Sectoral Volatility and the Investment Channel of Monetary Policy*

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Abstract

How does the dispersion of firm-level shocks affect the investment channel of monetary policy? Using firm-level panel data, we construct several measures of dispersion of productivity shocks, time-pooled and time-varying, and interact high-frequency identified monetary policy shocks with these measures of idiosyncratic shock volatility. We document a novel fact: monetary policy has dampened real effects via the investment channel when firm-level TFP shock volatility is high. Our estimates for dampening effects of volatility are statistically and economically significant - moving from the tenth to the ninetieth percentile of the volatility distribution approximately halves point estimates of impulse response functions to contractionary monetary policy shocks. Given that dispersion rises in recessions, these findings offer further evidence as to why monetary policy is weaker in recessions, and emphasize the importance of firm heterogeneity in monetary policy transmission.

Keywords: Firm Risk, Second Moment, Investment, Policy Effectiveness, Idiosyncratic Shocks.

JEL classification codes: E52, E22, D81

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1 Introduction

Firms' investment is a key transmission channel from monetary policy operations to the real economy. This aggregate response of business capital formation is shaped by firm heterogeneity in a number of dimensions (for example: firm's age and dividend status (Cloyne, Ferreira, Froemel and Surico, 2018); financial position and liquidity (Jeenas, 2018); leverage (Anderson and Cesa-Bianchi, 2020), and distance to default (Ottonello and Winberry, 2018)). In this work, the dimension of heterogeneity we focus on is idiosyncratic firm risk.

Idiosyncratic firm risk is large and matters for firm adjustment decisions. Firms exhibit large variation in their measured total factor productivity, and most of that productivity variation comes from idiosyncratic shocks (Syverson (2011); Castro, Clementi and Lee (2015)). We document substantial differences in idiosyncratic shock variance across sectors in the cross-section, and through time within sectors. Dispersion of firm-level shocks influences investment behaviour because it affects the triggering of the extensive margin of adjustment, and therefore plays a key role in firm investment, hiring, and production decisions.In this paper we study how dispersion of idiosyncratic productivity shocks affects the investment channel of monetary policy.

The study of this interaction is important for two reasons. Firstly, investment is the most volatile component of GDP, and is strongly procyclical. Secondly, the business investment response is a major component of the total macroeconomic response to monetary policy operations. A better understanding of the drivers of heterogeneous investment responses at the micro-level is important for the study of the business cycle dynamics, and for a better understanding of what constitutes effective countercyclical macroeconomic policy.

Our empirical strategy involves constructing firm-level productivity, and its shocks, according to several methodologies in the literature. We compute second moments of firm shocks to measure idiosyncratic risk at the sector and sector-year levels. Our empirical analysis involves regressing firm investment on an identified monetary policy shock interacted with our measures of volatility. This approach allows us to use both cross-sectional variation (making comparisons across sectors with high and low overall volatility) and panel variation (following a given sector through time, comparing when its volatility is high versus low).

This work contributes in two ways to our understanding of the interaction between idiosyncratic firm shocks and their variance, firm capital adjustment decisions, and asymmetric monetary policy transmission over the business cycle. Firstly, our results document new evidence on the role of dispersion of idiosyncratic shocks in determining firms' investment response to monetary policy actions. Regression analysis implies qualitatively significant dampening of the investment channel of monetary policy. Moving from the 10th to the 90th percentile of sectoral volatility implies up to approximately a 50 percent reduction in response point estimates. Combining findings across three measures of productivity, and by both time-pooled and time-varying volatility measures, the majority of our volatility interaction coefficients imply a volatility-dampening effect on the investment channel that is statistically significant and economically meaningful in relative size. Secondly, our results also offer an explanation as to why monetary policy is weaker in recessions. As shown by Tenreyro and Thwaites (2016), this asymmetry along the business cycle is particularly strong in business investment. Our results suggest this weakening of monetary policy in bad times is (in part) due to higher idiosyncratic risk, making firms reluctant to take the extensive-margin step of investment. Overall our findings reiterate the importance of firm heterogeneity at the micro-level in monetary policy transmission to the real economy and its effectiveness at fighting recessions.

Related Literature This work is connected to several branches of the existing literature. Firstly work focusing on investment and uncertainty, especially the so-called "options approach" of Bernanke (1983) and Dixit and Pindyck (1994) which emphasizes the timing margin of firm investment decisions, and not just simple NPV rules[1] usually based on one-period investment opportunities. The options approach is discussed in more detail in the following section. Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2018) argue that uncertainty drastically dampens firm-level investment and hiring decisions when subject to rich factor adjustment costs, featuring convex and nonconvex costs of adjustment as well as partial irreversibility. They indicate that firms freeze their capital/labor adjustment decisions and enter a "wait-and-see" mode, due to the "real options" effect induced by increased uncertainty.

We add to this important finding by providing empirical evidence that firms are reluctant to make capital adjustments in response to aggregate monetary policy shocks when they face higher dispersion of idiosyncratic shocks.

Relatedly, by employing a menu cost model[2], Vavra (2014) links volatility in nominal income to price adjustment behavior, and shows that firms are forced to change their prices more frequently when there is higher volatility. Vavra (2014) further argues that due to this fact price change dispersion and frequency of price adjustment are counter-cyclical. On the empirical side, Bachmann, Born, Elstner and Grimme (2019) provide additional evidence on the interaction between volatility and firm behaviour. They point out that higher volatility is associated with a higher probability of price adjustment, and the likelihood of this price adjustment is higher in recessions.

Our work is related to the literature that studies the cyclicality of monetary policy effectiveness. Tenreyro and Thwaites (2016) indicate that the macroeconomy is less responsive to monetary policy

[1]Dixit and Pindyck (1994) define the net present value rule as: invest if the net present value of an investment opportunity is greater than zero, without accounting for irreversibility, and the possibility to delay the decision.

[2]Dotsey, King and Wolman (1999); Golosov and Lucas Jr (2007)

shocks during recessions compared to expansionary periods - "pushing on a string" as they phrase it - with an especially pronounced asymmetry in the reaction of investment. Our work complements these findings and offers an explanation: elevated dispersion of idiosyncratic shocks in bad times leads to lower responsiveness to monetary policy operations because of stronger real options effects and a greater share of adjustment occurring through nominal as opposed to real channels.

This paper also relates to the literature that studies heterogeneity in monetary policy transmission. In recent years there has been an increased focus on examining macroeconomic questions with microdata, looking at firm-level responses to monetary policy operations, and how those responses are patterned across heterogeneous firms. After employing rich firm-level controls, recent work finds significant heterogeneity along the dimensions: distance to default Ottonello and Winberry (2018), liquidity position Jeenas (2018), heterogeneity in markups Meier and Reinelt (2019), leverage Anderson and Cesa-Bianchi (2020) and Ferrando, Vermeulen and Durante (2020). Closely related to our paper is Fang (2020), who studies volatility's effects on the investment channel in a rich theoretical framework, and provides empirical results using the interquartile range of sales growth as his volatility measure. Our paper acts as a complementary study focusing on a novel channel —idiosyncratic firm risk, and provides a detailed analysis of TFP shock dispersion's dampening effects on the investment channel of monetary policy.

All employ high-frequency identified monetary policy shocks (in the spirit of Gertler and Karadi (2015)) with firm-level panel data. We employ a similar econometric methodology.

Road Map In Section 2, we describe our firm-level data and empirical strategy. Section 2.1 discusses the approaches we employ to estimate firm level productivity. Then, Section 2.2 presents our constructed volatility measures. Section 3 motivates our empirical analysis through the lens of two theoretical models in the literature. Section 3.1 stresses that increased dispersion of shocks leads to less effective monetary policy through the real options channel, while Section 3.2 focuses on the nominal adjustment channel. Section 4 presents our baseline regressions identifying average investment response to monetary policy. We then present regression analysis interacting the monetary policy shock with measures of volatility to identify patterns of heterogeneity in the investment response to monetary policy. Section 5 concludes. The appendix contains further robustness checks.

2 Cross-Sectional Distribution of Productivity across Sectors

This section describes how we measure idiosyncratic firm risk in productivity. Our empirical strategy involves three main parts. First, we compute firm level productivity, and fit an autoregressive process to productivity in order to fit productivity shocks. Second, we pool these shocks in order to construct moments of the shock distribution by 2-digit sector. Finally in our local projection regression analysis we interact monetary policy shocks with measures of shock dispersion.

