixed effects are included. This barely brings any change to the main results.

cut its markup. For this, we proceed as follows. We first consider a firm with a given initial markup and compute the probability for this firm to raise or cut its markup, when the oil supply shock is set to zero. This first step provides a set of baseline probabilities. Formally, baseline probabilities write for $j = \{-1; +1\}$, as $\Pr[P^m_{i,t}(e) = j | \mu_{i,t-1} = \mu; \text{OIL}^p_t = 0]$. Then we compute the probability for that same firm to raise or cut its markup when a positive oil supply shock hits, which provides a set of conditional probabilities. Formally, using the same notation as above and denoting s the positive oil supply shock, these conditional probabilities write for $j = \{-1; +1\}$, as $\Pr[P^m_{i,t}(e) = j | \mu_{i,t-1} = \mu; \text{OIL}^p_t = s]$.[32,33]

In Figure 8, we quantify the impact of oil supply shocks on the likelihood that firms cut or raise their markup. Specifically, we plot the difference between the conditional and the baseline probabilities (of raising or cutting the markup), using estimates in columns (5) and (6) in Panel A of Table 7, considering all possible values for the oil supply shock.

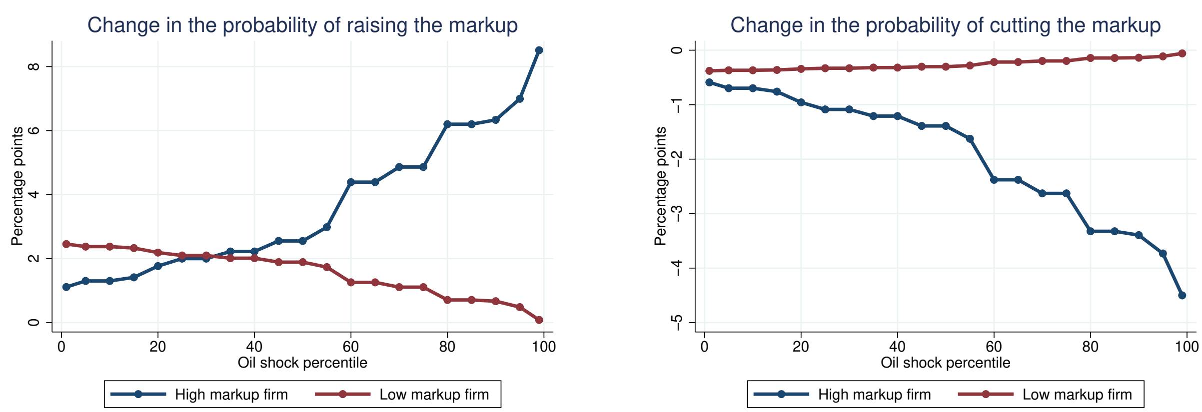

Figure 8: Quantifying the probability of raising and cutting the markup. The left-hand panel (right-hand panel) shows the change in the probability of raising (cutting) the markup after a positive oil supply shock, relative to the baseline probability when no shock hits. In both panels, the blue line represents the change in the probability to raise the markup for a high-markup firm, i.e. at the 90$^{\text{th}}$ percentile of the markup distribution, and the red line represents the change in the probability to raise the markup for a low-markup firm, i.e. at the 10$^{\text{th}}$ percentile of the initial markup distribution.

The left-hand panel (right-hand panel) of Figure 8 plots the change in the probability of raising (cutting) the markup for different values of the oil shock, considering a firm with a relatively low markup (red line) and a firm with a relatively high markup (blue line).[34]

[32] In both cases, probabilities are computed setting explanatory variables other than the initial markup and the oil supply shock at their sample averages, while the negative oil supply shock variable and its interaction with the firm-level markup are both set to zero, given the focus on *positive* oil supply shocks.

[33] Appendix B.2 provides estimated baseline and conditional probabilities of raising/cutting the markup for an oil shock at the 75$^{\text{th}}$ percentile considering various thresholds e.

[34] We consider as a high-markup firm (resp. a low-markup firm), a firm whose markup is at the 90$^{\text{th}}$ (resp.

Estimates show that the impact of oil shocks is relatively similar across high- and low-markup firms, when the oil shock is below the sample median. However, as the shock gets larger, the likelihood of raising the markup increases steeply for high-markup firms, while it steadily converges to the baseline for low-markup firms. At the 75th percentile of the oil shock distribution, the likelihood of raising the markup is approximately 5 percentage points higher than the baseline for high-markup firms, but only 1 percentage point higher for low-markup firms, yielding a difference-in-difference effect for the probability to raise the markup of about 4 percentage points.

Positive oil shocks also affect the probability that firms *reduce* their markup (right-hand panel). Starting with low-markup firms, positive oil supply shocks have barely any impact on the probability that such firms cut their markup, no matter the size of the shock. If anything, larger shocks seem to have a smaller impact. Conversely, positive oil shocks reduce the likelihood that a high-markup firm cuts its markup, larger shocks being associated with larger reductions in the probability of markup cuts. For a positive oil supply shock at the 25th percentile, the difference in the likelihood of cutting the markup, between high and low-markup firms, is small, approximately 0.8 percentage point. But for a shock at the 75th percentile, the difference grows to approximately 2.5 percentage points. Altogether, this yields a total difference-in-difference effect of about 6.5 percentage points, a strikingly similar figure to the 7.5 percentage point estimate obtained using linear probability models.

