Heterogeneous Markups Cyclicality and Monetary Policy*

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This paper revisits the cyclicality of the aggregate markup using a micro-to-macro approach that emphasizes the role of firm-level heterogeneity, reallocation, and aggregation. Using US firm-level data from 1990-2016, we find that young firms have procyclical markups conditional on monetary shocks, while older firms show countercyclical markups. We show that economic activity reallocates from old to young firms after these shocks, and that firm aging has shifted the distribution toward older firms, changing the aggregate markup response from acyclical to countercyclical to monetary shocks. This may reconcile prior conflicting findings on the cyclicality of the aggregate markup, and has implications for the transmission of monetary policy and the relative importance of demand and supply shocks in driving business cycles.

Keywords: Heterogeneous Firms, Markups Cyclicality, Monetary Policy Shocks

JEL Codes: E32, E52, D22, L11

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1 Introduction

The cyclicality of markups conditional on economic shocks plays a central role in sticky-price New Keynesian models and in the transmission of monetary policy (e.g., Galí, 2015). In this framework, countercyclical markups reflect firms' incentives to reduce prices during downturns and increase them during booms; this behavior moderates inflation in recessions and amplifies it in expansions, aligning the cyclicality of inflation with that of GDP. Yet, despite the substantial attention recived by researchers, consensus on markup cyclicality remains elusive, with leading studies reaching opposite conclusions (e.g., Bils, Klenow and Malin, 2018; Nekarda and Ramey, 2020).

A key challenge is that this literature has historically relied on aggregate markup proxies, reflecting both data limitations and the prevalence of representative-agent frameworks. However, price-setting decisions — and hence markup adjustments — occur at the firm level (e.g., Mongey, 2021). We therefore revisit the cyclicality of the aggregate markup, focusing on its response to monetary policy (MP) shocks, using state-of-the-art IO measures of firm-level markups and a micro-to-macro strategy that explicitly accounts for firm-level heterogeneity, reallocation, and aggregation.

Our approach yields three insights. First, in the US, markups of old firms are countercyclical to MP shocks, whereas those of young firms are procyclical. Second, aggregating these heterogeneous firm-level responses implies an aggregate markup that is countercyclical over our sample. Third, changes in the firm age distribution have shifted aggregate markup cyclicality over time – from acyclical or mildly procyclical to countercyclical – offering a unified explanation for previously empirical findings.

We begin by reviewing the conventional New Keynesian (NK) logic linking demand shocks, markups, and inflation. We then connect this aggregate view to firm-level markup responses and develop a micro-to-macro framework separating three forces: firm-level markup cyclicality, the reallocation of economic activity across firms, and aggregation. In so doing, we consider three dimensions of firm heterogeneity that the literature suggests could directly inform the source and direction of firm-level markup cyclicality: financial frictions, demand frictions, and nominal pricing frictions.

We implement our strategy using quarterly Compustat data. Although Compustat covers only publicly listed firms, it offers high-frequency information on firm financial statements and input expenditures, reports firm age and industry classification, and includes firms that account for much of US business-cycle fluctuations (Crouzet and Mehrotra, 2020). We measure firm-level markups using state-of-the-art IO methods, as in De Loecker, Eeckhout and Unger (2020),[1] and exploit high-frequency identified MP shocks from Jarociński and Karadi (2020) as our measure of demand shocks.

To estimate firm-level markup responses, we use local projections following Jordà (2005). We interact MP shocks with firm characteristics that proxy for different sources of heterogeneity: firm age (Cloyne, Ferreira, Froemel and Surico, 2023), assets (Gertler and Gilchrist, 1994), leverage (Ottonello and Winberry, 2020), and liquidity (Jeenas, 2024) for financial frictions; sales share and markups for demand frictions; and sector-time fixed effects to absorb sectoral differences in nominal pricing frictions.

Our firm-level results show that age is the strongest predictor of heterogeneous markup responses to MP shocks. Old firms increase markups after a contractionary MP shock, consistent with a countercyclical behavior, while young firms lower their markups, consistent with procyclicality. We also find a small reallocation of economic activity from old to young firms after MP shocks, in line with the theoretical mechanism in Baqaee, Farhi and Sangani (2024). The age gradient is consistent with both financial and demand-side mechanisms: young firms may be more financially constrained and therefore reduce markups to generate cash flows, while older firms may face more inelastic demand because they are more established in their markets.

Following our micro-to-macro approach, we next aggregate the firm-level responses using variable-cost weights, which are theoretically grounded (e.g., Grassi, 2017; Edmond, Midrigan and Xu, 2023) and make our aggregate markup comparable to the inverse labor share proxy commonly used in the literature. Although estimates are not always strongly significant, the aggregate markup increases after a contractionary

[1] This is our baseline measure because our focus is on markup changes, for which De Ridder, Grassi and Morzenti (2026) show that revenue- and output-based measures are highly correlated. To address the concerns in Bond, Hashemi, Kaplan and Zoch (2021), we also verify our findings using the accounting markup measure of Baqaee and Farhi (2020).

MP shock over our sample, consistent with the predictions of sticky-price NK models.

We then show that changes in the age distribution of firms are central for understanding how aggregate markup cyclicality has evolved over time. A growing literature documents a sustained decline in firm formation and in the exit rate of older firms, leading to a progressive aging of the US firm population (e.g., Hathaway and Litan, 2014; Decker, Haltiwanger, Jarmin and Miranda, 2016). In our framework, this shift matters because older firms have countercyclical markups and account for a growing share of economic activity. Assessing the impact of firm aging on aggregate markup cyclicality over time, we find that early in our sample – when young, procyclical firms were more prevalent – the aggregate markup was acyclical or mildly procyclical. In the latter part of the sample, as older, countercyclical firms become dominant, the aggregate markup turns countercyclical, more strongly so than in estimates based on the full sample. We corroborate these results by directly estimating the response of the aggregate markup to MP shocks over time, which yields consistent conclusions.

This result suggests firm aging affects business-cycle fluctuations beyond its impact on factor shares and long-run trends (e.g., Hopenhayn, Neira and Singhania, 2022; Karahan, Pugsley and Şahin, 2024) and helps reconcile conflicting evidence in the aggregate markup literature. Studies using longer samples that largely predate the aging of the firm population tend to find mildly procyclical markups (e.g., Nekarda and Ramey, 2020; Cantore, Ferroni and León-Ledesma, 2021), whereas studies focusing on more recent periods identify a role for countercyclical markups (e.g., Bils, Klenow and Malin, 2018). Accounting for firm-level heterogeneity and aggregation, our approach shows how changes in the firm distribution can generate these divergent findings.

Finally, we discuss two additional macroeconomic implications of our findings. First, using a closed-form comparative static, we demonstrate that the evolution of aggregate markup cyclicality could materially affect the transmission of monetary policy. Second, we show that the countercyclical response of the aggregate markup conditional on MP shocks – contrasted with its unconditional procyclical behavior – points to an important role for supply shocks in driving business cycle fluctuations.

Literature review. We contribute to the empirical literature on the cyclicality of aggregate markups. Studies using aggregate data have reached differing conclusions, including Bils (1987), Galeotti and Schiantarelli (1998), Rotemberg and Woodford (1999), Bils and Kahn (2000), Gali, Gertler and Lopez-Salido (2007), Hall (2014), Bils, Klenow and Malin (2018), Cantore, Ferroni and León-Ledesma (2021), and Nekarda and Ramey (2020). Note that these works rely on aggregate markup proxies and typically treat aggregation as innocuous, abstracting from firm-level heterogeneity, across-firm reallocation, and changes in the firm distribution that may shape the aggregate response.

A separate strand studies the unconditional cyclicality of firm-level markups, including Hong (2017), Alati (2020), Burstein, Carvalho and Grassi (2020), and Afrouzi and Caloi (2022). While informative about firm-level pricing, unconditional evidence is difficult to map into theories whose predictions depend on the shock considered: sticky-price New Keynesian models, for example, predict countercyclical markups conditional on demand shocks but procyclical markups conditional on productivity shocks. Closely related to our analysis, Meier and Reinelt (2022) document an increase in markup dispersion following MP shocks, while Santos, Costa and Brito (2022) study the response of average firm-level markups to demand and productivity shocks.

We bridge these strands by providing evidence on *heterogeneous* firm-level markup cyclicality *conditional* on MP shocks, and by tracing how aggregation shapes the resulting aggregate markup response. Accounting jointly for firm-level heterogeneity, reallocation, and changes in the firm age distribution offers a unified explanation for the contrasting findings in the aggregate markup literature across sample periods.

Our paper also contributes to the literature on heterogeneous firm-level effects of monetary policy. Existing work studies the heterogeneous impact of MP shocks on firm-level investment (Gertler and Gilchrist, 1994; Crouzet and Mehrotra, 2020; Ottonello and Winberry, 2020; Deng and Fang, 2022; Cloyne, Ferreira, Froemel and Surico, 2023; Anderson and Cesa-Bianchi, 2024; González, Nuño, Thaler and Albrizio, 2024; Jeenas, 2024; Jungherr, Meier, Reinelt and Schott, 2024), stock-prices (Ippolito, Ozdagli and Perez-Orive, 2018; Darmouni, Giesecke and Rodnyansky, 2022; Gürkaynak, Karasoy-Can and Lee, 2022), and debt maturity (Fabiani, Falasconi and Heineken, 2020). We add to this literature by providing, to the best of our knowledge, the first evidence of heterogeneity in firm-level markup responses to MP shocks — a key mechanism in sticky-price New Keynesian models. We further show that firm age shapes this heterogeneity and, through aggregation, the cyclicality of the aggregate markup.

Outline. Section 2 presents the conceptual framework used throughout the paper. Section 3 details our data and measures. Section 4 outlines our empirical strategy and firm-level results. Section 5 discusses the aggregate results. Section 6 concludes.

2 Conceptual Framework

This section frames our empirical analysis. We first review why aggregate markup cyclicality is central in standard NK models; we then link aggregate markup dynamics to firm-level markup responses; finally, we discuss distinct theories that could ground the macroeconomic role of the heterogeneous cyclicality of firm-level markups.

Theoretical role of markups in NK models. The markup of price over marginal cost is central to sticky-price New Keynesian macroeconomic models (Galí, 2015). To see this, consider the following firm-level NK Phillips Curve (hereafter NKPC):

$$\pi_{i,t} = \beta \mathbb{E}_t \left[\pi_{i,t+1}\right] - \lambda_i \Delta_0 \log \mu_{i,t} = -\lambda_i \sum_{h=0}^{\infty} \beta^h \mathbb{E}_t \left[\Delta_h \log \mu_{i,t+h}\right], \tag{1}$$

where $\pi_{i,t}$ is firm-level inflation, β is the discount factor, λ_i is the slope of the firm-level NKPC, $\mu_{i,t}$ is the firm-level markup, and $\Delta_h \log \mu_{i,t+h} \equiv \log \mu_{i,t+h} - \log \mu_i$ denotes the cumulative log deviation of the markup from its steady-state value at horizon h.

Equation (1) posits that current inflation is negatively related to current and expected future deviations of markups from their desired levels. Intuitively, if firms expect future markups to be below their desired level, sticky prices induce them to raise prices already today. This logic is what links markups and inflation in the NKPC.

In the standard NK model, demand shocks — including MP shocks — move output and firms' marginal costs in the same direction. When prices cannot adjust freely, markups over marginal costs instead move in the opposite direction. Thus, a positive demand shock raises output, lowers markups below desired levels, and generates higher inflation through the NKPC. This mechanism delivers the expected co-movement between output and inflation, and Debortoli and Galí (2022, 2024) show that the same logic also operates in two-agent and heterogeneous-agent NK models.

Micro-to-macro link. While much of the empirical literature has focused on aggregate markups due to data constraints, most price-setting decisions — and therefore markup movements — are likely to occur at the firm level. Here, we present a conceptual framework to relate firm-level markups to aggregate markups (and, later, in Section 5.3.1 to inflation) empirically. We start by defining the aggregate markup $\mathcal{M}$ as:

$$\mathcal{M}_t = \sum_i \omega^v_{i,t} \mu_{i,t}, \tag{2}$$

where $\omega^v_{i,t}$ is the firm-level variable-cost weight, and $\mu_{i,t}$ is the firm-level markup. We use this cost-weighted measure because, in a broad class of models including the NK framework, it is the theoretically welfare-relevant object capturing the aggregate wedge between prices and marginal costs (Grassi, 2017; Edmond, Midrigan and Xu, 2023). Moreover, under standard assumptions such as labor being the primary variable input, Equation (2) aligns with the inverse labor share, the standard aggregate markup proxy in the cyclicality literature (e.g., Nekarda and Ramey, 2020).

Log-linearizing Equation (2) around the steady state, the impulse response function (IRF) of the aggregate markup to a demand shock at horizon h is written as:

$$\frac{\partial \Delta_h \log \mathcal{M}_{t+h}}{\partial \varepsilon^m_t} = \underbrace{\sum_i \frac{\omega^v_i \mu_i}{\mathcal{M}} \frac{\partial \Delta_h \log \mu_{i,t+h}}{\partial \varepsilon^m_t}}_{\text{Firm-level effect}} + \underbrace{\sum_i \frac{\mu_i}{\mathcal{M}} \frac{\partial \Delta_h \omega^v_{i,t+h}}{\partial \varepsilon^m_t}}_{\text{Reallocation effect}}, \tag{3}$$

with $\sum_i \frac{\partial \Delta_h \omega^v_{i,t+h}}{\partial \varepsilon^m_t} = 0$, where ε^m_t is the demand shock, $\frac{\partial \Delta_h \log \mu_{i,t+h}}{\partial \varepsilon^m_t}$ is the firm-level markup IRF, and $\frac{\partial \Delta_h \omega^v_{i,t+h}}{\partial \varepsilon^m_t}$ is the firm-level IRF of variable-cost weights. The first term in Equation (3) captures how demand shocks affect markups *within* firms; the second captures how demand shocks reallocate costs *across* firms.[2] Equation (3) will guide our subsequent empirical analysis by separating the role of heterogeneous firm-level markup responses from the role of cost-reallocation after demand shocks.

Dimensions of firm-level heterogeneity in markup responses to shocks. Theoretical studies have identified three main forces that can generate heterogeneous markup responses across firms: financial frictions, demand frictions, and pricing frictions.

Financial frictions. Recent work emphasizes that financial frictions shape firms' pricing decisions over the business cycle (e.g., Gilchrist, Schoenle, Sim and Zakrajšek, 2017; Kim, 2021; Meinen and Soares, 2022). Since direct measures of financial constraints are difficult to implement with available firm data, we use standard proxies: firm age (Cloyne, Ferreira, Froemel and Surico, 2023), assets (Gertler and Gilchrist, 1994), leverage (Ottonello and Winberry, 2020), and liquidity (Jeenas, 2024).

Demand frictions. Heterogeneous markup responses to aggregate shocks may also arise from oligopolistic-like forces (e.g., Gopinath and Itskhoki, 2010; Klenow and Willis, 2016; Mongey, 2021; Wang and Werning, 2022; Baqaee, Farhi and Sangani, 2024; Alvarez, Lippi and Souganidis, 2022), customer capital (e.g., Ravn, Schmitt-Grohé and Uribe, 2006; Nakamura and Steinsson, 2011; Argente and Yeh, 2022), or accumulated intangibles (e.g., Bronnenberg, Dubé and Syverson, 2022). These strands of literature suggest that relative firm size may be central for differential markup responses. We proxy relative size using firms' sales shares within narrowly defined industries and their markups, both of which closely relate to relative size in this class of models.

Pricing frictions. Finally, Meier and Reinelt (2022) theoretically show that heterogeneous nominal rigidities can generate heterogeneous markup responses to shocks. Since, to our knowledge, available measures of nominal rigidities are only sectoral, our empirical analysis controls for this source of variation with sector-time fixed effects, identifying firm-level heterogeneity net of sectoral differences in price rigidity.

[2] Baqaee, Farhi and Sangani, 2024 theoretically discuss the macroeconomic role of reallocation effects.

3 Firm Data, MP Shocks, and Markups Measurement

Here, we outline the data used for the analysis, detailing our firm-level sources and the series of MP shocks. Following that, we describe our measure of firm-level markups.

3.1 Firm-Level Data and MP Shocks

Firm-level data. We use quarterly Compustat data, which provide balance-sheet information for North American publicly listed firms, and have three advantages for our purposes. First, its quarterly frequency is well suited to business-cycle analysis. Second, Compustat contains information on firm age, sales, input expenditures, capital, liabilities, and industry classification. Third, while publicly listed firms are only a subset of all US firms, they are large and account for a sizable share of aggregate activity, including approximately 30% of employment (Davis, Haltiwanger, Jarmin, Miranda, Foote and Nagypal, 2006) and much of business-cycle fluctuations (e.g., Crouzet and Mehrotra, 2020).[3] Our sample runs from 1990q1 to 2016q4, matching the availability of the MP shock series described below, and Appendix A details its construction.

We measure firm-level production using sales (`SALEQ`), variable inputs using cost of goods sold (`COGSQ`), tangible capital using gross property, plant, and equipment (`PPEGTQ`), overhead costs using selling, general, and administrative expenses (`XSGAQ`), and assets using total assets (`ATQ`). Liquidity is cash and short-term investments over assets, `CHEQ/ATQ`, while leverage is short (`DLCQ/ATQ`) plus long-term liabilities over assets (`DLTTQ/ATQ`). Finally, relative firm size is measured as a firm's sales share among firms in the same 4-digit NAICS sector. Appendix A reports summary statistics.

