# Monetary Policy, Markup Dispersion, and Aggregate TFP*

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**Abstract**

Motivated by empirical evidence that monetary policy affects aggregate TFP, we study the role of markup dispersion for monetary transmission. Empirically, we show that the response of markup dispersion to monetary policy shocks can account for a significant fraction of the aggregate TFP response in the first two years after the shock. Analytically, we show that heterogeneous price rigidity can explain the response of markup dispersion if firms have a precautionary price setting motive, which is present in common New Keynesian environments. We provide empirical evidence on the relationship between markups and price rigidity in support of this explanation. Finally, we study the mechanism and its implications in a quantitative model.

**Keywords:** Monetary policy, markup dispersion, heterogeneous price rigidity, aggregate productivity.

**JEL codes:** E30, E50.

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# 1 Introduction

We revisit one of the long-standing questions in macroeconomics: What are the channels through which monetary policy affects real economic outcomes? Our paper is motivated by empirical evidence that monetary policy shocks have sizable effects on measured aggregate productivity.[1] A potential explanation for fluctuations in measured aggregate TFP is changing resource misallocation across firms. The TFP-misallocation link has been widely studied in the macro-development literature (e.g., Hsieh and Klenow, 2009), and is well understood in the New Keynesian literature. While in New Keynesian models, misallocation is commonly captured by price dispersion, our preferred empirical measure of misallocation is dispersion in markups across firms. Markup dispersion is price dispersion when controlling for differences in marginal costs across firms.

We study the role of markup dispersion for monetary transmission by asking two questions: First, does markup dispersion respond to monetary policy shocks? Using US data, we document a significant response of markup dispersion, which can account for a significant fraction of the aggregate TFP response up to two years after the shock. Second, what explains the response of markup dispersion? Analytically, we show that heterogeneity in price setting frictions – in an otherwise standard New Keynesian framework – can explain the response of markup dispersion. The fundamental reason is that firms with stickier prices have a stronger precautionary price setting motive. This channel has testable implications, which, as we show, are supported empirically. Finally, we study the mechanism and its implications in a quantitative model.

We estimate the response of markup dispersion to monetary policy shocks based on quarterly balance-sheet data and high-frequency identified monetary policy shocks. A central contribution of this paper is to show that the dispersion of markups across firms (within industries) significantly increases after contractionary monetary policy shocks and decreases after expansionary monetary policy shocks. The response is persistent and peaks about two years after the shock. To translate the estimated response of markup dispersion into an aggregate TFP response, we follow Hsieh and Klenow (2009) and Baqaee and Farhi (2020). The response of markup dispersion implies a response in aggregate TFP between -0.2% and -0.4% two years after a one standard deviation contractionary monetary policy shock. For comparison, the directly estimated empirical response of utilization-adjusted aggregate TFP is -0.4% at a two-year horizon. At more distant horizons, markup dispersion accounts for a decreasing fraction of the aggregate TFP response.

[1] Using US data, we document that monetary policy shocks lower measured aggregate productivity, which reconfirms the evidence in Evans and Santos (2002), Christiano et al. (2005), Moran and Queralto (2018), Garga and Singh (2019), and Jordà et al. (2020).

Our evidence sheds new light on the TFP effects of monetary policy. Strikingly, the estimated response of markup dispersion cannot be explained by a large class of New Keynesian models, at least when solved with standard perturbation methods. In many New Keynesian models, including medium-scale models (e.g., Christiano et al., 2005) and models with heterogeneous price rigidity (e.g., Carvalho, 2006), markup dispersion does not respond to monetary policy shocks up to a first-order approximation around the deterministic steady state. In the second-order approximation, markup dispersion responds, but counterfactually increases in response to both positive and negative shocks. In models with trend inflation (e.g., Ascari and Sbordone, 2014), markup dispersion decreases after contractionary and increases after expansionary monetary shocks, which contradicts our empirical evidence.

What can explain the response of markup dispersion to monetary policy shocks instead? We propose a novel mechanism that arises from heterogeneity in the severity of price setting frictions across firms. A sufficient condition for higher markup dispersion after a monetary tightening is that firms with higher markups have lower pass-through from marginal costs to prices, i.e., relatively strong price setting frictions. A contractionary monetary shock that lowers marginal costs increases the relative markup of low pass-through firms, which increases markup dispersion. Analogously, expansionary monetary shocks that raise marginal costs will lower markup dispersion. We show that a negative correlation between firm-level markup and pass-through can arise endogenously from heterogeneity in price-setting frictions. The types of price-setting frictions we consider are a Calvo (1983) friction, Taylor (1979) staggered price setting, Rotemberg (1982) convex adjustment costs, and Barro (1972) menu costs. The intuition for this negative correlation is a precautionary price setting motive. The firm profit function in the common New Keynesian environment is asymmetric, i.e., it penalizes markups below more than markups above the static optimal one. A higher reset markup provides insurance against low profits before the next price adjustment opportunity (Calvo/Taylor), or lowers the expected costs of future price re-adjustments (Rotemberg/Barro).[2] To summarize, heterogeneous price-setting frictions imply markup dispersion and hence TFP effects of monetary policy. Importantly, precautionary price setting is absent in the deterministic steady state. By extension, our transmission mechanism is absent in model with heterogeneous price-setting frictions when solved around the deterministic steady state.

We empirically test two implications of this transmission mechanism. First, precautionary price setting implies that firms with stickier prices charge higher markups. Second, the markups of firms with stickier prices should increase by relatively more. A caveat is that we do not observe firm-specific price adjustment frequencies. Instead, we capture variation

[2]Relatedly, in a setup with homogeneous price setting frictions Fernandez-Villaverde et al. (2015) study precautionary price setting as a channel through which higher uncertainty leads to higher markups.

in price adjustment frequencies across firms using price adjustment frequencies in five-digit industries together with the firm-specific sales composition across industries. We find that firms with stickier prices indeed have higher markups on average and increase their markups by more after monetary policy shocks. These two results hold when controlling for two-digit sector fixed effects, firm size, leverage, and liquidity.

Finally, we study the mechanism and its implications in a quantitative New Keynesian model with heterogeneous price rigidity. To capture precautionary price setting, we use non-linear solution methods to solve the model dynamics around the stochastic steady state, to which the economy converges in the presence of uncertainty but absent of shocks. We find that indeed firms with stickier prices set higher markups on average, and monetary policy shocks raise markup dispersion. Quantitatively, a one standard deviation contractionary monetary policy shock lowers aggregate TFP by -0.34%. We use the model to study two implications of our mechanism. Whereas a contractionary monetary shock increases aggregate markups in many New Keynesian models, the empirically estimated responses of aggregate markups in Nekarda and Ramey (2019) have the opposite sign. In our model, the aggregate markup falls if contractionary monetary shocks lower aggregate TFP sufficiently strongly. This argument extends to sector or firm-level markups if price rigidities are heterogeneous within sectors or firms such that sector or firm-level TFP responds to monetary policy. We further analyze the effectiveness of monetary policy when the endogenous TFP effects are ignored by the monetary authority. If the monetary authority attributes all TFP fluctuations to technology shocks, interest rates are adjusted less aggressively and monetary policy shocks lead to larger GDP fluctuations.

This paper is closely related to four branches of the literature. First, a growing literature studies the positive and normative implications of heterogeneous price rigidity, see, e.g., Aoki (2001), Carvalho (2006), Nakamura and Steinsson (2010), Eusepi et al. (2011), Carvalho and Schwartzman (2015), Pasten et al. (forthcoming), and Rubbo (2020). We show that such heterogeneity gives rise to productivity effects of monetary policy. Similarly, Baqaee and Farhi (2017) show that negative money supply shocks lower aggregate TFP if sticky-price firms have exogenously higher ex-ante markups than flexible-price firms. We provide empirical evidence which supports this transmission channel and show that the rigidity–markup correlation can arise endogenously from differences in price rigidity.

Second, this paper relates to a literature that studies the productivity effects of monetary policy, e.g., Evans and Santos (2002), Christiano et al. (2005), Comin and Gertler (2006), Moran and Queralto (2018), Garga and Singh (2019), and Jordà et al. (2020). We confirm the empirical finding that monetary policy shocks lower aggregate productivity, but provide a novel explanation based on markup dispersion. In terms of alternative explanations, Christiano et al. (2005) show that variable utilization and fixed costs explain a relatively small fraction of the aggregate productivity response. Moran and Queralto (2018) and Garga and Singh (2019) show that R&D investment falls after monetary policy shocks, which may ultimately lower productivity. However, it is unclear whether the R&D response can explain a large response of aggregate productivity at short horizons. For example, Comin and Hobijn (2010) estimate that new technologies are adopted with an average lag of five years. Conversely, price rigidities are a more natural candidate for the effects at shorter horizons.

Third, our paper relates to a literature on the relation between inflation and price dispersion. Whereas we show that contractionary monetary policy shocks raise markup dispersion, Nakamura et al. (2018) document flat price dispersion across periods of high and low inflation since the 1970s. This suggests that long-lived changes in inflation have different effects than short-lived monetary policy shocks. For example, when trend inflation increases managers may schedule more frequent meetings to discuss price changes (Romer, 1990; Levin and Yun, 2007), while monetary policy shocks are less likely to trigger such responses.

Fourth, this paper relates to a growing literature that studies allocative efficiency over the business cycle. Eisfeldt and Rampini (2006) show that capital misallocation is countercyclical. Fluctuations in allocative efficiency may be driven by various business cycle shocks, e.g., aggregate demand shocks (Basu, 1995), aggregate productivity shocks (Khan and Thomas, 2008), uncertainty shocks (Bloom, 2009), financial shocks (Khan and Thomas, 2013), or supply chain disruptions (Meier, 2020). We relate to this literature by studying the transmission of monetary policy shocks through allocative efficiency. Interestingly, the effects of short- versus long-run changes in interest rates on allocative efficiency seem to differ in sign. Whereas we show that short-run expansionary monetary policy decreases misallocation, Gopinath et al. (2017) show that, in the case of Southern Europe, persistently lower interest rates have increased misallocation. Relatedly, Oikawa and Ueda (2018) study the long-run effects of nominal growth through reallocation across heterogeneous firms.

The remainder of this paper is organized as follows. Section 2 presents the main empirical evidence. Section 3 studies monetary transmission with heterogeneous price rigidity. Section 4 presents a quantitative model. Section 5 concludes and an Appendix follows.

# 2 Evidence on markup dispersion and TFP

In this section, we present novel empirical evidence that monetary policy shocks increase the markup dispersion across firms. We further show that aggregate TFP falls after monetary policy shocks and that a sizable share of this response can be accounted for by the response of markup dispersion.

## 2.1 Data

**Firm-level markups.** We use quarterly balance-sheet data of publicly-listed US firms from Compustat.[3] We estimate firm-level markups using the approach of Hall (1986, 1988) and De Loecker and Warzynski (2012). If firms have a flexible input factor, $V_{it}$, cost minimization implies that the markup $\mu_{it}$ of firm $i$ in quarter $t$ can be computed as

$$\mu_{it} = \frac{\text{output elasticity of } V_{it}}{\text{revenue share of } V_{it}}. \tag{2.1}$$

We focus on differences of firm-level log markups from their industry-quarter mean, primarily to control for industry-specific characteristics such as competitiveness and production technology. We define these differences as $\hat{\mu}_{it} \equiv \log \mu_{it} - \frac{1}{N_{st}} \sum_{j \in \mathcal{J}_{st}} \log \mu_{jt}$, where $\mathcal{J}_{st}$ is the set of firms $j$ in industry $s$, quarter $t$, and $N_{st}$ is the cardinality of $\mathcal{J}_{st}$. For our main empirical results, we assume firms in the same two-digit industry-quarter have a common output elasticity.[4] Hence, firm-level log markups in deviation from their respective industry-quarter mean do not depend on the output elasticity, i.e., we do not need to estimate the output elasticity.[5] Our main results are therefore not affected by the critique in Bond et al. (2020) of estimating output elasticities from revenue data.

Following De Loecker et al. (2020), we assume firms produce output using capital and a composite input of labor and materials, with the latter the flexible factor. We estimate the revenue share as the firm-quarter-specific ratio of costs of goods sold to sales. In Section 2.4, we consider two robustness exercises in which we depart from common output elasticities within two-digit industry-quarters. First, we estimate a four-digit industry-specific translog

[3] Compustat data has two central advantages over many other firm-level balance-sheet datasets: First, it covers all sectors. Second, it is available at quarterly frequency instead of annually (e.g., ASM) or every five years (e.g., Census). This is important to estimate responses to monetary policy shocks.

[4] This is consistent with firms in a given industry-quarter using a common Cobb-Douglas technology.

[5] When assuming common output elasticities for all $j$ in $\mathcal{J}_{st}$, we can simplify $\hat{\mu}_{it}$ to

$$\hat{\mu}_{it} = -\Big(\log\left(\text{revenue share of } V_{it}\right) - \frac{1}{N_{st}} \sum_{j \in \mathcal{J}_{st}} \log\left(\text{revenue share of } V_{jt}\right)\Big).$$

production technology. Second, we estimate four-digit industry-quarter specific output elasticities through cost shares.

We consider all industries except public administration, finance, insurance, real estate, and utilities. We drop firm-quarter observations if sales, costs of goods sold, or fixed assets are reported only once in the associated year. We further drop observations if quarterly sales growth is above 100% or below -67% or if real sales are below 1 million USD. We finally drop the bottom and top 5% of the estimated markups. Appendix A.1 provides more details and summary statistics in Table 3. Our results are robust to variations in the data treatment as we discuss toward the end of this section.

**Monetary policy shocks.** Using high-frequency data of federal fund future prices, we identify monetary policy shocks through changes of the future price in a narrow time window around FOMC announcements. The identifying restrictions are that the risk premium does not change and that no other macroeconomic shock materializes within the time window. We denote the price of a future by f, and by $\tau$ the time of a monetary announcement.[6] We use a thirty-minute window around FOMC announcements, as in Gorodnichenko and Weber (2016). Let $\Delta\tau^- = 10$ minutes and $\Delta\tau^+ = 20$ minutes, then monetary policy shocks are

$$\varepsilon_\tau^{\mathrm{MP}} = \mathrm{f}_{\tau+\Delta\tau^+} - \mathrm{f}_{\tau-\Delta\tau^-}. \tag{2.2}$$

To aggregate the shocks to quarterly frequency, we follow Ottonello and Winberry (2020). We assign daily shocks fully to the current quarter if they occur on the first day of the quarter. If they occur within the quarter, we partially assign the shock to the subsequent quarter. This procedure weights shocks across quarters corresponding to the amount of time agents have to respond. Formally, we compute quarterly shocks as

$$\varepsilon_t^{\mathrm{MP}} = \sum_{\tau\in\mathcal{D}(t)} \phi(\tau)\varepsilon_\tau^{\mathrm{MP}} + \sum_{\tau\in\mathcal{D}(t-1)} (1-\phi(\tau))\varepsilon_\tau^{\mathrm{MP}}, \tag{2.3}$$

where $\mathcal{D}(t)$ is the set of days in quarter $t$ and $\phi(\tau)$ = (remaining number of days in quarter $t$ after announcement in $\tau$) / (total number of days in quarter $t$).

As a baseline, we construct monetary policy shocks from the three-months ahead federal funds future, as in Gertler and Karadi (2015). Our baseline excludes unscheduled meetings and conference calls.[7] Following Nakamura and Steinsson (2018), our baseline further

[6]We obtain time and classification of FOMC meetings from Nakamura and Steinsson (2018) and the FRB. We obtain time stamps of the press release from Gorodnichenko and Weber (2016) and Lucca and Moench (2015).

[7]Unscheduled meetings and conference calls are often the immediate response to adverse economic devel-

excludes the apex of the financial crisis from 2008Q3 to 2009Q2.[8] The monetary policy shock series covers 1995Q2 through 2018Q3. We discuss alternative monetary policy shocks in Section 2.4. Table 4 in the Appendix reports summary statistics and Figure 6 (a) and (b) shows the shock series.

## 2.2 Markup dispersion

We estimate the response of markup dispersion to monetary policy shocks. Our baseline measure of markup dispersion is the cross-sectional variance $\mathbb{V}_t(\hat{\mu}_{it})$, where $\hat{\mu}_{it}$ denotes firm-level log markups in deviation from their respective industry-quarter mean. Recall that an estimator of $\hat{\mu}_{it}$ does not depend on an estimator of the output elasticity under our baseline assumption that firms within a two-digit industry-quarter have a common output elasticity. Figure 6 (c) and (d) in the Appendix show the evolution of markup dispersion over time.[9] To estimate the effects of monetary policy shocks on markup dispersion, we use the local projection

$$y_{t+h} - y_{t-1} = \alpha^h + \beta^h \varepsilon_t^{\mathrm{MP}} + \gamma_0^h \varepsilon_{t-1}^{\mathrm{MP}} + \gamma_1^h (y_{t-1} - y_{t-2}) + u_t^h, \tag{2.4}$$

for $h = 0, \ldots, 16$ quarters and where $y_t$ is markup dispersion.

The central empirical finding of this paper is shown in panel (a) of Figure 1, which plots the response of markup dispersion, captured by the estimates of the coefficients $\{\beta^h\}$. The key finding is that markup dispersion increases significantly and persistently. The response of markup dispersion peaks at about two years after the shock and reverts back to zero afterwards. Whether we compute markup dispersion within two-digit or four-digit industry-quarters changes this result by little.

The specification of (2.4) implicitly assumes that the responses, as estimated in panel (a), are symmetric in the sign of the monetary policy shock. To test the symmetry of responses, we estimate the separate effects of contractionary and expansionary monetary policy shocks, denoted $\varepsilon_t^{MP,con} = \varepsilon_t^{\mathrm{MP}} \cdot \mathbb{1}\{\varepsilon_t^{\mathrm{MP}} > 0\}$ and $\varepsilon_t^{MP,exp} = -\varepsilon_t^{\mathrm{MP}} \cdot \mathbb{1}\{\varepsilon_t^{\mathrm{MP}} < 0\}$, respectively. To be precise, we consider an adjusted specification of (2.4) in which we replace $\varepsilon_t^{\mathrm{MP}}$ by these sign-dependent shocks. Panel (b) of Figure 1 shows the sign-dependent responses of (within 4-digit industry-quarter) markup dispersion. The evidence suggests that the responses are

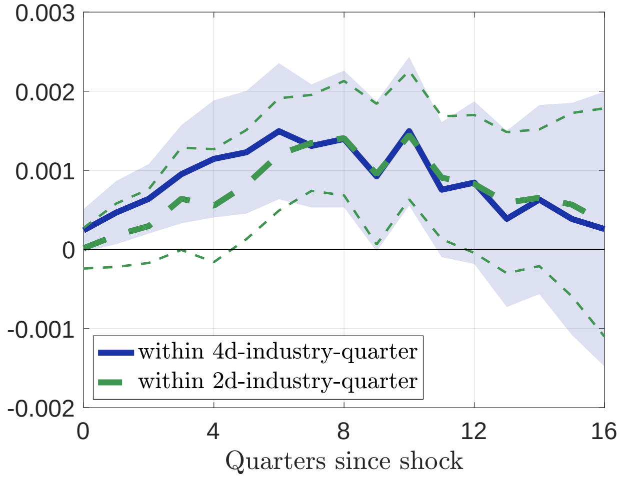
opments. Price changes around such meetings may directly reflect these developments, which invalidates the identifying restriction. Non-scheduled meetings are also more likely to communicate private information about the state of the economy. Our results remain broadly robust when including these meetings.

[8] We discard shocks during 2008Q3 to 2009Q2 and we do not regress post-2009Q2 outcomes on pre-2008Q3 shocks. Our results are robust to including this period.

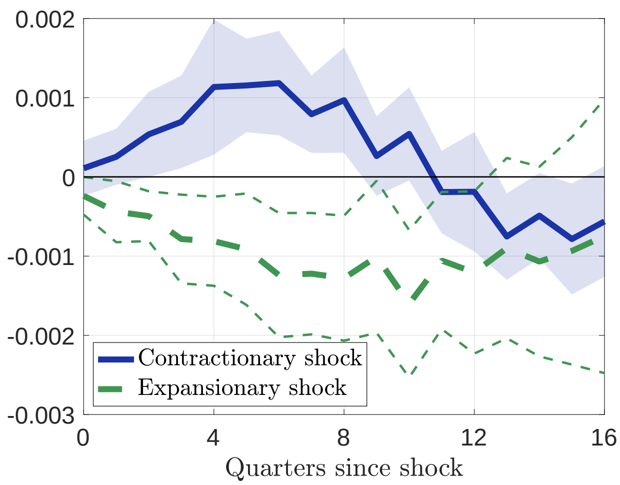
[9] Similar to De Loecker et al. (2020), we find that markup dispersion has increased over time.

Figure 1: Responses of markup dispersion to monetary policy shocks

(a) Symmetric specification




(b) Asymmetric specification




Notes: The figure in panel (a) shows the responses of markup dispersion to a one standard deviation monetary policy shock, coefficients in $\beta^h$ in (2.4). In panel (b) we allow for asymmetric effects by extending (2.4) to separately estimate the response to positive and negative shocks. Panel (b) shows the responses of (within 4-digit industry-quarter) markup dispersion to a one standard deviation contractionary and expansionary monetary policy shock, respectively. The shaded and bordered areas indicate one standard error bands based on the Newey–West estimator.

indeed symmetric in shock sign. While contractionary monetary policy shocks significantly increase markup dispersion, expansionary shocks significantly lower markup dispersion. In addition, the estimated magnitudes are comparable across shock sign. The results in panel (a) and (b) prove robust in a large number of dimensions as we discuss in Section 2.4.