To confirm these conclusions, we put together the two panels of Figure 8 and plot the overall markup change $\Delta\, Markup$, following a positive oil supply shock, contrasting again high- and low-markup firms. For this, we first compute the product of a typical markup increase $\overline{\Delta\mu^{(+)}}$, (resp. a typical markup decrease $\overline{\Delta\mu^{(-)}}$) with the estimated change in the probability of increasing the markup (resp. the probability of decreasing the markup). We then estimate the overall change in the markup $\Delta\, Markup$ by summing up these two products:[35]:

$$\Delta\, Markup = \left[\Delta P_{j=1}(\mu, s)\right] \overline{\Delta\mu^{(+)}} + \left[\Delta P_{j=-1}(\mu, s)\right] \overline{\Delta\mu^{(-)}} \tag{16}$$

at the 10th) percentile of the sample distribution.

[35]Note that $\Delta P_{j=0}(\mu, s)$ does not show up on the right-hand side of (16) because the distribution of markup changes being symmetric, the corresponding average markup change is essentially zero.

Figure 9 shows that positive oil supply shocks lead high-markup firms to raise their markup, while low-markup firms barely change theirs. However, it takes relatively large shocks for high-markup firms to raise their markup significantly relative to low-markup firms. For instance, the relative increase in markups is about 2 percentage points, for oil shocks at the 75$^{\text{th}}$ percentile of the sample distribution. This 2 percentage point change corresponds to about 10% of the standard deviation of markup changes observed in the sample, confirming that the estimated effect is relatively small.

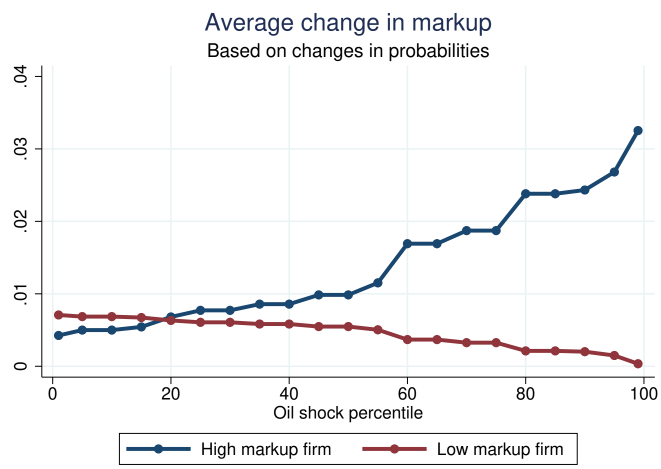

Figure 9: How much do firms change their markup following a positive oil supply shock? The blue line shows the average change in markup for a firm whose markup is at the 90$^{\text{th}}$ percentile of the initial markup distribution, the red line shows the average change in markup for a firm, whose markup is at the 10$^{\text{th}}$ percentile of the initial markup distribution. Markup changes are computed following specification (16).

The estimated magnitude of the markup changes, around a few percentage points at most, seems too small to account, on its own, for a meaningful reduction of the pass-through of positive oil supply shocks at the sector level. One possibility could be that, the driving force behind the low pass-through in high-markup sectors is not so much that firms raise their markup, but that firms with relatively high markups, are able to outgrow their low-markup peers. In this case, high-markup firms would account for a large share of the market, which would contribute to dampen the impact of positive oil supply shocks, even in the absence of large markup changes at the firm-level. This is what we investigate in the next section.

5.2 Oil shocks and firm growth

To investigate whether firms with high markups are able to outgrow their competitors with lower markups following positive oil supply shocks, we look into the dynamics of revenues and profit at the firm-level. Specifically, we ask the following question: following an oil supply shock, do we see high-markup firms expanding relative to low-markup firms? And how does relative growth differences depend on positive vs. negative oil shocks?

To answer these questions, we estimate a set of regressions, where the dependent variable $Y_{i,t}$ is the current change in revenues or the current change in gross profits — defined as the difference between revenues and cost of goods sold—, both being normalised by 1-year lagged level of revenues:

$$Y_{i,t} = \frac{REV_{i,t} - REV_{i,t-1}}{REV_{i,t-1}} \text{ or } Y_{i,t} = \frac{(REV_{i,t} - COGS_{i,t}) - (REV_{i,t-1} - COGS_{i,t-1})}{REV_{i,t-1}} \tag{17}$$

As previously, we include as explanatory variables the positive and negative oil supply shocks $\mathrm{OIL}^{\mathrm{p}}_{\mathrm{t-1}}$ and $\mathrm{OIL}^{\mathrm{n}}_{\mathrm{t-1}}$.[36] In addition, we include the 1-year lagged level of the firm's markup $\mu_{i,t-1}$, and a vector $X_{i,t-1}$ of firm-level control variables including, log-revenues, leverage, Tobin's Q, cash over total assets, and net property, plant and equipment over total assets, other notations being unchanged:[37]

$$Y_{i,t} = \alpha_{s,j} + \alpha_{t,j} + \sum_{i=p,n}\left[\beta^{i}_{1,j}\mathrm{OIL}^{i}_{t-1} + \beta^{i}_{2,j}\mathrm{OIL}^{i}_{t-1} \times \mu_{i,t-1}\right] + \beta_{3,j}\mu_{i,t-1} + \beta_{4,j}X_{i,t-1} + \varepsilon_{i,t} \tag{18}$$

Columns (1) to (3) in Table 8 report estimation results using revenue growth as a dependent variable. They show that firms that start with higher markups tend to systematically outgrow their low-markup peers, following positive oil supply shocks (second row). Moreover, this result is robust to the inclusion of sector-time fixed effects (column 3), implying that high-markup firms tend to outgrow low-markups following positive oil shocks, irrespective of sector-wide developments.[38]

[36]We follow the same fiscal year end alignment procedure as in Equation 13.