Two limitations are worth noting. First, Compustat measures corporate age, i.e., time since incorporation into the dataset, rather than true firm age. We therefore validate our findings using Jay Ritter's database, which contains founding years for a subset of Compustat firms. Second, Compustat does not provide firm-level deflators, so our baseline measure is based on revenues rather than physical quantities. We dis-

[3] This observation is also consistent with the granularity literature pioneered by Gabaix (2011).

cuss the implications of this limitation for the measurement of markups in Section 3.2.

MP shock series. We use MP shocks as identified demand shocks. Our benchmark series is from Jarociński and Karadi (2020), who refine the standard identification of high-frequency MP shocks by accounting for the information revealed to private agents by Fed announcements. The series is constructed from interest-rate surprises, measured as changes in Fed Funds Futures within 30-minute windows around policy announcements, and has been widely used in empirical work. For robustness, we also use the alternative MP shock series from Gürkaynak, Sack and Swanson (2005).

Additional data sources. After merging Compustat with the MP shock series, we add quarterly macroeconomic controls: GDP growth, Consumer Price Index (CPI) growth, the Excess Bond Premium (EBP), and the 1-Year Treasury rate change, all from FRED.

3.2 Markups Measurement

Firm-level markups are our main object of interest. Since prices and marginal costs are not directly observed, we follow the production-function approach of De Loecker and Warzynski (2012), as implemented by De Loecker, Eeckhout and Unger (2020). Under cost minimization for given prices and demand, the markup of firm i is written as:

$$\mu_{i,t} = \mathcal{E}^{v}_{s,t} \frac{P_{i,t} Q_{i,t}}{P^{v}_{i,t} X^{v}_{i,t}}, \tag{4}$$

where $\mathcal{E}^{v}_{s,t}$ is the elasticity of output with respect to the variable input X^{v}, $P_{i,t}Q_{i,t}$ is sales, and $P^{v}_{i,t}X^{v}_{i,t}$ is variable input expenditure. Thus, measuring markups requires sales, variable input expenditure, and an output elasticity. In our baseline, sales and variable input expenditure are measured using `SALEQ` and `COGSQ`, while output elasticities are the sector-year estimates from De Loecker, Eeckhout and Unger (2020). Appendix A reports summary statistics for the resulting markup measure. In Appendix B.1.7, we verify the robustness of our results using elasticities estimated at the quarter-sector level under Cobb-Douglas and Translog production functions.

Several well-known concerns apply to this popular estimator. To being, measurement error can add noise to firm-level markups. Moreover, because Compustat contains revenues rather than physical quantities, the use of revenue elasticities in Equation (4) may differ from the output elasticities required by theory; Bond, Hashemi, Kaplan and Zoch (2021) also raise concerns about the first-stage inversion used in standard IO production-function estimators. Finally, Flynn, Traina and Gandhi (2019) and Gandhi, Navarro and Rivers (2020) show that estimating gross-output production functions can complicate the identification of variable-input elasticities.

Our empirical strategy addresses these concerns in three ways. First, our baseline specifications include firm and sector-time fixed effects, which absorb permanent measurement differences across firms, time-varying sectoral shocks, and much of the variation associated with output elasticities. As a result, identification relies primarily on changes in the ratio of sales to variable input expenditure. Second, our object of interest is the *change* in firm-level markups after aggregate shocks, not the level of markups per se. This distinction is relevant because De Ridder, Grassi and Morzenti (2026) show that markup changes computed using revenue elasticities and output-based elasticities are highly correlated. Third, we check robustness using alternative markup measures. In particular, Appendix B.1.8 uses the Lerner index employed by Baqaee and Farhi (2020),[4] while additional exercises compute markups using output elasticities from dynamic panel estimators with restricted and unrestricted returns to scale, which avoid the first-stage inversion required by standard IO approaches.

A final caveat is that Compustat only allows us to measure the variable input bill with `COGSQ`, which combines labor and material costs. If firms have monopsony power, our markup measure may partly capture that margin as well (e.g., Yeh, Macaluso and Hershbein, 2022). While we follow the literature in using this estimator as our baseline markup measure, this caveat should be kept in mind when interpreting the results.

[4] The Lerner index allows us not to rely on data on the cost of goods sold for the markup estimation, and hence on the assumption that this variable captures frictionless factors. The Lerner index uses instead information on sales and operating income before depreciation, as discussed in Appendix B.1.8.

4 Firm-Level Analysis

This section studies whether firm characteristics predict heterogeneous markup responses to MP shocks. We first describe the local-projection specifications used to estimate relative and level responses, and then present the firm-level evidence.

4.1 Empirical Strategy

Relative response across firms. We estimate relative markup responses across firm groups using panel local projections (LP – Jordà (2005)) by ordinary least squares:

$$\begin{aligned}\Delta_h \log \mu_{i,t+h} = \sum_{x\in\mathcal{X}} \left(\alpha_{x,h} + \beta_{x,h}\Delta Y_{t-1} + \sum_{k=-\kappa}^{h} \gamma_{x,h}^{k}\varepsilon_{t+k}^{m}\right) \times \mathbb{1}_{i\in\mathcal{I}^x} \\ + \sum_{\ell=1}^{L} \boldsymbol{\delta_h'} \boldsymbol{X_{i,t-\ell}} + \varphi_{i,h} + \varphi_{s,t,h} + \boldsymbol{\vartheta_h t} + u_{i,t+h},\end{aligned} \tag{5}$$

with horizons given by $h = 0, 1, \ldots, H$. The dependent variable is the cumulative change in markups for firm i at horizon h, defined by the following expression:

$$\Delta_h \log \mu_{i,t+h} \equiv \log \mu_{i,t+h} - \log \mu_{i,t-1}. \tag{6}$$

As for the independent variables, the indicator $\mathbb{1}_{i\in\mathcal{I}^x}$ in Equation (5) equals one if firm i was above the median value of characteristic x in the previous year, with $\mathcal{X} = \{age, assets, sales\ share, leverage, liquidity, markup\}$. These firm-level characteristics serve as proxies for leading theories of performance heterogeneity, as discussed in Section 2. The coefficients of interest are $\gamma_{x,h}^{0}$, which measure the relative markup response of firms above the median of characteristic x to the contemporaneous MP shock ε_t^m .

Our baseline specification is semi-parametric, using median dummies rather than linear interactions between firm characteristics and MP shocks, though we confirm results are similar when using a parametric specification with linear interaction terms. We include past and future MP shocks, with $\kappa = 4$, to control for serial correlation in the shock series and reduce attenuation bias in panel LPs (Teulings and Zubanov, 2014). Firm fixed effects (FEs) , $\varphi_{i,h}$, absorb permanent firm heterogeneity, while sector-time FEs, $\varphi_{s,t,h}$, control for aggregate and sectoral shocks, including sectoral differences in nominal rigidities, though we show that removing both set of FEs, thereby fully exploiting permanent cross-firm variation and time variation, yields similar results. Our baseline also includes linear and quadratic trends, $\boldsymbol{\vartheta_h t}$, to account for the growth in markups documented by De Loecker, Eeckhout and Unger (2020).

Following Ottonello and Winberry (2020), we interact $\mathbb{1}_{i\in\mathcal{I}^x}$ with previous-quarter GDP growth ΔY_{t-1} to account for varying sensitivities of firm markups to the business cycle. We include this control in line with best practices, but robustness checks confirm that its inclusion does not affect the results. Additionally, the vector $\boldsymbol{X_{i,t}}$ comprises: (i) firm-level controls such as sales growth and overhead costs relative to sales, (ii) macro-level controls including GDP and CPI growth, changes in the 1-year Treasury rate, and the EBP,[5] and (iii) their lags (i.e., $L = 4$). The vector also includes fiscal-quarter dummies to address seasonality in accounting practices, as noted by Ottonello and Winberry (2020). Finally, standard errors $u_{i,t}$ are clustered at both the firm and quarter level to control for any serial correlation in the error term.[6]

Level response across firms. Equation (5) identifies *relative* responses to MP shocks across firms but, because of sector-time fixed effects, does not identify the *level* response of each group. To determine whether markups are procyclical or countercyclical within each group, we hence drop sector-time FEs and estimate:

$$\begin{aligned}\Delta_h \log \mu_{i,t+h} = \alpha_h + \beta_h \Delta Y_{t-1} + \sum_{k=-\kappa}^{h} \gamma_h^k \varepsilon_{t+k}^m \\ + \left(\alpha_{x,h} + \beta_{x,h} \Delta Y_{t-1} + \sum_{k=-\kappa}^{h} \gamma_{x,h}^k \varepsilon_{t+k}^m \right) \times \mathbb{1}_{i\in\mathcal{I}^x} \\ + \sum_{\ell=1}^{L} \boldsymbol{\delta_h' X_{i,t-\ell}} + \varphi_{i,h} + \boldsymbol{\vartheta_h t} + u_{i,t+h},\end{aligned} \tag{7}$$

[5]We include these aggregate controls, despite the fact that sector-time fixed effects should absorb them, only to maintain comparability with the specification in Equation (7) later on.

[6]Clustering at the firm level accommodates flexible error term dependence across time within each firm, while clustering by time is necessary to account for firm-level shocks correlated within a quarter, beyond the co-movement due to industry-level shocks captured by sector-quarter dummies. Without quarter-level clustering, confidence intervals would be significantly narrower.

again for $h = 0, 1, \ldots, H$ and $x \in \mathcal{X}$. This second specification exploits time-variation to estimate the level effect of MP shocks on markups, as captured by γ_h^0, as well as the relative additional effect of belonging to group $x \in \mathcal{X}$, which is captured by $\gamma_{x,h}^0$. All firm and macro controls, trends, shock terms, and clustering are as in Equation (5).

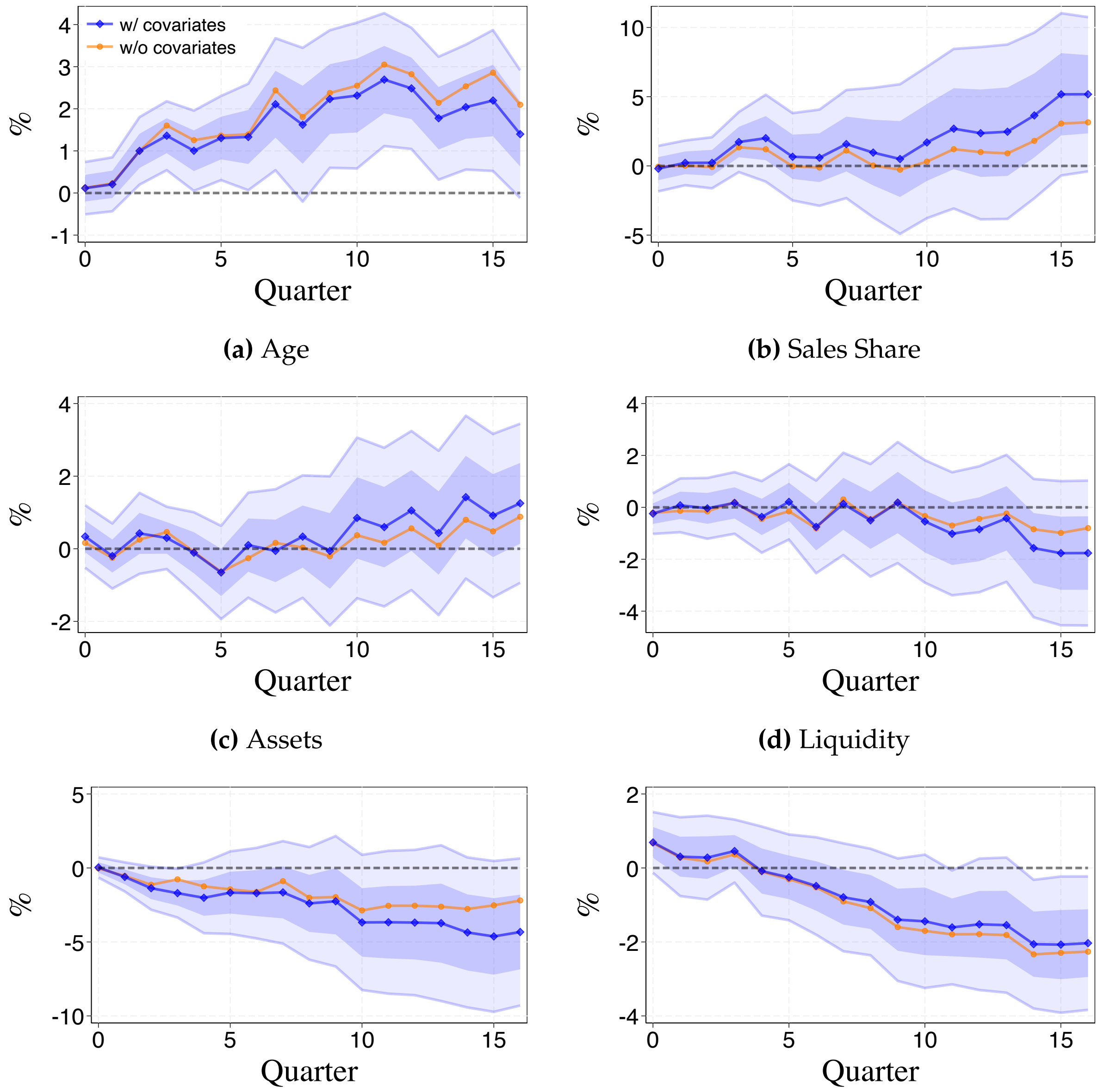
4.2 Results

4.2.1 Main Results

Relative response across firms. Figure 1 reports the estimated $\gamma_{x,h}^0$ coefficients from Equation (5) and horizons $h = 1, ..., 16$, normalized to a 25 basis point (b.p.) contractionary MP shock, along with confidence intervals around point estimates. Firm age is the clearest predictor of heterogeneous markup responses: firms above the median age increase their markups relative to younger firms, with the difference reaching 2.69% and becoming statistically significant. Sales share and leverage also display suggestive differences, but these are smaller and only weakly significant. By contrast, assets, liquidity, and the level of markups do not robustly predict heterogeneous responses. The estimates are similar whether characteristics are included jointly or one at a time — the solid blue and orange lines respectively. Appendix B.2 shows that, among the same characteristics, age is also the strongest predictor of heterogeneous responses in sales and cost of goods sold, the two components of our markup measure.

Level response across firms. Figure 2 reports the level responses estimated from Equation (7). Old firms increase markups by up to 3.76% after a 25 b.p. contractionary MP shock, while young firms reduce markups by up to 2%. Thus, old firms display countercyclical markups, while young ones display procyclical markups. Firms with larger sales shares show a similar pattern, but the estimates are smaller and less precise. The last two panels of Figure 2 highlight instead that firms below the median leverage show a more countercyclical markup response to MP shocks, with markups of low-leverage firms significantly increasing between q5 and q10 after a 25 b.p. monetary tightening. Moreover, firms below the median markup before a contractionary MP

Figure 1: Heterogeneous Markups Cyclicality By Firm-Level Characteristics



(a) Age **(b)** Sales Share

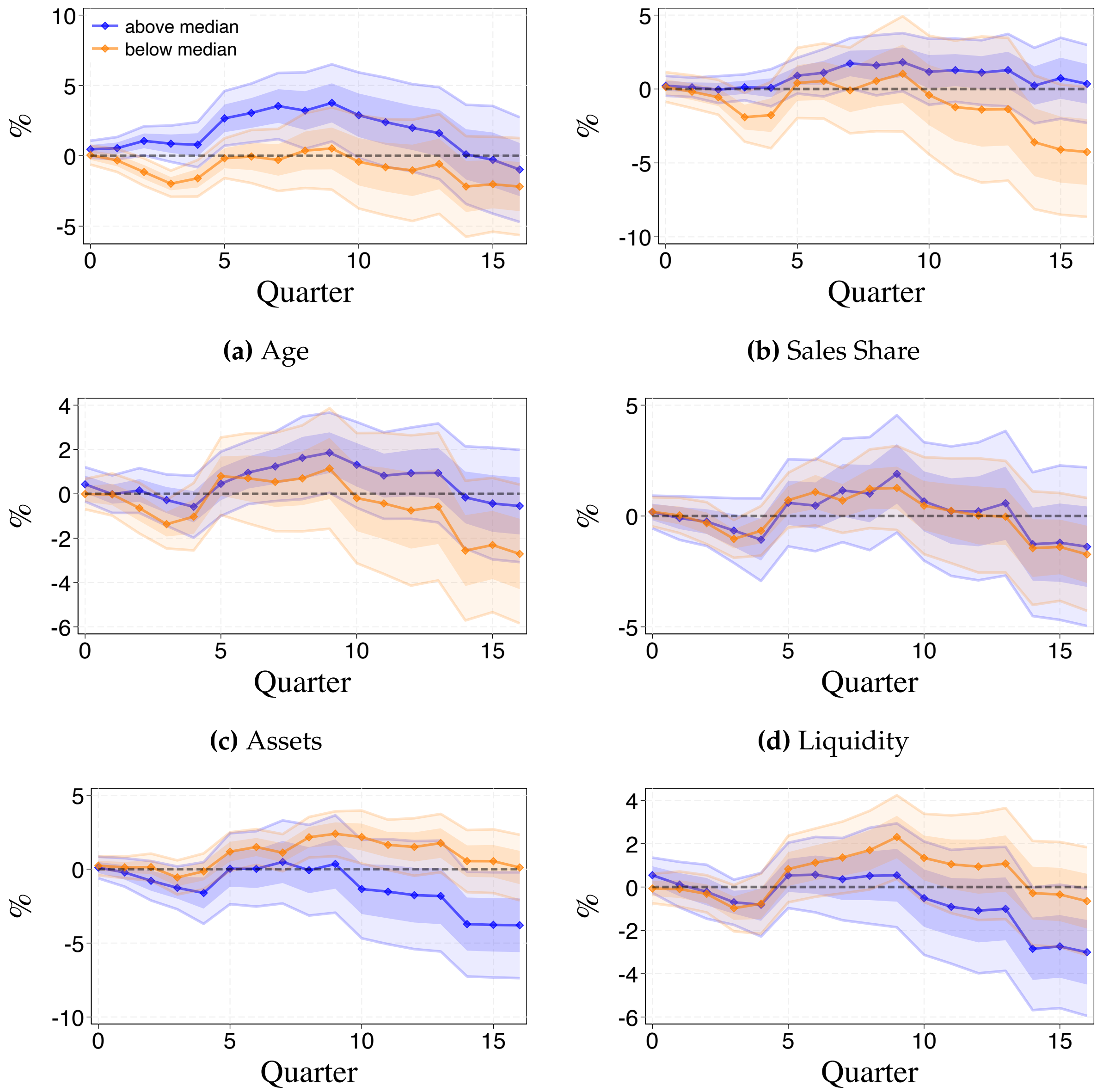
(c) Assets **(d)** Liquidity

(e) Leverage **(f)** Markups

Note: Figure 1 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a monetary policy (MP) shock. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with and without covariates — the blue and orange lines — and for horizons $h = 1, ..., 16$. Note that Figure 1 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$ when estimating Equation (5) with all covariates. Standard errors clustered at the firm and quarter level.

shock seem to adjust downwards their markups by more in the short run and increase them by more in the medium run. Firms above the median markup have a qualitatively similar response, but the estimated coefficients are not significant.