## 2.3 Aggregate productivity

Fluctuations in markup dispersion lead to changes in allocative efficiency of inputs across firms and thereby to fluctuations in aggregate TFP. To characterize this link, we build on Hsieh and Klenow (2009) and Baqaee and Farhi (2020). In a model with monopolistic competition and Dixit–Stiglitz aggregation, we can approximately express changes in aggregate TFP as

$$\Delta \log \mathrm{TFP}_t = -\frac{\eta}{2}\Delta \mathbb{V}_t(\log \mu_{it}) \;+\; \Big[\Delta \text{ exogenous productivity}\Big], \tag{2.5}$$

where $\eta$ is the substitution elasticity between variety goods. The details of the derivation are provided in Appendix E.1.[10] An increase in the variance of log markups by 0.01 lowers aggregate TFP by $\frac{\eta}{2}$%. To provide some intuition, first suppose firms are homogeneous. Aggregate output is maximal for given aggregate inputs if all firms produce the same quantity, which implies equal markups across firms. If instead firms have heterogeneous productivity and demand shifts, the efficient allocation of inputs is not homogeneous across firms, but still implies equal markups. Conversely, markup dispersion is associated with an allocation of inputs across firms that implies aggregate TFP losses.

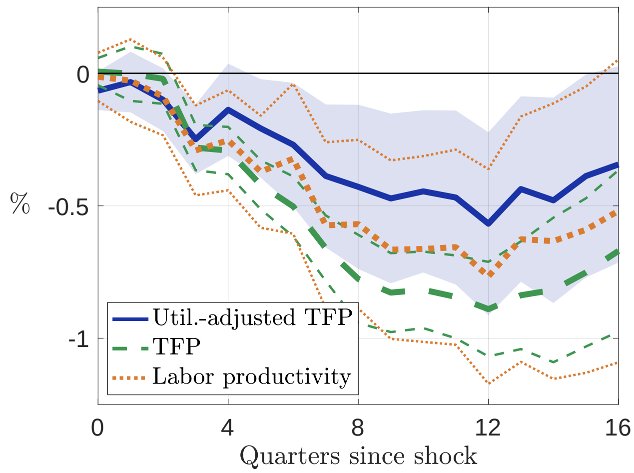
We empirically estimate the aggregate productivity response to monetary policy shocks and compare it with the productivity response implied by equation (2.5) and the response of markup dispersion in panel (a) of Figure 1. We consider aggregate TFP and utilization-adjusted aggregate TFP from Fernald (2014), as well as labor productivity and estimate their responses to monetary policy shocks through equation (2.4).[11] Panel (a) of Figure 2 shows that the responses of all three aggregate productivity measures are significantly negative and persistent. At a two-year horizon, a one standard deviation monetary policy shock lowers aggregate TFP by 0.8%, labor productivity by 0.6% and utilization-adjusted aggregate TFP by 0.4%. For comparison, we show the responses of interest rates, aggregate output and inputs in Figure 8 in the Appendix. A monetary policy shock of this magnitude raises the federal funds rate by up to 30 basis points and lowers aggregate output by about 1% at a two-year horizon. Aggregate factor inputs respond little and thus aggregate TFP accounts for 50–80% of the output response at a two-year horizon.

[10] In the calibrated New Keynesian model of Section 4, equation (2.5) is a close approximation to the joint behavior of aggregate TFP and markup dispersion, see Figure 4.

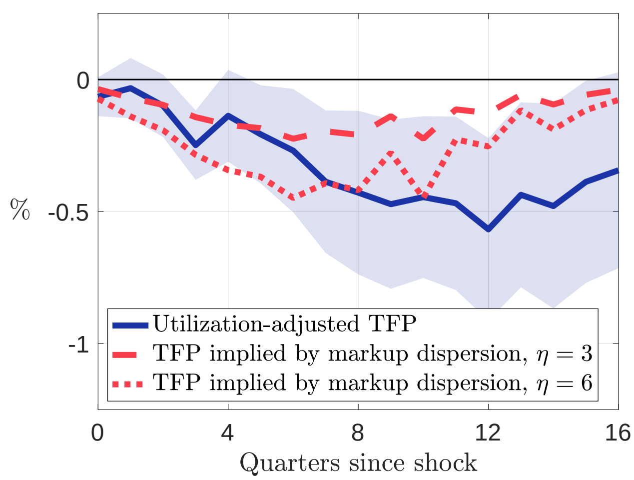
[11] Aggregate TFP is $\Delta \log \mathrm{TFP} = \Delta y - w_k \Delta k - (1 - w_k)\Delta \ell$, with $\Delta y$ real business output growth, $w_k$ the capital income share, $\Delta k$ real capital growth (based on separate perpetual inventory methods for 15 types of capital), $\Delta \ell$ the growth of hours worked plus growth in labor composition/quality. Utilization-adjustment follows Basu et al. (2006) and uses hours per worker to proxy factor utilization. Labor productivity is real output per hour in the nonfarm business sector. Figure 6 (d) in the Appendix shows the different aggregate productivity time series.

Figure 2: Aggregate productivity response to monetary policy shocks

(a) Estimated productivity responses




(b) Implied productivity responses




Notes: Panel (a) shows the responses of aggregate productivity measures to a one standard deviation contractionary monetary policy shock. Panel (b) shows the imputed response of TFP, implied by the response of markup dispersion within four-digit industry-quarters, according to $\Delta \log \mathrm{TFP}_t = -\frac{\eta}{2} \Delta \mathbb{V}_t(\log \mu_{it})$, see equation (2.5), and using $\eta = 3$ and $\eta = 6$, respectively. Alongside, it shows the empirical response of utilization-adjusted TFP from panel (a). The shaded and bordered areas indicate one standard error bands based on the Newey–West estimator.

Using equation (2.5), we compute the implied TFP response by multiplying the response of markup dispersion by $-\frac{\eta}{2}\%$. In Figure 2 (b), we show the implied response for $\eta = 6$, which is the estimate in Christiano et al. (2005), and $\eta = 3$, the assumption in Hsieh and Klenow (2009). The imputed TFP responses closely match the estimated TFP response within the first two years of the shock. This suggests that the response in markup dispersion is quantitatively important to understand the productivity effects of monetary policy.

An alternative explanation why aggregate productivity declines after monetary policy shocks is a reduction in R&D investment. In fact, Figure 7 in the Appendix shows that aggregate R&D expenditures fall after contractionary monetary policy shocks, which reconfirms the findings in Moran and Queralto (2018) and Garga and Singh (2019). Hence, there is scope for R&D to explain part of the aggregate TFP response. It is less clear how much of the short-run productivity response can be explained by R&D investment. The evidence on technology adoption suggests that R&D has rather medium-run than short-run productivity effects. For example, Comin and Hobijn (2010) estimates an average adoption lag of 5 years. A sluggish effect of R&D investment on aggregate productivity is consistent with the finding in Figure 2 (b) that markup dispersion accounts for a relatively small fraction of the TFP response 3–4 years after a monetary policy shock.

## 2.4 Robustness

**Markup estimation.** Our baseline specification assumes that firms in the same two-digit industry-quarter have a common output elasticity with respect to labor and materials. Based on De Loecker et al. (2020), we consider two alternatives. First, we estimate a translog production function with four-digit industry-specific coefficients. This gives rise to firm- and time-specific output elasticities. Second, we estimate the output elasticity through the cost share (costs of goods sold divided by total costs) at the four-digit-industry-quarter level. This is a valid estimator of the output elasticity under flexible adjustment of all input factors. All our results are robust to computing markups based on a translog production function or cost shares. Figure 9 (a) and (b) in the Appendix shows the response of markup dispersion to monetary policy shocks under the translog and cost share approach. Figure 10 shows the responses of markup dispersion dependent on the sign of the monetary policy shock. In addition, based on Traina (2020) and Basu (2019) we consider as expenses for labor and materials the costs of goods sold plus selling, general, and administrative expenses when estimating markups. Panel (c) of Figure 9 shows that markup dispersion still increases.

**Firm-level data treatment.** We examine the robustness of our results under alternative data treatments. First, we keep firms with real sales growth above 100% or below -67%. Second, we keep small firms with real quarterly sales below 1 million 2012 USD. Third, instead of dropping the top/bottom 5% of the markup distribution per quarter, we drop the top/bottom 1%. Fourth, we condition on firms with at least 16 quarters of consecutive observations. Figure 11 shows that markup dispersion robustly increases after contractionary monetary policy shocks. Figure 12 shows the responses of markup dispersion remain symmetric in the sign of the monetary policy shock. A well-known recent trend is the delisting of public firms. We address the concern that this may affect our results in two ways. First, when only considering firms that are in the sample for at least 16 consecutive quarters, we find our results to be robust, as discussed above. Second, we estimate whether the number of firms in the sample responds to monetary policy shocks. Figure 13 shows that the response is insignificant and small.

**Monetary policy shocks.** We show that our results are robust to a variety of alternative monetary policy shock series. Similar to Nakamura and Steinsson (2018), we consider the first principal component of the current/three-month federal funds futures and the 2/3/4-quarters ahead Eurodollar futures. We further address the concern that high-frequency future price changes may not only capture monetary policy shocks, but also release private central bank information about the state of the economy. To control for such information effects we employ two alternative strategies. First, following Miranda-Agrippino and Ricco (2018), we regress daily monetary policy shocks on internal Greenbook forecasts and revisions for output growth, inflation, and unemployment. Second, following Jarocinski and Karadi (2020), we discard daily monetary policy shocks if the associated high-frequency change in the S&P500 moves in the same direction. While our baseline series exclude unscheduled meetings and conference calls, which plausibly diminishes the role of information effects, we also reassess our results when including these events. A different concern may be that unconventional monetary policy drives our result. We address this by setting daily monetary policy shocks at Quantitative Easing (QE) announcements to zero. Figure 14 in the Appendix shows the response of markup dispersion for all monetary policy shock series. Figure 15 shows the sign-dependent responses of markup dispersion to monetary policy shock. Figure 16 in the Appendix shows the responses of aggregate productivity for all monetary policy shock series.

**LP-IV.** We revisit our main results with the LP-IV method (Stock and Watson, 2018). More precisely, we replace the monetary policy shocks $\varepsilon_t^{\text{MP}}$ in equations (2.4) and (3.5) by the quarterly change in the one-year treasury rate and use $\varepsilon_t^{\text{MP}}$ as an instrument. Figure 17 (a) and (b) in the Appendix shows that our results are robust to the LP-IV method.

**Great Recession.** We exclude the apex of the Great Recession from 2008Q3 to 2009Q2 in our baseline estimations. However, our results do not depend on this choice. Moreover, the results are robust to using the Pre-Great Recession period until 2008Q2. Panels (d) and (e) of Figures 11 and 12 in the Appendix show that our results are robust across samples.

**TFP measurement.** Hall (1986) shows that the Solow residual is misspecified in the presence of market power. Hall shows that the correct Solow weights are not the income share for capital $w_{kt}$ and labor $1 - w_{kt}$, but instead $\mu_t w_{kt}$ and $1 - \mu_t w_{kt}$, where $\mu_t$ is the aggregate markup. We examine the response of markup-corrected (utilization-adjusted) aggregate TFP to monetary policy shocks. We use the average markup series from De Loecker et al. (2020) to compute Hall's weights. Figure 18 (a) in the Appendix shows that this barely affects our results. We also assess the symmetry of the TFP response to monetary shocks. Figure 19 shows a significant increase of TFP measures to expansionary shocks, while the response to contractionary shocks is insignificant. We further investigate whether measurement error in quarterly TFP data is responsible for the effect of monetary policy. This problem was flagged for defense spending shocks by Zeev and Pappa (2015). We follow them in re-computing TFP using measurement error corrected quarterly GDP from Aruoba et al. (2016). Figure 18 (b) shows that measurement error corrected TFP also falls after monetary policy shocks. In addition, we show that Fernald's (2014) investment-specific and consumption-specific aggregate TFP series significantly falls after contractionary monetary policy shocks, see Figure 18 (c) and (d). Notably, the response of investment-specific TFP is significantly stronger than that of consumption-specific TFP.

# 3 Heterogeneous price setting frictions

In this section, we characterize a novel mechanism through which heterogeneity in price setting frictions across firms may explain why markup dispersion increases in response to contractionary monetary policy shocks and decreases after expansionary ones. In addition, we provide empirical evidence in support of this mechanism.

## 3.1 Sufficient condition

We first propose a sufficient condition for monetary policy shocks, which lower real marginal costs, to increase the dispersion of markups across firms. Let $i$ index a firm and $t$ time. A firm's markup is $\mu_{it} \equiv P_{it}/(P_t X_t)$, where $P_{it}$ is the firm's price, $P_t$ the aggregate price, and $X_t$ real marginal cost. Let pass-through from marginal cost to price be defined as

$$\rho_{it} \equiv \frac{\partial \log P_{it}}{\partial \log X_t}. \tag{3.1}$$

This is the percentage price change in response to a percentage change in real marginal cost (without conditioning on price adjustment). The correlation between firm-level markup and firm-level pass-through is a key moment for the response of markup dispersion to shocks.

**Proposition 1.** *If* $\mathrm{Corr}_t(\rho_{it}, \log \mu_{it}) < 0$*, markup dispersion decreases in real marginal costs*

$$\frac{\partial \mathbb{V}_t(\log \mu_{it})}{\partial \log X_t} < 0,$$

*and markup dispersion increases if* $\mathrm{Corr}_t(\rho_{it}, \log \mu_{it}) > 0$*.*

Proof: See Appendix E.2.

Contractionary monetary policy shocks that lower real marginal costs increase the dispersion of markups if firms with higher markups have lower pass-through. While we focus on monetary policy shocks in this paper, in principle any shock that lowers real marginal costs will raise markup dispersion as long as markups and pass-through are negatively correlated across firms.

### 3.2 Precautionary price setting

We next show that firm-level heterogeneity in the severity of various price-setting frictions may explain a negative correlation between firm-level pass-through and markup. It follows from Proposition 1 that heterogeneous price-setting frictions can explain why contractionary monetary policy shocks raise markup dispersion.

Consider a risk-neutral investor that sets prices in a monopolistically competitive environment with an isoelastic demand curve[12] and subject to adjustment costs:

$$\max_{\{P_{it+j}\}_{j=0}^{\infty}} \mathbb{E}_t \sum_{j=0}^{\infty} \beta^t \left[ \left( \frac{P_{it+j}}{P_{t+j}} - X_{t+j} \right) \left( \frac{P_{it+j}}{P_{t+j}} \right)^{-\eta} Y_{t+j} - \text{adjustment cost}_{it+j} \right] \tag{3.2}$$

Adjustment costs differ across firms and may be deterministic or stochastic. This formulation nests the Calvo (1983) random adjustment, Taylor (1979) staggered price setting, Rotemberg (1982) convex adjustment costs, and Barro (1972) menu costs.

Importantly, the period profit (net of adjustment costs) is asymmetric in the price $P_{it}$ and hence in the markup $\mu_{it}$. Profits fall more rapidly for low markups than for high markups. This gives rise to a precautionary price setting motive: when price adjustment is

[12] An isoelastic demand curve can be derived from a Dixit-Stiglitz aggregator. An alternative is a Kimball (1995) aggregator, which implies that the demand elasticity changes in the firm's relative price. The evidence for Kimball-type demand curves is mixed, however, see Klenow and Willis (2016).

frictional, firms have an incentive to set a markup above the frictionless optimal markup. Setting a higher markup today provides some insurance against low profits before the next price adjustment opportunity (Calvo/Taylor), or lowers the expected costs of future price re-adjustments (Rotemberg/Barro).

To characterize precautionary price setting, we study the problem in partial equilibrium. Analytically solving the non-linear price-setting problem with adjustment costs and aggregate uncertainty in general equilibrium is not feasible. We assume that aggregate price, real marginal costs, and aggregate demand, denoted by $(P_t, X_t, Y_t)$, follow an i.i.d. joint log-normal process around the unconditional means $\bar{P}$, $\bar{X}$, and $\bar{Y}$. The (co-)variances of innovations are $\sigma_k^2$ and $\sigma_{kl}$ for $k, l \in \{p, x, y\}$.

**Calvo friction.** Consider a Calvo (1983) friction, parametrized by a *firm-specific* price adjustment probability $1 - \theta_i \in (0, 1)$. The profit-maximizing reset price is

$$P_{it}^* = \frac{\eta}{\eta - 1} P_t X_t \frac{\mathbb{E}_t \left[ \sum_{j=0}^{\infty} \beta^j \theta_i^j \frac{X_{t+j}}{X_t} \left( \frac{P_{t+j}}{P_t} \right)^{\eta} \frac{Y_{t+j}}{Y_t} \right]}{\mathbb{E}_t \left[ \sum_{j=0}^{\infty} \beta^j \theta_i^j \left( \frac{P_{t+j}}{P_t} \right)^{\eta - 1} \frac{Y_{t+j}}{Y_t} \right]}, \tag{3.3}$$

and we denote the associated markup by $\mu_{it}^*$. To isolate the role of uncertainty in price setting, we focus on the dynamics around the stochastic steady state, which is described by the unconditional means $(\bar{P}, \bar{X}, \bar{Y})$. The following proposition characterizes the precautionary upward price-setting bias – relative to the frictionless environment – as a function of $\theta_i$, and establishes a condition under which firms with lower pass-through set higher markups.

**Proposition 2.** *If $P_t = \bar{P}$, $X_t = \bar{X}$, $Y_t = \bar{Y}$, and $(\eta - 1)\sigma_p^2 + \sigma_{py} + \eta\sigma_{px} + \sigma_{xy} > 0$, the firm sets a markup above the frictionless optimal one and the markup further increases the less likely price re-adjustment is,*

$$\mu_{it}^* > \frac{\eta}{\eta - 1} \quad \textit{and} \quad \frac{\partial \mu_{it}^*}{\partial \theta_i} > 0.$$

*Pass-through $\rho_{it}$ is zero with probability $\theta_i$ and positive otherwise. Expected pass-through, denoted by $\bar{\rho}_{it}$, of either a transitory or permanent change in $X_t$, falls monotonically in $\theta_i$,*

$$\frac{\partial \bar{\rho}_{it}}{\partial \theta_i} < 0.$$

*If the above conditions are satisfied, then* $\mathrm{Corr}_t(\rho_{it}, \log \mu_{it}^*) < 0$.

Proof: See Appendix E.3.

A permanent decrease in real marginal costs leads to an permanent increase in the optimal reset price by the same factor. The pass-through is hence one for adjusting firms and zero for non-adjusting firms. A transitory decrease in real marginal costs increases the optimal reset price by less than the marginal cost change if the future reset probability is below one. The pass-through of adjusting firms is hence less than one and falling in price stickiness.

**Staggered price setting.** Consider Taylor (1979) staggered price setting and assume that firms adjust asynchronously and at different deterministic frequencies. Staggered price setting is a deterministic variant of the Calvo setup and yields very similar results.

**Rotemberg friction.** Consider the price-setting problem subject to Rotemberg (1982) quadratic price adjustment costs, parametrized by a *firm-specific* cost shifter $\phi_i \geq 0$, i.e., adjustment $\text{cost}_{it} = \frac{\phi_i}{2}\left(\frac{P_{it}}{P_{it-1}} - 1\right)^2$. The first-order condition for $P_{it}$ is

$$[(1-\eta) + \eta X_t]\left(\frac{P_{it}}{P_t}\right)^{-\eta} Y_t = \phi_i \left(\frac{P_{it}}{P_{it-1}} - 1\right)\frac{P_{it}}{P_{it-1}} - \phi_i \mathbb{E}_t\left[\left(\frac{P_{it+1}}{P_{it}} - 1\right)\frac{P_{it+1}}{P_{it}}\right]. \quad (3.4)$$

The following proposition summarizes our analytical results.

**Proposition 3.** *If $P_{t-1} = P_t = \bar{P}$, $X_t = \bar{X}$, $Y_t = \bar{Y}$, and $\frac{\sigma_{px}}{\sigma_p \sigma_x} > -1$, then up to a first-order approximation of* (3.4) *around $\phi_i = 0$, it holds that*

$$\mu_{it} \geq \frac{\eta}{\eta - 1} \quad \textit{and} \quad \frac{\partial \mu_{it}}{\partial \phi_i} \geq 0, \quad \textit{with strict inequality if } \phi_i > 0.$$

*If in addition $\eta \in (1, \tilde{\eta})$, where $\tilde{\eta} = 1 + (\exp\{\frac{3}{2}\sigma_p^2 + \frac{3}{2}\sigma_x^2 + 4\sigma_{px}\} - \exp\{\sigma_{px}\})^{-1}$, the pass-through, of either a transitory or permanent change in $X_t$, falls monotonically in $\phi_i$,*

$$\frac{\partial \rho_{it}}{\partial \phi_i} < 0.$$

*If the above conditions are satisfied, then* $\text{Corr}_t(\rho_{it}, \log \mu_{it}) < 0$.

Proof: See Appendix E.4.

**Menu costs.** Consider the price-setting problem subject to firm-specific menu costs. Due to the asymmetry of the profit function, price adjustment is more rapidly triggered for markups below the frictionless optimal markup than above. Thus, a higher reset markup may be optimal to economize on adjustment costs. Analytical results, however, are not available for the fully non-linear menu cost problem. Instead, we investigate this problem quantitatively. We find that markups increase in menu costs, consistent with precautionary price setting. Consequently, the correlation between pass-through and markup is negative. More details on calibration, solution, and results are provided in Appendix F.