[37]Note that sector-time fixed effects are measured at the year-month level to make use of the additional time variation in firms' fiscal year end.

[38]Sector-time fixed effects control being a control for any time-varying sectoral development, e.g. sectoral inflation, a quick comparison of empirical estimates in columns (2) and (3) suggests that about 70% of the

	Revenue Growth			Gross Profit Growth		
	(1)	(2)	(3)	(4)	(5)	(6)
Positive oil supply shock	-0.144***			-0.078***		
	(0.045)			*(0.028)*		
Positive oil supply shock × firm markup	0.108***	0.110***	0.080**	0.049**	0.052**	0.051**
	(0.036)	*(0.036)*	*(0.038)*	*(0.024)*	*(0.023)*	*(0.025)*
Negative oil supply shock	0.008			-0.004		
	(0.036)			*(0.030)*		
Negative oil supply shock × firm markup	0.029	0.031	0.010	0.022	0.022	0.007
	(0.029)	*(0.025)*	*(0.029)*	*(0.023)*	*(0.022)*	*(0.024)*
Observations	40,002	40,002	39,282	40,002	40,002	39,282
R-squared	0.357	0.380	0.417	0.322	0.351	0.384
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	No	No	Yes	No
Industry-year-month FE	No	No	Yes	No	No	Yes

Table 8: Revenues and gross profits following an oil supply shock. This table presents estimation results from specification (18). The unit of observation is firm i in year(-month) t. The dependent variable *Revenue growth* in Columns (1) to (3) is the 1-year ahead growth rate in nominal revenues $\frac{\Delta Revenuei,t}{Revenue_{i,t-1}}$. The dependent variable *Gross profit growth* in columns (4) to (6) is the ratio of the 1-year change in gross profits to the 1-year lagged revenues $\frac{\Delta Gross\,Profit_{i,t}}{Revenue_{i,t-1}}$. The positive (negative) oil supply shock is the yearly average oil supply shock if it is positive (negative), and zero otherwise, matched to each firm's fiscal year end. Likewise, sector, time and sector-time fixed effects are introduced at the year-month level to match firms' fiscal year end. *Firm markup* denotes the lagged firm markup. For the sake of brevity, coefficients on firm control variables are not reported. Standard errors, reported in parentheses, are clustered at the NAICS 2-digit industry × year-month level. *** p<0.01, ** p<0.05, * p<0.1.

These findings therefore suggest that high-markup firms not only raise their markups, although modestly, in the aftermath of positive oil supply shocks, but also effectively capitalise on the input price decrease to expand their market share. Conversely, we do not find evidence that, following negative oil supply shocks, high-markup firms grow significantly faster than low-markup firms. If anything, estimated coefficients, which are all very close to zero, suggest that negative oil supply shocks barely affect revenue growth at the firm-level, be it in absolute and in relative terms.

Quantitatively, positive oil supply shocks can lead to large growth differences between high- and low-markup firms. Based on estimates from column (1), a high-markup firm is able to grow its revenues by about 6.5 percentage points relative to a low-markup firm following a large positive oil supply shock, i.e. a shock at the 75th percentile of the historical distribution.[39] This 6.5 percentage point difference in growth rates compares with a sample

impact of positive oil supply shocks on revenue growth is about quantities while 30% is about prices.

[39] We take the markups of high- and low-markup firms, respectively at the 90th and 10th percentiles of the markup distribution, i.e. 1.8 and 0.7 respectively.

average for revenue growth of about 14% and a within-standard deviation of about 34%.

Following positive oil supply shocks, high-markup firms are able to increase their revenues, relative to firms with lower markups, and also at the same time to raise — although modestly— their markups. Combining these two, high-markup firms should also grow their profits relative to low-markup firms, following positive oil supply shocks. We test for this implication in columns (4) to (6) in Table 8, where we estimate the response of gross operating profits (expressed as a ratio of revenues) to oil supply shocks for firms with different markups.

Consistent with previous evidence, empirical results in column (4) of Table 8 show that firms with relatively high markups are able to increase their profits following positive oil supply shocks. Conversely, firms with relatively low markups actually see their profits falling, after positive oil supply shocks. Also consistent with past evidence, negative oil supply shocks do not lead to significant changes (up or down) in profits, neither for firms charging high or low markups. Interestingly, as we augment the specification with time and sector-time fixed effects, the results barely change. In particular following positive oil supply shocks, high-markup firms are still able to grow their profits relative to low-markup firms in a significant way (columns (5) and (6)).