Figure 2: Heterogeneous Markups Cyclicality Across Firms



(a) Age

(b) Sales Share

(c) Assets

(d) Liquidity

(e) Leverage

(f) Markups

Note: Figure 2 shows the markup response of (a) old and young, (b) high and low sales share, (c) big and small, (d) high and low liquidity, (e) high and low leverage, (f) high and low markup firms conditional on a monetary policy (MP) shock. We plot the response of firms above (blue) and below (orange) the median in each category. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with covariates and for horizons $h = 1, ..., 16$. Note that Figure 2 is normalized to a 25 basis points contractionary MP shock. The dark and light-shaded areas report the 68% and the 90% confidence intervals. Standard errors clustered at the firm and quarter level.

Summary of findings. We show that firm age strongly predicts markup cyclicality conditional on MP shocks: markups of old firms are countercyclical, while markups of young firms are procyclical. Once age is accounted for, other characteristics — assets, sales share, leverage, liquidity, and markups — have more limited predictive power.

4.2.2 Robustness Analysis

Appendix B.1 reports a battery of robustness checks for Equation (5); analogous checks for Equation (7) are available upon request. We exclude the ZLB period, omit future MP shocks, use linear interactions instead of median dummies, employ the MP shock series from Gürkaynak, Sack and Swanson (2005), measure age using Jay Ritter's founding-year data, define firm groups within sector-quarter cells, compute markups using Cobb-Douglas and Translog elasticities, use Lerner-index markups with constant and non-constant returns to scale, remove controls, remove all fixed effects, and estimate elasticities using dynamic-panel methods by Arellano and Bond (1991) and Blundell and Bond (1998) to compute alternative markup measures. Across these exercises, age remains a robust predictor of heterogeneous markup responses to MP shocks, although some alternative markup measures attenuate statistical significance.

4.2.3 Results Interpretation and Discussion

Our goal is not to microfound why age predicts heterogeneous markup responses to MP shocks, but to identify the firm characteristics that matter empirically and trace their aggregate implications though changes in the firm distribution. Still, the age gradient is consistent with two mechanisms discussed in Section 2. First, age may proxy for financial frictions. Young firms are more likely to lack stable cash flows, long credit histories, and unconstrained access to external finance (Haltiwanger, Jarmin and Miranda, 2013; Davis and Haltiwanger, 2024; Cloyne, Ferreira, Froemel and Surico, 2023; Dinlersoz, Kalemli-Ozcan, Hyatt and Penciakova, 2018). After a contractionary MP shock, such firms may face rising marginal costs or cut prices to generate cash flows, consistent with procyclical markups and with the evidence in Kim (2021).

Second, age may proxy for demand-side frictions. Older firms are more established in their markets, have accumulated customers and intangible capital, and may face less elastic demand (Foster, Haltiwanger and Syverson, 2008; Ravn, Schmitt-Grohé and Uribe, 2006; Argente and Yeh, 2022). This interpretation is also consistent with models in which large or established firms pass through cost shocks less aggressively (Gopinath and Itskhoki, 2010; Klenow and Willis, 2016; Mongey, 2021; Wang and Werning, 2022; Baqaee, Farhi and Sangani, 2024; Alvarez, Lippi and Souganidis, 2022).

In conclusion, our evidence suggests that both demand and financial frictions may explain the role of age in driving the differential response of firm markups to MP shocks, and more granular data would be necessary to carefully disentangle these channels. We stress again that the specific reason behind the significance of firm age for the cyclicality of markups does not change the scope of our question, as we rather aim to highlight the contribution of the documented heterogeneity in firms' markups cyclicality to the cyclicality of the aggregate US markup conditional on MP shocks.

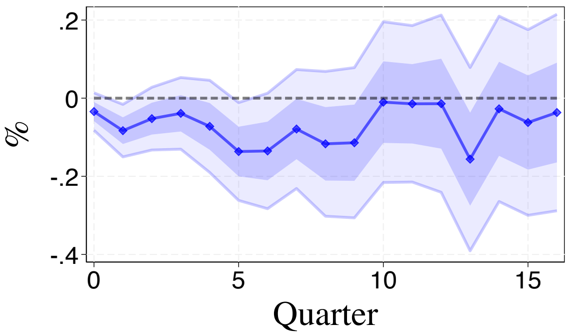
4.2.4 Reallocation Across Firm-Age Groups

Having established firm age as a plausible predictor of heterogeneous firm-level responses of markups to MP shocks, we go back to the conceptual framework outlined in Section (2) and examine the reallocation component highlighted by Equation (3). We re-estimate Equation (5) using firm-level variable-cost shares, rather than markups, as the dependent variable. Since variable-cost shares sum to one across age groups by construction, the relative response of old firms is also their level cost-share response.

Figure 3 shows that the variable-cost share of older firms falls by about 0.1% after a 25 b.p. contractionary MP shock, implying a corresponding increase for younger firms. The estimate is only weakly significant, but it points to a modest reallocation of economic activity from old to young firms, consistent with the reallocation from large to small firms in Baqaee, Farhi and Sangani (2024). Appendix C.2 shows that the same pattern emerges when using sales shares instead of variable-cost shares.

The next section combines the micro-level evidence on the heterogeneity in the conditional cyclicality of markups by firm age with evidence on the aging of US firms

Figure 3: Heterogeneous Cost Shares Cyclicality



Note: Figure 3 shows the variable cost shares response of old firms conditional on a monetary policy (MP) shock. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with covariates and for horizons $h = 1, ..., 16$. Figure 3 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

to derive potential implications for the conditional cyclicality of the aggregate markup.

5 Aggregate Implications

In this section, we first explain how we aggregate the previously discussed firm-level markup responses to gauge at the cyclicality of the aggregate markup in response to MP shocks across our entire sample. Next, we explore how shifts in the distribution of firms towards older ones could shape the cyclicality of the aggregate markup conditional on MP shocks in different periods of our sample. We then conclude by examining some additional aggregate implications carried out by our findings.

5.1 Aggregate Markup Cyclicality

We begin by arguing that the firm-level analysis in Section 4 is a starting point to explore the cyclicality of the aggregate markup. Given that one dimension of heterogeneity — e.g. firm age — proved potentially significant in predicting the response of markups to MP shocks, we redefine the aggregate markup from Section 2 as:

$$\mathcal{M} = \omega_O^v \mu_O + (1 - \omega_O^v)\mu_Y, \tag{8}$$

where ω_O^v is the variable-cost share of old firms, defined as firms above the median age, while μ_O and μ_Y are the variable-cost-weighted markups of old and young firms. Log-linearizing Equation (8) around the steady state conditional on a MP shock gives:

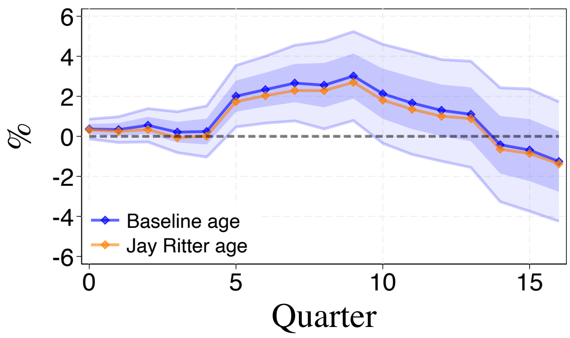
$$\frac{\partial \Delta_h \log \mathcal{M}_h}{\partial \varepsilon^m} = \underbrace{\frac{\omega_O^v \mu_O}{\mathcal{M}} \frac{\partial \Delta_h \log \mu_{O,h}}{\partial \varepsilon^m} + \frac{(1-\omega_O^v)\mu_Y}{\mathcal{M}} \frac{\partial \Delta_h \log \mu_{Y,h}}{\partial \varepsilon^m}}_{\text{Direct effect}} + \underbrace{\frac{\mu_O - \mu_Y}{\mathcal{M}} \frac{\partial \Delta_h \omega_{O,h}^v}{\partial \varepsilon^m}}_{\text{Indirect effect}} \tag{9}$$

where $\frac{\partial \Delta_h \log \mu_{O,h}}{\partial \varepsilon^m}$, $\frac{\partial \Delta_h \log \mu_{Y,h}}{\partial \varepsilon^m}$, and $\frac{\partial \Delta_h \omega_{O,h}^v}{\partial \varepsilon^m}$ represent the IRFs of markups of old and young firms, and the old firms' variable cost share, respectively, as estimated in Section 4 conditional on MP shocks. Equation (9) is indeed the two-group counterpart of Equation (3): the direct effect captures heterogeneous markup responses across age groups, while the indirect effect captures reallocation in variable-cost shares.

Using our baseline age measure, $\omega_O^v = 0.76$, $\mu_O = 1.30$, $\mu_Y = 1.21$, and $\mathcal{M} = 1.28$. Using Jay Ritter's founding-year age measure, the corresponding values are 0.66, 1.33, 1.24, and 1.29. Combining these moments with the impulse responses estimated in Section 4 and Equation (9), we compute the aggregate markup response to MP shocks.

Figure 4 shows that the aggregate markup rises after a 25 b.p. contractionary MP shock. The response averages about 3% between q5 and q10 and is significant at the 90% level, consistent with the countercyclical markup response predicted by sticky-price NK models and with the evidence in Bils, Klenow and Malin (2018). The response is similar when using Jay Ritter's age measure. Moreover, Appendix C.1 shows that the IRF in Figure 4 is primarily driven by the direct effect, meaning that the heterogeneous impact across different firm-age groups is what matters for the conditional cyclicality of the aggregate markup. The indirect effect, while determining the reallocation of costs across firms discussed in Section 4.2.4, is quantitatively small because old and young firms have similar average markups, so $(\mu_O - \mu_Y)/\mathcal{M}$ is close to zero.

Figure 4: Aggregate Markup Cyclicality



Note: Figure 4 presents the aggregate markup response conditional on a monetary policy (MP) shock, derived using Equation (9). The results in Figure 4 are normalized to a 25 basis point contractionary MP shock. The dark blue line represents the results obtained using our baseline measure of age, while the orange line represents the results using the Jay Ritter age measure. The dark and light blue shaded areas indicate the 68% and 90% confidence intervals around the point estimates, respectively. A delta method based on Equation (9) is used to construct confidence intervals around the point estimates.

Finally, although the most robust weighting method for the aggregate markup involves variable costs (e.g., Grassi, 2017; Edmond, Midrigan and Xu, 2023), Appendix C.2 demonstrates that using sales weights to compute the aggregate markup, as proposed by De Loecker et al. (2020), yields similar results. This holds true for (i) estimates of the reallocation of economic activity across firm-age groups after MP shocks, (ii) the aggregate markup's IRF conditional on the same shocks, and (iii) estimates of the strength of the direct and indirect effects for the cyclicality of the aggregate markup.

Since we have argued for the importance of the firm distribution for the response of the aggregate markup, as per the explicit aggregation in Equation (9), we next investigate how changes in the age distribution of firms may influence the conditional cyclicality of the aggregate markup, relating to existing findings in the literature.

5.2 Changing Markups Cyclicality: Firm Aging

5.2.1 Micro-to-Macro Approach

Equation (9) implies that aggregate markup cyclicality depends not only on firm-level markup responses and reallocation, but also on the relative size of each firm-age group. This is important because a growing literature documents a decline in firm formation and in the exit rate of older firms, leading to an aging of the US firm population (e.g., Hathaway and Litan, 2014; Decker, Haltiwanger, Jarmin and Miranda, 2016). While Hopenhayn, Neira and Singhania (2022) emphasize the implications of firm aging for aggregate factor shares, our framework suggests that firm aging may also affect business-cycle dynamics through markup cyclicality.

Table 1: Macroeconomic Implications of Firm Aging

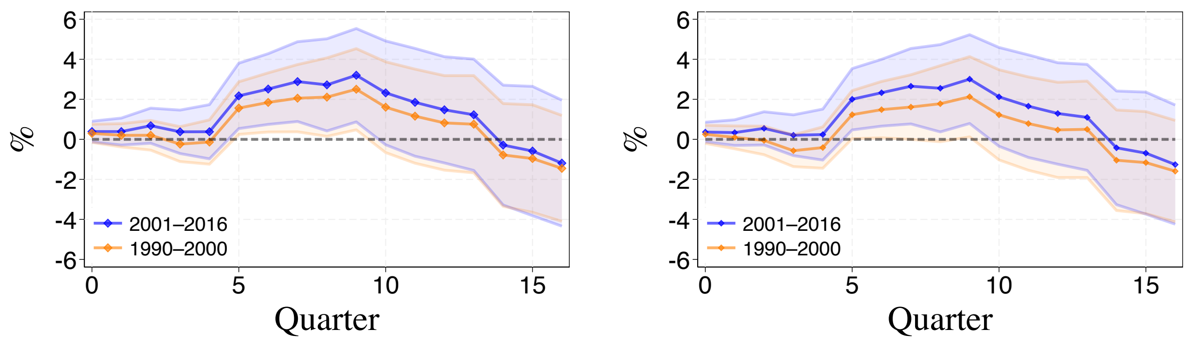
	1990-2000	**2001-2016**
Using *Years Since Incorporation*		
Average firm age	6	13
Share of old firms	20%	56%
Cost share by old firms (ω_O)	60%	82%
Markup old firms (μ_O)	1.30	1.30
Markup young firms (μ_Y)	1.22	1.20
Aggregate markup ($\mathcal{M}$)	1.27	1.28
Using *Foundation Year* by Jay Ritter		
Average firm age	20	27
Share of old firms	26%	54%
Cost share by old firms (ω_O^v)	48%	76%
Markup old firms (μ_O)	1.33	1.33
Markup young firms (μ_Y)	1.23	1.25
Aggregate markup ($\mathcal{M}$)	1.27	1.31

Note: Data is from Compustat 1990-2016. Cost shares are computed using the variable input measure employed in the empirical analysis, i.e., cost of goods sold. The markup for young and old firms is the average variable cost-weighted markup for firms above and below the median age, respectively. The aggregate markup is calculated as the sum of the markups for old and young firms, each weighted by their respective variable cost shares.

Table 1 confirms that firms in our sample age substantially over time. Between 1990–2000 and 2001–2016,[7] the share of old firms roughly doubles under both age measures, and their variable-cost share rises from 60% to 82% using Compustat age, and from 48% to 76% using Jay Ritter's founding-year measure. Average markups are stable across subperiods and align with the evidence in De Loecker, Eeckhout and Unger (2020), so the key change for aggregation is the growing weight of old firms.

[7] We use the year 2000 as the cutoff as it is roughly in the middle of the pre-ZLB period. Importantly, while Compustat is a sample of relatively big and old producers, the firm distribution that emerges from Business Dynamics Statistics data shows similar patterns of aging over the period of analysis, suggesting the mechanisms we uncovered may replicate in a more representative sample of firms.

Figure 5: Firm Aging and Aggregate Markup Cyclicality – Micro-to-Macro Approach



(a) Compustat Age

(b) Jay Ritter Age

Note: Figure 5 shows the markup response to a monetary policy (MP) shock before and after 2000 for changes in the age distribution of firms using (a) Compustat age and (b) Jay Ritter age. Figure 5 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$ estimating Equation (5) with all covariates. Standard errors clustered at the firm and quarter level. A delta method based on Equation (9) is used to construct confidence intervals around point estimates.

To uncover the implications of firm aging on the conditional cyclicality of the aggregate markup, we then follow the procedure outlined in Section 5.1 using the data from Table 1, and recompute Equation (9) separately before and after 2000. Figure 5 shows that the aggregate markup is mostly acyclical before 2000, with point estimates leaning mildly procyclical. After 2000, it becomes mildly countercyclical under both age measures, with positive and statistically significant responses from q5 to q10. Appendix C.3 further shows that the differential markup response of old relative to young firms does not materially change across the two subperiods. Thus, the shift in aggregate markup cyclicality should be driven mainly by changes in the firm age distribution, rather than by changes in the responsiveness of a given firm-age group. Through the lens of the NK model, this could indicate a channel through which amplification forces are intensifying in the US economy. Next, we validate this finding by further employing a direct aggregate approach to assess the aggregate markup cyclicality.