### 3.3 Empirical evidence for the mechanism

We corroborate the mechanism by considering two testable implications. First, firms with higher markups adjust prices less frequently. Second, monetary policy shocks increase the relative markup of firms that adjust prices less frequently. We show that both implications are supported empirically.

For the subsequent empirical analysis, we use data on price adjustment frequencies together with the data described in Section 2. We observe average price adjustment frequencies over 2005–2011 for five-digit industries, computed in Pasten et al. (forthcoming) from PPI micro data. We further use the Compustat segment files, which provide sales and industry codes of business segments within firms. The firm-specific sales composition across industries allows us to compute firm-specific price adjustment frequencies as sales-weighted average of industry-specific price adjustment frequencies. We expect this procedure to underestimate the true extent of heterogeneity across firms, which should bias our subsequent regression coefficients toward zero. For some firms, Compustat segment files are not available and for others, they report only one segment per firm. We can construct firm-specific price adjustment frequencies for 42% of firms. For the remaining firms, we use the price adjustment frequency of the five-digit industry they operate in.[13] More details are provided in Appendix A.4. To measure price rigidity, we consider both the price adjustment frequency and the implied price duration, defined as $-1/\log(1-\text{price adjustment frequency})$.

**Testable implication 1: Firms with stickier prices charge higher markups.** We provide empirical evidence that firms with stickier prices tend to charge higher markups. To compare markups with average price adjustment frequencies and implied price durations for 2005–2011, we compute average firm-level markups over the same time period. Columns (1) and (3) of Table 1 show that firms, which have more rigid prices than other firms in the same two-digit industry, charge markups significantly above the industry average. The correlation is statistically significant for both implied price duration and price adjustment frequency as measures of price rigidity. While this correlation is consistent with precautionary price setting, it may reflect omitted factors. In columns (2) and (4) we control for firm-specific

[13] Our results are robust when only using sectoral price adjustment frequencies.

size, leverage, and liquidity, all averages over 2005–2011. The conditional correlations remain of the same sign and statistically significant at the 1% level. In Table 1 we have excluded firms for which price setting frictions are practically irrelevant, in particular, firms with a price adjustment frequency above 99% per quarter, which are about 3% of all firms. When including these, the relation between stickiness and markup remains positive, albeit somewhat less significant, see Table 5 in the Appendix. Note that we have not considered four-digit industry FE, because for many firms our measure of rigidity is based on the five-digit industry average, which limits the variation in rigidity measures within four-digit industries.

Table 1: Regressions of markup on price stickiness

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Implied price duration | 0.0538 | 0.0471 | | |
| | (0.0180) | (0.0154) | | |
| Price adjustment frequency | | | -0.389 | -0.333 |
| | | | (0.100) | (0.0853) |
| Size | | 0.0107 | | 0.0113 |
| | | (0.00340) | | (0.00343) |
| Leverage | | -0.00173 | | -0.00167 |
| | | (0.000649) | | (0.000652) |
| Liquidity | | 0.553 | | 0.545 |
| | | (0.0627) | | (0.0640) |
| 2-digit industry FE | Yes | Yes | Yes | Yes |
| Observations | 3870 | 3867 | 3870 | 3867 |
| Adjusted $R^2$ | 0.144 | 0.228 | 0.149 | 0.231 |

Notes: Regressions of firm-level markup on firm-level price adjustment frequency and implied price duration, respectively. Standard errors are clustered at the two-digit industry level and shown in parentheses.

**Testable implication 2: Monetary policy shocks increase the relative markups of firms with stickier prices.** We investigate whether contractionary monetary policy shocks increase the relative markup of firms with stickier prices. This is not necessarily the case if the average stickiness differs from the stickiness after monetary policy shocks, or if the marginal costs of firms with stickier prices respond differently from other firms.

We estimate panel local projections of firm-level log markups on the interaction between monetary policy shocks and firm-level price rigidity. We measure firm-level price rigidity by the price adjustment frequency or the implied price duration. Let $Z_{it}$ denote a vector of firm-specific characteristics. We consider two specifications for $Z_{it}$: (i) including one of the two rigidity measures, and (ii) additionally including lags of firm size (log of total assets), leverage (total debt per total assets), and the ratio of liquid assets to total assets.[14] Our selection of controls is motivated by recent work in Ottonello and Winberry (2020) and Jeenas (2019), who study the transmission of monetary policy shocks through financial constraints. We use the panel local projection

$$y_{it+h} - y_{it-1} = \alpha_i^h + \alpha_{st}^h + B^h Z_{it}\varepsilon_t^{\mathrm{MP}} + \Gamma^h Z_{it} + \gamma^h (y_{it-1} - y_{it-2}) + u_{it}^h \tag{3.5}$$

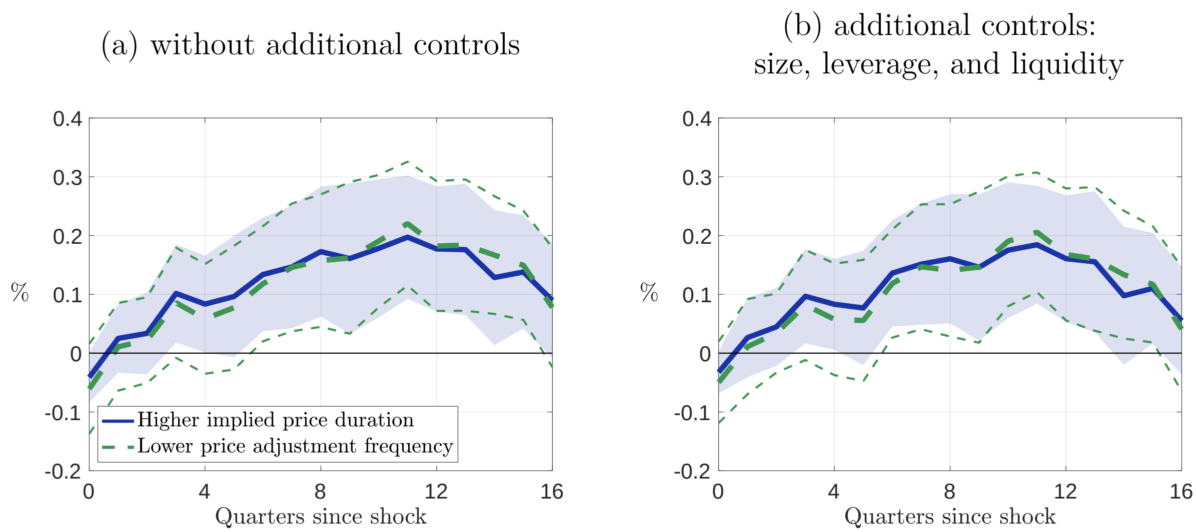
for $h = 0, \ldots, 16$ quarters, in which we include two-digit-industry-time and firm fixed effects. To focus on the within-industry variation in the interaction between monetary policy shock and price rigidity, we subtract the corresponding two-digit industry mean from the measure of price rigidity. The main coefficients of interest are the coefficients in $\{B^h\}$ associated with price rigidity. These capture the relative markup increase for firms with stickier prices. Figure 3 shows the results. The markups of firms with stickier prices increase by significantly more after monetary policy shocks.[15] Firms with a price adjustment frequency one standard deviation above the associated two-digit-industry mean increase their markup by up to 0.2% more. Importantly, the estimates are almost identical when adding controls, see panel (b) of Figure 3.

**Robustness.** We review the above two empirical findings along similar dimensions as in Section 2.4 and find them to be robust. We first consider alternative markup estimates based on a translog production function or cost shares instead of the baseline assumption of a common output elasticity within two-digit industry-quarters. Table 6 shows the correlation between average markup and price rigidity. Figure 20 shows the relative markup response of firms with stickier prices to monetary policy shocks. Second, we consider the role of alternative data treatments. Table 7 in the Appendix shows that the correlation between markups and price rigidity is robust across data treatments. Figure 21 shows that the relative markup response to monetary policy shocks is sensitive to removing outliers in the firm-level markups, but robust to other data treatments. Third, we consider alternative monetary policy shock series. Figure 22 in the Appendix shows the robustness of the interaction of firm-level price rigidity with the monetary policy shock for all monetary policy shock

[14] We demean the additional firm-level controls by the firm-level mean to focus on within-firm variation.

[15] Using Driscoll–Krayy standard errors yields almost the same confidence bands as in Figure 3.

Figure 3: Relative markup response of firms with stickier prices to monetary policy shocks




Notes: The figures show the relative markup response of firms with a price adjustment frequency one standard deviation below (or with an implied price duration one standard deviation above) the two-digit-industry mean to a one standard deviation monetary policy shock. That is, we plot the appropriately scaled coefficients in $B^h$ that are associated to price rigidity in the panel local projections (3.5). In panel (a), $Z_{it}$ contains only price stickiness. In panel (b), $Z_{it}$ also contains lagged log assets, leverage, and liquidity. The shaded and bordered areas indicate 90% error bands clustered by firm and quarter.

series. Fourth, we consider an LP-IV setup as described in Section 2.4. Figure 17 (c) in the Appendix shows that our results are robust to the LP-IV method. Finally, we include the apex of the Great Recession. Figure 11 and Figure 21 (d) and (e) show that the firm-level heterogeneity in the markup response and the increase in markup dispersion, respectively, after contractionary monetary policy shocks is robust across samples.

# 4 Quantitative example

In this section, we investigate the transmission mechanism and its implications in a New Keynesian model with heterogeneous price rigidity.

## 4.1 Model setup

Our model setup builds on Carvalho (2006) and Gorodnichenko and Weber (2016). We discuss the model only briefly and relegate a formal description to Appendix G. An infinitely-lived representative household has additively separable preference in consumption and leisure, and discounts future utility by $\beta$. The intertemporal elasticity of substitution for consumption is $\gamma$ and the Frisch elasticity of labor supply is $\varphi$. The consumption good is a Dixit–Stiglitz aggregate of differentiated goods with constant elasticity of substitution $\eta$. In contrast to Carvalho (2006) and the subsequent literature which consider models with cross-sector differences in price rigidity, our model is a one-sector economy, in which price rigidity differs between firms. This speaks more directly to our empirical within-industry evidence. In addition, it seems more plausible to assume equal demand elasticities within than across sectors. There is a continuum of monopolistically competitive intermediate goods firms that produce with a linear technology in labor. Firms can reset their prices with a firm-specific probability $1 - \theta_i$ in any given period. They set prices to maximize the value of the firm to the households. The monetary authority aims to stabilize inflation and the output gap. The output gap is defined as deviations of aggregate output from its natural level, defined as the flexible-price equilibrium output. Monetary policy follows a Taylor rule with interest rate smoothing and is subject to monetary policy shocks, $\nu_t \sim \mathcal{N}(0, \sigma_\nu^2)$.

We expect that some modeling choices dampen the TFP channel of monetary policy while other choices amplify it. On the one hand, we assume a time-dependent price setting friction. On the other hand, we abstract from input-output networks and real rigidities.

## 4.2 Calibration and solution

A model period is a quarter. We set the elasticity of substitution between differentiated goods at $\eta = 6$, as estimated in Christiano et al. (2005). This is conservative when compared to $\eta = 21$ in Fernandez-Villaverde et al. (2015), who study precautionary price setting as transmission of uncertainty shocks. A higher $\eta$ means more curvature in the profit function, hence more precautionary price setting, and larger TFP losses from markup dispersion. We use standard values for the discount factor $\beta$ and the intertemporal elasticity of substitution $\gamma$. We set the former to match an annual real interest rate of 3%, and the latter to a value of 2. We use the estimates in Christiano et al. (2016) for the Taylor rule and set $\rho_r = 0.85$, $\phi_\pi = 1.5$, and $\phi_y = 0.05$.

The parameters which play a key role in this model are the price adjustment frequencies. We assume that there are five equally large groups of firms, indexed by $k \in \{1, \ldots, 5\}$, which differ in their price adjustment frequencies $1 - \theta_k$. We calibrate $\{\theta_k\}$ to match the empirical distribution of within-industry price adjustment frequencies based on Gorodnichenko and Weber (2016). They document mean and standard deviation of monthly price adjustment frequencies for five sectors. We first compute the value-added-weighted average of the means and variances. The monthly mean price adjustment frequency is 0.1315 and the standard deviation is 0.1131. Second, we fit a log-normal distribution to these moments. Third,

Table 2: Calibration

| Parameter | | Value | Source/Target |
|---|---|---|---|
| Discount factor | $\beta$ | $1.03^{-1/4}$ | Risk-free rate of 3% |
| Elasticity of intertemporal substitution | $\gamma$ | 2 | Standard |
| Elasticity of substitution between goods | $\eta$ | 6 | Christiano et al. (2005) |
| Interest rate smoothing | $\rho_r$ | 0.85 | Christiano et al. (2016) |
| Policy reaction to inflation | $\phi_\pi$ | 1.5 | Christiano et al. (2016) |
| Policy reaction to output | $\phi_y$ | 0.05 | Christiano et al. (2016) |
| Standard deviation of MP shock | $\sigma_\nu$ | 0.00415 | 30bp effect on nominal rate |
| Frisch elasticity of labor supply | $\varphi$ | 0.1175 | Relative hours response of 11.7% |
| *Distribution of price adjustment frequencies* | | | |
| Firm type $k$ | | Share | Price adjustment frequency $1-\theta_k$ |
| 1 | | 0.2 | 0.0231 |
| 2 | | 0.2 | 0.0678 |
| 3 | | 0.2 | 0.1396 |
| 4 | | 0.2 | 0.2829 |
| 5 | | 0.2 | 0.8470 |

Notes: The distribution of price adjustment frequencies is chosen to match the within-sector distribution reported in Gorodnichenko and Weber (2016).

we compute the mean frequencies within the five quintile groups of the fitted distribution. Finally, we transform the monthly frequencies into quarterly ones to obtain $\{\theta_k\}$.

We calibrate the Frisch elasticity of labor supply internally. The hours response to monetary policy shocks is small on impact, but larger at longer horizons, see Figure 8 in the Appendix. The utilization-adjusted TFP response is immediately negative but has a flatter profile at longer horizons. On average, the two responses have similar magnitude. The average difference of the hours response relative to the response of utilization-adjusted TFP, computed as the mean of $\frac{1\,-\,\text{response of hours in }\%}{1\,-\,\text{response of util-adj. TFP in }\%}-1$ up to 16 quarters after the shock, is 11.7%. In the model, we compute the relative hours response in the same way and target 11.7% to calibrate the Frisch elasticity. Importantly, we do not directly target the absolute magnitude of the TFP response, but only a relative quantity. The calibrated Frisch elasticity is $\varphi = 0.1175$, which is low compared to the macroeconomics literature, but which is within the range of empirical estimates surveyed by Ashenfelter et al. (2010). The remaining parameter is the standard deviation of monetary policy shocks $\sigma_\nu$, which we also calibrate internally. The target is the peak nominal interest rate response to a one standard deviation monetary policy shock of 30bp, see Figure 8. This yields $\sigma_\nu = 0.00415$.

For markup dispersion to arise from precautionary price setting, it is important to use an adequate model solution technique. We rely on local solution techniques, but, importantly, solve the model around its stochastic steady state. Whereas markup are the same across firms in the deterministic steady state, differences across firms may exist in the stochastic steady state. We apply the method developed by Meyer-Gohde (2014), which uses a third-order perturbation around the deterministic steady state to compute the stochastic steady state as well as a first-order approximation of the model dynamics around it.[16] In the stochastic steady state, precautionary price setting has large effects. Firms with the most rigid prices have 10.9% higher markups than firms with the most flexible prices. As follows from Proposition 1, the negative correlation between markups and pass-through implies that contractionary monetary policy shocks increase markup dispersion and lower aggregate TFP.

## 4.3 Results

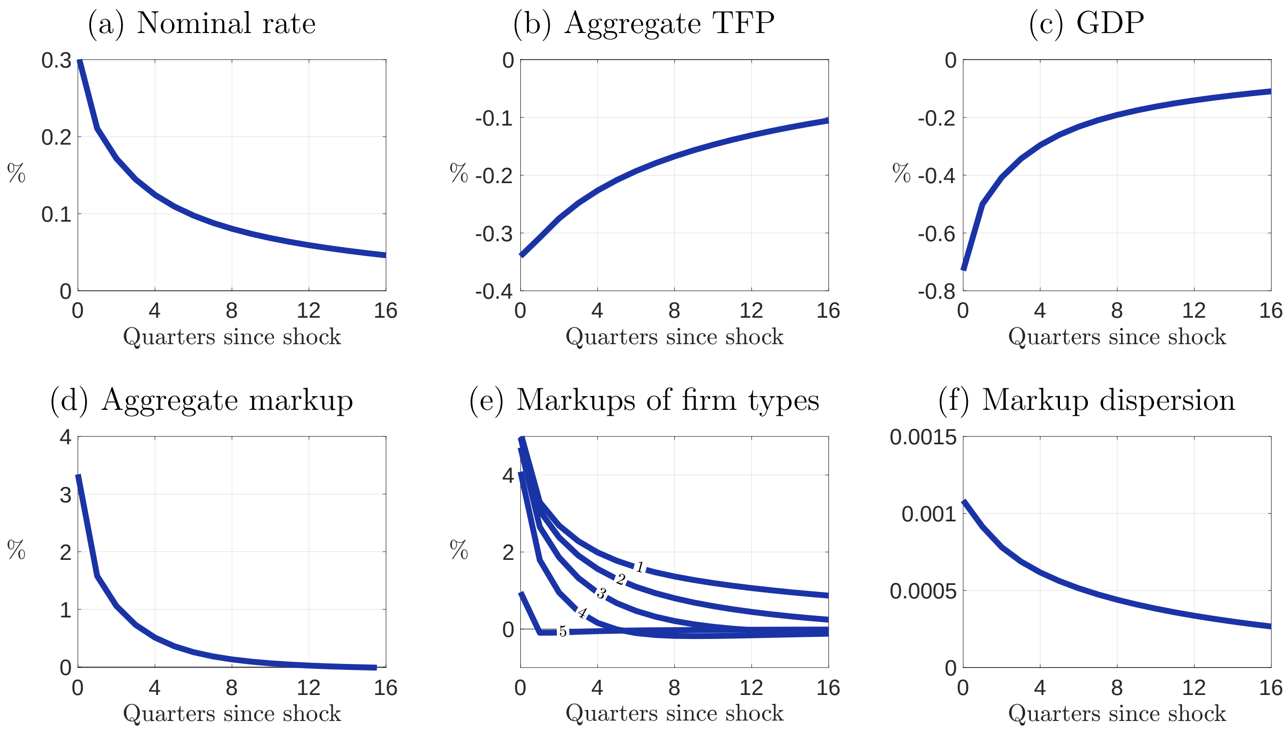
Figure 4 shows the responses to a one-standard deviation monetary policy shock. The shock depresses aggregate demand and lowers real marginal costs. In response, firms want to lower their prices. For firms with stickier prices, however, pass-through is lower and on average their markups increase by more. Since firms with stickier prices have higher initial markups, markup dispersion increases. This worsens the allocation of factors across firms and thereby depresses aggregate TFP. The mechanism is quantitatively important. The increase in markup dispersion is about 75% of the peak empirical response, see Figure 1, and the model explains 60% of the peak empirical response in utilization-adjusted TFP, see Figure 2. In addition, the responses show the frequency composition effect described by Carvalho (2006). The firms with flexible prices are quick to adjust. Hence, at longer horizons, the distribution of firms with non-adjusted prices is dominated by the stickier type of firms. This generates additional persistence in the responses.

An important aspect of the monetary transmission channel is the response of aggregate TFP. In contrast, traditional business cycle models assume that fluctuations in aggregate TFP are solely driven by exogenous technology shocks. This motivates us to examine the success of a Taylor rule in stabilizing output if the monetary authority in the model (mis-)perceives the aggregate TFP response to demand shocks as originating from technology shocks. We compute a counterfactual change in natural output supposing the TFP response to monetary policy shocks is driven by technology shocks.[17] Panel (a) in Figure 5 shows the difference between the GDP responses under the counterfactual technology shock and the

[16] At an earlier stage of this paper, we have also solved the model globally using a time iteration algorithm for the case of two firm types with one of them having perfectly flexible prices. This yields very similar quantitative results compared to using the Meyer-Gohde (2014) algorithm. However, the computational costs of time iteration are exceedingly large for more general setup of heterogeneous price rigidities.

[17] We recalibrate $\sigma_\nu$ to ensure the same interest rate response to a one standard deviation monetary policy shock, but keep all other parameters unchanged.

Figure 4: Model responses to monetary policy shocks




Notes: This figure shows responses to a one standard deviation contractionary monetary policy shock. In panel (e), the responses are the average markup responses of the firm types $k = 1, \dots, 5$, where $k = 1$ is the stickiest and $k = 5$ the most flexible type of firms.

baseline response.[18] Output drops by up to 0.17 percentage points more if the monetary authority attributes aggregate TFP fluctuations to technology shocks, and the response is markedly more persistent. This finding highlights the importance for the monetary authority to assess the sources of observed aggregate TFP fluctuations.