Putting together the different pieces, the results suggest that high-markup firms draw significant benefits from dis-inflationary oil shocks, as they are able to raise their markups and expand their revenues, thereby earning larger profits. Quantitatively speaking, differences in the pass-through of oil supply shocks, estimated using firm-level data, are comparable to those estimated using sector-level data. According to estimates in Figure 7, the difference in pass-through (for a positive oil supply shock) between a low- and a high-markup sector is about 0.2 percentage point after 12 months, this being for an oil supply shock corresponding to a 1 percentage point decrease in the monthly growth rate of real WTI oil price. Then turning to our firm-level estimates, based on Figure 9 and Table 8, the difference in pass-through between a high- and a low- markup sector for an oil shock at the 75$^{\text{th}}$ percentile of the oil shock distribution is about 0.8 percentage points after one year. Given that such shock corresponds to a 2.8 percentage points (average) monthly decrease in the growth rate of real WTI oil price, our estimate imply a difference in a pass-through about 0.3 percentage points, an arguably close estimate to the 0.2 percentage points based on the sector-level estimates.[40]

6 Conclusion

In this paper, we investigate how prices and markups respond to cost push shocks, taking the example of global oil supply shocks. Using data for US firms and sectors, we obtain two main empirical results. First, we confirm past studies showing that the pass-through of global oil shocks to sectoral PPI inflation is weaker in sectors where firms charge higher markups. However, high markups mainly reduce the pass-through of dis-inflationary oil shocks, i.e. positive global oil supply shocks, while they barely affect that of inflationary oil shocks. Second, we find evidence that high-markup firms are more likely to increase their markup, as well as their revenues and profits, relative to low-markup firms following a positive global oil supply shock. Conversely, there is no evidence that high- and low-markup firms adjust markups, revenues or profits differently to inflationary oil shocks, confirming the asymmetric impact of markups on the pass-through of global oil price shocks.

Altogether, these results suggest that high-markup firms draw significant benefits from dis-inflationary oil shocks, as they are able to raise their markups *and* expand their revenues, thereby increasing their profits. In addition, high-markup firms seem to be able to insulate themselves from the fall-out of inflationary shocks, implying that high markups provide little cushion against prices pressures stemming from inflationary oil shocks.

Several factors could account for these regularities, some playing out on the supply side, others on the demand side. On the supply side, high-markup firms may be better at reorganising their activities following different shocks, thereby increasing their edge over low-markup competitors. On the demand side, there may just be more demand from consumers for high-end goods and services coming from high-markup firms when basic necessities like energy get cheaper. More broadly, additional research will be needed to tease out these factors and identify precisely the main relevant channels.

[40] Appendix B details the assumptions needed to get to the estimated difference in pass-through at 0.8.

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Online Appendix

Markups and the Asymmetric Pass-Through of Cost Push Shocks

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November 2023

Appendix A Additional descriptive statistics

Input and Output Prices in the Euro Area. Figure A.1 plots the sensitivity of output prices to input prices in the Euro Area when input prices are rising or falling.

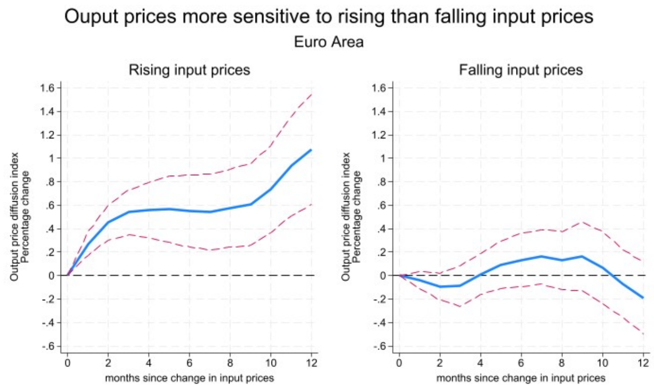

Figure A.1: Output price sensitivity to input price. The blue line in each panel represents the percentage change in the PMI diffusion index for output prices following a one percentage point increase in the PMI diffusion index for input prices, for a horizon running from zero to 12 months, controlling for the current level of the PMI diffusion index for output prices. The left-hand panel (right-hand panel) estimates this relationship when the input price variable is above (below) the median. Dashed red lines display the 90% confidence interval around the mean estimate (in blue).

Comparing aggregated revenues to gross output. Figure A.2 compares the growth rate of gross output, based on BEA data, to the growth rate of revenues, aggregated from our firm-level data.

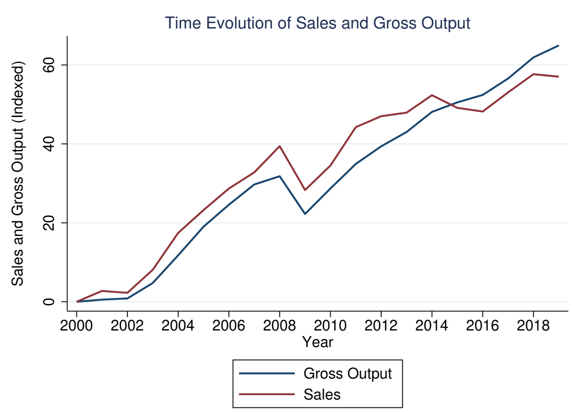

Figure A.2: Time evolution of aggregated revenues and gross output. The figure plots the growth rate of gross output and aggregated revenues in percent relative to 2000. Both aggregates exclude finance, insurance, real estate, government and oil sectors as well as 3-digit NAICS sectors with missing revenue data.