Data We use Compustat firm-level panel data to conduct our empirical analysis. This dataset provides rich financial information for a broad range of firms, and is relatively high frequency, with most data reported quarterly, as opposed to yearly for other similar datasets. The principal drawback in the use of the Compustat data relates to representativity – only listed firms are included in the sample. As noted by Axtell (2001) Compustat firms are approximately lognormally distibuted, while the population of firms in census data is more accurately modelled by a power law (Gabaix (2016)) meaning Compustat has too few small firms relative to the population of firms. Moreover, the number of firms sampled in sector-cells do not correspond with the aggregate sector shares. We do not see this as problematic for the following reasons: (i) our empirical strategy exploits variation both across and within sectors (ii) aggregates calculated from explicitly summing the microdata yield time series which behave very similarly to the national accounts aggregates (investment growth, for example, Cloyne et al. (2018)) (iii) our focus is on the investment channel of monetary policy, as such relatively small firms are not likely to hold enough capital to be meaningful to aggregated dynamics at the sector or economy-wide level.

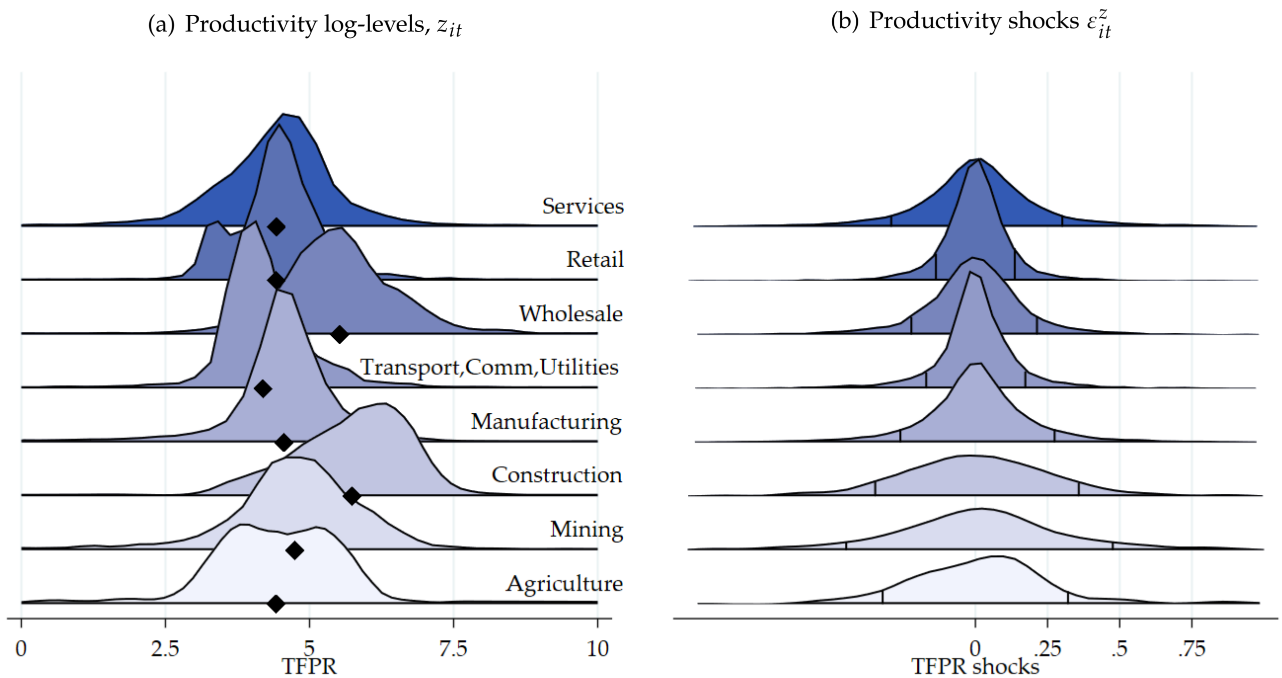
Sample Following similar work in the literature (e.g. Ottonello and Winberry (2018)) we exclude the so-called "FIRE" sectors (finance and real estate) due to the very different balance sheet composition of firms in these sectors, as well as utility firms. We drop any of the following firms: not based in USA, not trading in USD, making acquisitions above 5 percent of the value of total assets in nominal values. Nonsensical values such as negative capital or negative sales are also dropped. Where gaps in series are only one quarter we use linear interpolation to fill in the gaps following similar papers in the literature.

2.1 Firm Productivity

Estimating Firm Productivity Among several approaches to estimating firm productivity, we begin by using a Cost Share approach: imposing a functional form on production and computing functional parameters based on observed factor usage shares. We check the robustness of such a measure using Generalized Method of Moments and the Olley and Pakes (1996) Control Function approach.

The distributions of TFP and its innovations are show in Figure (1), pooling firms according to broadly defined sector groups. Sectors exhibit significant variation in both the mean and dispersion of productivity (left panel) as well as significant differences in the dispersion of shocks in TFP (right panel). We investigate what are the monetary implications of sectoral differences like these, but at a more disaggregated 2-digit level.

Figure 1: Total Factor Productivity by Sector



Note: pooled TFP levels and innovations calculated according to Cost Share method. Filled diamonds mark sectoral means (left) and vertial lines mark the tenth and ninetieth percentiles respectively (right)

2.1.1 Cost-Share approach

We take a Cost Share approach following works such as Foster, Haltiwanger and Syverson (2008),Bloom et al. (2018), Decker, Haltiwanger, Jarmin and Miranda (2018) and we identify productivity via structural assumptions on the production function. We impose a Cobb-Douglass production function, and assume inputs of capital and labor only. We calculate factor intensity parameters from median cost-shares within sector-years. This is done for two reasons. At the firm level this method is vulnerable to measurement error, while the median helps filter out extreme values. Moreover, even though in any given period adjustment costs are likely to induce a fraction of firms not to adjust either factor, over many firms we can recover average cost-shares. We construct this measure with time-varying parameters. For a given firm i in sector s in year t productivity in logs, z_{ist}, is constructed as the following, where y_{ist} is observed log sales revenue[3].

$$z_{ist} = y_{ist} - \alpha^{(N)}_{s,t} n_{ist} - \alpha^{(K)}_{s,t} k_{ist} \tag{1}$$

[3]For notational clarity we report k_{ist} however Compustat reports end of period values after adjustment, hence k_{ist} refers to last period's end-of-period capital brought into period t

2.1.2 Generalized Method of Moments

As a robustness check we calculate TFP according to several other methodologies to gauge how sensitive the main results are to TFP computation methods. Following Cooper and Haltiwanger (2006), we assume z_{it} follows an AR(1) process we can make the following quasi-first-difference transformation. To allow for trends in TFP we detrend log sales using sector-year and firm fixed effects.

$$\tilde{y}_{ist} - \rho_s \tilde{y}_{it-1} = (1-\rho_s)c_s + \alpha_s(k_{ist} - \rho_s k_{ist-1}) + \beta_s(n_{ist} - \rho_s n_{ist-1}) + \varepsilon_{ist} \tag{2}$$

Parameters $\theta_s = (c_s, \rho_s, \alpha_s, \beta_s)$ are then estimated using the moment condition $E(z_{ist}\varepsilon_{ist}) = 0$, setting the innovation term orthogonal to current and lagged values of k_{ist}, since it is taken as predetermined, and lagged n_{ist}. In this approach production function parameters are constant over time and can only vary across sectors.

$$\hat{\theta}_{GMM} = \arg\min_{\theta} \left\{ N^{-1} \sum_{i,s,t} z_{ist}\varepsilon_{ist}(\theta) \right\}' W \left\{ N^{-1} \sum_{i,s,t} z_{ist}\varepsilon_{ist}(\theta) \right\} \tag{3}$$

In economic terms, this moment condition enforces that the innovation in TFP behaves like a shock - unforecastable with $t-1$ information. The weighting matrix is set to minimize estimate variation.