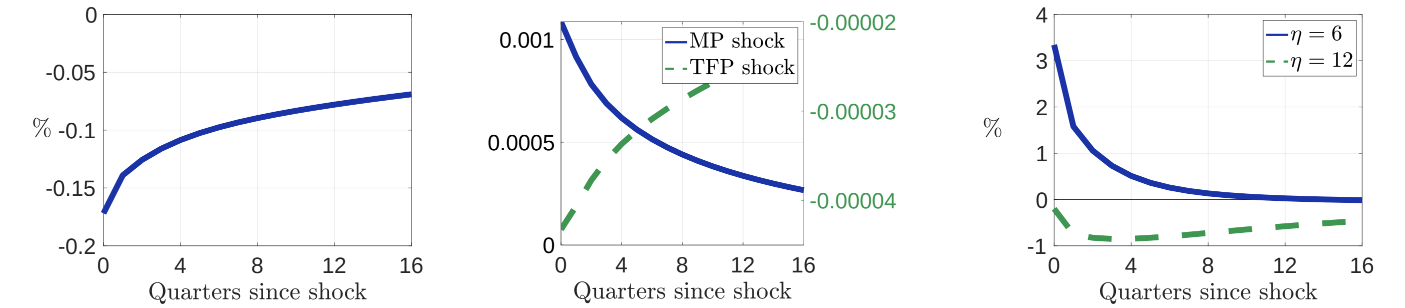
Panel (b) in Figure 5 shows the response of markup dispersion to a negative technology shock with the size and persistence that matches the endogenous response of TFP to a monetary policy shock.[19] The behavior of markup dispersion helps to discriminate between productivity and monetary policy shocks. It increases after contractionary monetary policy shocks but decreases after contractionary productivity shocks.

The fact that aggregate TFP responds to monetary policy shocks can change the sign of the (aggregate) markup response to monetary policy shocks. This relates to a recent debate. While monetary policy shocks raise markups in a large class of New Keynesian models, recent evidence in Nekarda and Ramey (2019) points in the opposite direction. Following

[18]Figure 24 in the Appendix provides further impulse responses for this counterfactual scenario.
[19]Figure 25 in the Appendix provides further impulse responses for the technology shock.

Figure 5: Additional model results and counterfactuals

(a) Differential GDP response, counterfactual technology shock | (b) Markup dispersion response to technology shock | (c) Aggregate markup response, low vs. high substitution elasticity




Notes: Panel (a) shows the difference between the response to a monetary policy shock in the baseline model and the same model using a Taylor rule in which the output gap is computed by counterfactually assuming the TFP responses are driven by technology shocks. Panel (b) compares the response of markup dispersion to a monetary policy shock (left y-axis) with a technology shock (right y-axis). Panel (c) compares the response of the aggregate markup to a monetary policy shock for two values of the elasticity of substitution between differentiated goods.

Hall (1988), the aggregate markup in our model is

$$\mu_t = \frac{\text{TFP}_t}{W_t/P_t}, \tag{4.1}$$

where $W_t/P_t$ denotes the real wage. In standard New Keynesian models, tighter monetary policy reduces aggregate demand which lowers real marginal costs and, hence, markups increase. In contrast, equation (4.1) shows that the aggregate markup falls if aggregate TFP falls sufficiently strongly in response to tighter monetary policy. This argument extends to sectoral and even firm-level markups, if monetary policy shocks affect TFP at more disaggregated levels. In general equilibrium, an endogenous decline in aggregate TFP will feed back into real marginal costs, which also affects markups.

Panel (c) in Figure 5 shows the aggregate markup response to monetary policy shocks. In our baseline calibration with an elasticity of substitution $\eta = 6$ the aggregate markup raises. In some sense, that is because aggregate TFP does not fall strongly enough. We next compare our baseline results with the results when doubling the elasticity to $\eta = 12$. A larger $\eta$ increases the misallocation costs of markup dispersion and thus the TFP loss after a monetary policy shock. For $\eta = 12$, the aggregate TFP response is almost twice as large, see Figure 26 in the Appendix. This is sufficient to explain lower aggregate markups after monetary policy shocks. Dynamically, the TFP loss leads to an increase in hours worked, which additionally increases marginal costs and lowers firm-level markups, reinforcing the effect on the aggregate markup.

# 5 Conclusion

This paper studies how markup dispersion matters for monetary transmission. Monetary policy shocks increase the dispersion of markups across firms if firms with stickier prices have higher pre-shock markups. Increased markup dispersion implies a change in the allocation of inputs across firms, which lowers measured aggregate TFP. Using aggregate and firm-level data, we document three new facts, which are consistent with this mechanism. First, firms that adjust prices less frequently have higher markups. Second, monetary policy shocks increase the relative markup of firms with stickier prices. Third, monetary policy shocks increase the markup dispersion across firms, and lower aggregate productivity. The empirically estimated magnitudes suggest that the response in markup dispersion is quantitatively important to understand the response of aggregate productivity. We show that an explanation for the negative correlation between markup and price stickiness are differences in price stickiness across firms. Firms with stickier prices optimally set higher markups for precautionary reasons. We show that our novel mechanism has implications for monetary policy and for the markup response to monetary policy shocks.

# References


Aoki, K. (2001): "Optimal monetary policy responses to relative-price changes," *Journal of Monetary Economics*, 48, 55 – 80.

Aruoba, S. B., F. X. Diebold, J. Nalewaik, F. Schorfheide, and D. Song (2016): "Improving GDP measurement: A measurement-error perspective," *Journal of Econometrics*, 191, 384–397.

Ascari, G. and A. M. Sbordone (2014): "The Macroeconomics of Trend Inflation," *Journal of Economic Literature*, 52, 679–739.

Ashenfelter, O. C., H. Farber, and M. R. Ransom (2010): "Labor market monopsony," *Journal of Labor Economics*, 28, 203–210.

Baqaee, D. R. and E. Farhi (2017): "Productivity and Misallocation in General Equilibrium," *NBER Working Paper Series*.

——— (2020): "Productivity and Misallocation in General Equilibrium," *The Quarterly Journal of Economics*, 135, 105–163.

Barro, R. (1972): "A Theory of Monopolistic Price Adjustment," *Review of Economic Studies*, 39, 17–26.

Basu, S. (1995): "Intermediate Goods and Business Cycles: Implications for Productivity and Welfare," *The American Economic Review*, 85, 512–531.

——— (2019): "Are Price-Cost Markups Rising in the United States? A Discussion of the Evidence," *Journal of Economic Perspectives*, 33, 3–22.

Basu, S., J. G. Fernald, and M. S. Kimball (2006): "Are Technology Improvements Contractionary?" *American Economic Review*, 96, 1418–1448.

Bloom, N. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77, 623–685.

Bond, S., A. Hashemi, G. Kaplan, and P. Zoch (2020): "Some Unpleasant Markup Arithmetic: Production Function Elasticities and their Estimation from Production Data," mimeo, University of Oxford.

Calvo, G. (1983): "Staggered prices in a utility-maximizing framework," *Journal of Monetary Economics*, 12, 383–398.

Cantore, C., F. Ferroni, and M. León-Ledesma (2020): "The Missing Link: Monetary Policy and The Labor Share," *Journal of the European Economic Association*, jvaa034.

Carvalho, C. (2006): "Heterogeneity in Price Stickiness and the Real Effects of Monetary Shocks," *The B.E. Journal of Macroeconomics*, 6, 1–58.

Carvalho, C. and F. Schwartzman (2015): "Selection and monetary non-neutrality in time-dependent pricing models," *Journal of Monetary Economics*, 76, 141–156.

Chetty, R., A. Guren, D. Manoli, and A. Weber (2011): "Are Micro and Macro Labor Supply Elasticities Consistent? A Review of Evidence on the Intensive and Extensive Margins," *American Economic Review*, 101, 471–75.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (2005): "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113, 1–45.

Christiano, L. J., M. S. Eichenbaum, and M. Trabandt (2016): "Unemployment and Business Cycles," *Econometrica*, 84, 1523–1569.

Comin, D. and M. Gertler (2006): "Medium-Term Business Cycles," *American Economic Review*, 96, 523–551.

Comin, D. and B. Hobijn (2010): "An Exploration of Technology Diffusion," *American Economic Review*, 100, 2031–59.

De Loecker, J., J. Eeckhout, and G. Unger (2020): "The Rise of Market Power and the Macroeconomic Implications," *The Quarterly Journal of Economics*.

De Loecker, J. and F. Warzynski (2012): "Markups and Firm-Level Export Status," *American Economic Review*, 102, 2437–71.

Eisfeldt, A. L. and A. A. Rampini (2006): "Capital reallocation and liquidity," *Journal of Monetary Economics*, 53, 369–399.

Eusepi, S., B. Hobijn, and A. Tambalotti (2011): "CONDI: A Cost-of-Nominal-Distortions Index," *American Economic Journal: Macroeconomics*, 3, 53–91.

Evans, C. L. and F. T. Santos (2002): "Monetary policy shocks and productivity measures in the G-7 countries," *Portugese Economic Journal*, 1, 47–70.

Fernald, J. (2014): "A quarterly, utilization-adjusted series on total factor productivity," *Federal Reserve Bank of San Francisco Working Paper Series*.

Fernandez-Villaverde, J., P. Guerron-Quintana, K. Kuester, and J. Rubio-Ramirez (2015): "Fiscal Volatility Shocks and Economic Activity," *American Economic Review*, 105, 3352–84.

Galí, J. (2015): *Monetary Policy, Inflation, and the Business Cycle: an Introduction to the New Keynesian Framework and its Applications*, Princeton University Press.

Gali, J., M. Gertler, and D. Lopez-Salido (2007): "Markups, Gaps, and the Welfare Costs of Business Fluctuations," *The Review of Economics and Statistics*, 89, 44–59.

Garga, V. and S. R. Singh (2019): "Output Hysteresis and Optimal Monetary Policy," Tech. rep., University of California Davis.

Gertler, M. and P. Karadi (2015): "Monetary Policy Surprises, Credit Costs and Economic Activity," *American Economic Journal: Macroeconomics*, 7, 44–76.

Gopinath, G., S. Kalemli-Özcan, L. Karabarbounis, and C. Villegas-Sanchez (2017): "Capital Allocation and Productivity in South Europe," *Quarterly Journal of Economics*, 132, 1915–1967.

Gorodnichenko, Y. and M. Weber (2016): "Are Sticky Prices Costly? Evidence from the Stock Market," *American Economic Review*, 106, 165–99.

Hall, R. (1986): "Market Structure and Macroeconomic Fluctuations," *Brookings Papers on Economic Activity*, 17, 285–338.

——— (1988): "The Relation between Price and Marginal Cost in U.S. Industry," *Journal of Political Economy*, 96, 921–47.

Hsieh, C.-T. and P. J. Klenow (2009): "Misallocation and Manufacturing TFP in China and India," *The Quarterly Journal of Economics*, CXXIV, 1403–1448.

Jarocinski, M. and P. Karadi (2020): "Deconstructing monetary policy surprises: the role of information shocks," *American Economic Journal: Macroeconomics*.

Jeenas, P. (2019): "Firm Balance Sheet Liquidity, Monetary Policy Shocks, and Investment Dynamics," *mimeo*.

Jordà, Ò., S. Singh, and A. M. Taylor (2020): "The long-run effects of monetary policy," *mimeo*.

Khan, A. and J. K. Thomas (2008): "Idiosyncratic Shocks and the Role of Nonconvexities in Plant and Aggregate Investment Dynamics," *Econometrica*, 76, 395–436.

——— (2013): "Credit Shocks and Aggregate Fluctuations in an Economy with Production Heterogeneity," *Journal of Political Economy*, 121, 1055–1107.

Kimball, M. S. (1995): "The Quantitative Analytics of the Basic Neomonetarist Model," *Journal of Money, Credit and Banking*, 27, 1241–1277.

Klenow, P. J. and J. L. Willis (2016): "Real Rigidities and Nominal Price Changes," *Economica*, 83, 443–472.

Levin, A. and T. Yun (2007): "Reconsidering the natural rate hypothesis in a New Keynesian framework," *Journal of Monetary Economics*, 54, 1344–1365.

Lucca, D. O. and E. Moench (2015): "The pre-FOMC announcement drift," *The Journal of Finance*, 70, 329–371.

Meier, M. (2020): "Supply Chain Disruptions, Time To Build, and the Business Cycle," *mimeo U Mannheim.*

Meyer-Gohde, A. (2014): "Risky linear approximations," mimeo, Goethe University Frankfurt.

Miranda-Agrippino, S. and G. Ricco (2018): "The Transmission of Monetary Policy Shocks," mimeo, University of Warwick.

Moran, P. and A. Queralto (2018): "Innovation, productivity, and monetary policy," *Journal of Monetary Economics*, 93, 24–41, carnegie-Rochester-NYU Conference on Public Policy held at the Stern School of Business at New York University.

Nakamura, E. and J. Steinsson (2010): "Monetary Non-neutrality in a Multisector Menu Cost Model*," *The Quarterly Journal of Economics*, 125, 961–1013.

——— (2018): "High Frequency Identification of Monetary Non-Neutrality: The Information Effect," *Quarterly Journal of Economics*, 133, 1283–1330.

Nakamura, E., J. Steinsson, P. Sun, and D. Villar (2018): "The Elusive Costs of Inflation: Price Dispersion during the U.S. Great Inflation*," *The Quarterly Journal of Economics*, 133, 1933–1980.

Nekarda, C. J. and V. A. Ramey (2019): "The Cyclical Behavior of the Price-Cost Markup," mimeo, University of California San Diego.

Oikawa, K. and K. Ueda (2018): "Reallocation Effects of Monetary Policy," *RIETI Discussion Paper Series 18-E-056.*

Ottonello, P. and T. Winberry (2020): "Financial Heterogeneity and the Investment Channel of Monetary Policy," *mimeo.*

Pasten, E., R. Schoenle, and M. Weber (forthcoming): "The Propagation of Monetary Policy Shocks in a Heterogeneous Production Economy," *Journal of Monetary Economics.*

Romer, D. (1990): "Staggered price setting with endogenous frequency of adjustment," *Economics Letters*, 32, 205–210.

Rotemberg, J. J. (1982): "Monopolistic Price Adjustment and Aggregate Output," *The Review of Economic Studies*, 49, 517–531.

Rubbo, E. (2020): "Networks, Phillips Curves and Monetary Policy," mimeo, Harvard University.

Sheremirov, V. (2019): "Price dispersion and inflation: New facts and theoretical implications," *Journal of Monetary Economics*.

Stock, J. H. and M. W. Watson (2018): "Identification and estimation of dynamic causal effects in macroeconomics using external instruments," *The Economic Journal*, 128, 917–948.

Taylor, J. B. (1979): "Staggered Wage Setting in a Macro Model," *American Economic Review*, 69, 108–113.

Traina, J. (2020): "Is Aggregate Market Power Increasing? Production Trends Using Financial Statements," New working paper series, Stigler Center.

Zeev, N. B. and E. Pappa (2015): "Multipliers of unexpected increases in defense spending: An empirical investigation," *Journal of Economic Dynamics and Control*, 57, 205–226.

# Appendix

# A Data construction and descriptive statistics

## A.1 Firm-level balance sheet data

We use quarterly firm-level balance sheet data of listed US firms for the period 1995Q1 to 2017Q2 from Compustat. We delete duplicate firm-quarter observations. We use the NAICS industry classification and exclude firms in utilities (NAICS code 22), finance, insurance, and real estate (52 and 53), and public administration (99). We discard observations of sales (`saleq`), costs of goods sold (`cogsq`), and property, plant, and equipment (net PPE, `ppentq`, and gross PPE, `ppegtq`), that are non-positive. We fill one-quarter gaps in the firm-specific series of these variables by linear interpolation. All variables are deflated using the GDP deflator, except PPE, which is deflated by the investment-specific GDP deflator. We construct a measure of the capital stock of firms using the perpetual inventory method: We initialize $K_{i0} = \texttt{ppegtq}_{i0}$ and recursively compute $K_{it} = K_{it-1} + (\texttt{ppentq}_{it} - \texttt{ppentq}_{it-1})$. We drop firm-quarter observations if sales, costs of goods sold, or fixed assets are only reported once in the associated year. We further drop observations if quarterly sales growth is above 100% or below -67% or if real sales are below 1 million USD. Table 3 shows descriptive statistics for our baseline sample.

Table 3: Summary statistics for Compustat data

| | mean | sd | min | max | count |
|---|---|---|---|---|---|
| Sales | 632.22 | 3067.46 | 1.00 | 132182.15 | 329173 |
| Fixed assets | 987.38 | 5490.96 | 0.00 | 273545.97 | 326223 |
| Variable costs | 439.58 | 2317.01 | 0.13 | 104456.86 | 329173 |
| Total Assets | 2716.05 | 13374.72 | 0.00 | 559922.78 | 326632 |

Notes: Summary statistics for Compustat data. All variables are in millions of 2012Q1 US$.

## A.2 Monetary policy shocks

We construct high-frequency identified monetary policy shocks as described in Subsection 2.1. Table 4 reports summary statistics for shock series and Figure 6 shows the time series.

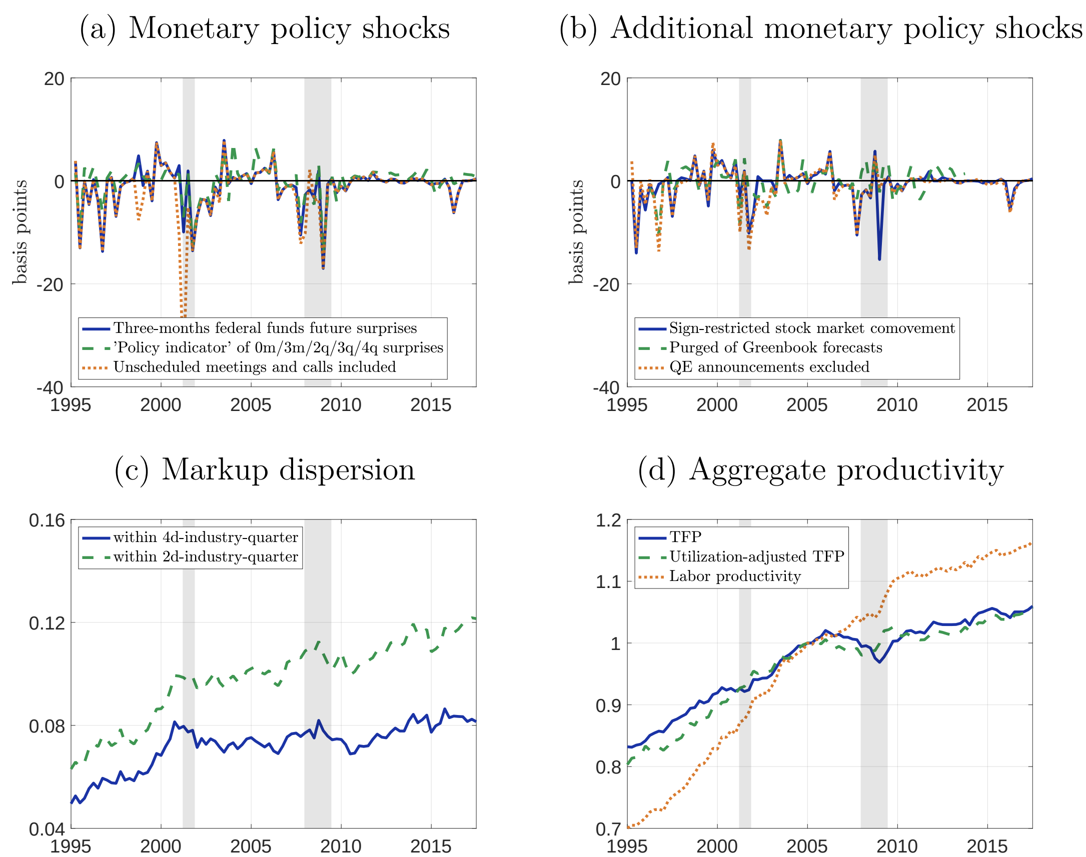
Table 4: Summary statistics of monetary policy shocks

| | mean | sd | min | max | count |
|---|---|---|---|---|---|
| Three-month Fed funds future surprises | -1.00 | 4.06 | -17.01 | 7.87 | 94 |
| ... unscheduled meetings and conference calls included | -1.84 | 5.70 | -38.33 | 7.86 | 94 |
| ... purged of Greenbook forecasts | -0.00 | 3.10 | -10.47 | 7.98 | 71 |
| ... sign-restricted stock market comovement | -0.52 | 3.47 | -15.27 | 7.87 | 94 |
| ... QE announcements excluded | -0.83 | 3.72 | -13.71 | 7.87 | 94 |
| 'Policy indicator' surprise | -0.05 | 3.43 | -14.13 | 7.45 | 94 |

Notes: Summary statistics for monetary policy shocks in basis points.

## A.3 Time series plots of monetary policy shocks, markup dispersion, and aggregate productivity

Figure 6: Monetary policy shocks, aggregate productivity, and markup dispersion




Notes: Aggregate productivity (in logs), markup dispersion, and monetary policy shocks are at quarterly frequency. Aggregate (utilization-adjusted) TFP is from Fernald (2014). Labor productivity is from FRED. Markup dispersion is computed from Compustat balance sheet data. Shaded gray areas indicate NBER recession dates.