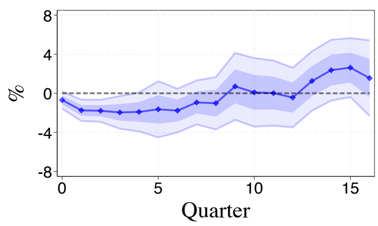
5.2.2 Macro Validation of the Micro-to-Macro Approach

We validate the micro-to-macro evidence by computing the response of the aggregate markup directly. Specifically, we estimate the following aggregate LP:

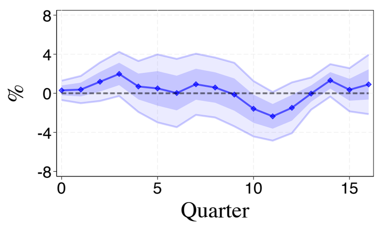
$$\Delta_h \log \mathcal{M}_{t+h} = \alpha_h + \left(\alpha_{t>2000q4,h} + \beta_{t>2000q4,h} \Delta Y_{t-1} + \sum_{k=-\kappa}^{h} \gamma^k_{t>2000q4,h} \varepsilon^m_{t+k} \right) \times \mathbb{1}_{t>2000q4}$$
$$+ \beta_h \Delta Y_{t-1} + \sum_{k=-\kappa}^{h} \gamma^k_h \varepsilon^m_{t+k} + \sum_{\ell=1}^{L} \boldsymbol{\delta}'_h \mathbf{X}_{t-\ell} + \boldsymbol{\vartheta}_h \boldsymbol{t} + u_{t+h}, \tag{10}$$

with horizons given by $h = 0, 1, \ldots, 16$. The dependent variable is the cumulative change in the aggregate markup, namely the cost-weighted average of firms' markups. The interaction between MP shocks and the dummy $\mathbb{1}_{t>2000q4}$ captures the change in aggregate markup cyclicality after 2000. Controls, lags, and trends follow the firm-level specifications from Section 4, with additional dummies for the Great Financial Crisis and the ZLB. Standard errors are Newey–West with three lags,[8] to control for autocorrelation. For robustness, we also interact the MP shocks with a linear trend instead of the post-2000q4 dummy to capture changes in the response of $\mathcal{M}$ over time.

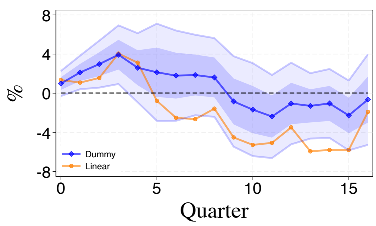
Figure 6: Aggregate Markup Cyclicality Macro Approach



(a) Before 2000



(b) After 2000



(c) Difference

Note: Figure 6 presents the aggregate markup response to a contractionary monetary policy (MP) shocks before (Figure 6a) and after 2000 (Figure 6b) and the estimated difference (using a dummy or a linear specification) between the two impulse responses (Figure 6c). Impulse responses are normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors are calculated following Newey-West with 3 lags.

Figure 6 reports the aggregate markup response to a 25 b.p. contractionary MP shock before (Figure 6a) and after 2000 (Figure 6b), plus the estimated difference be-

[8] We chose 3 lags following the rule of thumb $T^{1/4} = ((2016 - 1990) \times 4)^{1/4} \approx 3$.

tween the two IRFs (Figure 6c). Results echoes the micro-to-macro findings in Figure 5: the aggregate markup response shifts from mildly procyclical before 2000 to mildly countercyclical afterward, and the difference between the two IRFs is significant at the 90% level until q4. To better compare the two approaches, we also compute the cumulative impulse response function (CIR), which measures the area under the IRF and summarizes the impact and persistence of the economy's response (Alvarez, Le Bihan and Lippi (2016)). Under the micro-to-macro approach, the CIR of the pre/post difference in Figure 5 is 8.41 using Compustat age, 11.62 using Jay Ritter's age-measure. Under the aggregate-economics approach, the CIR for Panel (c) in Figure 6 is 7.19.[9]

5.2.3 Changing Markups Cyclicality in Relation to the Literature

The results in Sections 5.2.1 and 5.2.2 suggest that the period of analysis matters when assessing the conditional cyclicality of the aggregate markup. Changes in the age structure of US firms began in the 1980s, so the growing role of older firms – whose markups are countercyclical to MP shocks – may have become increasingly relevant for aggregate dynamics. To highlight the role of sample selection, rather than provide an exhaustive review, we compare our findings with two influential aggregate-data studies: Bils, Klenow and Malin (2018), which argues for countercyclical markups and aligns with our full-sample results in Section 5.1, and Nekarda and Ramey (2020), which finds markups to be mildly procyclical or acyclical in response to MP shocks.

A key difference between these papers is the sample period. Bils, Klenow and Malin (2018) focus on a sample starting in the late 1980s, whereas Nekarda and Ramey (2020) use data going back to the 1950s.[10] As discussed above, these periods feature different firm distributions: the former is increasingly dominated by older firms, whose markups are countercyclical, while the latter places more weight on younger firms, whose markups lean procyclical. Differences in sample periods may therefore

[9] This remains valid, though to a lesser extent, if we use the absolute deviation at the peak as the metric of comparison. In that case, the absolute deviation at the peak for the micro-to-macro approach would be 1 p.p., while for the aggregate-economics approach, the difference would be around 4 p.p.

[10] The same holds for Cantore, Ferroni and León-Ledesma (2021), who find a countercyclical labor share, i.e., a procyclical aggregate markup, conditional on MP shocks in a sample dating back to the 1960s.

reconcile these divergent findings, and support our micro-to-macro approach, which estimates the primitive firm-level markup responses to MP shocks and highlights the role of aggregation in shaping aggregate markup cyclicality.

5.3 Magnitudes of the Findings and Macro Implications

We close with an admittedly partial discussion of two potential implications of our methodology for macroeconomic frameworks: monetary policy transmission and the relative importance of demand and supply shocks in driving business cycles.

5.3.1 Monetary Policy Transmission

In the NKPC, inflation depends on current and expected future markup gaps. Hence, the same firm-level markup responses that shape aggregate markup cyclicality may also inform the inflation response to MP shocks. Following common approaches to aggregate price indexes (e.g., Divisia price index and PPI) and Baqaee, Farhi and Sangani (2024), define aggregate inflation as the sales-weighted average of firm-level inflation:

$$\pi_t = \sum_i \omega^s_{i,t} \pi_{i,t}, \tag{11}$$

where $\omega^s_{i,t}$ are sales weights. Combining Equation (11) with the firm-level NKPC in Equation (1), and splitting firms into old and young groups, gives:

$$\begin{aligned} \frac{\partial \pi_t}{\partial \varepsilon^m_t} &= \omega^s_O \frac{\partial \pi_{i,t}}{\partial \varepsilon^m_t} + (1-\omega^s_O)\frac{\partial \pi_{i,t}}{\partial \varepsilon^m_t} \\ &= -\omega^s_O \lambda_O \sum_{h=0}^{\infty} \beta^h \mathbb{E}_t \left[\frac{\partial \Delta_h \log \mu_{O,t+h}}{\partial \varepsilon^m_t} \right] - (1-\omega^s_O)\lambda_Y \sum_{h=0}^{\infty} \beta^h \mathbb{E}_t \left[\frac{\partial \Delta_h \log \mu_{Y,t+h}}{\partial \varepsilon^m_t} \right] \end{aligned} \tag{12}$$

Equation (12) provides a simple comparative static linking the estimated markup responses, the sales share of old firms, and the inflation response to MP shocks. We implement it using the estimated markup IRFs of old and young firms from Equation (7), the sales shares of old firms, a quarterly discount factor $\beta = 0.99$, and a common NKPC slope $\lambda_O = \lambda_Y = 0.006$ from Hazell, Herreno, Nakamura and Steinsson (2022).

Table 2: Macroeconomic Implications of Firm Aging

	1990-2016	1990-2000	2001-2016
Using *Years Since Incorporation*			
Sales share by old firms (ω_O^s)	76%	62%	82%
Aggregate inflation response to MP shocks $\left(\frac{\partial \pi_t}{\partial \varepsilon_t^m}\right)$	-0.10p.p.	-0.07p.p.	-0.11p.p.
Using *Foundation Year* by Jay Ritter			
Sales share by old firms (ω_O^s)	65%	48%	76%
Aggregate inflation response to MP shocks $\left(\frac{\partial \pi_t}{\partial \varepsilon_t^m}\right)$	-0.07.p.	-0.03p.p.	-0.10p.p.

Note: Compustat data, 1990-2016. Sales shares are computed for firms above and below the median age, across two definitions. The aggregate inflation response is calculated as per Equation (12), with $\beta = 0.99$, $\lambda_i = \lambda = 0.006$ and using the estimated markup response of old firms from Equation (7).

Table 2 reports the results of this exercise. Across age definitions, the implied aggregate inflation response to a 25 b.p. contractionary MP shock ranges from -0.07 to -0.10 p.p. over the full sample, within the range of previous estimates (e.g., Galı and Gertler, 1999; Christiano, Eichenbaum and Evans, 2005; Nakamura and Steinsson, 2018). The response is stronger after 2000, because old firms account for a larger sales share (between 65 and 76% – similar to their cost share in Table 1) and have countercyclical markups. Thus, changes in aggregate markup cyclicality may be quantitatively relevant for monetary transmission through the lens of standard NK models.[11]

This exercise is only a comparative static. In particular, it holds the firm-level NKPC slope λ_i fixed, whereas firm aging could itself affect price sensitivity if λ_i is an equilibrium object rather than a primitive (e.g., Baqaee, Farhi and Sangani, 2024). For instance, if older firms face more inelastic demand or lower cost pass-through, their growing weight could flatten the effective NKPC and offset the mechanism illustrated above. Viewed in this light, this section should be interpreted as a proof of concept aimed at assessing the quantitative relevance of changes in aggregate markup cyclicality, holding all else equal. A full empirical and structural assessment of how monetary

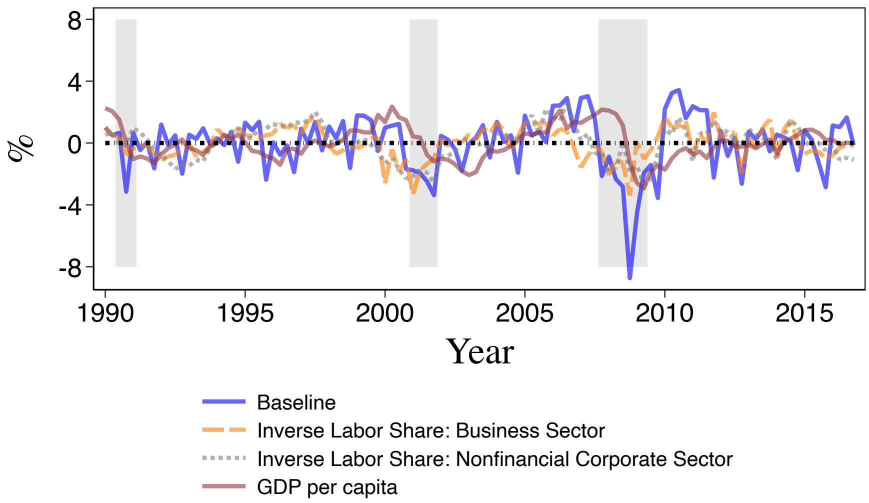
[11] To further gauge the economic significance of this result, the difference between 0.07 and 0.11 p.p. (as implied by our calculations based on years since incorporation) might translate into roughly 60% more cumulative monetary tightening to achieve the same reduction in inflation. To fix ideas, offsetting a 0.3 p.p. inflationary shock would require at most three 25 b.p. rate hikes if each hike lowers inflation by 0.11 p.p., but closer to four or five hikes if the effect is only 0.07 p.p.

policy transmission has evolved over time, allowing firm behaviors and equilibrium objects to adjust endogenously, lies beyond the scope of the present analysis.

5.3.2 Demand vs. Supply Shocks

We conclude with a brief note on how the unconditional cyclicality of the aggregate markup, together with its conditional cyclicality to demand shocks studied in our empirical analysis, sheds light on which shocks are likely to drive the business cycle.

Figure 7: HP-Filtered Aggregate Markup Measures



Note: Figure 7 shows (i) GDP per capita, (ii) the aggregate markup derived from the estimates of firm-level markups in Compustat between 1990 and 2016, and (iii) alternative HP-filtered measures of the aggregate markup based on the inverse of the labor share, each in percentage deviation from its trend.

To this end, Figure 7 plots GDP per capita against our baseline aggregate markup and alternative inverse-labor-share measures, all expressed as percentage deviations from HP-filtered trends. These measures are unconditionally procyclical. By contrast, our estimates show that aggregate markups are countercyclical conditional on demand, or MP, shocks. If demand shocks were the only drivers of business cycles, aggregate markups should therefore be unconditionally countercyclical. Their unconditional procyclicality points instead to an important role for supply shocks, which generate procyclical markups even in standard NK models. This provides an additional benchmark for business-cycle models with firm heterogeneity.

6 Conclusion

This paper revisits the question of the cyclicality of the aggregate markup through a micro-to-macro lens. Rather than studying unconditional co-movements, whose interpretation depends on the shocks driving the cycle, we focus on identified MP shocks – a class of demand shocks – and decompose the aggregate response into firm-level markup adjustments, reallocation of economic activity, and aggregation channels.

Using quarterly Compustat data from 1990q1 to 2016q4, we document substantial heterogeneity in conditional markup cyclicality by firm age. After a contractionary MP shock, young firms lower markups, whereas older firms raise them; economic activity also reallocates modestly from old to young firms. Aggregating these responses with variable-cost weights implies that the aggregate markup is countercyclical to MP shocks over the full sample, but this average masks an important change over time. As the US firm distribution shifted toward older firms, aggregate markup cyclicality moved from acyclical or mildly procyclical in the early part of the sample to countercyclical in the later period. Direct aggregate estimates support the same pattern.

These findings help reconcile conflicting evidence in the aggregate markup literature and suggest that changes in the firm distribution can matter for business-cycle dynamics. Going forward, we view our findings as providing a set of firm-level empirical benchmarks for macroeconomic models of price setting and monetary transmission. By documenting heterogeneity in markup cyclicality across firms and showing how changes in the firm distribution shape aggregate outcomes, our results highlight dimensions of firm behavior that are typically abstracted from in standard New Keynesian frameworks. We hope our evidence will inform the development of microfounded New Keynesian models with firm heterogeneity that replicate the observed markup dynamics, and spur further research on how changes in the firm population affect monetary policy transmission. These are exciting avenues for future studies.

References

Afrouzi, Hassan and Luigi Caloi, "Endogenous firm competition and the cyclicality of markups," *The Review of Economics and Statistics*, 2022, pp. 1–45.

Alati, Andrea, "Essays on firms heterogeneity and business cycles." PhD dissertation, The London School of Economics and Political Science (LSE) 2020.

Alvarez, Fernando E, Francesco Lippi, and Takis Souganidis, "Price setting with strategic complementarities as a mean field game," Technical Report, National Bureau of Economic Research 2022.

Alvarez, Fernando, Hervé Le Bihan, and Francesco Lippi, "The real effects of monetary shocks in sticky price models: a sufficient statistic approach," *American Economic Review*, 2016, *106* (10), 2817–2851.

Anderson, Gareth and Ambrogio Cesa-Bianchi, "Crossing the credit channel: Credit spreads and firm heterogeneity," *American Economic Journal: Macroeconomics*, 2024, *16* (3), 417–446.

Arellano, Manuel and Stephen Bond, "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations," *The Review of Economic Studies*, 1991, *58* (2), 277–297.

Argente, David and Chen Yeh, "Product life cycle, learning, and nominal shocks," *The Review of Economic Studies*, 2022, *89* (6), 2992–3054.

Baqaee, David R, Emmanuel Farhi, and Kunal Sangani, "The supply-side effects of monetary policy," *Journal of Political Economy*, 2024, *132* (4), 1065–1112.

Baqaee, David Rezza and Emmanuel Farhi, "Productivity and misallocation in general equilibrium," *The Quarterly Journal of Economics*, 2020, *135* (1), 105–163.

Bils, Mark, "The cyclical behavior of marginal cost and price," *The American Economic Review*, 1987, pp. 838–855.

— **and James A Kahn**, "What inventory behavior tells us about business cycles," *American Economic Review*, 2000, *90* (3), 458–481.

—**, Peter J Klenow, and Benjamin A Malin**, "Resurrecting the role of the product market wedge in recessions," *American Economic Review*, 2018, *108* (4-5), 1118–46.

Blundell, Richard and Stephen Bond, "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics*, 1998, *87* (1), 115–143.

Bond, Steve, Arshia Hashemi, Greg Kaplan, and Piotr Zoch, "Some unpleasant markup arithmetic: Production function elasticities and their estimation from production data," *Journal of Monetary Economics*, 2021, *121*, 1–14.

Bronnenberg, Bart J, Jean-Pierre Dubé, and Chad Syverson, "Marketing investment and intangible brand capital," *Journal of Economic Perspectives*, 2022, *36* (3), 53–74.

Burstein, Ariel, Vasco M Carvalho, and Basile Grassi, "Bottom-up markup fluctuations," Technical Report, National Bureau of Economic Research 2020.

Cantore, Cristiano, Filippo Ferroni, and Miguel León-Ledesma, "The missing link: monetary policy and the labor share," *Journal of the European Economic Association*, 2021, *19* (3), 1592–1620.

Christiano, Lawrence J, Martin Eichenbaum, and Charles L Evans, "Nominal rigidities and the dynamic effects of a shock to monetary policy," *Journal of Political Economy*, 2005, *113* (1), 1–45.

Cloyne, James, Clodomiro Ferreira, Maren Froemel, and Paolo Surico, "Monetary policy, corporate finance, and investment," *Journal of the European Economic Association*, 2023, *21* (6), 2586–2634.