2.1.3 Olley-Pakes Control Function

The above methods may suffer from two problems: simultaneity and selection bias. Simultaneity problems arise due to the fact some portion of the productivity shock is known to the firm, but not to the econometrician. More productive firms may invest more or hire more labor with the expectation of higher returns. The second issue is the selection bias which originates from the correlation between negative productivity shocks and the probability of exiting the market. Namely, firms with a larger capital stock are more likely to stay in the market despite a low productivity shock. This situation will cause the coefficient of the capital variable to be biased downward. By employing the methodology in Olley and Pakes (1996), we account for both the endogeneity of factor inputs as well as selection bias due to low productivity firms exiting the sample. If we assume firm investment is a function of state variables age, capital stock, and productivity, provided investment is not zero we can invert the investment function $z_{ist} = h(a_{ist}, k_{ist}, i_{ist})$. Making this substitution we can then recover β_n

$$y_{ist} = \beta_0 + \beta_a a_{ist} + \beta_k k_{it} + \beta_n n_{ist} + h(a_{it}, k_{ist}, i_{it}) \tag{4}$$

$$= \beta_n n_{ist} + \phi(a_{ist}, k_{ist}, i_{ist}) + e_{ist} \tag{5}$$

Finally, accounting for selection, the Olley-Pakes method estimates the following by non-linear least squares:

$$E(y_{ist} - \beta_n n_{ist} | a_{ist}, k_{ist}, \text{exit}_{it-1} = 0) = \beta_a a_{ist} + \beta_k k_{ist} + E(z_{ist} | z_{ist-1}, \text{exit}_{ist-1} = 0) \tag{6}$$

To close the estimation section: all measures of productivity are computed separately for each 2-digit sector. However only the Cost Share method allows for time and sector variation in parameters. Olley Pakes and GMM both estimate parameters which are fixed for the duration of the sample. We do not see this as problematic given our final regression sample only runs from the 1990s to 2010 based on the availability of the monetary policy shock variable we employ.

2.2 Volatility

We estimate a process for firm-level productivity in logs (z_{ist}). The AR(1) component determines the speed with which shocks decay and productivity returns to its trend, while sector-year dummies (λ_{st}) account for systematic comovement among firms within a given sector, but allow those stochastic trends to vary freely. This component is potentially non-stationary. Firm-level fixed-effects (f_i) control for permanent differences in productivity between firms. Finally we also control for size and age effects in the level of productivity. A separate regression is run for each 2-digit sector. Volatility is taken as the standard deviation of ε_{ist}, pooling firms at the sector- and sector-year levels[4]:

$$z_{ist} = \rho_s z_{ist} + \beta_s(\log \text{size}_{ist}) + \gamma_s(\log \text{age}_{ist}) + \lambda_{st} + f_i + \varepsilon_{ist} \tag{7}$$

We define volatility as:

$$\text{sectoral volatility: } \sigma_s = sd(\varepsilon_{ist} | s) \tag{8}$$

$$\text{time-varying sectoral volatility: } \sigma_{s,t} = sd(\varepsilon_{ist} | s, t) \tag{9}$$

Productivity Distributions within Sectors TFP calculated this way shows high levels of dispersion at the firm level (Table 4). Firms in the unconditional 95th percentile are more than twice as productive (in sales revenue), for given inputs, than firms in the 5th percentile. On average this ratio is tending towards 5 if we compare the top and bottom one percent of firms overall, and within some sectors this number is over 7. This qualitatively matches many other papers in the firm productivity literature which find significant dispersion of firm productivity.

[4] Our strategy to pool at the 2-digit sector level is to avoid imprecisely measuring volatility at finer levels of aggregation, for example at the firm level

Productivity Distributions across Sectors Figure (1) plots the cross-sectional distributions of TFP, pooling firms across time. Significant heterogeneity in the moments of TFP (mean level, dispersion, and moments governing shape) are clear from the left panel. The right panel displays significant variation across sectors in TFPR shock dispersion. 10th and 90th percentiles are marked.

3 Stylized Theoretical Framework

Having constructed measures of firm-level productivity dispersion, and established stylized facts, we now turn to motivating our empirical analysis of monetary policy's ability to affect firm-level investment, based on two mechanisms highlighted in the literature.

We rationalize our empirical findings by drawing a line from the results of Tenreyro and Thwaites (2016), who show that monetary policy has asymmetric effectiveness in booms and recessions, through the work of Bloom et al. (2018) and Vavra (2014) to our own results.

Monetary policy may have dampened effectiveness via the investment channel of transmission during periods of higher dispersion of shocks due to (1) a real options/option value channel (Bloom (2009) and Bloom et al. (2018)) and (2) a nominal adjustment channel (Vavra (2014)). Our results can be interpreted through the lens of both models, and are consistent with model predictions, however we remain agnostic between the two channels.

Firstly, Bloom et al. (2018) links recessions with periods of higher uncertainty and more dispersion of firm-level productivity shocks, and we would expect to see more wait-and-see behaviour and a postponement of firms' labour and capital input adjustments. The downstream consequence of this insensitivity to prices and market conditions is that firms will likely respond less to monetary policy when shock dispersion is high, which tends to be the case in recessions.

Leading on from this inaction in factor choices, work by Vavra (2014) would suggest more adjustment to shocks will occur through nominal as opposed to real channels when volatility is high. Greater price flexibility has implications for monetary policy transmission. If prices were fully flexible, monetary stimulus would have no real effects.

3.1 Real Options Channel

The first mechanism through which our work can be seen is the "options approach" to firm investment in work such as Bernanke (1983) and Dixit and Pindyck (1994), in which the interaction of irreversibility and uncertainty plays a key role in investment dynamics. A simple NPV approach of whether to invest or not ignores the timing dimension of the firm's problem. The "when" of investment matters if such outlays are costly to unwind in the future if things go wrong. Moreover, a firm with an opportunity to invest is essentially holding a call option - the right but not the obligation to invest. The opportunity cost of investing is to give up the option value of waiting.

Recent work by Bloom (2009) and Bloom et al. (2018) emphasizes the role of uncertainty in firms' factor input choices, especially in recessions. Empirical evidence shows that uncertainty, or measures of shock dispersion more generally, goes up in recessions.

The uncertainty effect acts through changes in the expected future distribution of idiosyncratic shocks, which combined with time-to-build can induce wait-and-see behaviour in firms if they expect the chance they are ejected from the inaction region of the state-space next period is higher. High dispersion of shocks, and with it a higher option value of inaction, makes firms temporarily insensitive to factor prices and causes them to freeze hiring and investment decisions in order to avoid double-paying nonconvex adjustment costs.

In these two models of firm dynamics with fluctuations in uncertainty, firms learn today that tomorrow's shock distribution will be more dispersed. There is no direct effect today, since the variance of today's shocks hasn't changed, however the firm now forms expectations over a wider distribution of shocks.

Bloom et al. (2018) setup a rich, heterogeneous firm environment to capture the several impacts of uncertainty shocks observed in the data. The model incorporates nonconvex adjustment costs of capital and labor, to create a real options channel of uncertainty shocks in their model. The capital adjustment cost includes a fixed disruption cost, as well as partial irreversibility of investment. Irreversibility is integrated via an asymmetric price of capital, which depends on whether the transaction is a capital purchase or sale. A sale only receives a partial share of capital's full price. Irreversibility results in an asymmetric behavior, making negative shocks more important as capital sales cause extra losses.[5]

This is an Ss type model, therefore if the productivity (combination aggregate and idiosyncratic components) falls into the inaction region, firms do not hire and invest and thus do not suffer the corresponding adjustment cost. However, if productivity reaches the boundary of this region, then the firm pays the necessary costs, and adjusts its capital and/or labor inputs.

The authors first state that the presence of adjustment costs in the above-mentioned formulation causes real options effects. The authors argue that an increase in uncertainty widens the inaction region, making any adjustment decision more difficult than before. This leads to an economy-wide freeze in extensive margin adjustments of hiring and investment decisions and making all firms insensitive to any policy changes (or shocks more generally).

Secondly, the authors argue for the existence of an Oi-Hartman-Abel effect, that is, in the absence

[5]Labor adjustment costs also include a very similar fixed disruption cost, and a partial irreversibility mechanism. For the sake of brevity, we are omitting labor adjustment discussion here. Interested readers may refer to the relevant section of Bloom et al. (2018).

of adjustment costs, and output is convex in productivity, then an increase in the standard deviation of the productivity distribution affects the economy positively, (*i.e.* output and investment increases, unemployment decreases). Moreover, if uncertainty is resolved, the Oi-Hartman-Abel effect is triggered, and firms start to invest and hire again, and output rises.