Unweighted markup distribution over time. Figure A.3 shows the same markup distribution figures as in Figure 3 but then based on an unweighted time series.

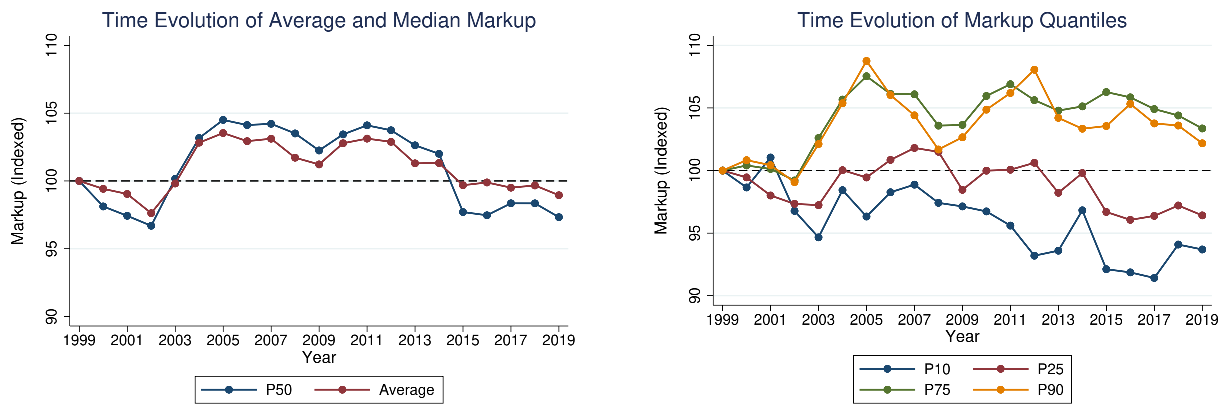

Figure A.3: Time evolution in the average markup and markup quantiles. The left-hand panel of the figure shows the time evolution of the unweighted median and average firm-level markup. The right-hand panel shows the time evolution of the unweighted P–10, P–25, P–75 and P–90 markup quantiles. All quantiles are rebased at 100 in 1999.

Oil supply shock distribution. The left-hand panel of Figure A.4 shows the descriptive statistics of the oil supply shocks and the right-hand panel plots the density curve.

Descriptive statistics oil supply shocks	
Mean	-0.111
Standard deviation	1.048
P25	-0.687
P50	-0.118
P75	0.384
Min	-3.479
Max	3.416
Skewness	0.204
Kurtosis	4.010

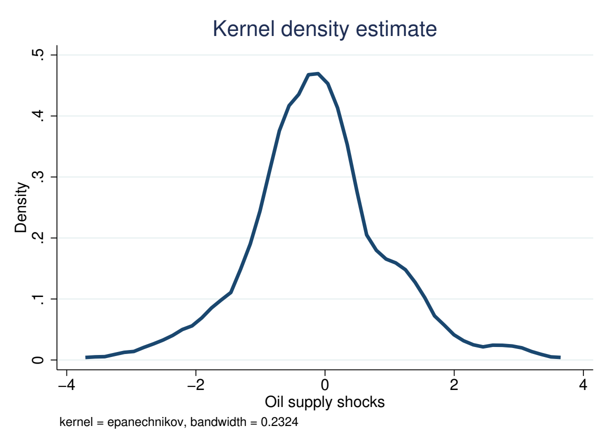

Figure A.4: Descriptive statistics and density plot of oil supply shocks. The graphs show the descriptive statistics and the density plot of oil supply shocks over the sample period 1997-2019 at a monthly frequency, taken from Baumeister and Hamilton (2019).

PPI growth by industry (seasonally adjusted). Table A.1 shows the summary statistics for the annual growth rate of the seasonally-adjusted Producer Price Index (PPI) series per 3-digit NAICS sector.