Crouzet, Nicolas and Neil R Mehrotra, "Small and large firms over the business cycle," *American Economic Review*, 2020, *110* (11), 3549–3601.

Darmouni, Olivier, Oliver Giesecke, and Alexander Rodnyansky, "The bond lending channel of monetary policy," *Columbia Business School Research Paper Forthcoming*, 2022.

Davis, Steven J and John Haltiwanger, "Dynamism diminished: The role of housing markets and credit conditions," *American Economic Journal: Macroeconomics*, 2024, *16* (2), 29–61.

__ , __ , Ron Jarmin, Javier Miranda, Christopher Foote, and Eva Nagypal, "Volatility and dispersion in business growth rates: Publicly traded versus privately held firms [with comments and discussion]," *NBER Macroeconomics Annual*, 2006, *21*, 107–179.

Debortoli, Davide and Jordi Galí, "Idiosyncratic income risk and aggregate fluctuations," Technical Report, National Bureau of Economic Research 2022.

__ and __ , "Heterogeneity and aggregate fluctuations: insights from TANK models," Technical Report, National Bureau of Economic Research 2024.

Decker, Ryan A, John Haltiwanger, Ron S Jarmin, and Javier Miranda, "Declining business dynamism: What we know and the way forward," *American Economic Review*, 2016, *106* (5), 203–207.

Deng, Minjie and Min Fang, "Debt maturity heterogeneity and investment responses to monetary policy," *European Economic Review*, 2022, *144*, 104095.

Dinlersoz, Emin, Sebnem Kalemli-Ozcan, Henry Hyatt, and Veronika Penciakova, "Leverage over the life cycle and implications for firm growth and shock responsiveness," Technical Report, National Bureau of Economic Research 2018.

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu, "How costly are markups?," *Journal of Political Economy*, 2023, *131* (7), 1619–1675.

Fabiani, Andrea, Luigi Falasconi, and Janko Heineken, "Monetary Policy and Corporate Debt Maturity," *SSRN Electronic Journal*, 2020.

Flynn, Zach, James Traina, and Amit Gandhi, "Measuring markups with production data," *Available at SSRN 3358472*, 2019.

Foster, Lucia, John Haltiwanger, and Chad Syverson, "Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?," *American Economic Review*, 2008, *98* (1), 394–425.

Gabaix, Xavier, "The granular origins of aggregate fluctuations," *Econometrica*, 2011, *79* (3), 733–772.

Galeotti, Marzio and Fabio Schiantarelli, "The cyclicality of markups in a model with adjustment costs: econometric evidence for US industry," *Oxford Bulletin of Economics and Statistics*, 1998, *60* (2), 121–142.

Galí, Jordi, *Monetary policy, inflation, and the business cycle: an introduction to the new Keynesian framework and its applications*, Princeton University Press, 2015.

Galı, Jordi and Mark Gertler, "Inflation dynamics: A structural econometric analysis," *Journal of Monetary Economics*, 1999, *44* (2), 195–222.

Gali, Jordi, Mark Gertler, and J David Lopez-Salido, "Markups, gaps, and the welfare costs of business fluctuations," *The Review of Economics and Statistics*, 2007, *89* (1), 44–59.

Gandhi, Amit, Salvador Navarro, and David A Rivers, "On the identification of gross output production functions," *Journal of Political Economy*, 2020, *128* (8), 2973–3016.

Gertler, Mark and Simon Gilchrist, "Monetary policy, business cycles, and the behavior of small manufacturing firms," *The Quarterly Journal of Economics*, 1994, *109* (2), 309–340.

Gilchrist, Simon, Raphael Schoenle, Jae Sim, and Egon Zakrajšek, "Inflation dynamics during the financial crisis," *American Economic Review*, 2017, *107* (3), 785–823.

González, Beatriz, Galo Nuño, Dominik Thaler, and Silvia Albrizio, "Firm heterogeneity, capital misallocation and optimal monetary policy," *European Central Bank Working Paper Series*, 2024, *2890.*

Gopinath, Gita and Oleg Itskhoki, "Frequency of price adjustment and pass-through," *The Quarterly Journal of Economics*, 2010, *125* (2), 675–727.

Grassi, Basile, "IO in IO: Competition and volatility in input-output networks," *Unpublished Manuscript, Bocconi University*, 2017.

Gürkaynak, Refet, Hatice Gökçe Karasoy-Can, and Sang Seok Lee, "Stock market's assessment of monetary policy transmission: The cash flow effect," *The Journal of Finance*, 2022, *77* (4), 2375–2421.

Gürkaynak, Refet S, Brian Sack, and Eric Swanson, "The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models," *American Economic Review*, 2005, *95* (1), 425–436.

Hall, Robert E, "What the cyclical response of advertising reveals about markups and other macroeconomic wedges," *NBER Working Paper*, 2014, *18370.*

Haltiwanger, John, Ron S Jarmin, and Javier Miranda, "Who creates jobs? Small versus large versus young," *Review of Economics and Statistics*, 2013, *95* (2), 347–361.

Hathaway, Ian and Robert E Litan, "Declining business dynamism in the United States: A look at states and metros," *Brookings Institution*, 2014, *2.*

Hazell, Jonathon, Juan Herreno, Emi Nakamura, and Jón Steinsson, "The slope of the Phillips Curve: evidence from US states," *The Quarterly Journal of Economics*, 2022, *137* (3), 1299–1344.

Hong, Sungki, "Customer capital, markup cyclicality, and amplification," *FRB St. Louis Working Paper*, 2017, (2017-33).

Hopenhayn, Hugo, Julian Neira, and Rish Singhania, "From population growth to firm demographics: Implications for concentration, entrepreneurship and the labor share," *Econometrica*, 2022, *90* (4), 1879–1914.

Ippolito, Filippo, Ali K Ozdagli, and Ander Perez-Orive, "The transmission of monetary policy through bank lending: The floating rate channel," *Journal of Monetary Economics*, 2018, *95*, 49–71.

Jarociński, Marek and Peter Karadi, "Deconstructing monetary policy surprises—the role of information shocks," *American Economic Journal: Macroeconomics*, 2020, *12* (2), 1–43.

Jeenas, Priit, "Firm Balance Sheet Liquidity, Monetary Policy Shocks, and Investment Dynamics," *Barcelona School of Economics Working Paper*, 2024, *1409.*

Jordà, Òscar, "Estimation and inference of impulse responses by local projections," *American Economic Review*, 2005, *95* (1), 161–182.

Jungherr, Joachim, Matthias Meier, Timo Reinelt, and Immo Schott, "Corporate debt maturity matters for monetary policy," *Federal Reserve Bank of San Francisco Working Paper Series*, 2024, *2024-30.*

Karahan, Fatih, Benjamin Pugsley, and Ayşegül Şahin, "Demographic Origins of the start-up Deficit," *American Economic Review*, 2024, *114* (7), 1986–2023.

Kim, Ryan, "The effect of the credit crunch on output price dynamics: The corporate inventory and liquidity management channel," *The Quarterly Journal of Economics*, 2021, *136* (1), 563–619.

Klenow, Peter J and Jonathan L Willis, "Real rigidities and nominal price changes," *Economica*, 2016, *83* (331), 443–472.

Loecker, Jan De and Frederic Warzynski, "Markups and firm-level export status," *American Economic Review*, 2012, *102* (6), 2437–71.

—, Jan Eeckhout, and Gabriel Unger, "The rise of market power and the macroeconomic implications," *The Quarterly Journal of Economics*, 2020, *135* (2), 561–644.

Meier, Matthias and Timo Reinelt, "Monetary policy, markup dispersion, and aggregate tfp," *Review of Economics and Statistics*, 2022, pp. 1–45.

Meinen, Philipp and Ana Cristina Soares, "Markups and Financial Shocks," *The Economic Journal*, 2022, *132* (647), 2471–2499.

Mongey, Simon, "Market structure and monetary non-neutrality," Technical Report, National Bureau of Economic Research 2021.

Nakamura, Emi and Jón Steinsson, "Price setting in forward-looking customer markets," *Journal of Monetary Economics*, 2011, *58* (3), 220–233.

— and —, "High-frequency identification of monetary non-neutrality: the information effect," *The Quarterly Journal of Economics*, 2018, *133* (3), 1283–1330.

Nekarda, Christopher J and Valerie A Ramey, "The cyclical behavior of the price-cost markup," *Journal of Money, Credit and Banking*, 2020, *52* (S2), 319–353.

Ottonello, Pablo and Thomas Winberry, "Financial heterogeneity and the investment channel of monetary policy," *Econometrica*, 2020, *88* (6), 2473–2502.

Ravn, Morten, Stephanie Schmitt-Grohé, and Martin Uribe, "Deep habits," *The Review of Economic Studies*, 2006, *73* (1), 195–218.

Ridder, Maarten De, Basile Grassi, and Giovanni Morzenti, "The Hitchhiker's Guide to Markup Estimation: Assessing Estimates from Financial Data," *Econometrica*, 2026, *94* (1), 137–168.

Rotemberg, Julio J and Michael Woodford, "The cyclical behavior of prices and costs," *Handbook of Macroeconomics*, 1999, *1*, 1051–1135.

Santos, Carlos D, Luís F Costa, and Paulo B Brito, "Demand, supply and markup fluctuations," *The Economic Journal*, 2022, *132* (644), 1620–1645.

Teulings, Coen N and Nikolay Zubanov, "Is economic recovery a myth? Robust estimation of impulse responses," *Journal of Applied Econometrics*, 2014, *29* (3), 497–514.

Wang, Olivier and Iván Werning, "Dynamic oligopoly and price stickiness," *American Economic Review*, 2022, *112* (8), 2815–2849.

Yeh, Chen, Claudia Macaluso, and Brad Hershbein, "Monopsony in the US labor market," *American Economic Review*, 2022, *112* (7), 2099–2138.

Heterogeneous Markups Cyclicality and Monetary Policy

Andrea Chiavari, Marta Morazzoni, and Danila Smirnov

Online Appendix

Contents

A Data Appendix

This section provides details on the variables used in the analysis. First, following standard practices in the literature and ensuring that firms in our Compustat sample face the interest rate set by the FED as their benchmark, we restrict our attention to firms that are incorporated in the US. Second, we exclude firms in utilities (SIC codes between 4900 and 4999) because they have heavily regulated prices. Finally, we exclude financial firms (SIC codes between 6000 and 6999) because their balance sheets are extremely different from those of other firms.

Furthermore, we drop all the observations in our sample with missing industry classification, as well as those observations with negative or missing sales (`SALEQ`) and cost of goods sold (`COGSQ`). Whenever applicable, we deflate variables using a GDP deflator from the NIPA tables. Table A.1 reports summary statistics for the variables used in our regression analyses.

Table A.1: Summary Statistics

	Sales	**Cogs**	**Assets**	**Leverage**	**Liquidity**	**Age (Compustat)**	**Age (Jay Ritter)**	**Markups**
Mean	447.69	303.17	4919.69	0.45	0.16	9.46	23.61	1.78
P25	6.06	3.31	37.83	0.03	0.02	4	9	1.03
P50	31.00	17.18	229.50	0.18	0.07	8	16	1.30
P75	164.58	100.60	1118.33	0.39	0.22	14	29	1.86
N	715,874	715,874	685,784	641,316	683,696	715,874	146,112	715,874

Note: Summary statistics of cleaned quarterly Compustat between 1990q1 and 2016q4. Sales, Cogs, and Assets are measured in millions of real 2012 US$, while Leverage and Liquidity are ratios and Age is in years since IPO (Compustat) and since foundation (Jay Ritter).

We exploit information on sales (`SALEQ`) to measure firm-level production, while we use the cost of goods sold (`COGSQ`) to determine the variable inputs used in production, and gross capital (`PPEGTQ`) to measure tangible capital. In line with the literature, we use selling, general, and administrative expenses (`XSGAQ`) as a measure of overhead costs, and the variable `ATQ` as a measure of total assets. Finally, we use cash and short-term investments (`CHEQ`) and short and long-term liabilities (`DLCQ` and `DLTTQ`) to compute liquidity and leverage (i.e. $\mathtt{CHEQ}/\mathtt{ATQ}$ and $\mathtt{DLCQ}/\mathtt{ATQ} + \mathtt{DLTTQ}/\mathtt{ATQ}$ respectively).

As explained in Section 3, our benchmark measure for markups is the ratio between sales and cost of goods sold, multiplied by the input-output elasticities computed by De Loecker, Eeckhout and Unger (2020).

B Firm-Level Analysis Robustness and Additional Results

B.1 Robustness

B.1.1 Excluding the ZLB

In what follows, we estimate Equation (5) between 1990q1 and 2008q4, thereby excluding the Zero Lower Bound (ZLB) period. We do this for several reasons: during the ZLB period, (i) the measure of monetary policy (MP) shocks from Jarociński and Karadi (2020) exhibits nearly no variation, and (ii) central banks favored new unconventional monetary policy practices over standard ones. Both reasons suggest that the ZLB period could be atypical and we want to ensure that this is not driving our main insights. Figure B.1 shows the result. Overall, we notice that excluding the ZLB from the period of analysis does not affect our qualitative conclusions, but increases the magnitude and significance of the estimated coefficient $\widehat{\gamma^0_{age,h}}$.

B.1.2 Excluding Future Shocks

In the following robustness analysis, we estimate an alternative specification of Equation (5) in which we do not include future monetary policy shocks as controls, and that is given by:

$$\begin{aligned}\Delta_h \log \mu_{i,t+h} = \textstyle\sum_{x\in\mathcal{X}} \left(\alpha_{x,h} + \beta_{x,h}\Delta Y_{t-1} + \textstyle\sum_{k=0}^{\kappa}\gamma^k_{x,h}\varepsilon^m_{t-k}\right) \times \mathbb{1}_{i\in\mathcal{I}^x} \\ + \textstyle\sum_{\ell=1}^{L}\boldsymbol{\delta}'_{\boldsymbol{h}}\boldsymbol{X}_{\boldsymbol{i,t-\ell}} + \varphi_{i,h} + \varphi_{s,t,h} + \boldsymbol{\vartheta}_{\boldsymbol{h}}\boldsymbol{t} + u_{i,t+h},\end{aligned} \tag{13}$$

with horizons $h = 0, 1, \ldots, H$. Figure B.2 shows the result. Overall, excluding future MP shocks from Equation (5) does not qualitatively affect our results, but it increases the downward bias present in LP models, consistent with the insights in Teulings and Zubanov (2014).

Figure B.1: Heterogeneous Markups Cyclicality - No Zero Lower Bound Period

(a) Age **(b)** Sales Share **(c)** Assets

(d) Liquidity **(e)** Leverage **(f)** Markups

Note: Figure B.1 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with all covariates and for horizons $h = 1, ..., 16$, limiting the sample between 1990q1 and 2008 q4 (before the zero lower bound period). Figure B.1 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

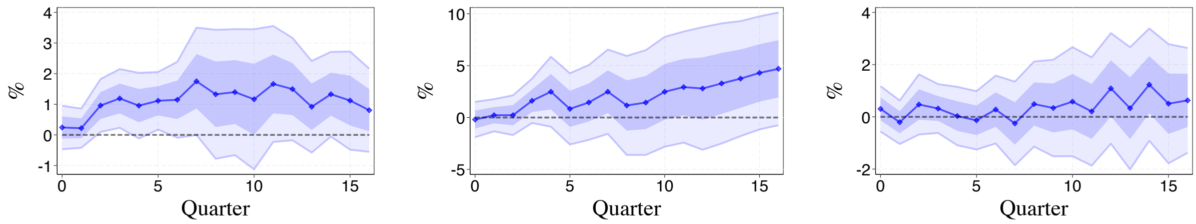
B.1.3 Linear Parametric Interaction

In the following exercise, we estimate an alternative specification of Equation (5) in which we use a linear parametric approach, similarly in spirit to the analysis in Ottonello and Winberry (2020). Instead of characterizing firms with dummies, we linearly interact the MP shock series with measures of firm age, assets, sales share, leverage, liquidity and markup, and estimate:

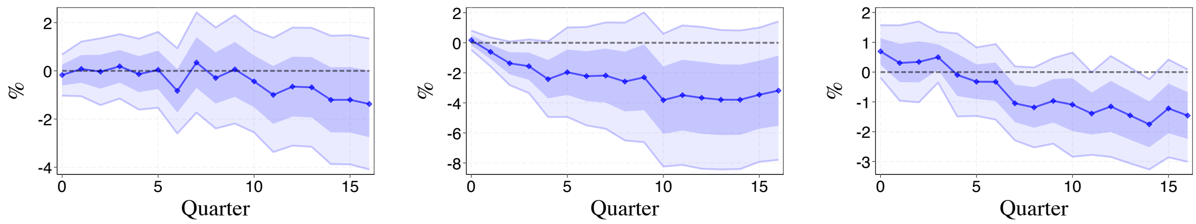
$$\begin{aligned}\Delta_h \log \mu_{i,t+h} = \textstyle\sum_{x\in\mathcal{X}} \left(\alpha_{x,h} + \beta_{x,h}\Delta Y_{t-1} + \sum_{k=-\kappa}^{h} \gamma^k_{x,h}\varepsilon^m_{t+k} \right) \times x_{t-1} \\ + \textstyle\sum_{\ell=1}^{L} \boldsymbol{\delta}'_h \mathbf{X}_{i,t-\ell} + \varphi_{i,h} + \varphi_{s,t,h} + \boldsymbol{\vartheta}_h \boldsymbol{t} + u_{i,t+h},\end{aligned} \tag{14}$$

for horizons $h = 0, 1, \ldots, H$. Figure B.3 shows our results. Overall, we notice that the coefficients estimated through Equation (14) still reflect the main insights of

Figure B.2: Heterogeneous Markups Cyclicality - Excluding Future Shocks



(a) Age **(b)** Sales Share **(c)** Assets



(d) Liquidity **(e)** Leverage **(f)** Markups

Note: Figure B.2 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with all covariates except for future MP shocks (note that the baseline estimation contains instead 4 leads), and for horizons $h = 1, ..., 16$. Figure B.2 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

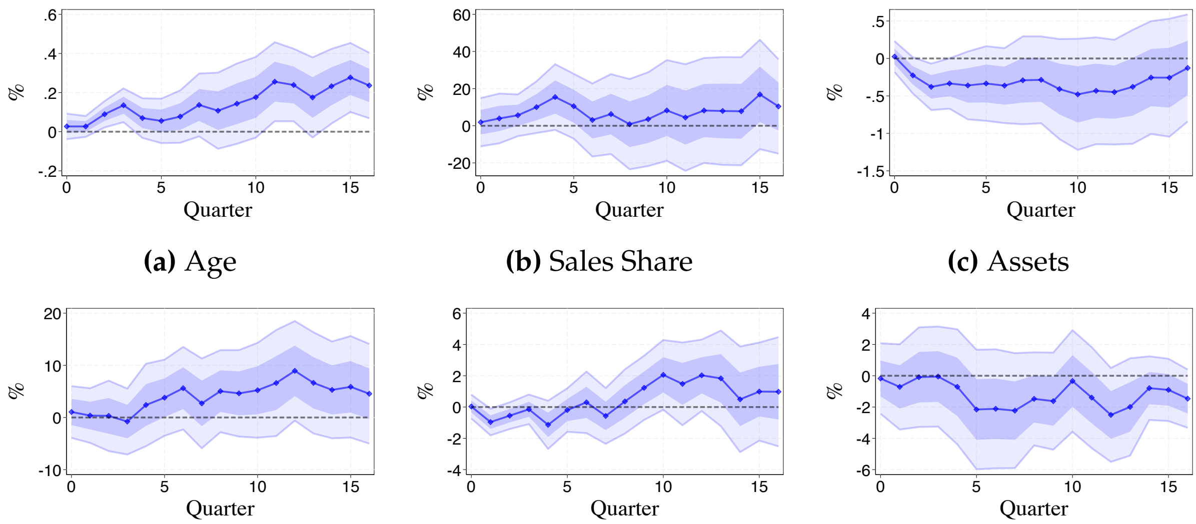
our benchmark specification. Specifically, Figure B.3 confirms that older firms show more countercyclical markups in response to MP shocks, while there is no evident heterogeneity in the response of markups by firms' size, sales share, leverage, liquidity, or the level of their markup.