As noted by Bloom (2009), it is plausible that such wait-and-see effects have consequences for monetary policy transmission, and macroeconomic stabilisation more broadly. Higher uncertainty in recessions would make firms much less sensitive to monetary policy operations directly, that is, where monetary policy variables enter the firm's dynamic problem becomes less important. This however would still allow monetary policy to act via other indirect channels.

Our findings are in line with the predictions and explanations of Bloom et al. (2018). The authors' predict that firms freeze their investment and hiring decisions when facing higher uncertainty. According to our empirical findings, if a sector has higher dispersion of idiosyncratic productivity shocks, then in that sector, firms' investment response to a monetary policy shock is weaker.

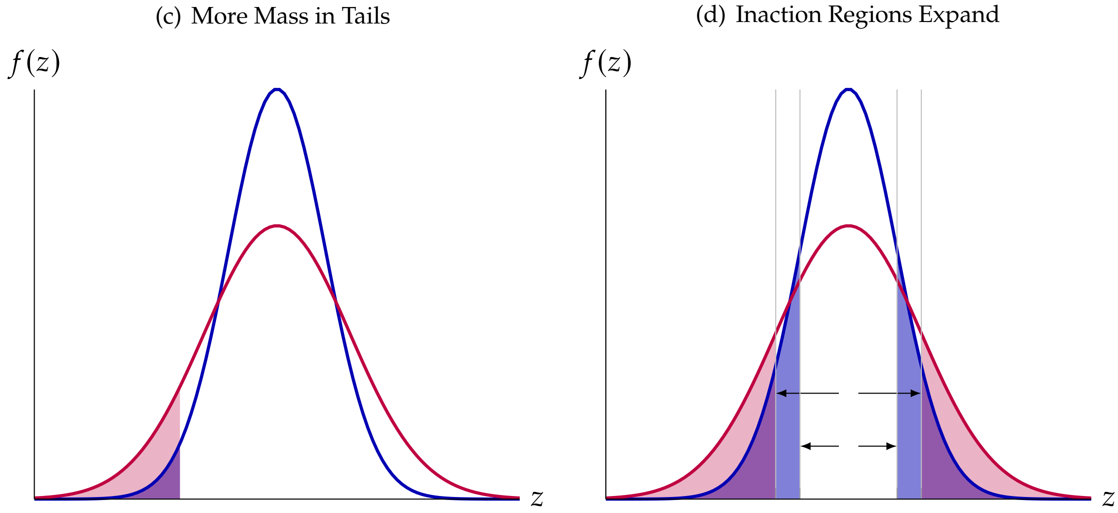
3.2 Nominal Adjustment Channel

Dispersion of shocks also plays a role in the frequency of price changes.The nominal adjustment mechanism acts through price adjustments counteracting monetary policy actions. Vavra (2014) shows empirically that during recessions typical volatility measures rise, and the cross-sectional standard deviation of price changes increases. He then argues that with higher dispersion of firm-level shocks, firms adjust their prices more frequently, and so more firm adjustment takes place through the nominal margin rather than through quantities. Any nominal stimulus attempt induced by the monetary authority generates more inflation and gives less of a boost to the real economy when volatility is high in recessions.

Vavra (2014) discusses that there are both direct and indirect effects of second moment shocks. The direct effect is the notion that more dispersed shocks increase the likelihood of pushing firms to the action region of the state space, thus firms adjust their prices more frequently. If the firm faces a choice of adjusting in several dimensions, it is plausible to think short-run changes in prices are easier for the firm than changes in factors, especially capital subject to partial irreversibility.

However, as discussed in the section above on real options, volatility also raises the option value of waiting, therefore the inaction region gets wider which makes firms temporarily suspend their decisions (including price adjustment). The latter effect is called indirect effect in Vavra's language. Vavra (2014) indicates that in case of a persistent increase in volatility, the direct effect dominates the indirect effect, therefore during recessions more firms adjust their prices and prices get more flexible which undermines the effectiveness of any nominal changes. Figure 2 shows both effects in a stylized way.

Figure 2: Direct and Indirect Effects of Second Moment Shocks



Note: Panel (a) $F(z|v_H) > F(z|v_L)$ for extreme values of z in the left tail. Panel (b) Inaction regions expand with volatility as the option value of waiting increases.

In order to explain these results, he also uses an Ss type model. First, he assumes that idiosyncratic volatility is perfectly negatively correlated with aggregate productivity (*i.e.* as the aggregate productivity increases the dispersion of idiosyncratic productivity shocks decreases). In the model, aggregate states are the aggregate nominal spending, and aggregate productivity, while the idiosyncratic states are previous period's nominal price, current period idiosyncratic productivity and the menu cost.

Firms operate as follows. In each period, after observing their own idiosyncratic productivity and a menu cost draw, and knowing its own inherited price, aggregate nominal spending, and aggregate productivity, firms decide either to change their posted nominal price or keep prices unchanged for another period. If firms decide to change price, then they pay the menu costs, enabling them to set their optimal nominal price. On the other hand, if they decide not to change their price, then they keep their inherited price.

He explains the above-mentioned empirical facts by the direct channel of second moment shocks dominating the indirect effects, in the context of price setting. Higher dispersion leads to more frequent price changes, which makes prices more flexible. Therefore, as the volatility increases, nominal shocks should have smaller real effects.

Our empirical findings state that as the dispersion of idiosyncratic productivity shocks at the sector level increases, the investment responsiveness of firms to monetary policy shocks falls. While this is consistent with the mechanism proposed by Vavra, we should differentiate our setting from his.

Firstly, Vavra (2014)'s model does not feature capital, so cannot speak directly to paths from volatility to the investment channel of monetary policy transmission, nevertheless the broader lessons of the model are informative externally: higher idiosyncratic shock volatility shifts the relative balance between real versus nominal channels of adjustment.

Secondly, he examines responses to monetary shocks as a function of dispersion pooled at the economy-wide level, while we examine dispersion at the sector level. His work focuses on variations in dispersion over time, while our work uses cross-sectional variation, comparing differences in dispersion across sectors, and the full panel variation of our dataset, using variation within sectors, moving over time.

Finally, we do not observe firms' pricing choices directly, and our labor data is at a lower frequency than needed. As such, there is not a direct mapping from his model to our data analysis, and our results only speak for capital adjustment. Nevertheless, we rely on the notion that higher shock dispersion forces more firm adjustment following monetary policy operations to be nominal (through prices) and less to be real (input quantities).

4 Monetary Policy Analysis

To analyse the impact of monetary policy on firm-level investment we employ a local projections specification. We regress investment at horizon h steps ahead $I_{i,t+h} = \log k_{i,t+h} - \log k_{i,t-1}$ on a constant, the monetary policy shock mps_t, firm-level controls, as well as firm and calendar-quarter seasonal effects.

Our vector of controls, $\mathbf{X}_{ist-1}$, comprises four lags of the shock and firm characteristics (age and size). Since we include firm fixed effects, we have no need f or sector effects. Sector fixed effects would be a linear combination of the firm effects. Thus we implicitly control for permanent differences in average investment behaviour across sectors. In this baseline regression, all sectors are pooled together.

$$\text{Firm Investment}_{ist+h} = c_h + \beta_h \text{mps}_t + \mathbf{X}_{ist-1}\Gamma_h + f_{hi} + \lambda_{hq} + v_{ist+h} \tag{10}$$

The monetary policy shock is scaled such that it induces a 25 basis points increase in the short-term interest rate (3-month Treasury bill rate), with monetary policy shocks proxied with the high frequency shock series of Miranda-Agrippino and Ricco (2017). This series proxies for the changes in policy which are separate from the endogeneous component which reacts to the state of the macroeconomy (e.g a Taylor-type rule creates a simaltaneity problem between policy and state of the economy).