3-digit NAICS	Industry description	Mean	Median	SD	Min	Max
212	Mining (except Oil and Gas)	0.272	0.593	1.956	-3.128	2.406
213	Support Activities for Mining	0.361	0.329	1.231	-1.472	2.703
311	Food Manufacturing	0.100	0.249	0.743	-1.448	1.474
312	Beverage and Tobacco Product Manufacturing	0.321	0.203	0.567	-0.385	1.765
313	Textile Mills	0.138	0.057	0.670	-0.718	2.257
314	Textile Product Mills	0.292	0.125	0.711	-0.275	2.762
316	Leather and Allied Product Manufacturing	0.146	-0.019	0.289	-0.097	0.579
321	Wood Product Manufacturing	-0.099	-0.072	0.746	-1.378	1.534
322	Paper Manufacturing	0.162	0.192	0.286	-0.546	0.524
323	Printing and Related Support Activities	0.085	0.029	0.214	-0.257	0.449
324	Petroleum and Coal Products Manufacturing	0.762	1.350	5.720	-11.702	8.286
325	Chemical Manufacturing	0.219	0.403	0.765	-1.772	1.219
326	Plastics and Rubber Products Manufacturing	0.208	0.154	0.494	-0.885	1.131
327	Nonmetallic Mineral Product Manufacturing	0.206	0.134	0.485	-0.386	1.621
331	Primary Metal Manufacturing	-0.004	-0.059	1.678	-5.323	1.951
332	Fabricated Metal Product Manufacturing	0.205	0.080	0.250	-0.171	0.662
333	Machinery Manufacturing	0.136	0.146	0.193	-0.312	0.428
334	Computer and Electronic Product Manufacturing	-0.059	-0.055	0.227	-0.440	0.453
335	Electrical Equipment, Appliance, and Component Manufacturing	0.230	0.162	0.348	-0.255	0.889
336	Transportation Equipment Manufacturing	0.151	0.138	0.228	-0.287	0.640
337	Furniture and Related Product Manufacturing	0.121	0.140	0.173	-0.221	0.435
339	Miscellaneous Manufacturing	0.131	0.138	0.260	-0.234	0.915
423	Merchant Wholesalers, Durable Goods	0.178	0.159	1.112	-1.412	2.360
424	Merchant Wholesalers, Nondurable Goods	0.471	0.413	1.359	-1.481	3.622
441	Motor Vehicle and Parts Dealers	0.078	0.057	0.763	-1.480	1.315
442	Furniture and Home Furnishings Stores	0.211	0.307	0.567	-0.599	0.843
443	Electronics and Appliance Stores	0.992	0.528	4.810	-5.160	11.829
444	Building Material and Garden Equipment and Supplies Dealers	0.250	-0.129	0.945	-1.063	2.243
445	Food and Beverage Stores	0.134	-0.111	1.334	-1.589	3.453
446	Health and Personal Care Stores	-0.223	-0.503	1.182	-2.132	2.579
447	Gasoline Stations	-1.055	-1.088	7.119	-11.702	11.829
448	Clothing and Clothing Accessories Stores	-0.412	0.224	2.894	-9.625	3.395
451	Sporting Goods, Hobby, Book, and Music Stores	0.274	0.219	1.353	-1.394	4.091
452	General Merchandise Stores	0.229	0.531	2.092	-3.387	3.619
454	Nonstore Retailers	0.361	-0.201	2.114	-2.383	5.389
481	Air Transportation	0.682	0.641	1.621	-2.907	4.917
482	Rail Transportation	0.243	0.275	1.052	-2.724	2.810
483	Water Transportation	-0.045	0.289	1.635	-4.487	2.224
484	Truck Transportation	0.254	0.310	0.480	-0.967	1.095
488	Support Activities for Transportation	0.162	0.099	0.423	-0.829	0.788
491	Postal Service	0.525	0.039	1.602	-0.724	6.125
511	Publishing Industries (except Internet)	0.120	0.077	0.416	-0.370	1.189
515	Broadcasting (except Internet)	0.064	-0.082	1.158	-2.389	2.522
517	Telecommunications	0.067	0.078	0.322	-0.914	0.602
622	Hospitals	0.216	0.167	0.246	-0.102	0.932
721	Accommodation	0.151	0.310	0.788	-1.558	1.552
Total		0.177	0.145	1.879	-11.702	11.829

Table A.1: Summary statistics seasonally adjusted PPI growth in %.

Median energy intensity by industry. Table A.2 shows the median energy intensity per 3-digit NAICS sector over our sample period. In Table A.2, we only report the median energy intensity for sectors for which we have both input data as well as PPI data, which is required for Specification 9 and 10.[41] Energy intensity is defined as the amount of energy inputs divided by the total amount of intermediate inputs and is measured on an annual basis. Note that in our regression framework described in Specification 9 and 10, we make use of the annual sectoral energy intensity.

Median energy intensity per sector		
3-digit NAICS	Industry description	Median energy intensity (%)
336	Motor vehicles, bodies and trailers, and parts	0.7%
515, 517	Broadcasting and telecommunications	0.9%
511	Publishing industries, except internet (includes software)	0.9%
333	Machinery	1.1%
334	Computer and electronic products	1.4%
339	Miscellaneous manufacturing	1.5%
335	Electrical equipment, appliances, and components	1.5%
337	Furniture and related products	1.7%
324	Petroleum and coal products	1.9%
316	Apparel and leather and allied products	2.6%
311, 312	Food and beverage and tobacco products	2.7%
332	Fabricated metal products	2.7%
622	Hospitals	3.1%
423, 424	Wholesale trade	3.2%
321	Wood products	3.5%
323	Printing and related support activities	3.5%
326	Plastics and rubber products	3.6%
313, 314	Textile mills and textile product mills	4.5%
441	Motor vehicle and parts dealers	4.7%
213	Support activities for mining	5.4%
325	Chemical products	5.6%
442, 443, 444, 446, 447, 448, 451, 454	Retail trade	5.6%
452	General merchandise stores	6.3%
721	Accomodation	6.8%
331	Primary metals	7.1%
322	Paper products	8.2%
445	Food and beverage stores	11.2%
327	Nonmetallic mineral products	11.3%
488	Other transportation and support activities	15.4%
212	Mining, except oil and gas	19.0%
491	Transportation and warehousing	19.7%
482	Rail transportation	19.7%
483	Water transportation	20.7%
484	Truck transportation	26.5%
481	Air transportation	33.2%

Table A.2: Median energy intensity per sector.