### A.4 Data on price rigidity

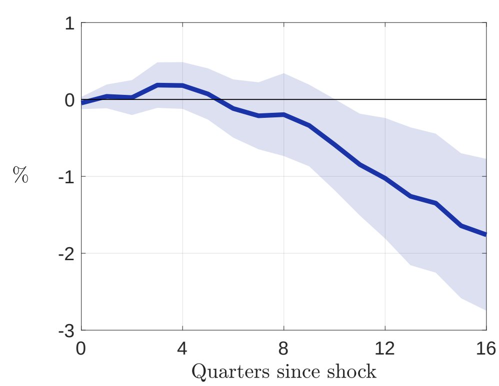
To maximize firm-level variation in price rigidity, we weight average industry-level price adjustment frequency with firms' industry sales from the Compustat segment files. Industry-level price adjustment frequency is based on Pasten et al. (forthcoming). We define the implied price duration as $-1/\log(1 - \text{price adjustment frequency})$.

We obtain firms' yearly industry sales composition using the operation segments and, if these are not available, the business segments from the Compustat segments file. We drop various types of duplicate observations: In case of exact duplicates, we keep one. In case there are different source dates or more than one accounting month per year, we keep the observation with the newest source dates or the later accounting month, respectively. We drop segment observations for firm-years if the industry code is not reported. If only some segment industry codes are missing, we assign the firm-specific industry code to the segments with missing industry code.

We then compute every firm's average price rigidity over segments weighted by sales. In case we do not observe the five-digit-industry-level price stickiness for all segments or we observe only one segment, we use the five-digit price rigidity measure associated to the firm's general five-digit industry code. Note that even in this case, there is variation across firms within four-digit industries. Our sample comprises 8,091 unique firms. For 1,891 firms (23%), we can compute a segment-based price stickiness level in some year. For firm-years with segment-based price stickiness, the mean (median) number of segments is 2.36 (2) with a standard deviation of 0.67.

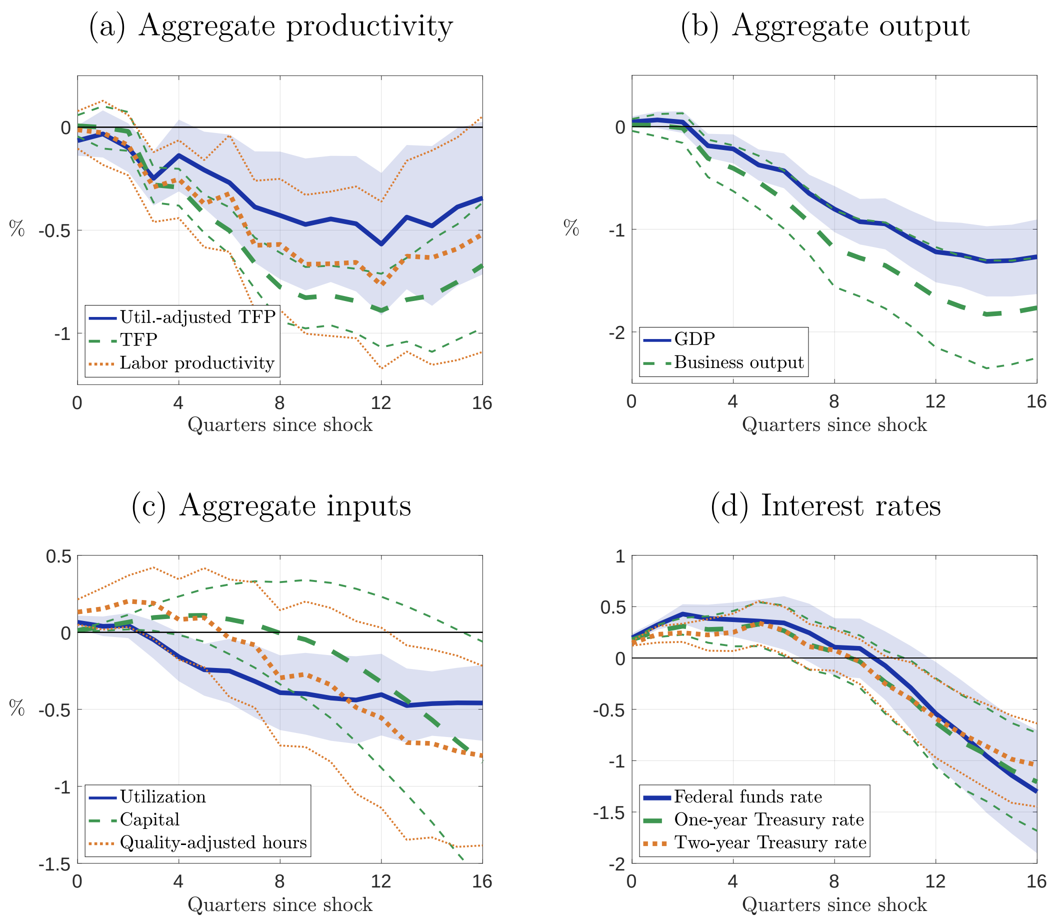
# B Additional empirical results

Figure 7: Aggregate R&D response to monetary policy shock




Notes: The plots show the response to a one standard deviation contractionary monetary policy shock. The shaded area indicate one standard error bands based on the Newey–West estimator.

Figure 8: Macroeconomic responses to monetary policy shocks

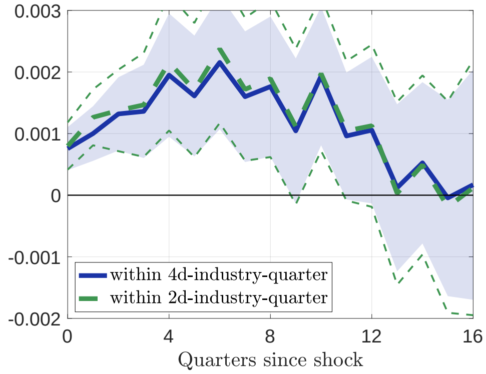



Notes: The plots show the responses to a one standard deviation contractionary monetary policy shock. The local projections in Panel (d) are estimated in levels rather than differences. The shaded and bordered areas indicate one standard error bands based on the Newey–West estimator.

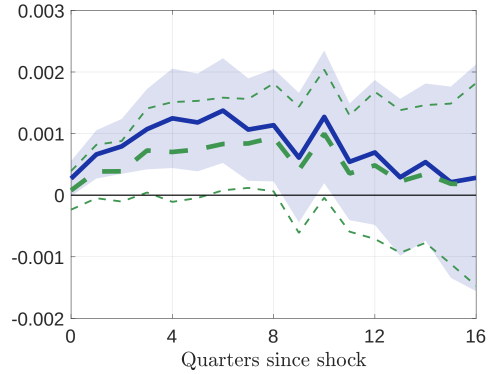
# C Robustness of evidence in Section 2

Figure 9: Responses of markup dispersion for alternative markup measures

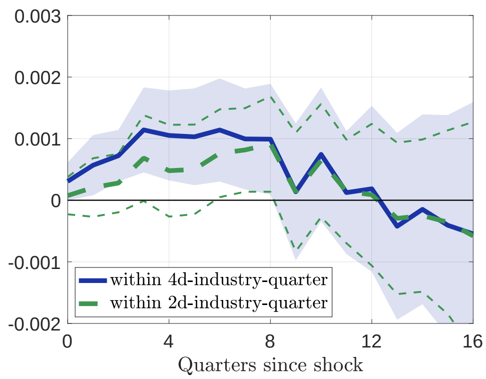
(a) Translog




(b) Cost shares



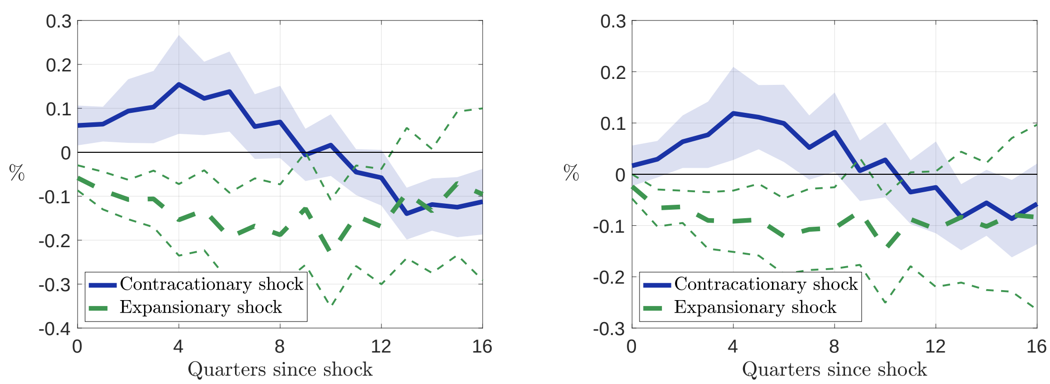

(c) Baseline incl. SGA




Notes: Responses to monetary policy shocks obtained from local projections as in equation (2.4). Panel (a) uses markups based on an industry-specific translog production function, which gives rise firm-quarter-specific output elasticities. Panel (b) uses markups based on output elasticities estimated as the industry-quarter-specific median cost share. Panel (c) uses markups based on our baseline assumption of common output elasticities within industry-quarters, but measures labor and material expenses using costs of goods sold (COGS) plus selling, general, and administrative expenses (SGA). Markup dispersion is measured within two-digit and four-digit industry-quarters as well as without fixed effects, respectively. The shaded and bordered areas indicate one standard error bands based on Newey–West.

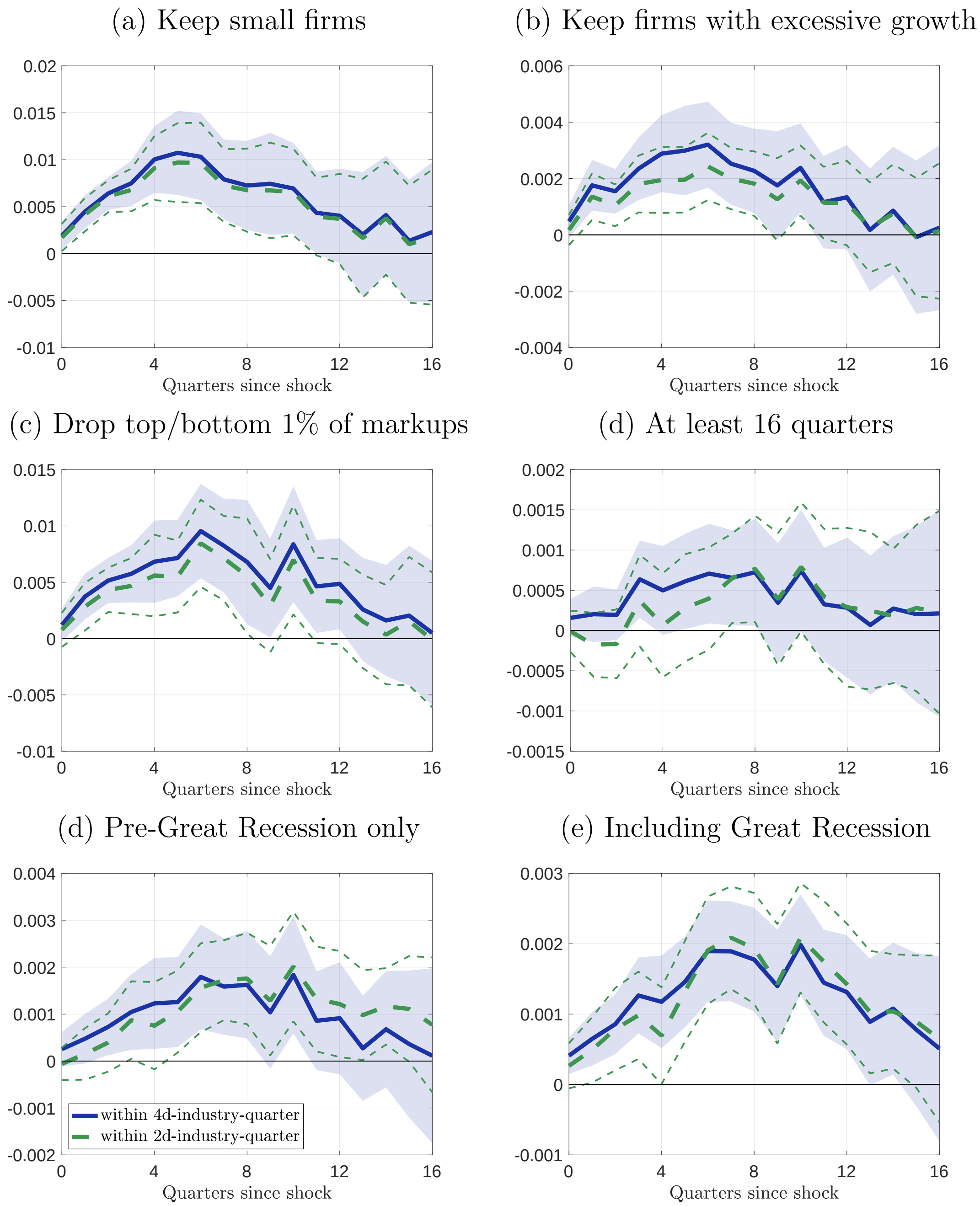
Figure 10: Asymmetric markup dispersion responses for alternative markup measures

(a) Translog (b) Cost shares



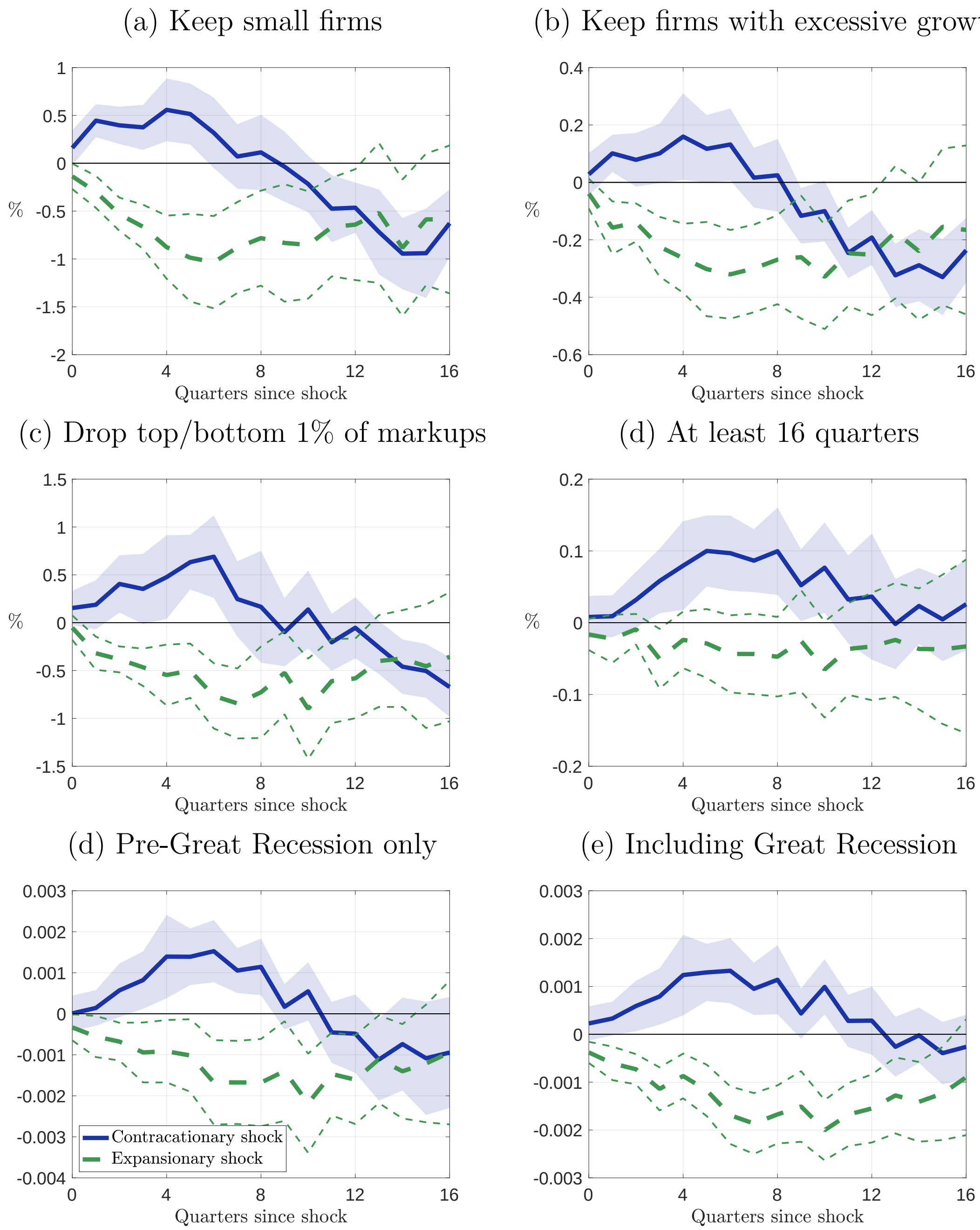

Notes: Responses to monetary policy shocks obtained from local projections extending specification (2.4) to separately estimate the response to positive and negative shocks. Panel (a) uses markups based on an industry-specific translog production function, which gives rise firm-quarter-specific output elasticities. Panel (b) uses markups based on output elasticities estimated as the industry-quarter-specific median cost share. The shaded and bordered areas indicate one standard error bands based on Newey–West.

Figure 11: Responses of markup dispersion under alternative data treatments



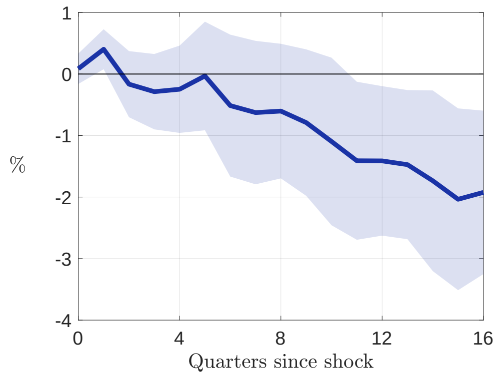

Notes: Responses to monetary policy shocks obtained from local projections as in equation (2.4). See the notes to Figure 21 for details on the data treatments. The shaded and bordered areas indicate one standard error bands based on Newey–West.

Figure 12: Asymmetric markup dispersion responses for alternative data treatments




Notes: Responses to monetary policy shocks obtained from local projections as in equation (**??**). The shaded and bordered areas indicate one standard error bands based on Newey–West.

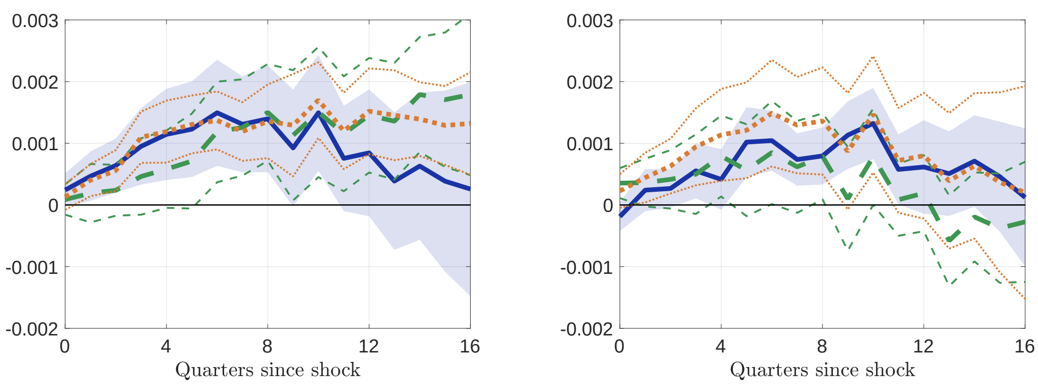
Figure 13: Response of firm-level observations after monetary policy shocks



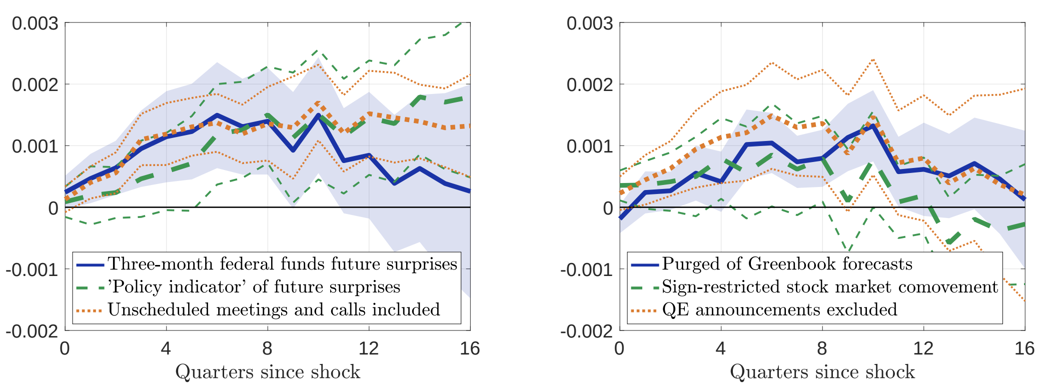

Notes: This figure shows the response of the number of firm-level observations in our sample to monetary policy shocks obtained from local projections as in equation (2.4). The shaded area is a one standard error band based on Newey–West.