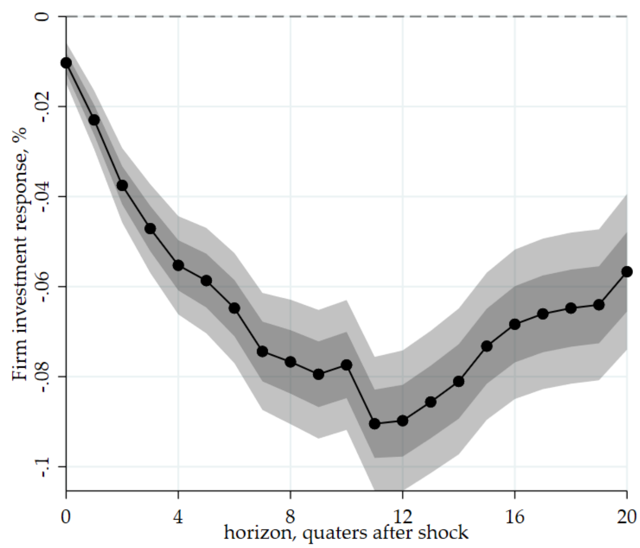
We prefer this proxy for monetary policy shocks since it does not generate the price or output puzzles of other similarly motivated proxies (Romer and Romer (1989), Gertler and Karadi (2015)), that is to say, empirical IRFs have the signs which match with economic theory (see Appendix for aggregate IRFs to RR, GK, and MAR shocks). Standard errors are clustered on the firm-level.

Our baseline regression sample runs from 1991q2 to 2009q4, made up of approximately 20,000 firms and 600,000 firm-quarters.

Impulse Response Functions Dynamic responses to monetary policy shocks are presented as impulse response functions (IRF). The sequence of coefficients $\{\beta_{(0)}, \beta_{(1)} ... \beta_{(H)}\}$ trace out the investment response to the shock mps_t over the horizon $h \in \{0, 1, ... H\}$ after a monetary policy shock. The IRF conducts the following thought experiment: comparing two observationally similar firms over periods $\{t, t+1, ..., t+H\}$, but one is subject to an isolated, one-period unit shock, and the other is not, holding constant certain characteristics of the two firms, for example recent histories of shocks, size, and age.

$$\beta_h = E\left[\text{Investment}_{it+h} \middle| \text{mps}_t = 1, \mathbf{X}_{t-1}\right] - E\left[\text{Investment}_{it+h} \middle| \text{mps}_t = 0, \mathbf{X}_{t-1}\right] \tag{11}$$

Figure 3: Impulse Response Functions of Firm Investment (%)



Note: Shaded regions represent 68 and 95 percent confidence intervals respectively. Standard errors are clustered at the firm level. Vertical axis is in percent difference, horizontal axis is quarters after shock hits

Figure (3) shows average investment is cut gradually, with a peak contraction of around 8-10 percent occurring around the end of the third year after impact.

4.1 Volatility Across Sectors and Monetary Policy

Next, we interact the monetary policy shock with volatility (time-pooled by sector). Given the exogeneity of the shock mps_t, this regression investigates the differential responses of investment to monetary policy across volatility by sector. In regression subscripts, sector s denotes the sector of firm i: $s = s(i)$.

$$\text{Investment}_{ist+h} = c_h + (\beta_h + \gamma_h \sigma_s) \cdot \text{mps}_t + \mathbf{X}_{ist-1}\Gamma_h + f_{hi} + \lambda_{hq} + v_{ist+h} \tag{12}$$

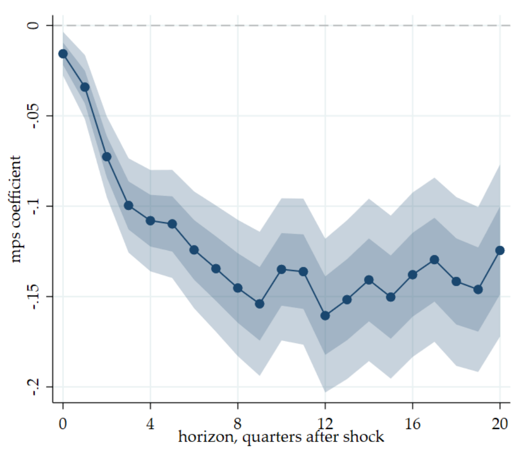
Controls remain unchanged from the baseline model. An estimate for γ_h with the opposite sign to β_h would suggest volatility decreases responsiveness to monetary policy shocks.

The second column of Figure (4) reports positive interaction coefficients along the horizon, for all three volatility measures. The first two remain statistically significant along the majority of the horizon shown. Results suggest that the investment channel of monetary policy is patterned across sectors by volatility, with sectors with higher overall volatility reacting significantly less to monetary policy shocks. Figure (5) uses the regression estimates to construct IRFs for firms at the tenth and ninetieth percentiles of the sectoral volatility distribution, for all three measures of volatility.

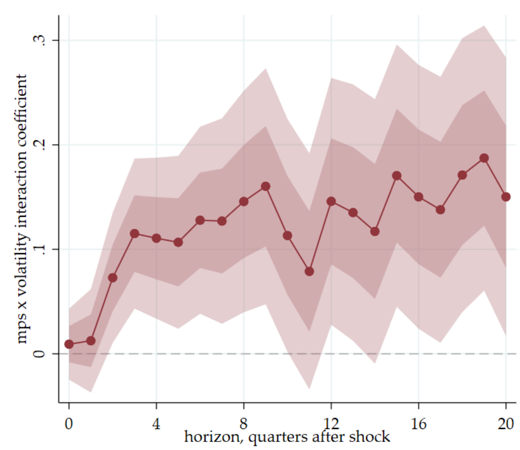
Figure 4: Investment Impulse Response Functions to Monetary Policy Shocks and MPS-Volatility Interactions

Cost Share

(a) Monetary Policy Shock Coefficient

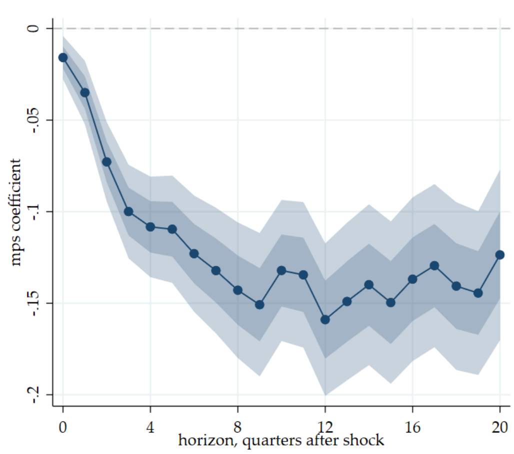


(b) MPS - Volatility Interaction Coefficient



Olley Pakes

(c) Monetary Policy Shock Coefficient



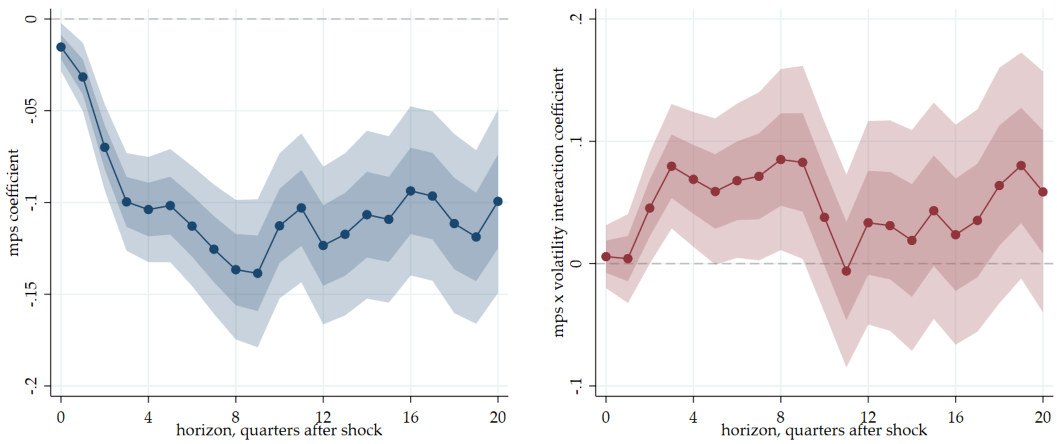
(d) MPS - Volatility Interaction Coefficient

Note: Shaded regions represent 68 and 95 percent confidence intervals respectively. Standard errors are clustered at the firm level. Vertical axis is in percent difference, horizontal axis is quarters after shock hits

Figure 4: Investment Impulse Response Functions to Monetary Policy Shocks and MPS-Volatility Interactions