B.1.4 Monetary Policy Shocks from Gürkaynak, Sack and Swanson (2005)

Here, we estimate Equation (5) using an alternative monetary policy shocks measure from Gürkaynak, Sack and Swanson (2005). Their series is similar compared to the one in Jarociński and Karadi (2020) but it does not take into account the information channel of monetary policy.

Figure B.4 shows the results. Overall, using alternative MP shocks by Gürkaynak, Sack and Swanson (2005) produces a set of impulse response functions (IRFs) that is both qualitatively and quantitatively close to the benchmark one, with stronger statis-

Figure B.3: Heterogeneous Markups Cyclicality - Linear Parametric Specification



(a) Age **(b)** Sales Share **(c)** Assets

(d) Liquidity **(e)** Leverage **(f)** Markups

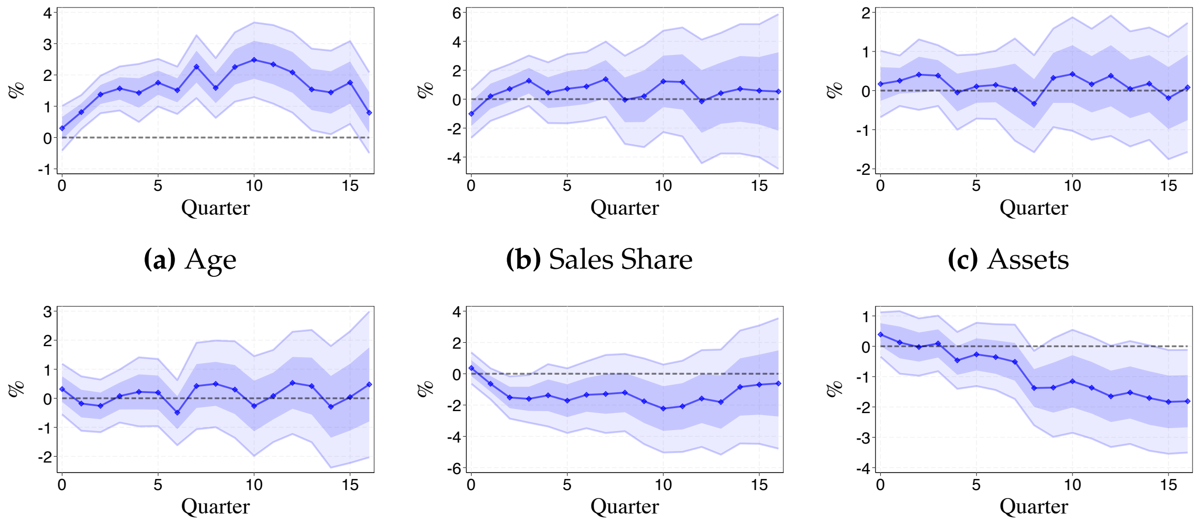
Note: Figure B.3 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (14) using a linear parametric approach, with all covariates and for horizons $h = 1, ..., 16$. Figure B.3 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

tical significance.

B.1.5 Using Founding Age by Jay Ritter

In the robustness analysis that follows, we estimate Equation (5) using the "true" founding age of firms instead of corporate age, which is made available by Jay Ritter for a subsample of Compustat (about 20% of the observations approximately, hence a significant empirical limitation if we were to use only founding age in our baseline estimation). Results are shown in Figure B.5. Overall, we see that using this alternative measure of firm age does not significantly alter our main conclusions. In particular, older firms keep their markups relatively higher compared to young ones after the arrival of an MP shock. Neither leverage, liquidity or absolute size (measured in assets) are strong predictors of heterogeneity in markup responses to a monetary tightening, as is also the case for sales share and the markup level.

Figure B.4: Heterogeneous Markups Cyclicality - Gürkaynak, Sack & Swanson (2005)



(a) Age **(b)** Sales Share **(c)** Assets

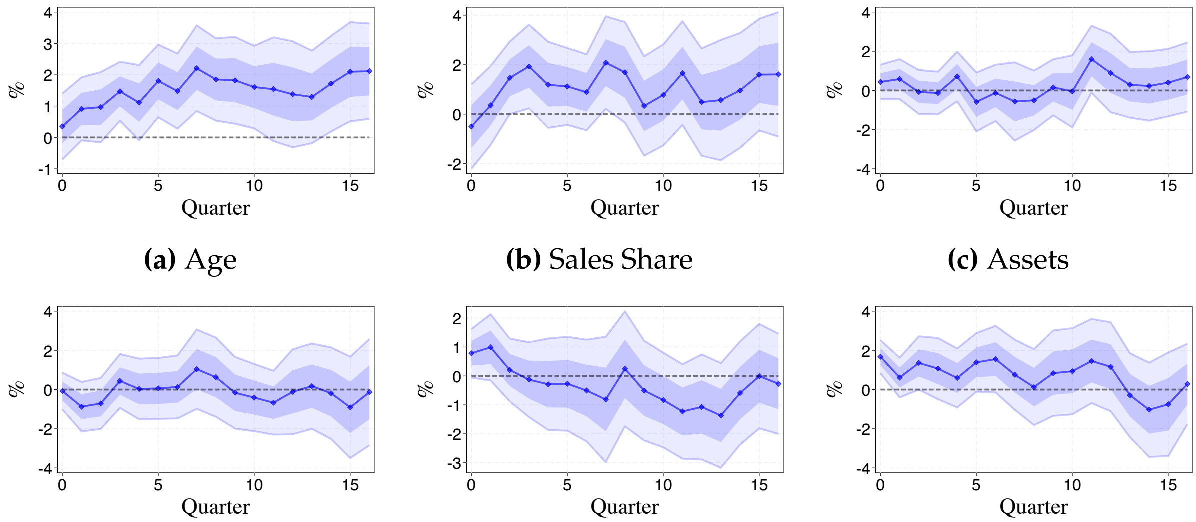
(d) Liquidity **(e)** Leverage **(f)** Markups

Note: Figure B.4 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. We use the MP shocks series exogenously identified in Gürkaynak, Sack and Swanson (2005). Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with covariates and for horizons $h = 1, ..., 16$. Figure B.4 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

B.1.6 Grouping Firms by Sector and Quarter

In the following exercise, we estimate Equation (5) using a different definition for firms' groups $\mathbb{1}_{i \in \mathcal{I}^x}$. In the main analysis, we define firms' dummies by being above or below the median of $x \in \mathcal{X} = \{age, \textit{sales share}, leverage, liquidity, assets\}$, considering the entire sample and according to firms' characteristics in the previous year. Here, we instead define firms' dummies by being above or below the median of those same variables but within a given sector and a given quarter of the previous year. Figure B.6 shows the result. Overall, using a different definition of $\mathbb{1}_{i \in \mathcal{I}^x}$ does not change our conclusions, suggesting that our results do not depend on the particular definition of the dummies capturing firm-level heterogeneity.

Figure B.5: Heterogeneous Markups Cyclicality - Using Founding Age



(a) Age **(b)** Sales Share **(c)** Assets

(d) Liquidity **(e)** Leverage **(f)** Markups

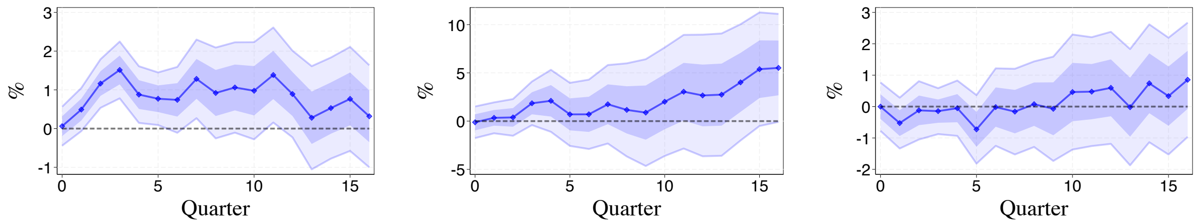
Note: Figure B.5 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. We use the founding age of firms in Compustat as collected in the database by Jay Ritter. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with covariates and for horizons $h = 1, ..., 16$. Figure B.5 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

B.1.7 Using Alternative Elasticities

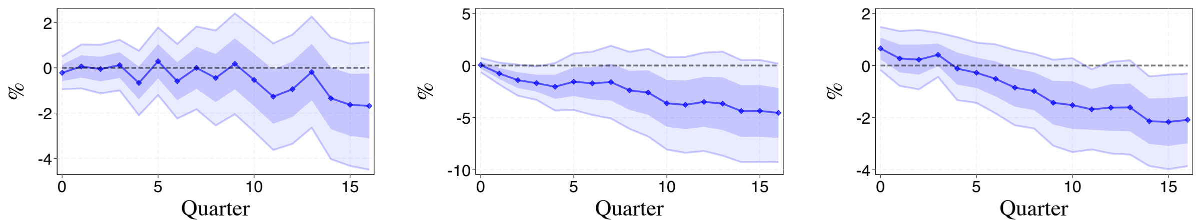
In the following robustness exercise, we estimate Equation (5) using firm-level markups calculated with different production function elasticities. In particular, instead of using the elasticities provided by De Loecker, Eeckhout and Unger (2020), which are common for all the quarters within a year, we calculate our own input-output elasticities allowing them to vary at a quarter level. In particular, we estimate (i) a Cobb-Douglas production function which varies at quarter and sector levels, and (ii) a Translog production function which also varies at quarter and sector levels. Note that this second specification also allows us to have production function elasticities that are heterogeneous across firms within sectors and quarters.[12]

[12]The elasticity coming from the Translog production function is a function of firm-level capital stock (PPEGT in Compustat). For data quality, we interpolate between adjacent points our estimates whenever this item is missing. We check that this does not affect results, although it improves estimation precision.

Figure B.6: Heterogeneous Markups Cyclicality - Sector/Quarter Dummies



(a) Age **(b)** Sales Share **(c)** Assets



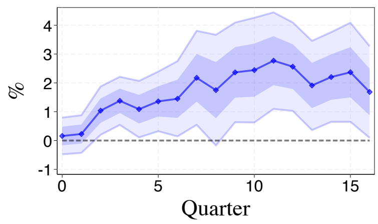
(d) Liquidity **(e)** Leverage **(f)** Markups

Note: Figure B.6 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. We construct dummies equal to one if the variable is above the median within a sector and quarter. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with covariates and for horizons $h = 1, ..., 16$. Figure B.6 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

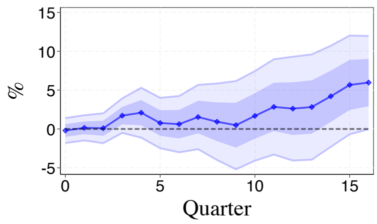
Results are shown in Figure B.7 and B.8. The Cobb-Douglas specification shows similar patterns regarding the magnitude and significance of the estimated coefficients compared to our benchmark. The Translog specification shows instead much noisier estimates, and the IRF of relatively older firms is significant at the 90% level only in quarter 11. Admittedly, estimating Translog production functions imposes heavy requirements on the data.

The somewhat mixed results of this specific robustness check call for a more cautious interpretation of the main findings regarding the different cyclicality of markups by firm-specific characteristics. However, they still suggest that the firm-level heterogeneous markup cyclicality we uncovered may not be just driven by heterogeneity in firm-level input-output elasticities, but also by heterogeneity in the firm-level ratio of sales to variable costs.

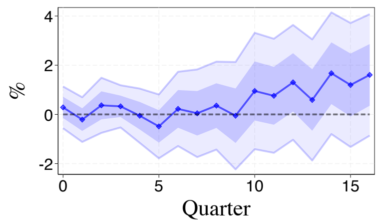
Figure B.7: Heterogeneous Markups Cyclicality - Cobb-Douglas Elasticity



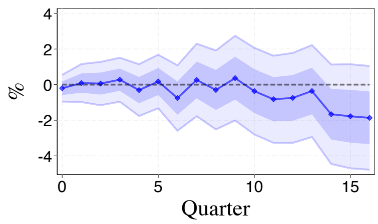
(a) Age



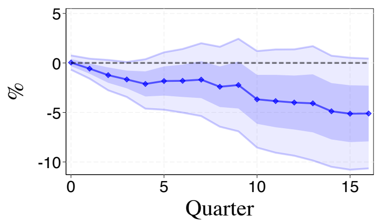
(b) Sales Share



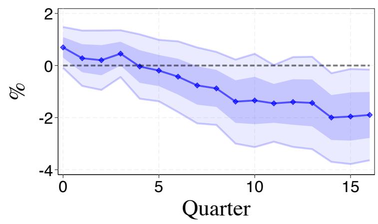
(c) Assets



(d) Liquidity



(e) Leverage



(f) Markups

Note: Figure B.7 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. When measuring firm-level markups, we calculate the input-output elasticity $\theta^{v}_{s,t}$ in Equation (4) by estimating a Cobb-Douglas production function that varies at quarter and sector-level. Coefficients $\widehat{\gamma^{0}_{x,h}}$ are shown for the estimation of Equation (5) with covariates and for horizons $h = 1, ..., 16$. Figure B.7 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^{0}_{x,h}}$. Standard errors clustered at the firm and quarter level.

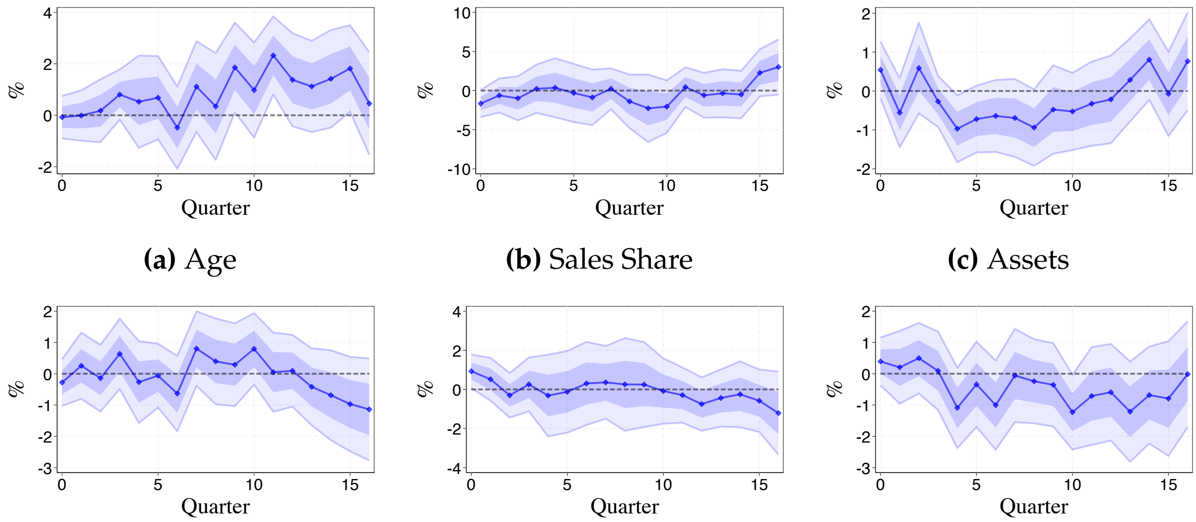
B.1.8 Using Alternative Markups Measure

In this exercise, we estimate again Equation (5) using firm-level markups calculated with a different methodology compared to that presented in Equation (4). In particular, we follow the "accounting-profit approach" adopted by Baqaee and Farhi (2020), where markups are:

$$\mu = \frac{v}{1-\ell} \quad \text{and} \quad \ell = \frac{\texttt{OIBDPQ} - \texttt{DPQ}}{\texttt{SALEQ}}, \tag{15}$$

v are the returns to scale in the firm's technology, and $\texttt{OIBDPQ} - \texttt{DPQ}$ denotes operating income before depreciation, net of depreciation. We first compute this measure — also known as the Lerner Index — imposing constant returns to scale across all firms, namely $v = 1$. Second, we allow for returns to scale to be heterogeneous across firms,

Figure B.8: Heterogeneous Markups Cyclicality - Translog Elasticity



(a) Age **(b)** Sales Share **(c)** Assets

(d) Liquidity **(e)** Leverage **(f)** Markups

Note: Figure B.8 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. When measuring firm-level markups, we calculate the input-output elasticity $\theta^{v}_{s,t}$ in Equation (4) by estimating a Translog production function that varies at quarter and sector level. Coefficients $\widehat{\gamma^{0}_{x,h}}$ are shown for the estimation of Equation (5) with covariates and for horizons $h = 1, ..., 16$. Figure B.8 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^{0}_{x,h}}$. Standard errors clustered at the firm and quarter level.