Figure 14: Responses of markup dispersion for alternative monetary policy shocks

(a) within 2d-industry-quarter

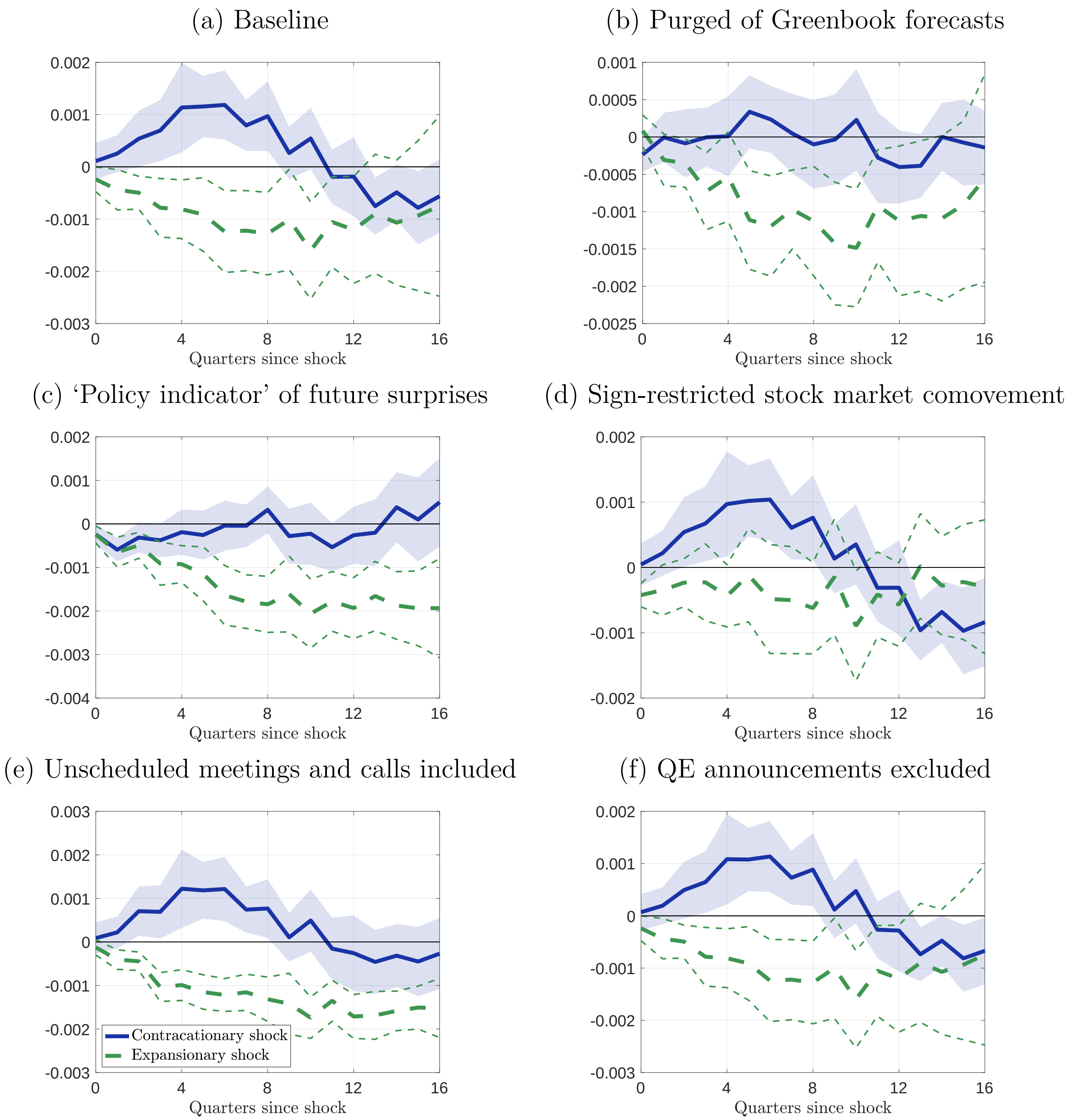



(b) within 4d-industry-quarter




Notes: Responses to monetary policy shocks obtained from local projections as in equation (2.4). The shaded and bordered areas indicate one standard error bands based on Newey–West.

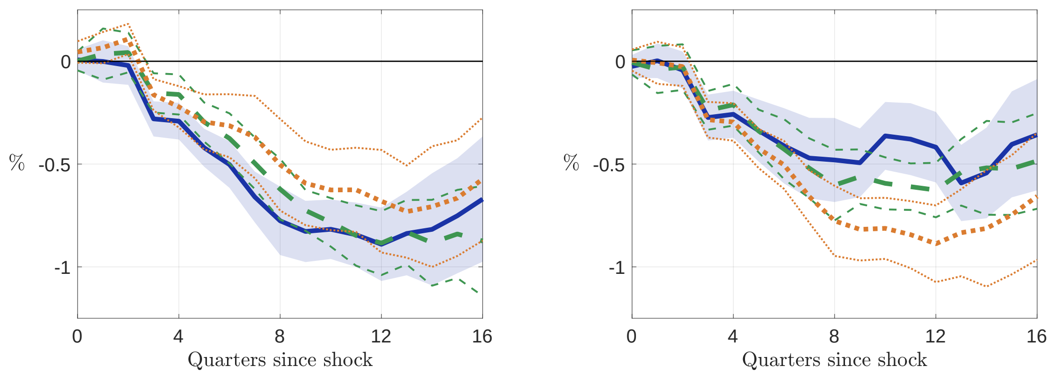
Figure 15: Asymmetric markup dispersion responses for alternative monetary policy shocks



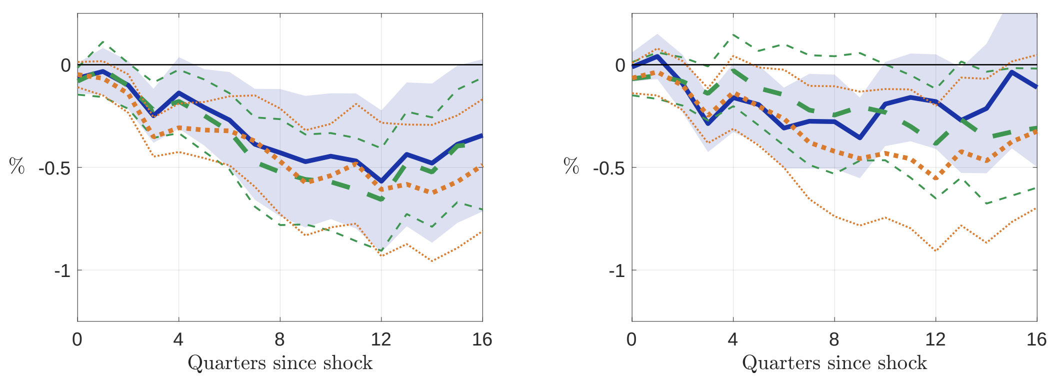

Notes: Responses to monetary policy shocks obtained from local projections as in equation (**??**). The shaded and bordered areas indicate one standard error bands based on Newey–West.

Figure 16: Aggregate productivity responses for alternative monetary policy shocks

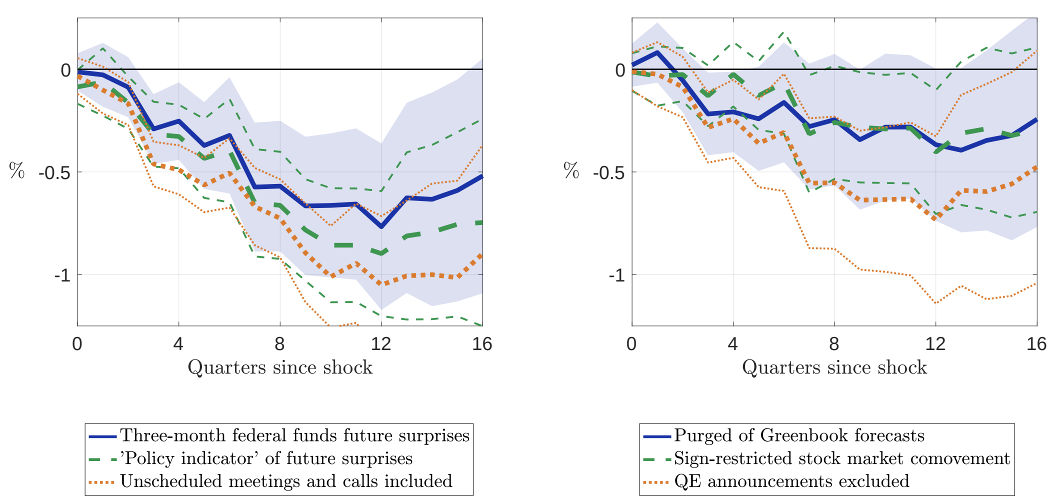
(a) TFP




(b) Utilization-adjusted TFP



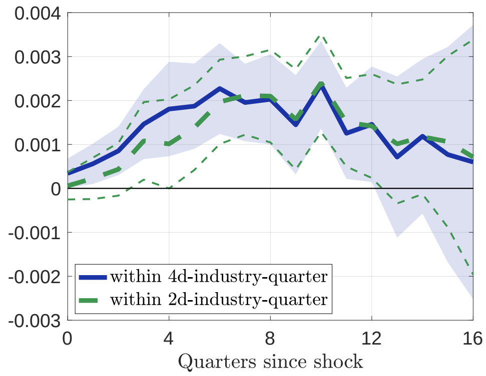

(c) Labor productivity



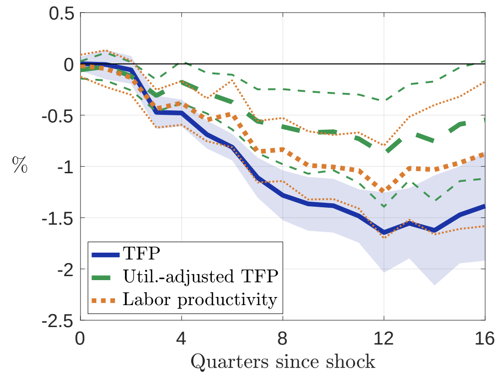

Notes: Responses to monetary policy shocks obtained from local projections as in equation (2.4). The shaded and bordered areas indicate one standard error bands based on Newey–West.

Figure 17: Main results using LP-IV

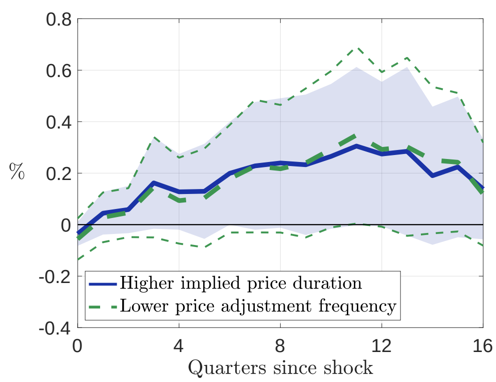
(a) Markup dispersion




(b) Aggregate productivity



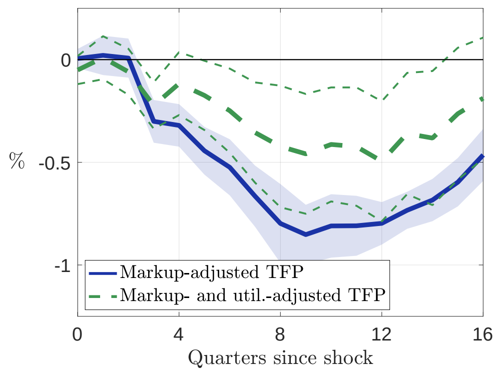

(c) Relative markup response of firms with stickier prices



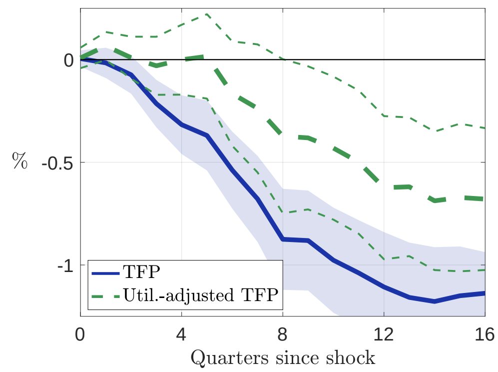

Notes: Responses to monetary policy shocks obtained from local projections with instrumental variables (LP-IV), $y_{t+h} - y_{t-1} = \alpha^h + \beta^h \Delta R_t + \gamma_1^h (y_{t-1} - y_{t-2}) + u_t^h$, and analogues of the panel local projections, where the changes in the one-year Treasury rate, $\Delta R_t$, are instrumented with the monetary policy shocks $\varepsilon_t^{\mathrm{MP}}$. The shaded and bordered areas in panels (a) and (b) indicate a one standard error band based on Newey–West, and in panels (c) they indicate a 90% error band clustered by firms and quarters.

Figure 18: Further productivity responses

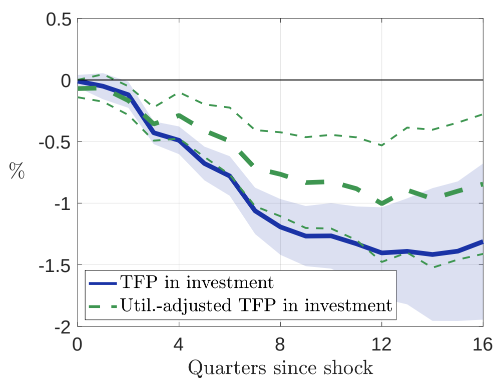
(a) Markup-adjusted TFP



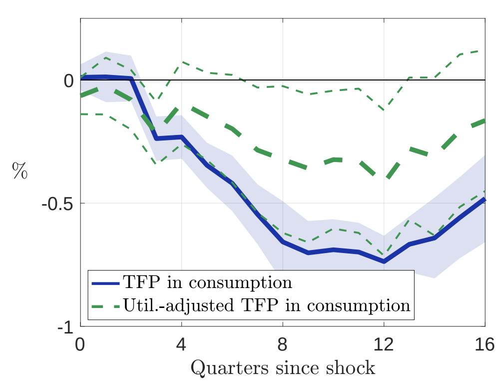

(b) Measurement error corrected TFP




(c) Investment TFP

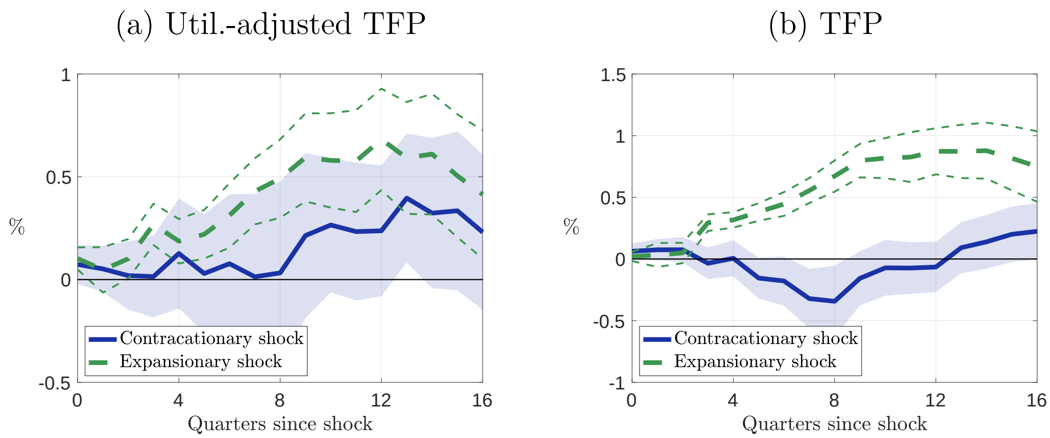



(d) Consumption TFP




Notes: Responses to monetary policy shocks obtained from local projections as in equation (2.4). Investment-TFP and Consumption-TFP are from Fernald (2014). Markup-corrected TFP is constructed following Hall (1988) using the average markup estimated by De Loecker et al. (2020). Measurement error corrected TFP is constructed using measurement error corrected GDP from Aruoba et al. (2016), total hours from the BLS, and capital stock and output elasticities from Fernald (2014). The utilization-adjusted measure subtracts utilization from Fernald (2014). The shaded and bordered areas indicate one standard error bands based on Newey–West.

Figure 19: Asymmetric responses of (util.-adjusted) TFP to monetary policy shocks




Notes: Responses to monetary policy shocks obtained from local projections extending specification (2.4) to separately estimate the response to positive and negative shocks. TFP and utilization-adjusted TFP are from Fernald (2014). The shaded and bordered areas indicate one standard error bands based on Newey–West.

# D Robustness of evidence in Section 3

Table 5: Regressions of markup on price stickiness including price adjustment frequencies above 99%

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Implied price duration | 0.0435 | 0.0362 | | |
| | (0.0197) | (0.0175) | | |
| Price adjustment frequency | | | -0.243 | -0.184 |
| | | | (0.143) | (0.134) |
| Size | | 0.00923 | | 0.00896 |
| | | (0.00361) | | (0.00387) |
| Leverage | | -0.00174 | | -0.00170 |
| | | (0.000667) | | (0.000673) |
| Liquidity | | 0.548 | | 0.548 |
| | | (0.0590) | | (0.0592) |
| 2-digit industry FE | Yes | Yes | Yes | Yes |
| Observations | 4027 | 4024 | 4027 | 4024 |
| Adjusted $R^2$ | 0.106 | 0.185 | 0.102 | 0.180 |

Notes: Regression of firm-level markup (averaged over 2005–2011) on firm-level price adjustment frequency and implied price duration, respectively. Standard errors are clustered at the two-digit industry level and shown in parentheses.

Table 6: Regressions of markup on price stickiness for alternative markup series

(a) Markups based on translog production function

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Implied price duration | 0.0272 | 0.0296 | | |
| | (0.0106) | (0.0102) | | |
| Price adjustment frequency | | | -0.210 | -0.226 |
| | | | (0.0731) | (0.0731) |
| Additional controls | No | Yes | No | Yes |
| 2-digit industry FE | Yes | Yes | Yes | Yes |
| Observations | 3830 | 3827 | 3830 | 3827 |
| Adjusted $R^2$ | 0.067 | 0.123 | 0.070 | 0.126 |

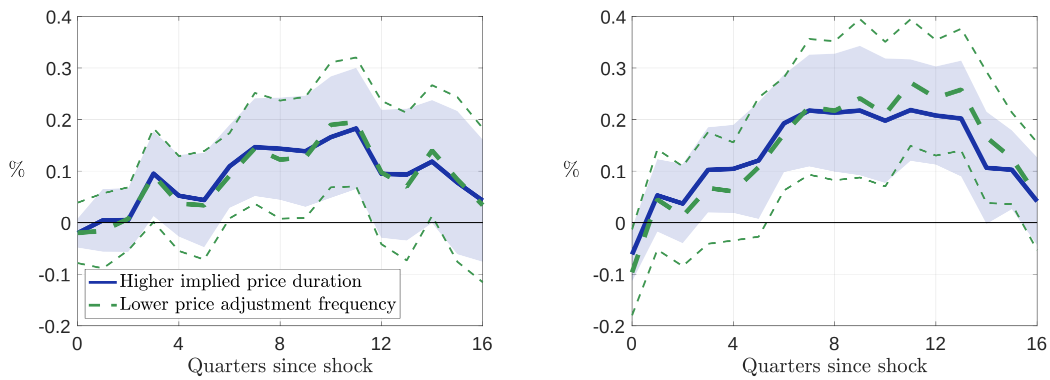
(b) Markups based on cost shares

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Implied price duration | 0.0584 | 0.0510 | | |
| | (0.0177) | (0.0151) | | |
| Price adjustment frequency | | | -0.431 | -0.371 |
| | | | (0.0931) | (0.0793) |
| Additional controls | No | Yes | No | Yes |
| 2-digit industry FE | Yes | Yes | Yes | Yes |
| Observations | 3873 | 3870 | 3873 | 3870 |
| Adjusted $R^2$ | 0.196 | 0.271 | 0.204 | 0.276 |

Notes: Regression of firm-level markup (averaged over 2005–2011) on firm-level price adjustment frequency and implied price duration, respectively. Panel (a) uses markups based on an industry-specific translog production function, which gives rise firm-quarter-specific output elasticities. Panel (b) uses markups based on output elasticities estimated as the industry-quarter-specific median cost share. Standard errors are clustered at the two-digit industry level and shown in parentheses.

Figure 20: Relative markup response of firms with stickier prices for alternative markup measures

(a) Translog (b) Cost shares




Notes: The figures show the response to a one standard deviation contractionary monetary policy shock of the firm-level markup of firms with a price adjustment frequency one standard deviation below (or with an implied price duration one standard deviation above) from panel local projections as in equation (3.5). The regressions include interactions with lagged log assets, leverage, and liquidity and their interactions with a monetary policy shock. Panel (a) uses markups based on an industry-specific translog production function, which gives rise firm-quarter-specific output elasticities. Panel (b) uses markups based on output elasticities estimated as the industry-quarter-specific median cost share. The shaded and bordered areas indicate 90% error bands clustered by firms and quarters.