GMM

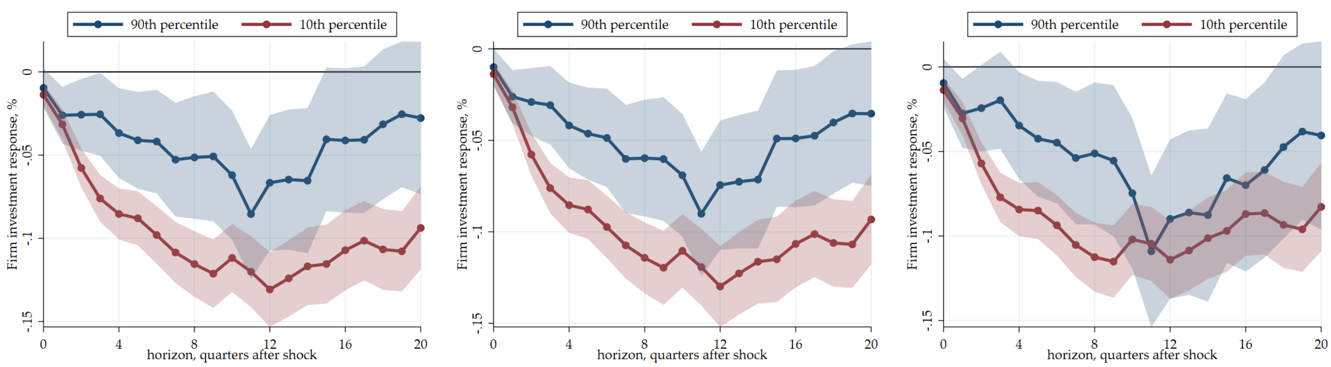
(a) Monetary Policy Shock Coefficient (b) MPS - Volatility Interaction Coefficient



Note: Shaded regions represent 68 and 95 percent confidence intervals respectively. Standard errors are clustered at the firm level. Vertical axis is in percent difference, horizontal axis is quarters after shock hits

Figure 5: Heterogeneity in Investment Channel of Monetary Policy by Sectoral Volatility

(c) Cost Share (d) Olley Pakes (e) GMM



Note: The above charts construct IRFs to a 25 basis points contractionary monetary policy shock, evaluated at the tenth and ninetieth percentile of the unconditional time-pooled volatility distribution.

Figure(4) shows that firms operating in sectors with higher *average* volatility of idiosyncractic TFP shocks adjust their capital on average less than those operating is less volatile sectors in response to a monetary policy shock. This pattern of volatility dampening the investment channel of monetary policy is robust to the choice of volatility construction.

Next, we look at time varying volatility, to see how volatility dampens real reactions *within* sectors, using panel variation following sectors through time.

4.2 Time-varying Volatility Interactions

We recalculate volatility so that that volatility can vary across sectors and through time, $\sigma_{s,y-1}$, however variation in volatility is at the yearly not quarterly frequency due to labor input data availablility only at the lower frequency. This time-varying volatility enters the regression lagged by one year $y(t)-1$ so that volatility is allowed to influence monetary policy transmission, but the measure of volatility is not contaminated by the effects monetary policy shock in period t.

$$\text{Investment}_{ist+h} = c_h + (\beta_h + \gamma_h \sigma_{s,y-1}) \cdot \text{mps}_t + \mathbf{X}_{ist-1}\Gamma_h + f_{hi} + \lambda_{hq} + v_{it+h} \tag{13}$$

Controls and regression structure remain otherwise the same as the baseline specification. Figure(6) presents IRFs to the monetary policy shock and the shock-volatility interaction coefficients.

If volatility is high for a given sector when the shock hits, the implied response is significantly dampened compared to if the shock hit in a period when baseline (time t) volatility was low.

Of the three measures of TFP shock volatility, CS and OP show results consistent with a dampening effect of volatility on the investment channel of monetary policy. Volatility interaction coefficients are typically positive, if not signficant along all of the horizon, however Olley-Pakes volatility interaction coefficients reach zero at certain horizons. One could expect a slight deterioration of signficance/preciison of estimates in the time-varying volatility case given that volatility enters with a one year lag and only evolves annually. In the next section we try to improve estimation by using other proxies for faster moving quarterly volatility.

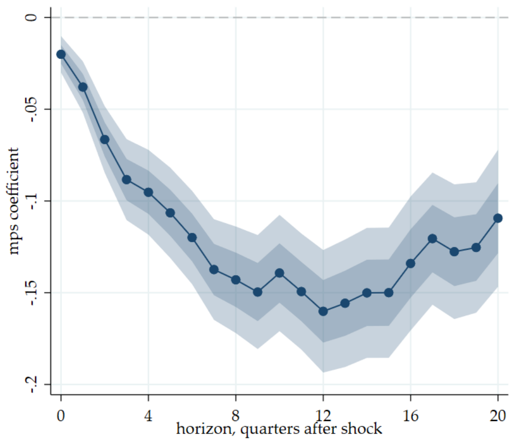
As in the previous regressions, we then use these coefficients to construct hypothetical IRFs at the tenth and ninetieth percentiles of the sector-year volatility distribution, shown in Figure(7).

Interpreting the results of the time-invariant volatility interactions and time-varying interactions jointly, it appears that only one of the possible six specifications tested in total produces results not consistent with some pattern of volatility dampening of the investment channel of monetary policy.

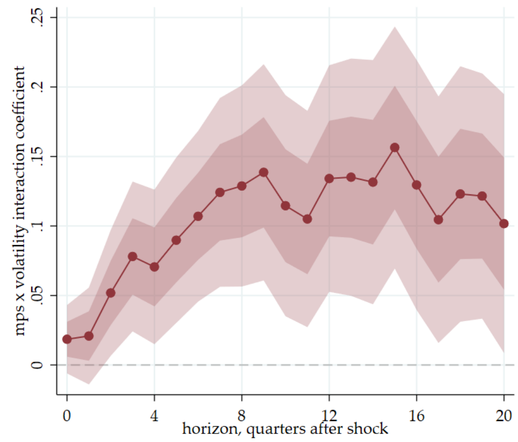
Figure 6: Investment Impulse Response Functions to Monetary Policy Shocks and MPS-Volatility Interactions (using time-varying sectoral volatility)