[41] The information on energy inputs is matched on the NAICS 3-digit level. In case no energy input information is available, we match the information on the NAICS 2-digit level. This can e.g. explain why 3-digit NAICS sector 'Motor Vehicle and Parts Dealers' has a separate energy intensity measure than 'Retail Trade'. It could have been included under 'Retail Trade' if we would have matched it on a 2-digit level.

Appendix B Additional firm-level results

Probability of raising / cutting markup. Table B.1 builds on Table 7 by adding time fixed effects next to industry fixed effects, as described in Specification (15). The inclusion of time fixed effects shows that our results continue to hold after controlling for macro-economic shocks.

Probability of raising / cutting markup by more than *e*								
	e = 0.050		e = 0.075		e = 0.100		e = 0.125	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Direction of markup change	down	up	down	up	down	up	down	up
Positive oil supply shock × firm markup	-0.459**	0.479	-0.131	0.738*	-0.103	0.983**	-0.069	0.916**
	(0.233)	*(0.337)*	*(0.242)*	*(0.379)*	*(0.268)*	*(0.413)*	*(0.277)*	*(0.439)*
Negative oil supply shock × firm markup	-0.144	0.101	-0.108	0.119	-0.083	0.307	0.057	0.469
	(0.208)	*(0.309)*	*(0.204)*	*(0.344)*	*(0.239)*	*(0.370)*	*(0.234)*	*(0.370)*
Observations	40,366		40,366		40,366		40,366	
Industry FE	Yes		Yes		Yes		Yes	
Year-month FE	Yes		Yes		Yes		Yes	

Table B.1: Probability of raising / cutting markup using a multinomial logit model with industry and time FE. This table presents the estimation results from multinomial logit regression (15), using both industry as well as time fixed effects. The unit of observation is firm i, year(-month) t and the dependent variable is defined as in (14). Positive (negative) oil supply shock is the average yearly oil supply shocks, matched to the firm-level data, based on the companies' fiscal year end, when it is positive (negative) and zero otherwise. Firm markup denotes the 1-year lagged firm markup. For the sake of brevity, we do not report estimated coefficients on firm-level control variables including the 1-year lagged values of firm markup, log of revenue, leverage, Tobin's Q, cash over total assets, and net PPE over total assets. Standard errors are clustered at the NAICS 2-digit industry × year-month level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Estimated probabilities of raising / cutting markup by more than *e*. Table B.2 adds Panel B to Table 7, in which we show the estimated probabilities of raising / cutting the markup by more than *e*, based on the results in Panel A.

Panel A. Dependent variable: indicator variable for raising / cutting markup by more than *e*								
	e = 0.050		e = 0.075		e = 0.100		e = 0.125	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Direction of markup change	down	up	down	up	down	up	down	up
Positive oil supply shock	0.605*	-0.365	0.119	-0.738	0.029	-1.009*	-0.046	-0.973
	(0.354)	*(0.494)*	*(0.398)*	*(0.547)*	*(0.446)*	*(0.603)*	*(0.482)*	*(0.639)*
Positive oil supply shock × firm markup	-0.401*	0.542	-0.064	0.825**	-0.040	1.072**	-0.018	1.017**
	(0.240)	*(0.380)*	*(0.268)*	*(0.411)*	*(0.286)*	*(0.459)*	*(0.302)*	*(0.496)*
Negative oil supply shock	0.147	-0.106	0.057	-0.205	0.002	-0.449	-0.184	-0.665
	(0.329)	*(0.402)*	*(0.344)*	*(0.441)*	*(0.402)*	*(0.481)*	*(0.394)*	*(0.492)*
Negative oil supply shock × firm markup	-0.108	0.102	-0.070	0.132	-0.045	0.325	0.107	0.502
	(0.213)	*(0.320)*	*(0.213)*	*(0.358)*	*(0.240)*	*(0.395)*	*(0.238)*	*(0.410)*
Observations	40,366		40,366		40,366		40,366	
Industry FE	Yes		Yes		Yes		Yes	
Year-month FE	No		No		No		No	
Panel B. Estimated probabilities of raising / cutting markup by more than *e*, based on the results in Panel A								
	e = 0.050		e = 0.075		e = 0.100		e = 0.125	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Type of oil supply shock and firm-level markup	down	up	down	up	down	up	down	up
No oil supply shock and high firm-level markup	**0.530**	**0.161**	0.448	0.124	0.389	0.092	**0.327**	**0.071**
	(0.015)	***(0.012)***	*(0.014)*	*(0.010)*	*(0.013)*	*(0.009)*	***(0.012)***	***(0.008)***
No oil supply shock and low firm-level markup	**0.158**	**0.510**	0.114	0.443	0.082	0.384	**0.061**	**0.334**
	(0.009)	***(0.016)***	*(0.008)*	*(0.017)*	*(0.006)*	*(0.017)*	***(0.005)***	***(0.017)***
Positive oil supply shock and high firm-level markup	**0.495**	**0.204**	0.429	0.162	0.367	0.131	**0.309**	**0.101**
	(0.018)	***(0.014)***	*(0.018)*	*(0.012)*	*(0.016)*	*(0.011)*	***(0.016)***	***(0.009)***
Positive oil supply shock and low firm-level markup	**0.173**	**0.507**	0.119	0.434	0.084	0.370	**0.061**	**0.320**
	(0.013)	***(0.021)***	*(0.010)*	*(0.022)*	*(0.008)*	*(0.022)*	***(0.007)***	***(0.020)***