Table 7: Regressions of markup on price stickiness under alternative data treatments

(a) Keep small firms

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Implied price duration | 0.0382<br>(0.0146) | 0.0447<br>(0.0166) | | |
| Price adjustment frequency | | | -0.280<br>(0.0655) | -0.327<br>(0.0792) |
| Additional controls | No | Yes | No | Yes |
| 2-digit industry FE | Yes | Yes | Yes | Yes |
| Observations | 4308 | 4300 | 4308 | 4300 |
| Adjusted $R^2$ | 0.168 | 0.194 | 0.170 | 0.196 |

(b) Keep firms with excessive growth

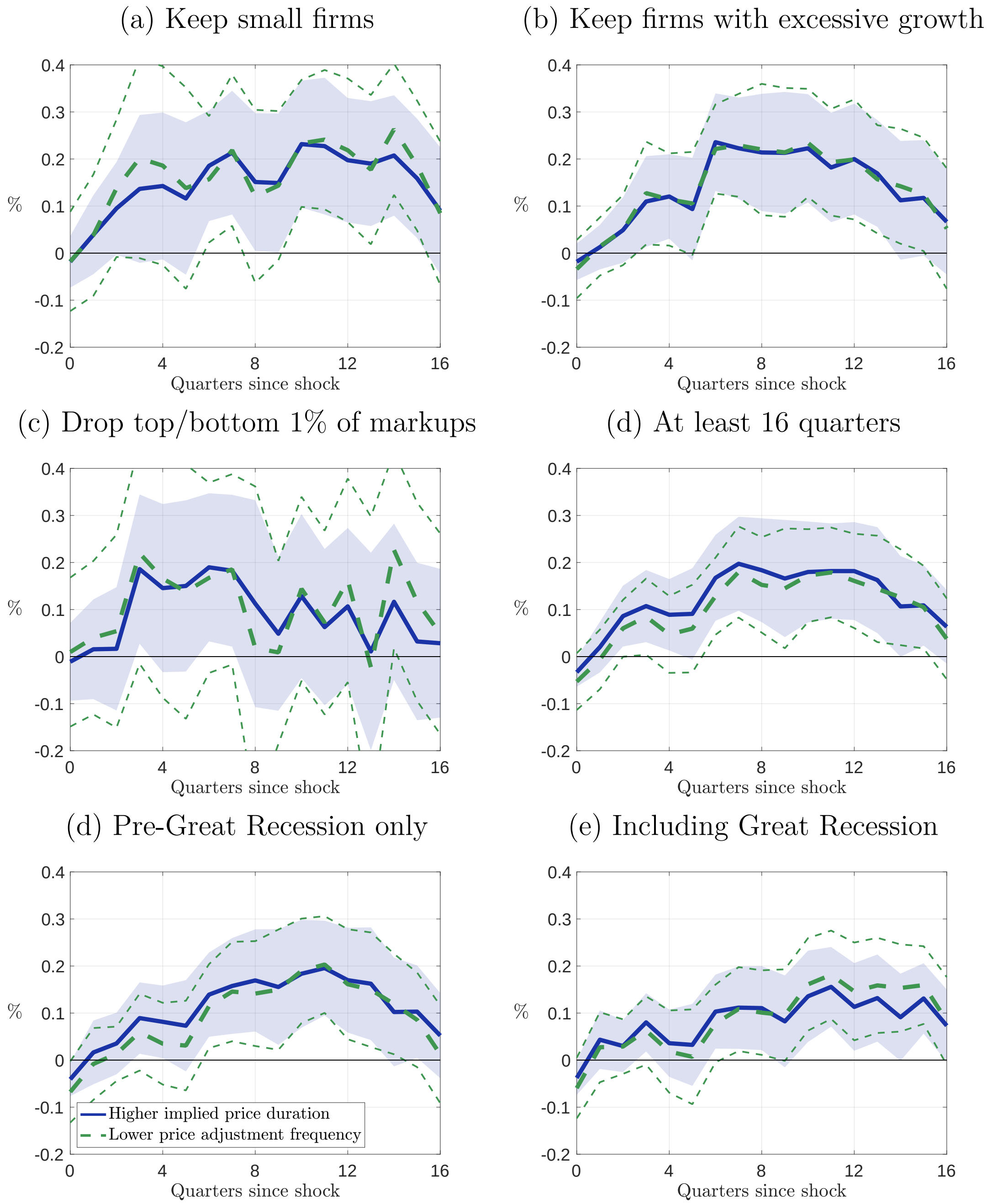
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Implied price duration | 0.0485<br>(0.0168) | 0.0438<br>(0.0148) | | |
| Price adjustment frequency | | | -0.361<br>(0.0836) | -0.317<br>(0.0750) |
| Additional controls | No | Yes | No | Yes |
| 2-digit industry FE | Yes | Yes | Yes | Yes |
| Observations | 4124 | 4074 | 4124 | 4074 |
| Adjusted $R^2$ | 0.131 | 0.196 | 0.138 | 0.199 |

(c) Drop top/bottom 1% of markups

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Implied price duration | 0.0404<br>(0.0252) | 0.0432<br>(0.0277) | | |
| Price adjustment frequency | | | -0.292<br>(0.126) | -0.312<br>(0.143) |
| Additional controls | No | Yes | No | Yes |
| 2-digit industry FE | Yes | Yes | Yes | Yes |
| Observations | 4032 | 4027 | 4032 | 4027 |
| Adjusted $R^2$ | 0.150 | 0.159 | 0.152 | 0.160 |

Notes: Regression of firm-level markup (averaged over 2005–2011) on firm-level price adjustment frequency and implied price duration, respectively. *Keep small firms* does not drop firms with sales below 1 million (in 2012 US$). *Keep firms with excessive growth* does not drop firms with growth above 100% or below -67%. *Drop top/bottom 1%* drops markups in the top/bottom 1% in the quarter instead of 5%. Standard errors are clustered at the two-digit industry level and shown in parentheses.

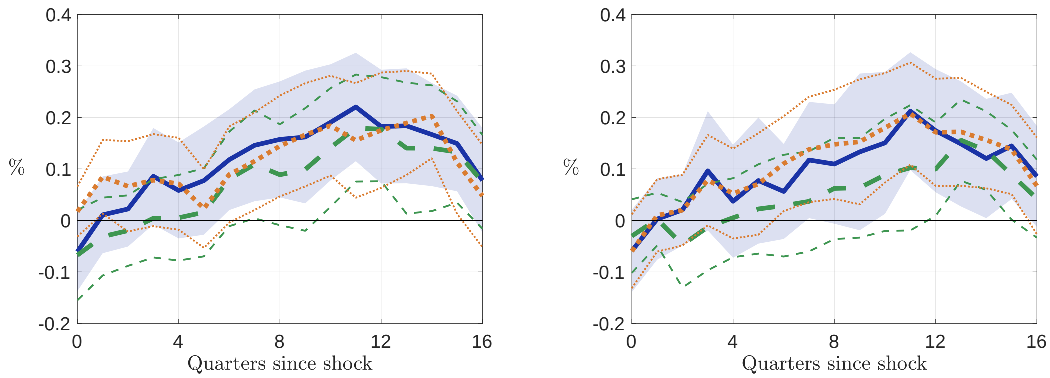
Figure 21: Relative markup response of firms with stickier prices under alternative data treatments



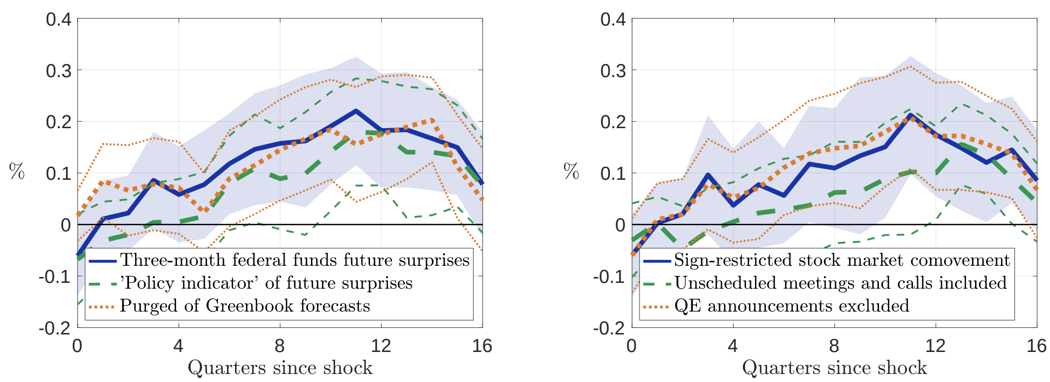

Notes: The figures show the response to a one standard deviation contractionary monetary policy shock of the firm-level markup of firms with a price adjustment frequency one standard deviation below (or with an implied price duration one standard deviation above) from panel local projections as in equation (3.5). The regressions include interactions with lagged log assets, leverage, and liquidity and their interactions with a monetary policy shock. *Keep small firms* does not drop firms with sales below 1 million (in 2012 US\$). *Keep firms with excessive growth* does not drop firms with growth above 100% or below -67%. *Drop top/bottom 1%* drops markups in the top/bottom 1% in the quarter instead of 5%. *At least 16 quarters* restricts the sample to firms with at least 16 quarters of consecutive observations. *Pre-Great Recession only* considers only observations before 2008Q3. *Including Great Recession* does not drop the period 2008Q3–2009Q2 from the sample. The shaded and bordered areas indicate 90% error bands clustered by firms and quarters.

Figure 22: Relative markup response of firms with stickier prices for alternative monetary policy shocks

(a) Higher implied price duration




(b) Lower price adjustment frequency




Notes: The figures show the response to a one standard deviation contractionary monetary policy shock of the firm-level markup of firms with a price adjustment frequency one standard deviation below (or with an implied price duration one standard deviation above) from panel local projections as in equation (3.5). The regressions include interactions with lagged log assets, leverage, and liquidity and their interactions with a monetary policy shock. The shaded and bordered areas indicate 90% error bands clustered by firms and quarters.

# E Proofs

## E.1 Markup dispersion and aggregate TFP

Consider a continuum of monopolistically competitive firms that produce variety goods $Y_{it}$. Firms employ a common constant-returns-to-scale production function $F(\cdot)$ that transforms a vector of inputs $L_{it}$ into output subject to firm-specific productivity shocks $Y_{it} = A_{it}F(L_{it})$. The cost minimization problem yields that firm-specific $X_{it} = X_t/A_{it}$, where $X_t$ denotes a common marginal costs term. Aggregate GDP is the output of a final good producer, which aggregates variety goods using a Dixit–Stiglitz aggregator $Y_t = (\int Y_{it}^{(\eta-1)/\eta} di)^{\eta/(\eta-1)}$. The cost minimization problem of the final good producer yields a demand curve for variety goods $Y_{it} = (P_{it}/P_t)^{-\eta} Y_t$, where $P_t$ is an aggregate price index. Variety good producers choose prices to maximize period profits

$$\max_{P_{it}} (\tau_{it} P_{it} - X_{it}) Y_{it} \qquad \text{s.t.} \quad Y_{it} = (P_{it}/P_t)^{-\eta} Y_t,$$

where $\tau_{it}$ is a *markup wedge* in the spirit of Hsieh and Klenow (2009) and Baqaee and Farhi (2020). This wedge may be viewed as a shortcut for price rigidities. Profit maximization yields a markup $\mu_{it} = P_{it}/X_{it} = \frac{1}{\tau_{it}} \frac{\eta}{\eta-1}$. We compute aggregate TFP as a Solow residual by

$$\log \mathrm{TFP}_t = \log \left( \int Y_{it}^{(\eta-1)/\eta} di \right)^{\eta/(\eta-1)} - \log \int \frac{Y_{it}}{A_{it}} di.$$

This Solow residual has a model consistent Solow weight of one for the aggregate cost term. If we (a) apply a second-order approximation to $\log \mathrm{TFP}_t$ in $\log A_{it}$ and $\log \tau_{it}$, or if we (b) assume that $A_{it}$ and $\tau_{it}$ are jointly log-normally distributed, we obtain

$$\log \mathrm{TFP}_t = -\frac{\eta}{2} \mathbb{V}_t(\log \mu_{it}) + \mathbb{E}_t(\log A_{it}) + \frac{\eta - 1}{2} \mathbb{V}_t(\log A_{it}).$$

Wedges $\tau_{it}$ drive markup dispersion and distort the economy away from allocative efficiency. Firms with high $\tau_{it}$ charge lower markups and use more inputs than socially optimal, and vice versa for low $\tau_{it}$. This misallocation across firms results in lower aggregate TFP.

## E.2 Proof of Proposition 1

Denote by $\mathbb{V}_t(\cdot)$, $\mathrm{Cov}_t(\cdot)$, $\mathrm{Corr}_t(\cdot)$ respectively the cross-sectional variance, covariance, correlation operator. The cross-sectional variance of the log markup is

$$\mathbb{V}_t(\log \mu_{it}) = \int (\log P_{it} - \log P_t - \log X_t)^2 di - \left[ \int (\log P_{it} - \log P_t - \log X_t) di \right]^2.$$

The derivative w.r.t. $\log X_t$ is

$$\frac{\partial \mathbb{V}_t(\log \mu_{it})}{\partial \log X_t} = 2\int \log(\mu_{it})\rho_{it} di - 2\int \log(\mu_{it}) di \int \rho_{it} di = 2\mathrm{Cov}_t(\rho_{it}, \log \mu_{it}).$$

Hence, the markup variance falls in $\log X_t$ if $\mathrm{Corr}_t(\rho_{it}, \log \mu_{it}) < 0$. $\square$

## E.3 Proof of Proposition 2

We assume that

$$\log \begin{pmatrix} P_t/\bar{P} \\ X_t/\bar{X} \\ Y_t/\bar{Y} \end{pmatrix} \sim \mathcal{N}\left( \begin{bmatrix} -\frac{\sigma_p^2}{2} \\ -\frac{\sigma_x^2}{2} \\ -\frac{\sigma_y^2}{2} \end{bmatrix}, \begin{bmatrix} \sigma_p^2 & & \\ \sigma_{px} & \sigma_x^2 & \\ \sigma_{py} & \sigma_{xy} & \sigma_y^2 \end{bmatrix} \right).$$

Define $\tilde{\theta}_i \equiv \frac{\beta\theta_i}{1-\beta\theta_i}$, as well as

$$\begin{aligned}
C_{it} &\equiv \mathbb{E}_t\left[ \frac{X_{t+1}}{X_t} \left(\frac{P_{t+1}}{P_t}\right)^{\eta} \frac{Y_{t+1}}{Y_t} \right], \\
D_{it} &\equiv \mathbb{E}_t\left[ \left(\frac{P_{t+1}}{P_t}\right)^{\eta-1} \frac{Y_{t+1}}{Y_t} \right], \\
\Psi_{it} &\equiv \frac{1+\tilde{\theta}_i C_{it}}{1+\tilde{\theta}_i D_{it}},
\end{aligned}$$

which allows us to rewrite the first-order condition in (3.3) as

$$P_{it}^* = \frac{\eta}{\eta-1} P_t X_t \Psi_{it}.$$

The terms $C_{it}$ and $D_{it}$ can be simplified

$$\begin{aligned}
C_{it} &= \frac{\bar{X}\bar{P}^{\eta}\bar{Y}}{X_t P_t^{\eta} Y_t} \exp\left\{ \eta(\eta-1)\frac{\sigma_p^2}{2} + \eta\sigma_{px} + \eta\sigma_{py} + \sigma_{xy} \right\}, \\
D_{it} &= \frac{\bar{P}^{\eta-1}\bar{Y}}{P_t^{\eta-1} Y_t} \exp\left\{ (\eta-1)(\eta-2)\frac{\sigma_p^2}{2} + (\eta-1)\sigma_{py} \right\}.
\end{aligned}$$

Since $\tilde{\theta}_i \in (0,1)$, we obtain $\Psi_{it} > 1$ when $P_t = \bar{P}$ and $X_t = \bar{X}$, if

$$(\eta-1)\sigma_p^2 + \sigma_{py} + \eta\sigma_{px} + \sigma_{xy} > 0.$$

Under this condition, we obtain $\mu_{it}^* > \frac{\eta}{\eta-1}$. Under the same condition, we further obtain

$$\frac{\partial \Psi_{it}}{\partial \tilde{\theta}_i} = \frac{C_{it} - D_{it}}{(1+\tilde{\theta}_i D_{it})^2} > 0, \quad \text{and hence} \quad \frac{\partial \Psi_{it}}{\partial \theta_i} > 0.$$

We next study the pass-through of a transitory or permanent change in $X_t$. Consider first a *transitory* change in $X_t$ away from $\bar{X}$. The expected pass-through is

$$\bar{\rho}_{it} = (1-\theta_i)\frac{\partial \log P_{it}}{\partial \log X_t} = (1-\theta_i)\left(1+\Phi_{it}\right), \quad \text{where} \quad \Phi_{it} = \frac{\partial \log \Psi_{it}}{\partial \log X_t}$$

and

$$\Phi_{it} = \frac{\tilde{\theta}_i \frac{\partial C_{it}}{\partial \log X_t}(1+\tilde{\theta}_i D_{it}) - (1+\tilde{\theta}_i C_{it})\tilde{\theta}_i \frac{\partial D_{it}}{\partial \log X_t}}{(1+\tilde{\theta}_i D_{it})^2}\Psi_{it}^{-1} = -\frac{\tilde{\theta}_i C_{it}}{1+\tilde{\theta}_i D_{it}}\Psi_{it}^{-1} = -\frac{\tilde{\theta}_i C_{it}}{1+\tilde{\theta}_i C_{it}} < 0.$$

Hence pass-through becomes

$$\bar{\rho}_{it} = \frac{1-\theta_i}{1+\tilde{\theta}_i C_{it}} \in (0,1).$$

In addition, the pass-through falls in $\theta_i$,

$$\frac{\partial \bar{\rho}_{it}}{\partial \theta_i} = -(1+\Phi_{it}) + (1-\theta_i)\frac{\partial \Phi_{it}}{\partial \theta_i} < 0.$$

We next examine a *permanent* change in $X_t$, which is a change in $\bar{X}$ (starting in period $t$). At $P_t = \bar{P}$ and $X_t = \bar{X}$,

$$\frac{\partial \log P^*_{it}}{\partial \log \bar{X}} = 1.$$

Expected pass-through is then $\bar{\rho}_{it} = 1-\theta_i$ and hence $\frac{\partial \bar{\rho}_{it}}{\partial \theta_i} < 0$. □

### E.4 Proof of Proposition 3

Let us first define

$$C_{it} = \left(\frac{P_{it}}{P_{i,t-1}} - 1\right)\frac{P_{it}}{P_{i,t-1}},$$
$$D_{it} = \mathbb{E}_t\left[\left(\frac{P_{i,t+1}}{P_{it}} - 1\right)\frac{P_{i,t+1}}{P_{it}}\right],$$

such that we can re-write the first-order condition in equation (3.4) more compactly as

$$(1-\eta)\left(\frac{P_{it}}{P_t}\right)^{1-\eta} Y_t + \eta X_t \left(\frac{P_{it}}{P_t}\right)^{-\eta} Y_t = \phi_i(C_{it} - D_{it}).$$

Further define $\bar{\phi}_i = 0$ and denote by an upper bar any object that is evaluated at $\bar{\phi}_i$, such as the price $P_{it}$, which is $\bar{P}_{it} = \frac{\eta}{\eta-1} P_t X_t$. In addition,

$$\bar{C}_{it} = \left( \frac{\bar{P}_{it}}{\bar{P}_{i,t-1}} - 1 \right) \frac{\bar{P}_{it}}{\bar{P}_{i,t-1}} = (\Pi_{pt}\Pi_{xt})^2 - \Pi_{pt}\Pi_{xt},$$

$$\bar{D}_{it} = E_t \left[ \left( \frac{\bar{P}_{i,t+1}}{\bar{P}_{it}} - 1 \right) \frac{\bar{P}_{i,t+1}}{\bar{P}_{it}} \right] = \frac{\exp\left\{ \frac{3}{2}\sigma_p^2 + \frac{3}{2}\sigma_x^2 + 4\sigma_{px} \right\}}{(\Pi_{pt}\Pi_{xt})^2} - \frac{\exp\{\sigma_{pw}\}}{\Pi_{pt}\Pi_{xt}}.$$

We next use a first-order approximation of the first-order condition at $\bar{\phi}_i$ and with respect to $\phi_i$ and $\log P_{it}$. Denoting $\mathrm{dlog}P_{it} = \log P_{it} - \log \bar{P}_{it}$ and $\mathrm{d}\phi_i = \phi_i$, we obtain

$$(1-\eta)^2 \left( \frac{P_{it}}{\bar{P}_t} \right)^{1-\eta} Y_t \mathrm{dlog}P_{it} - \eta^2 X_t \left( \frac{\bar{P}_{it}}{P_t} \right)^{-\eta} Y_t \mathrm{dlog}P_{it} = (\bar{C}_{it} - \bar{D}_{it})\mathrm{d}\phi_i.$$

This yields

$$\Psi_{it} \equiv \frac{\mathrm{dlog}P_{it}}{\mathrm{d}\phi_i} = \frac{\bar{D}_{it} - \bar{C}_{it}}{(\eta-1)^{\eta}\eta^{1-\eta}X_t^{1-\eta}Y_t},$$

and hence $\log P_{it} \approx \log \bar{P}_{it} + \Psi_{it} d\phi_i$. For $\phi_i > 0$, the markup is above the frictionless one if $P_{it} > \bar{P}_{it}$, which holds if $\Psi_{it} > 0$. For $P_t = \bar{P}$ and $X_t = \bar{X}$, $\Psi_{it} > 0$ if

$$\sigma_p^2 + \sigma_x^2 + 2\sigma_{px} > 0,$$

for which a sufficient condition is that the correlation

$$\rho_{px} \equiv \frac{\sigma_{px}}{\sigma_p \sigma_x} > -1.$$

Under the same condition, $\frac{\partial P_{it}}{\partial \phi_i} > 0$.