Cost Share

(a) Monetary Policy Shock Coefficient

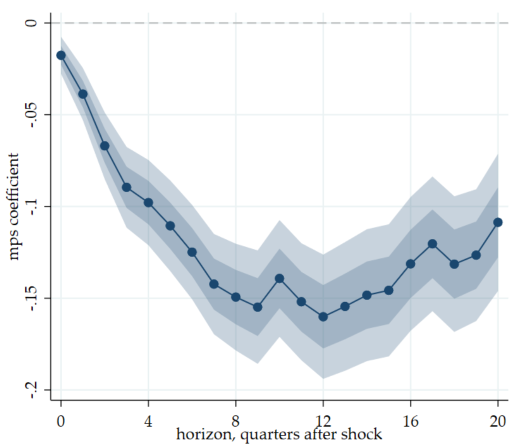


(b) MPS - Volatility Interaction Coefficient

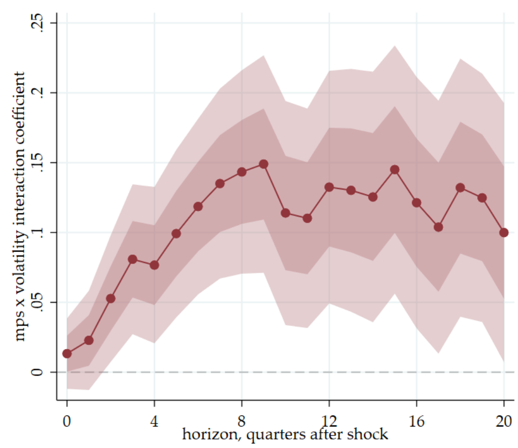


Olley Pakes

(c) Monetary Policy Shock Coefficient

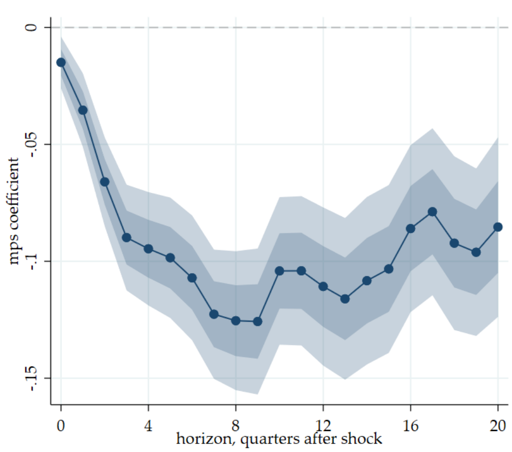


(d) MPS - Volatility Interaction Coefficient

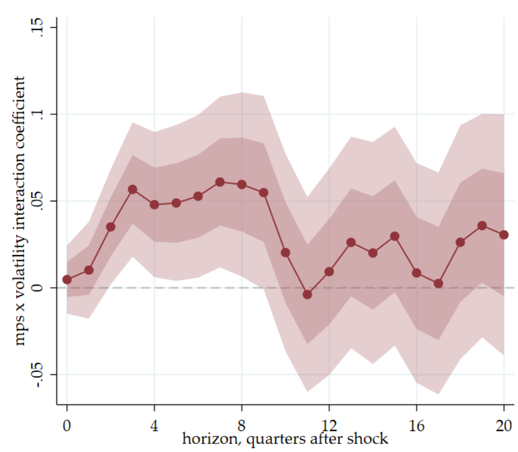


GMM

(e) Monetary Policy Shock Coefficient



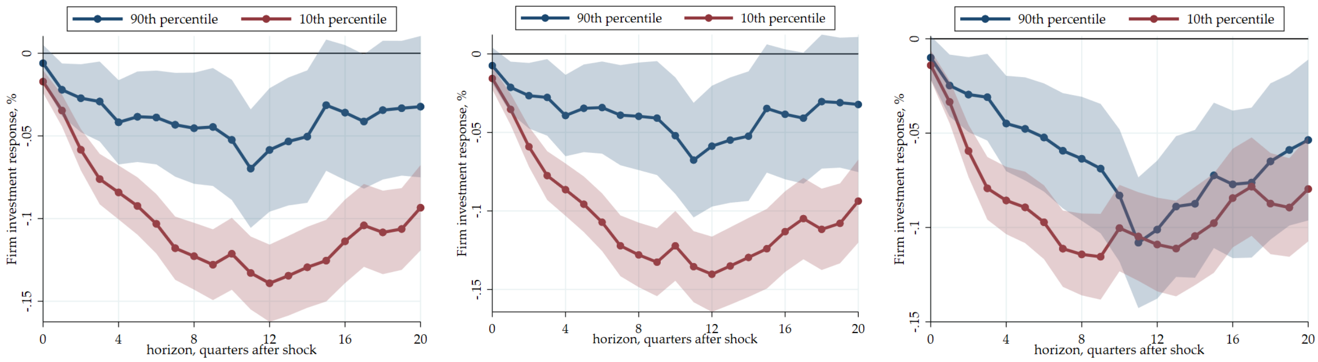
(f) MPS - Volatility Interaction Coefficient



Note: Shaded regions represent 68 and 95 percent confidence intervals respectively. Standard errors clustered at the firm level. Vertical axis is in percent difference, horizontal axis is quarters after shock hits

Figure 7: Heterogeneity in Investment Channel of Monetary Policy by Sectoral Volatility

(a) Cost Share (b) Olley Pakes (c) GMM



Note: The above charts construct IRFs to a 25 basis points contractionary monetary policy shock, evaluated at the tenth and ninetieth percentile of the unconditional time-varying volatility distribution.

Cost Share and Olley Pakes measure of time-varying volatility show evidence of volatility dampening, however the effect is stronger when using the CS measure. The p90-p10 IRFs are not significantly different for the GMM measure over the full horizon. While the p90-p10 IRFs in the right panel partially overlap for the OP measure, the partial separation at shorter horizons still implies a differential in the cumulative investment responses over the full horizon.

4.3 Firm-Level Sales Volatility and Aggregate Financial Volatility

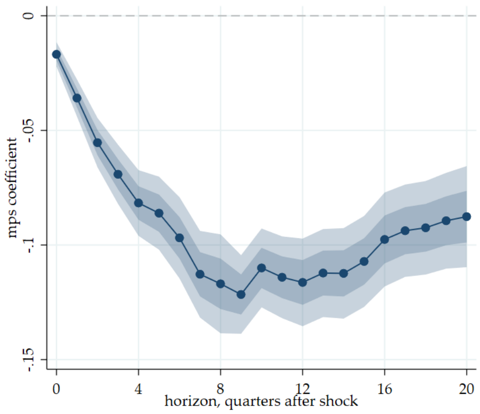
Given that our measures of volatility are at the annual frequency and enter regressions from the previous year in order to avoid the feedback from monetary policy to volatility, we now look at a faster moving proxy for sector level volatility, following Castro et al. (2015). This measure first purges log sales of variation due to log capital, log age as well as firm and sector-quarter non-parametric trends. From this filtering regression, the squared residuals (a time-varying shock variance proxy) are then regressed in a second stage on sector-quarter effects to estimate the component of shock variance which varies systematically at the sector-quarter-level. These transformed sector-quarter effects are then interacted with the monetary policy shock, proxying for sales volatility. Alternatively we use the VIX index as a proxy for aggregate volatility (although the VIX is forward looking in nature and a better proxy for uncertainty than volatility).

$$\text{Investment}_{ist+h} = c_h + (\beta_h + \gamma_h \text{vol}_{s,t-1}) \cdot \text{mps}_t + \mathbf{X}_{ist-1}\Gamma_h + f_{hi} + \lambda_{hq} + v_{ist+h} \tag{14}$$

Consistent with the results presented in previous sections, faster moving quarterly measures of volatility at the sector and aggregate level (proxied by adjusted sales volatility and the VIX) also show similar dampening patterns in the investment channel of monetary policy.

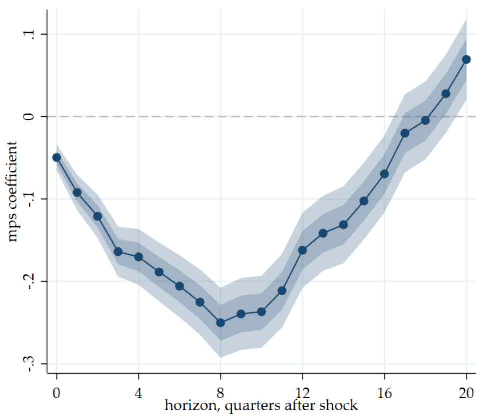
Figure 8: Sales Growth Volatility and Aggregate Volatility Interactions

(a) Monetary Policy Shock Coefficients



(b) Sales growth volatility Interaction Coefficients

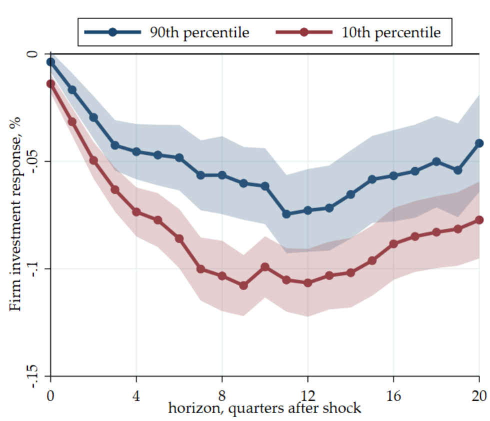
(c) Monetary Policy Shock Coefficients



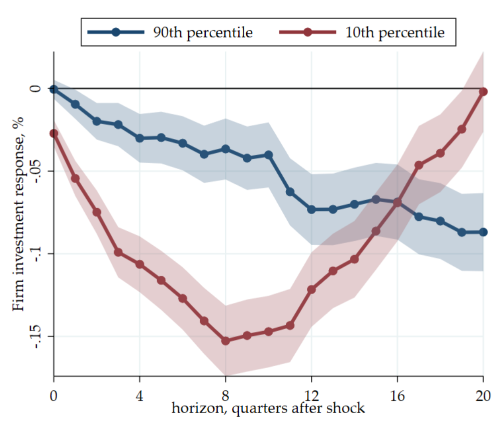
(d) VIX Interaction Coefficients

Figure 9: Heterogeneity in Investment Channel of Monetary Policy, Alternative Volatility Measures

(a) Sales Growth Volatility



(b) VIX



Note: The above charts construct IRFs to a 25 basis points contractionary monetary policy shock, evaluated at the tenth and ninetieth percentile of the unconditional time-varying volatility distribution.

High sales growth volatility implies less dampening of the investment channel of monetary policy compared to periods when the VIX index is high, possibly due to the very skewed nature of the VIX index and the occurance of high VIX values during a period of financial crisis.