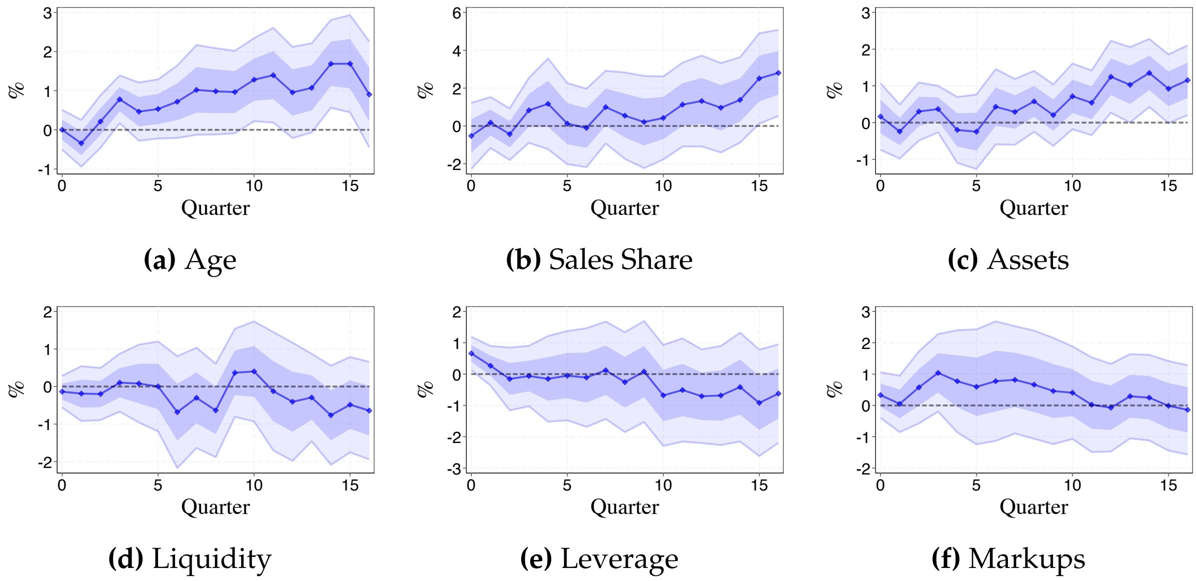
and informed by the Translog production-function estimation we have carried out in Section B.1.7.

Results are shown in Figure B.9 and B.10. Overall, using these alternative measures of market power, often considered second-best compared to our main measure, does not affect the qualitative implications of our results. We stress though that it dampens the magnitude and statistical significance of the firm-age coefficients compared to our benchmark estimates from the main analysis (i.e. coefficients are significant at the 90% level only in few quarters).

B.1.9 Excluding All Controls

In this exercise, we estimate again Equation (5) but excluding most of the controls from the analysis, to show that results are not driven by their inclusion. Specifically,

Figure B.9: Heterogeneous Markups Cyclicality - Alternative Markup Measure



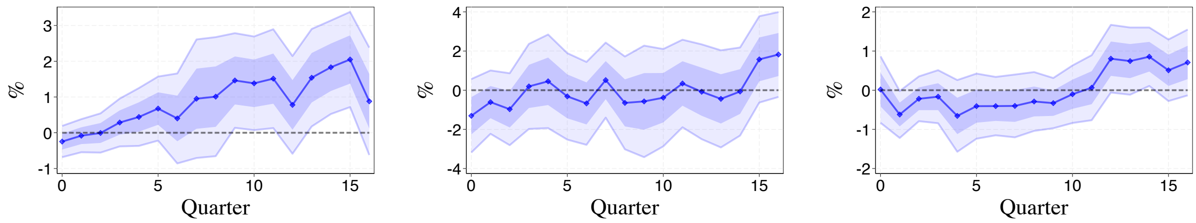
Note: Figure B.9 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. We use the Lerner index as an alternative measure to firms' markups, as defined in Equation (15). Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with covariates and for horizons $h = 1, ..., 16$. Figure B.9 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

we remove the interaction of the MP hock series with past GDP, as well as aggregate and firm-level controls. Recall that macro-level controls include GDP and CPI growth, changes in the 1-year Treasury rate, and the EBP (and 4 lags for each variable). Firm-level controls comprise sales growth and overhead costs relative to sales (and 4 lags for each variable). Results are presented in Figure B.11 and show no major qualitative change to our preferred specification.

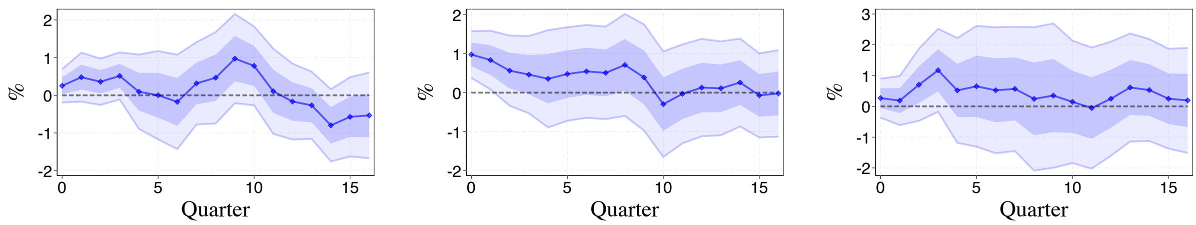
B.1.10 Excluding All Fixed Effects

In this exercise, we estimate again Equation (5) but excluding both firm and sector-time fixed effects, to show that results are not driven by their inclusion. Results are presented in Figure B.12 and show no significant qualitative change to our preferred specification.

Figure B.10: Heterogeneous Markups Cyclicality - Alternative Markup Measure without Constant Returns to Scale



(a) Age **(b)** Sales Share **(c)** Assets



(d) Liquidity **(e)** Leverage **(f)** Markups

Note: Figure B.10 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. We use the Lerner index as an alternative measure to firms' markups, as defined in Equation (**??**) and exploiting the Translog returns to scale estimated in B.8. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with covariates and for horizons $h = 1, ..., 16$. Figure B.9 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

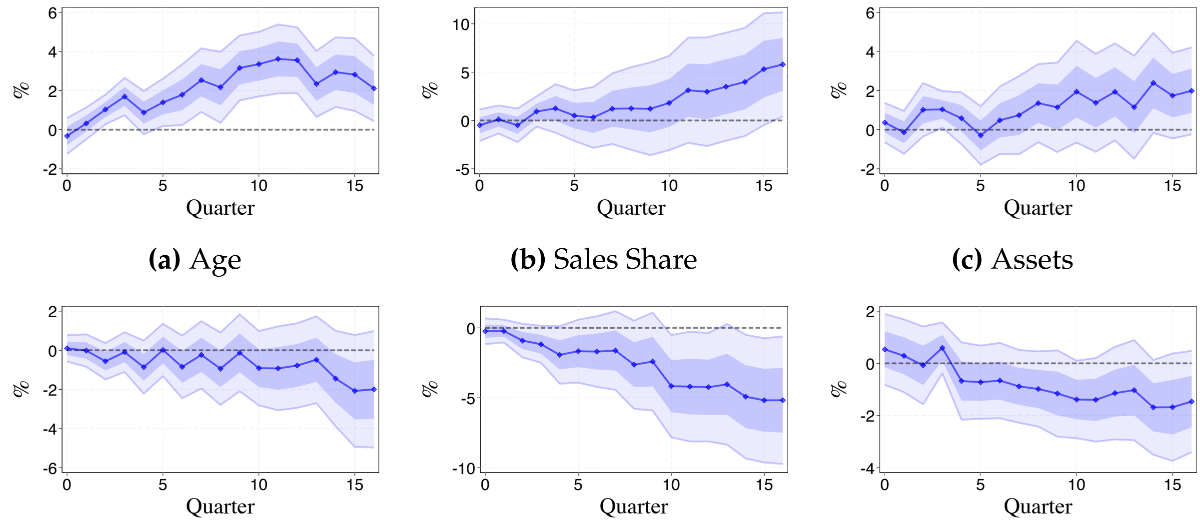
B.1.11 Using Dynamic Panel Data Approaches to Markups Measurement

Although in the main text we used output elasticities estimated with structural production function estimators following the approach in De Loecker et al. (2020), these estimators face their own challenges in the context of market power. These challenges arise both in the first-stage inversion (e.g., Bond et al., 2021) and when estimating gross output production functions (e.g., Flynn et al., 2019, Gandhi et al., 2020).

Because of this, here we exploit dynamic panel data approaches that do not require the first stage inversion, at the cost of assuming log-linear productivity dynamics. In particular, we estimate the output elastiticies of the production function using Arellano and Bond (1991) with non-constant and constant returns to scale and Blundell and Bond (1998) with non-constant returns to scale.

To address this, we exploit dynamic panel data approaches that do not require the

Figure B.11: Heterogeneous Markups Cyclicality - No Controls



(a) Age **(b)** Sales Share **(c)** Assets

(d) Liquidity **(e)** Leverage **(f)** Markups

Note: Figure B.11 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with all covariates and for horizons $h = 1, ..., 16$, but without any control. Figure B.11 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

first-stage inversion, at the cost of assuming log-linear productivity dynamics. Specifically, we estimate the output elasticities of the production function using Arellano and Bond (1991) with both non-constant and constant returns to scale, and Blundell and Bond (1998) with non-constant returns to scale.

Figure B.13 shows the results for the output elasticity estimated using Arellano and Bond (1991) with non-constant returns to scale. Figure B.14 shows the results for the output elasticity estimated using Arellano and Bond (1991) with constant returns to scale. Figure B.15 shows the results for the output elasticity estimated using Blundell and Bond (1998) with non-constant returns to scale. Overall, we find that all these different specifications yield results quantitatively similar to our baseline specification in the main text.

Figure B.12: Heterogeneous Markups Cyclicality - No Fixed Effects

(a) Age **(b)** Sales Share **(c)** Assets

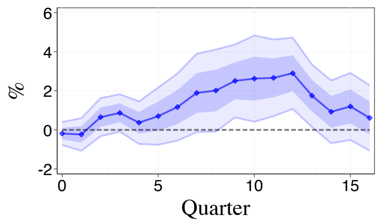
(d) Liquidity **(e)** Leverage **(f)** Markups

Note: Figure B.12 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with all covariates and for horizons $h = 1, ..., 16$, but without any FE. Figure B.12 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

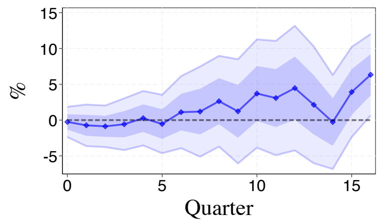
B.2 Relative Response of Sales and Cogs

Figure B.16 and Figure B.17 present additional results on the relative response of sales and cost of goods sold — the two main components of our firm-level markup estimator — across various firm characteristics, conditional on a MP shock. Despite its weak statistical significance (IRFs are significant at the 90% level only in few quarters), we find that firm age is the most relevant predictor of heterogeneity in response to MP shocks for both sales and cost of goods sold. Moreover, while both variables show a negative response, the cost of good sold declines more strongly and significantly for old firms, compared to firm sales, which is consistent with the relative increase of markups for old firms conditional on a contractionary MP shock.

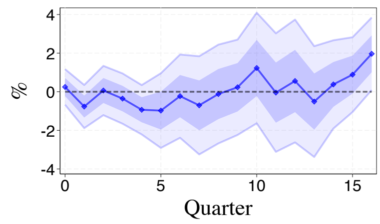
Figure B.13: Heterogeneous Markups Cyclicality - Arellano Bond Estimator w/o CRTS



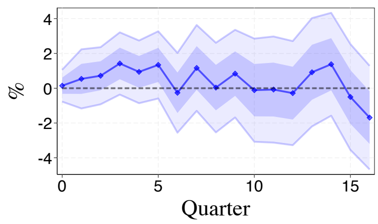
(a) Age



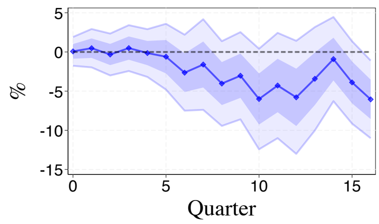
(b) Sales Share



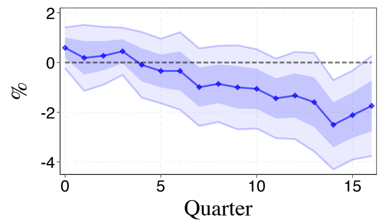
(c) Assets



(d) Liquidity



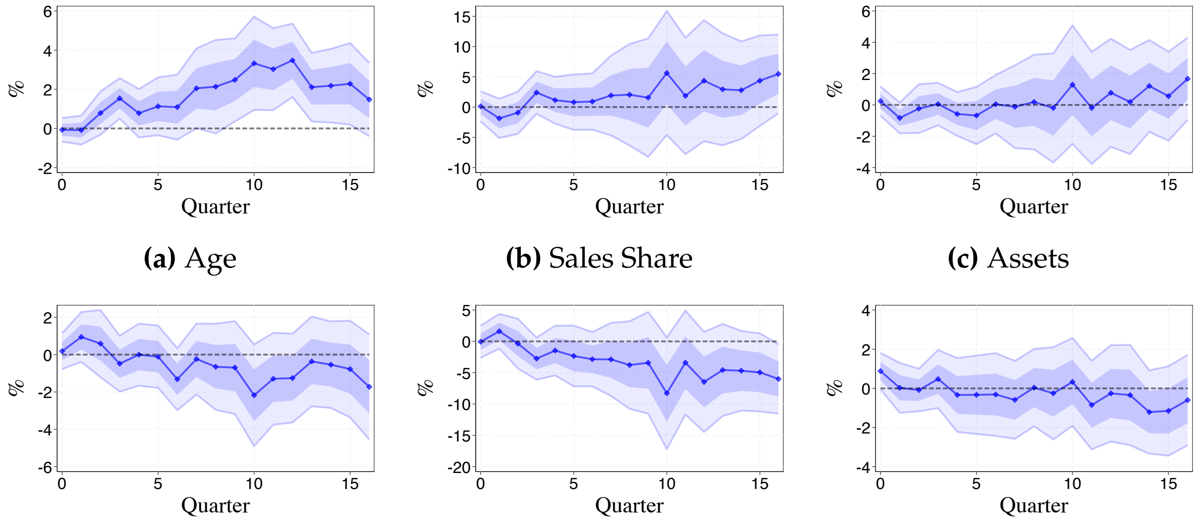
(e) Leverage



(f) Markups

Note: Figure B.13 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with all covariates and for horizons $h = 1, ..., 16$, limiting the sample between 1990q1 and 2008 q4 (before the zero lower bound period). Figure B.13 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

Figure B.14: Heterogeneous Markups Cyclicality - Arellano Bond Estimator w/ CRTS

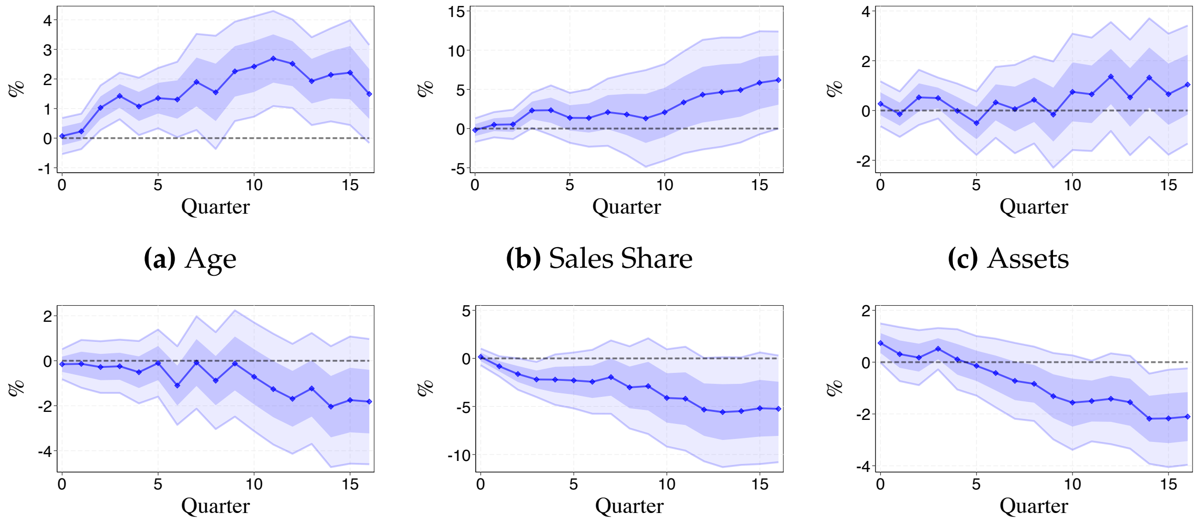


(a) Age **(b)** Sales Share **(c)** Assets

(d) Liquidity **(e)** Leverage **(f)** Markups

Note: Figure B.14 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with all covariates and for horizons $h = 1, ..., 16$, limiting the sample between 1990q1 and 2008 q4 (before the zero lower bound period). Figure B.14 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