Table B.2: Probability of raising / cutting markup using a multinomial logit model. Panel A presents the estimation results from the multinomial logit regressions (15). The unit of observation is firm *i*, year(-month) *t* and the dependent variable is defined as in (14). Positive (negative) oil supply shock is the average yearly oil supply shocks, matched to the firm-level data, based on the companies' fiscal year end, when it is positive (negative) and zero otherwise. Firm markup denotes the 1-year lagged firm markup. For the sake of brevity, we do not report estimated coefficients on firm-level control variables including the 1-year lagged values of firm markup, log of revenue, leverage, Tobin's Q, cash over total assets, and net PPE over total assets. Standard errors are clustered at the NAICS 2-digit industry × year-month level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Panel B provides estimated probabilities of cutting (down) and raising (up) the markup by more than threshold *e*, when the firm-level markup is initially low (at the 10th percentile of the sample distribution) or high (at the 90th percentile of the sample distribution) in the absence or presence of a positive oil supply shock (taken at the 75th percentile of the sample distribution). The estimated probabilities are based on our results in Panel A.

Estimates reported in Panel B provide two main results. First regarding firms starting with relatively high markups, positive oil supply shock typically reduce the likelihood of markup cuts and raise the likelihood of markup hikes. For instance, when the threshold *e* defining markup increases and decreases is set at 0.050, the probability of a markup cut falls by about 3.5 percentage points while that of a markup hike increases by about 4.3 percentage points, following a positive oil supply shock. Similarly, when the threshold e defining markup increases and decreases is more conservative and set at 0.125, then following a positive oil supply shock, the probability of a markup cut still falls by about 1.8 percentage points while that of a markup hike still increases by about 3 percentage points.

Second, in the case of firms starting with relatively low markups, the impact of oil supply shock tends to be more muted. For example, following a positive oil supply shock, the probability of a markup cut increases by at most 1.5 percentage points (when the threshold e defining markup increases and decreases is set at 0.050) while that of a markup hike falls by about 1.4 percentage points (when the threshold e defining markup increases and decreases is set at 0.125). Hence, the main-takeaway from Panel B is that (positive) oil supply shocks mainly affect markups of firms located at the top of the markup distribution, while they barely change those of firms located at the bottom of the markup distribution.

Computing the pass-through of oil shocks using firm-level estimates. Let us assume that the price p_{st} in sector s at time t writes as a geometric average of firm-level prices:

$$\ln p_s = m \ln p_h + (1 - m) \ln p_l$$

In this expression, firms charging the relatively high price p_s hold a market share m, while firms charging the relatively low price p_l hold a market share $1 - m$. Then assuming firms in a given sector s face the same marginal cost of production, it follows that the sector-level markup μ_s is a geometric average of firm-level markups $(\mu_h; \mu_l)$:

$$\ln \mu_s = m \ln \mu_h + (1 - m) \ln \mu_l$$

Taking respectively the 10$^{\text{th}}$ and the 90$^{\text{th}}$ percentiles of the distribution of firm-level markups for μ_h and μ_l, i.e. $\mu_h = 1.8$ and $\mu_l = 0.7$, we can vary the market share m of high-markup firms to replicate sector-level markups. Specifically, a high markup-sector having a markup $\mu_s \approx 1.6$, it follows that high markup firms then hold a market share of about 87% while low markup firms only account for 13% of the market. Conversely, in a low markup-sector where the sectoral markup is $\mu_s \approx 0.8$, the market share of high-markup firms is about 14%, while low markup firms account for 86% of the sector.

Then using estimates from Figure 9, a positive oil supply shock at the 75th of the historical distribution leads high-markup firms to raise their markup by 2 percentage points, while low-markup firms roughly keep their markup μ^l_{st} unchanged. Conversely, using estimates from Table 8, a positive oil supply shock at the 75th of the historical distribution raises revenue growth of high-markup firms by about 6.6 percentage point relative to low-markup firms. We therefore consider that high-markup firms increase their market share m by 3.3 percentage points while the market share of low-markup firms $1-m$ drops by the same amount. Putting these different elements together, and denoting $d\mu^h_s$ and dm, the respective increases in the markup and in the market share of high-markup firms, the impact of an positive energy supply shock at the 75th percentile of the historical distribution on the sector-wide markup writes as:

$$d\ln\mu_{st} = m\ln\left[\frac{\mu_h + d\mu_h}{\mu_h}\right] + dm\ln\left[\frac{\mu_h + d\mu_h}{\mu_l}\right] = \frac{1.1}{100}m + \frac{3.15}{100}$$

Then the change in the sector-level markup for a high-markup sector —where the market share m of high-markup firms is 87%— is about 4.1 percentage points. Conversely, the change in the sector-level markup for a low-markup sector —where the market share m of high-markup firms is 14%— is about 3.3 percentage. Taking the difference between these two changes, we end up with a relative increase in the sector-level markup of high- relative to low-markup sectors of about 0.8 percentage points. Given the oil supply shock corresponds to a 2.8 percentage point drop in the growth rate of real WTI oil price, the difference in the pass-through between high- and low-markup sectors for a shock that cuts oil prices by one percentage point would be about 0.3 percentage point.