We next study the pass-through of a transitory or permanent change in $X_t$. The pass-through is

$$\rho_{it} = 1 + \frac{\partial \Psi_i}{\partial \log X_t} d\phi_i.$$

We next examine the conditions under which pass-through falls in $\phi_i$, i.e., conditions under which

$$\frac{\partial \Psi_i}{\partial \log X_t} < 0,$$

which is equivalent to examining the conditions for

$$\frac{\partial \bar{D}_{it}}{\partial \log X_t} - \frac{\partial \bar{C}_{it}}{\partial \log X_t} + (\eta - 1)(\bar{D}_{it} - \bar{C}_{it}) < 0.$$

Consider first a *transitory* change in $X_t$ away from $\bar{X}$,

$$\frac{\partial \bar{C}_{it}}{\partial \log X_t} = 2(\Pi_{pt}\Pi_{xt})^2 - \Pi_{pt}\Pi_{xt},$$
$$\frac{\partial \bar{D}_{it}}{\partial \log X_t} = -2(\Pi_{pt}\Pi_{xt})^{-2} \exp\left\{\frac{3}{2}\sigma_p^2 + \frac{3}{2}\sigma_x^2 + 4\sigma_{px}\right\} + (\Pi_{pt}\Pi_{xt})^{-1} \exp\left\{\sigma_{px}\right\}.$$

For $P_t = \bar{P}$ and $X_t = \bar{X}$, we obtain

$$\frac{\partial \Psi_i}{\partial \log X_t} < 0 \qquad \text{if} \quad \eta < \tilde{\eta}^{\text{transitory}} = 2 + \frac{1 + \exp\left\{\frac{3}{2}\sigma_p^2 + \frac{3}{2}\sigma_x^2 + 4\sigma_{px}\right\}}{\exp\left\{\frac{3}{2}\sigma_p^2 + \frac{3}{2}\sigma_x^2 + 4\sigma_{px}\right\} - \exp\left\{\sigma_{px}\right\}}$$

We next consider a *permanent* change, for which we have

$$\frac{\partial \bar{C}_{it}}{\partial \log X_t} = 2(\Pi_{pt}\Pi_{wt})^2 - \Pi_{pt}\Pi_{wt}, \quad \frac{\partial \bar{D}_{it}}{\partial \log X_t} = 0.$$

For $P_t = \bar{P}$ and $X_t = \bar{X}$, we obtain

$$\frac{\partial \Psi_i}{\partial \log X_t} < 0 \qquad \text{if} \quad \eta < \tilde{\eta}^{\text{permanent}} = 1 + \frac{1}{\exp\left\{\frac{3}{2}\sigma_p^2 + \frac{3}{2}\sigma_x^2 + 4\sigma_{px}\right\} - \exp\left\{\sigma_{px}\right\}}$$

It always holds that $\eta^{\text{permanent}} < \eta^{\text{transitory}}$ and we define $\tilde{\eta} \equiv \eta^{\text{permanent}}$. $\square$

# F Menu cost model

To study the presence of precautionary price setting in menu cost models, we proceed numerically. Consider the partial equilibrium menu cost model

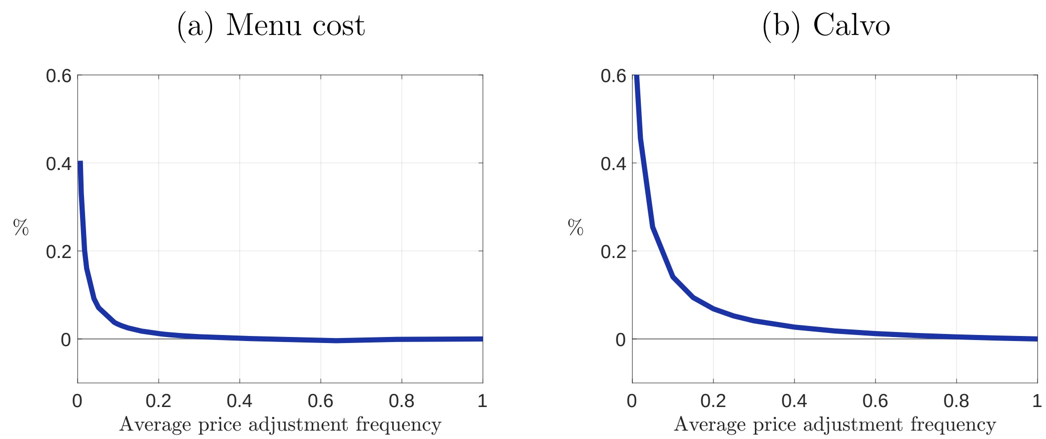
$$V(p, Z) = \mathbb{E}_\xi[\max\{V^A(Z) - \xi, V^N(Z)\}]$$
$$V^A(Z) = \max_{p^*}\left\{\left(\frac{p^*}{P} - X\right)\left(\frac{p^*}{P}\right)^{-\eta} + \beta\mathbb{E}_Z\left[V(p^*, Z')\right]\right\}$$
$$V^N(p, Z) = \left(\frac{p}{P} - X\right)\left(\frac{p}{P}\right)^{-\eta} + \beta\mathbb{E}_Z\left[V(p, Z')\right]$$

where $p$ is the price a firm sets and $Z$ denote a vector of the aggregate state variables price level ($P$), aggregate demand ($Y$), and marginal costs ($X$). The firm chooses to adjust prices in the presence of the menu cost $\xi$.

We set $\eta = 6$ and $\beta = 1.03^{-1/4}$. We solve the model using value function iteration with off-grid interpolation with respect to $p$ using cubic splines as basis function. To solve accurately for differences in $p^*$ that arise from small differences in $\xi$ requires a fine grid for both $p$ and $Z$. To alleviate the numerical challenge, we assume $\xi$ is stochastic and drawn from an iid exponential distribution, parametrized by $\bar{\xi}$. Results change only little when using a uniform distribution.

We assume 200 grid points on a log-spaced grid for $p$. To capture aggregate uncertainty in $Z$, we first estimate a first-order Markov process for $Z$ in the data and then discretize it using a Tauchen procedure. In the univariate case, when only allowing for inflation uncertainty, the precautionary price setting was accurately captured starting from about 49 grid points for $Z$. Discretizing a three-variate VAR with 49 grid points for each variable is costly. Even more importantly, the state space, on which to solve the model, becomes very large. We therefore proceed with the univariate case. We estimate an AR(1) on quarterly post-1984 data of the log CPI and apply the Tauchen method with 49 grid points.

Figure 23: Precautionary price setting under menu costs and Calvo




Notes: The figures show percentage difference between the dynamic optimal price relative to the frictionless optimal one.

We solve the stationary equilibrium of the menu cost and Calvo model for a vector of different $\bar{\xi}$, which imply different equilibrium price adjustment frequencies. Figure 23 plots the price setting policy $p^*$ at the unconditional mean of $Z$ for different average price adjustment frequencies. We compare menu costs in panel (a) with Calvo in panel (b). The figures shows that precautionary price setting exists and is amplified by the degree of price-setting friction in a menu cost environment. Compared to Calvo, menu costs generate somewhat muted precautionary price setting.

# G Details on the Quantitative New Keynesian Model

This section presents details on the quantitative New Keynesian model in Section 4. We assume a representative infinitely-lived household who maximizes

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left( \frac{C_t^{1-\frac{1}{\gamma}}}{1-\frac{1}{\gamma}} - \frac{N_t^{1+\frac{1}{\varphi}}}{1+\frac{1}{\varphi}} \right),$$

subject to the budget constraints $P_t C_t + R_t^{-1} B_t \leq B_{t-1} + W_t N_t + D_t$ for all $t$, where $C_t$ is aggregate consumption, $P_t$ an aggregate price index, $B_t$ denotes one-period discount bounds purchased at price $R_t^{-1}$, $N_t$ employment, $W_t$ the nominal wage, and $D_t$ aggregate dividends. We impose the solvency constraint $\lim_{T\to\infty} \mathbb{E}_t[\Lambda_{t,T} \frac{B_T}{P_T}] \geq 0$ for all $t$, where $\Lambda_{t,T} = \beta^{T-t}(C_T/C_t)^{-\frac{1}{\gamma}}$ is the stochastic discount factor. The final output good $Y_t$ is produced with a Dixit–Stiglitz aggregator

$$Y_t = \left( \int_0^1 Y_{it}^{\frac{\eta-1}{\eta}} \mathrm{d}i \right)^{\frac{\eta}{\eta-1}},$$

where $\eta$ is the elasticity of substitution between differentiated goods $\{Y_{it}\}$. Intermediate goods are with the technology $Y_{it} = A_t N_{it}$, where $A_t$ is a common technology shifter, which follows $\log A_t = \rho_a \log A_{t-1} + \varepsilon_{a,t}$ and $\varepsilon_{a,t} \sim \mathcal{N}(0, \sigma_a^2)$ are technology shocks. Final good aggregation implies an isoelastic demand schedule for intermediate goods given by $Y_{it} = (P_{it}/P_t)^{-\eta} Y_t$, where $P_t = (\int_0^1 P_{it}^{1-\eta} di)^{1/(1-\eta)}$ denotes the aggregate price index and $P_{it}$ the firm-level price. Firms may reset their prices $P_{it}$ with firm-specific probability $1-\theta_i$. The price setting policy maximizes the value of the firm to its shareholder,

$$\max_{P_{it}} \sum_{j=0}^{\infty} \theta_i^j \mathbb{E}_t \left[ \frac{\Lambda_{t,t+j}}{P_{t+j}} \left( \frac{P_{it}}{P_{t+j}} - W_{t+j} \right) \left( \frac{P_{it}}{P_{t+j}} \right)^{-\eta} Y_{t+j} \right].$$

The firm type $k$-specific price index is

$$P_{kt} = \left[ (1-\theta_k) \tilde{P}_{kt}^{1-\eta} + \theta_k P_{kt-1}^{1-\eta} \right]^{\frac{1}{1-\eta}}$$

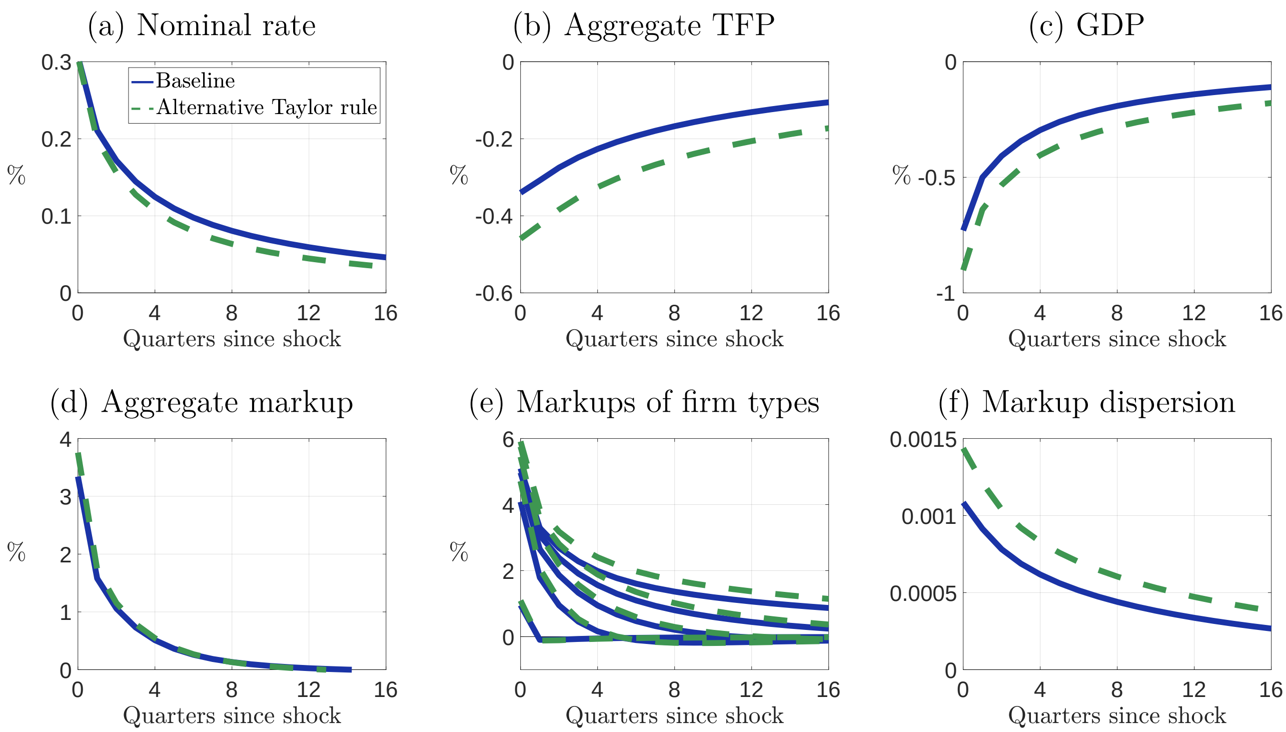
where $\tilde{P}_{kt}$ is the optimal reset price of a firm of type $k$. The monetary authority aims to stabilize inflation $(P_t/P_{t-1})$ and fluctuations in output, $Y_t$, around its natural level, denoted $\tilde{Y}_t$, by following the Taylor-type rule, subject to monetary policy shocks $\nu_t$,

$$R_t = R_{t-1}^{\rho_r} \left[ \frac{1}{\beta} \left( \frac{P_t}{P_{t-1}} \right)^{\phi_\pi} \left( \frac{Y_t}{\tilde{Y}_t} \right)^{\phi_y} \right]^{1-\rho_r} \exp\{\nu_t\}, \quad \nu_t \sim \mathcal{N}(0, \sigma_\nu^2).$$

The competitive equilibrium is defined by firm-level allocations $\{Y_{it}, N_{it}\}_{t=0}^{\infty}$ and prices $\{P_{it}\}_{t=0}^{\infty}$ for all $i$, and aggregate allocations and prices $\{Y_t, N_t, P_t, R_t\}_{t=0}^{\infty}$ such that households and firms maximize their objective functions, the monetary authority follows the policy rule. The final goods market clears, $Y_t = C_t$, and the labor market clears, $N_t = \int_0^1 N_{it} \mathrm{d}i$, in every period $t$.

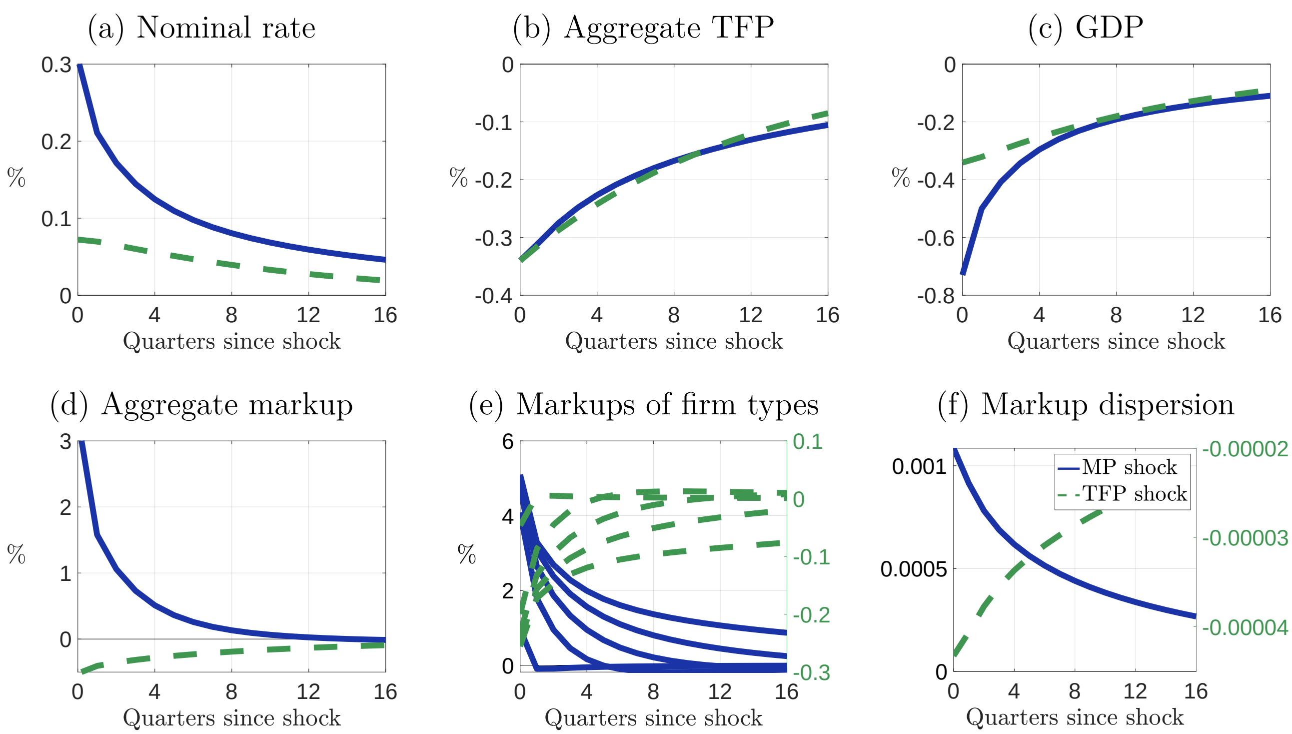
# H Additional Model Results

Figure 24: Model responses to monetary policy shocks under alternative Taylor rule



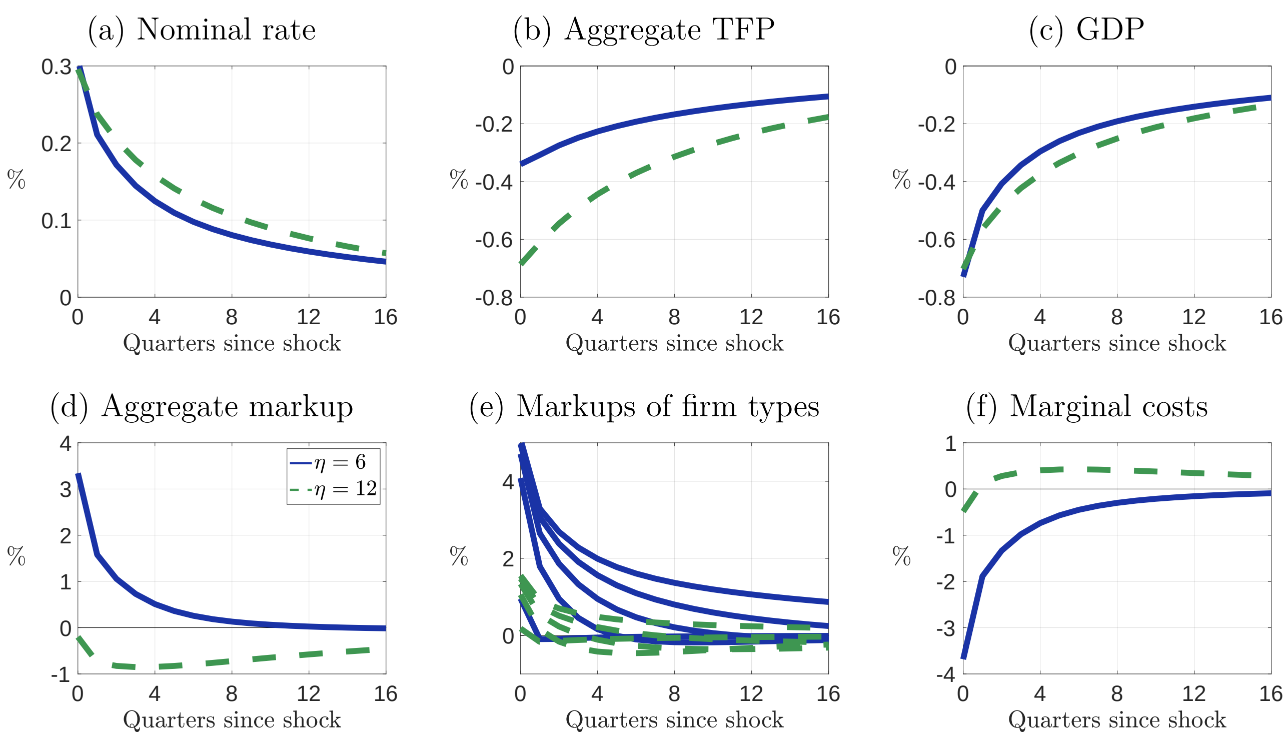

Notes: This figure shows impulse responses to a one standard deviation monetary policy shock. *Baseline* corresponds to the model in the main text. In particular, the central bank follows a Taylor rule, which reacts to fluctuation in the output gap. The gap is defined relative to natural output (the level prevailing under flexible prices), which is unchanged after monetary policy shocks. *Alternative Taylor rule* corresponds to a setup in which the central bank computes natural output based on the observed movements in aggregate TFP. Consequently, natural output is perceived to react to monetary policy shocks, which leads to a different policy response. The standard deviation of monetary policy shocks $\sigma_\nu$ is re-calibrated to match the response of the nominal rate of 30bp.

Figure 25: Model responses to technology shocks




Notes: This figure compares the impulse responses to a one standard deviation monetary policy shock to those to a technology shock. The persistence of TFP and the technology shock size are calibrated to match the shape of the TFP response to monetary policy shocks.

Figure 26: Model responses to monetary policy shocks when varying the elasticity of substitution




Notes: This figure shows impulse responses to a one standard deviation monetary policy shock for two values of the elasticity of substitution between variety goods $\eta$. The value 6 corresponds to our baseline calibration and the value 12 corresponds to an intermediate value of elasticities considered in the literature (e.g., Fernandez-Villaverde et al., 2015). The standard deviation of monetary policy shocks $\sigma_\nu$ is re-calibrated to match the response of the nominal rate of 30bp.