Figure B.15: Heterogeneous Markups Cyclicality - Blundell Bond Estimator w/o CRTS



(a) Age

(b) Sales Share

(c) Assets

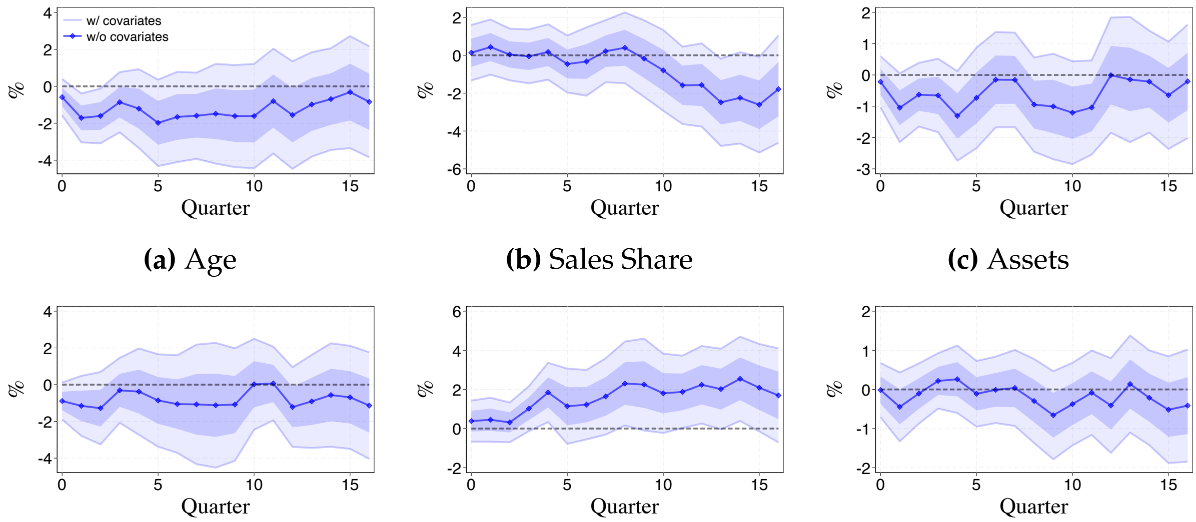
(d) Liquidity

(e) Leverage

(f) Markups

Note: Figure B.15 shows the relative markup response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with all covariates and for horizons $h = 1, ..., 16$, limiting the sample between 1990q1 and 2008 q4 (before the zero lower bound period). Figure B.15 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$. Standard errors clustered at the firm and quarter level.

Figure B.16: Heterogeneous Sales Cyclicality By Firm-Level Characteristics

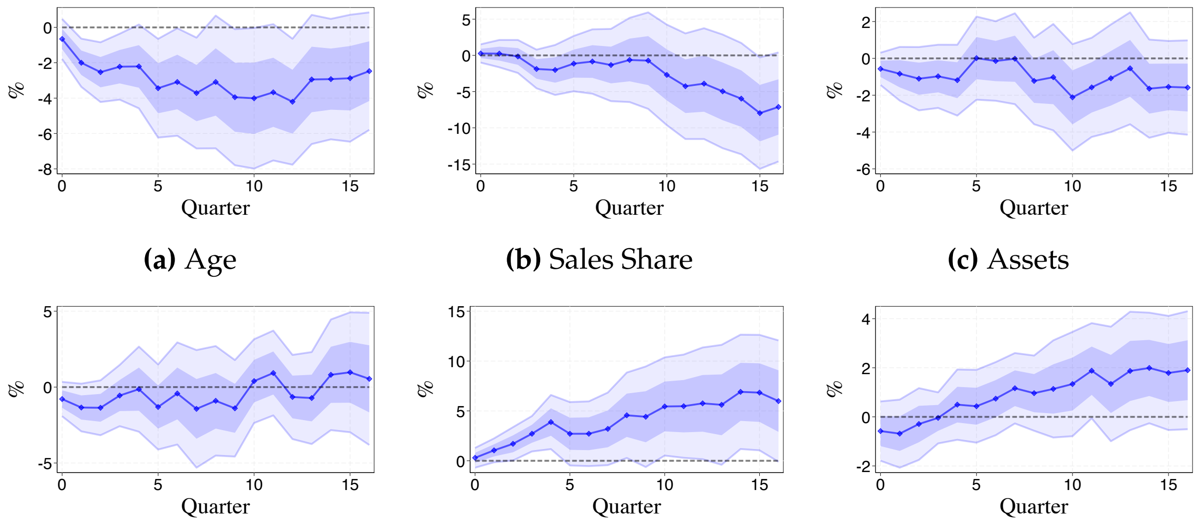


(a) Age **(b)** Sales Share **(c)** Assets

(d) Liquidity **(e)** Leverage **(f)** Markups

Note: Figure B.16 shows the relative sales response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with covariates and for horizons $h = 1, ..., 16$. Note that Figure B.16 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$ when estimating Equation (5) with all covariates. Standard errors clustered at the firm and quarter level.

Figure B.17: Heterogeneous Variable Costs Cyclicality By Firm-Level Characteristics



(a) Age **(b)** Sales Share **(c)** Assets

(d) Liquidity **(e)** Leverage **(f)** Markups

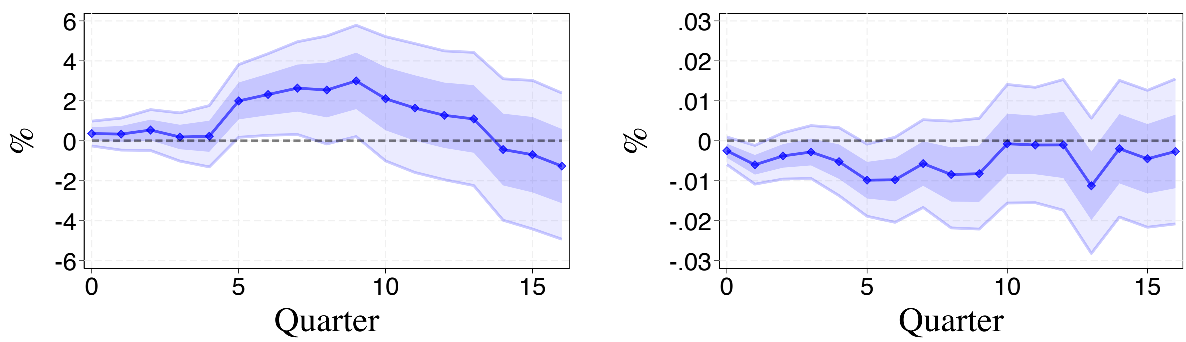
Note: Figure B.17 shows the relative variable costs response of (a) old vs young, (b) high vs low sales share, (c) big vs small, (d) high vs low liquidity, (e) high vs low leverage, (f) high vs low markup firms conditional on a MP shock. Coefficients $\widehat{\gamma^0_{x,h}}$ are shown for the estimation of Equation (5) with covariates and for horizons $h = 1, ..., 16$. Note that Figure B.17 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^0_{x,h}}$ when estimating Equation (5) with all covariates. Standard errors clustered at the firm and quarter level.

C Aggregate Implications: Additional Exercises

C.1 Direct and Indirect Effects

In what follows, we decompose the IRF estimated in Figure 4 to highlight the contribution of both the direct ad indirect effect of firm-level dynamics to the conditional cyclicality of the aggregate markup, as specified in Equation (9). Interestingly, Figure C.18 clarifies that the heterogeneous impact on markups across different firm-age groups is what quantitatively matters for the aggregate markup cyclicality in response to MP shocks. The indirect effect determines the reallocation of costs across firms discussed in Section 4.2.4, but remains quantitatively weak. This is due to the fact that the markups of young and old firms, irrespective of the age measure used, are quite similar — i.e., $(\mu_O - \mu_Y)/\mathcal{M}$ is approximately zero.

Figure C.18: Direct and Indirect Effects



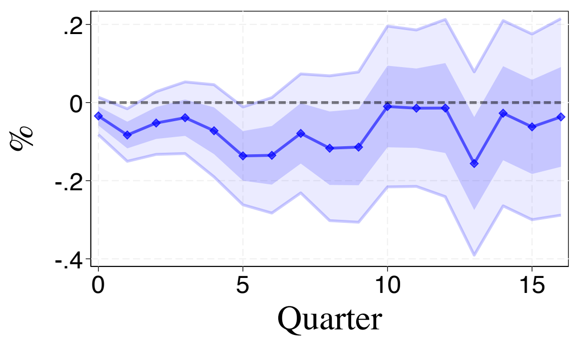
(a) Direct Effect **(b)** Indirect Effect

Note: Figure C.18a and Figure C.18b present the direct and indirect effects as defined in Equation (9). The IRFs are normalized to a 25 basis point contractionary MP shock. The dark blue line with squares represents the results obtained using our baseline measure of age. The dark and light blue shaded areas indicate the 68% and 90% confidence intervals around the point estimates, respectively.

C.2 Sales-Weighted Markup Aggregation

If we compute the aggregate markup as the sales — instead of the variable cost — weighted average of firm-level markups, we can examine how sales reallocate between young and old firms in response to MP shocks, as suggested by the conceptual framework outlined in Section (2). For this, we use Equation (5), but with firm-level sales shares as dependent variable on the left-hand side instead of firm-level (log) markups. Note that since the sum of sales responses to a MP shock between the two firm-age groups must be zero by construction, identifying the relative sales share response for old firms is equivalent to identifying the level of the sales-share response of old firms. Figure C.19 illustrates the response of sales shares for older firms following a contractionary MP shock of 25 b.p. and show a similar pattern to the one estimated for variable cost-shares in Figure 3. Specifically, there is reallocation of sales (and variable costs) from old to young firms, mirroring the theoretical result in Baqaee, Farhi and Sangani (2024), which describes a reallocation from large to small firms after a MP tightening.

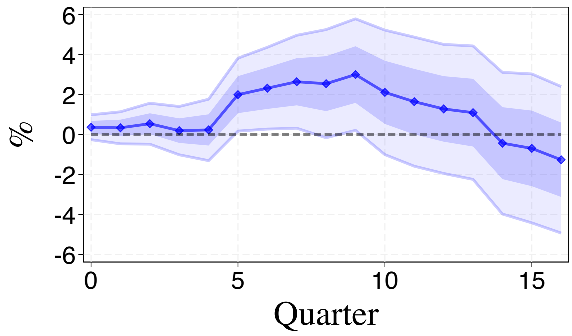
Figure C.19: Heterogeneous Sale Shares Cyclicality



Note: Figure C.19 shows the variable sale shares response of old firms conditional on a MP shock. Coefficients $\widehat{\gamma^{0}_{x,h}}$ are shown for the estimation of Equation (5) with covariates and for horizons $h = 1, ..., 16$. Note that Figure 3 is normalized to a 25 basis points contractionary MP shock. The dark and light blue areas report the 68% and the 90% confidence intervals around $\widehat{\gamma^{0}_{x,h}}$. Standard errors clustered at the firm and quarter level.

Using our baseline measure of age, we find that the share of variable sales for firms above the median age, ω^{s}_{O}, is 0.76; the variable sales-weighted markups for older firms, μ_O, is 1.62; the variable sales-weighted markups for younger firms, μ_Y, is 1.57; and the aggregate markup using sales instead of costs-weights, $\mathcal{M}$, is 1.61. Notice that here the aggregate markups is higher than the one calculated with cost shares, as explained in De Loecker et al. (2020).

Figure C.20: Aggregate Sales-Weighted Markup Cyclicality



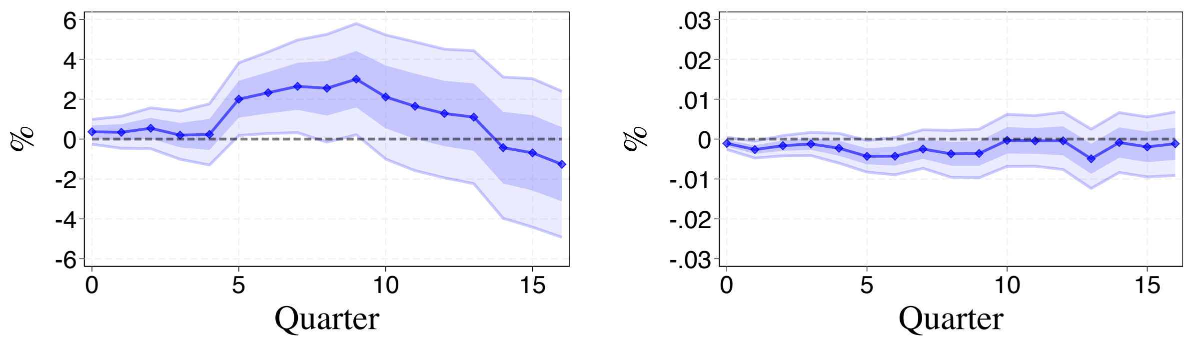
Note: Figure C.20 presents the aggregate markup response conditional on a MP shock, derived using Equation (9). The results in Figure C.20 are normalized to a 25 basis point contractionary MP shock. The dark blue line with squares represents the results obtained using our baseline measure of age. The dark and light blue shaded areas indicate the 68% and 90% confidence intervals around the point estimates, respectively.

By combining these numbers with our IRF estimates from Section 4 and Equation (9), we now compute the IRF of the aggregate markup in response to a MP shock, as well as its decomposition by direct and indirect effect. Figure C.20 shows that — conditional on a 25 b.p. MP tightening — the estimated sales-weighted markup cyclicality qualitatively and quantitatively reflect the cost-weighted markup cyclicality presented in our baseline specification (Figure 4). Similarly, Figure C.21 confirms that the "direct effect", summarized by the heterogeneous markup responses across different firm-age groups following a MP shock, is what drives the conditional countercyclicality of the aggregate markup. This is regardless of whether the aggregate markup is weighted using sales shares or cost shares, as in Figure C.18.

C.3 Changing Firm-Level Responses Over Time

In what follows, we estimate an alternative version of Equation (5) to show that firm-level markup cyclicality across different age groups has not changed over time, as firms' differential responses before and after 2000 are estimated to be close to zero. Figure C.22 illustrates the results of this estimation and suggests therefore that the shift in the response of the aggregate markup to MP shocks over time should be driven by

Figure C.21: Direct and Indirect Effects of Sales-Weighted Aggregate Markup



(a) Direct Effect

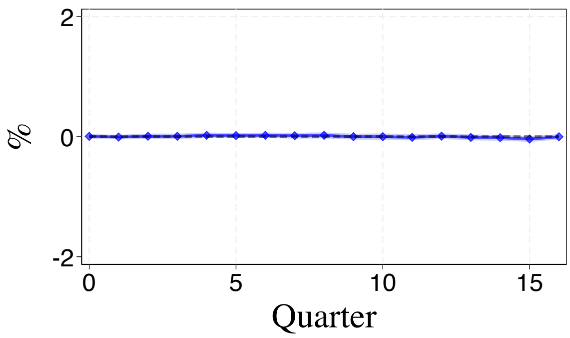
(b) Indirect Effect

Note: Figure C.21a and Figure C.21b present the direct and indirect effects as defined in Equation (9). The IRFs are normalized to a 25 basis point contractionary MP shock. The dark blue line with squares represents the results obtained using our baseline measure of age. The dark and light blue shaded areas indicate the 68% and 90% confidence intervals around the point estimates, respectively.

changes in the distribution of firms over time, and not by changes in the responsiveness of a particular group of firms over time.

$$\begin{aligned}\Delta_h \log \mu_{i,t+h} = &\sum_{x\in\mathcal{X}}\left(\alpha_{x,h} + \beta_{x,h}\Delta Y_{t-1} + \sum_{k=-\kappa}^{h}\gamma^{k}_{x,h}\varepsilon^{m}_{t+k}\right) \times \mathbb{1}_{i\in\mathcal{I}^x} \\ &+ \sum_{x\in\mathcal{X}}\left(\alpha_{t\geq 2000q4,x,h} + \beta_{t\geq 2000q4,x,h}\Delta Y_{t-1} + \sum_{k=-\kappa}^{h}\gamma^{k}_{t\geq 2000q4,x,h}\varepsilon^{m}_{t+k}\right) \\ &\times \mathbb{1}_{i\in\mathcal{I}^x} \times \mathbb{1}_{t\geq 2000q4} + \sum_{\ell=1}^{L}\boldsymbol{\delta}'_h \boldsymbol{X}_{i,t-\ell} + \varphi_{i,h} + \varphi_{s,t,h} + \boldsymbol{\vartheta}_h \boldsymbol{t} + u_{i,t+h}\end{aligned} \tag{16}$$

Figure C.22: Changing Firm-Level Responses Over Time



Note: Figure C.22 presents the estimate change before and after 2000 in the differential response of old relative to young firms. The results in Figure C.22 are normalized to a 25 basis point contractionary MP shock. The dark blue line with squares represents the point estimates. The dark and light blue shaded areas indicate the 68% and 90% confidence intervals around the point estimates, respectively.