5 Conclusion

In this paper, we explore the interaction between idiosyncratic firm risk and the investment channel of monetary policy. We contribute new findings that show significant heterogeneity in the investment channel of monetary policy transmission depending on the dispersion of idiosyncratic TFP shocks. More concretely, comparing sectors of different levels of dispersion of idiosyncratic shocks, we find that in more volatile sectors firms respond less to monetary policy shocks. Refining our measure of volatility to be time-varying, we also find evidence that within sectors, changes in sectoral volatility through time also play a role in dampening investment responsiveness to monetary policy.

Our results are of interest to monetary policymakers, as we find evidence of a dampening mechanism that directly affects firm responsiveness to monetary policy operations. Moreover, we contribute to evidence that monetary policy might be weakened in recessions - exactly when countercyclical stabilisation policies are most needed. Our results also suggest that volatility/uncertainty shocks reduce firms responsiveness to other types of aggregate shocks and not just idiosyncratic productivity shocks.

This work suggests much more aggressive monetary measures are needed to fight recessions versus tempering booms, or opens the door to alternative stabilisation policies by the fiscal authorities.

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Appendices

A Sample Descriptitve Statistics

Table 1: Firm Characteristics

	1960s	1970s	1980s	1990s	2000s	2010s	Total
Sales Revenue (M USD, 2015 prices)	1576.1	1193.2	1198.3	1341.2	2228.7	3553.4	1748.8
Employees (thousands)	11.21	6.995	5.621	5.391	7.308	10.50	6.999
Capital Stock (M USD)	643.6	452.9	503.7	515.5	771.3	1264.4	652.1
Value Added per Worker (000 USD)	51.80	80.32	121.9	120.4	139.0	173.1	120.9
Observations	8555	37183	43044	49169	40651	25696	204298

Table 2: Sectoral Sample Shares

SIC group	1960s	1970s	1980s	1990s	2000s	2010s	Total
1. Agriculutre, Forestry, Fishing	0.432	0.514	0.541	0.431	0.389	0.436	0.462
2. Mining	3.133	4.446	6.654	4.676	4.482	6.273	5.148
3. Construction	0.245	1.181	1.052	0.744	0.563	0.630	0.817
4. Manufacturing	67.38	56.51	48.59	45.83	45.76	46.34	49.31
5. Transportation*	6.148	5.535	6.368	6.034	6.384	5.468	6.017
6. Wholesale Trade	3.682	5.295	5.209	4.424	3.461	3.020	4.349
7. Retail Trade	9.912	9.472	7.866	8.326	7.242	7.266	8.155
8. Services	5.552	9.609	13.35	18.14	20.28	18.73	15.55
9. Miscellaneous	3.518	7.436	10.37	11.39	11.44	11.84	10.19
Observations	8555	37183	43044	49169	40651	25696	204298

$*$ Transportation, Communications, Electric, Gas, and Sanitary Services.

Real variables are deflated by the GDP deflator and normalized to 2015 dollars. Shares are unweighted, representing raw counts.

Table 3: SIC 2-digit Industry Shares

	Sales	%	Employment	%	Obs	%
A. Agriculture, Forestry, & Fishing						
Agricultural Production – Crops	1215.05	0.90	8.69	1.65	569	0.28
Agricultural Production – Livestock	120.71	0.09	0.38	0.07	172	0.08
Agricultural Services	191.43	0.14	2.26	0.43	123	0.06
Forestry	163.53	0.12	1.17	0.22	60	0.03
Fishing, Hunting, & Trapping	73.26	0.05	0.64	0.12	19	0.01
B: Mining						
Metal, Mining	579.02	0.43	2.03	0.39	1034	0.51
Coal Mining	1010.40	0.75	3.13	0.60	496	0.24
Oil & Gas Extraction	1261.38	0.93	1.93	0.37	8563	4.19
Nonmetallic Minerals, Except Fuels	694.76	0.51	2.60	0.49	425	0.21
C: Construction						
General Building Contractors	1107.47	0.82	1.78	0.34	1670	0.82
Heavy Construction, Except Building	1624.05	1.20	5.86	1.11	668	0.33
Special Trade Contractors	534.29	0.40	2.80	0.53	554	0.27
D: Manufacturing						
Food & Kindred Products	2682.37	1.99	10.30	1.96	5887	2.88
Tobacco Products	7844.94	5.81	18.78	3.57	229	0.11
Textile Mill Products	706.30	0.52	5.74	1.09	2018	0.99
Apparel & Other Textile Products	606.85	0.45	4.57	0.87	2721	1.33
Lumber & Wood Products	783.64	0.58	3.08	0.59	1656	0.81
Furniture & Fixtures	747.59	0.55	5.04	0.96	1609	0.79
Paper & Allied Products	2471.95	1.83	10.07	1.91	2376	1.16
Printing & Publishing	562.18	0.42	3.33	0.63	2918	1.43
Chemical & Allied Products	1386.12	1.03	4.43	0.84	16194	7.93
Petroleum & Coal Products	21957.81	16.28	19.47	3.70	1392	0.68
Rubber & Miscellaneous Plastics Products	1094.96	0.81	5.66	1.08	3023	1.48
Leather & Leather Products	535.25	0.40	3.45	0.66	864	0.42
Stone, Clay, & Glass Products	775.17	0.57	4.19	0.80	1989	0.97
Primary Metal Industries	1635.36	1.21	6.99	1.33	3558	1.74
Fabricated Metal Products	627.13	0.46	3.31	0.63	4602	2.25
Industrial Machinery & Equipment	1175.72	0.87	5.16	0.98	13529	6.62
Electronic & Other Electric Equipment	755.81	0.56	3.59	0.68	15931	7.80
Transportation Equipment	6053.56	4.49	22.74	4.32	5299	2.59
Instruments & Related Products	422.89	0.31	2.21	0.42	12518	6.13
Miscellaneous Manufacturing Industries	388.33	0.29	2.23	0.42	2418	1.18
E: Transportation & Public Utilities						
Railroad Transportation	4528.24	3.36	19.96	3.79	810	0.40
Local & Interurban Passenger Transit	1001.35	0.74	12.26	2.33	93	0.05
Trucking & Warehousing	2612.07	1.94	22.18	4.22	1820	0.89
Water Transportation	540.78	0.40	1.76	0.33	578	0.28
Transportation by Air	4065.98	3.01	17.93	3.41	1865	0.91
Pipelines, Except Natural Gas	1259.07	0.93	0.64	0.12	64	0.03
Transportation Services	943.04	0.70	3.34	0.64	648	0.32
Communications	3804.95	2.82	14.31	2.72	6414	3.14
F. Wholesale Trade						
Wholesale Trade – Durable Goods	1017.75	0.75	2.02	0.38	5638	2.76
Wholesale Trade – Nondurable Goods	3230.12	2.39	4.98	0.95	3246	1.59
G. Retail Trade						
Building Materials & Gardening Supplies	4219.42	3.13	18.40	3.50	680	0.33
General Merchandise Stores	9467.74	7.02	54.27	10.31	2346	1.15
Food Stores	4916.18	3.64	23.65	4.50	2185	1.07
Automative Dealers & Service Stations	2552.24	1.89	8.63	1.64	677	0.33
Apparel & Accessory Stores	1750.13	1.30	14.69	2.79	2204	1.08
Furniture & Homefurnishings Stores	1643.07	1.22	7.61	1.45	1123	0.55
Eating & Drinking Places	883.17	0.65	16.99	3.23	3595	1.76
Miscellaneous Retail	2245.13	1.66	8.41	1.60	3851	1.88
H: Finance and Real Estate						
Depository Institutions	1776.85	1.32	5.23	0.99	305	0.15
Nondepository Institutions	2411.58	1.79	4.42	0.84	3066	1.50
Security & Commodity Brokers	2715.88	2.01	3.49	0.66	2832	1.39
Insurance Carriers	4267.08	3.16	5.82	1.11	3706	1.81
Insurance Agents, Brokers, & Service	648.34	0.48	3.41	0.65	796	0.39
Real Estate	180.61	0.13	1.08	0.21	3222	1.58
Holding & Other Investment Offices	345.97	0.26	1.91	0.36	3122	1.53
I. Services						
Hotels & Other Lodging Places	606.86	0.45	8.64	1.64	1291	0.63
Personal Services	599.17	0.44	9.46	1.80	639	0.31
Business Services	790.16	0.59	6.08	1.16	18205	8.91
Auto Repair, Services, & Parking	1518.50	1.13	8.19	1.56	546	0.27
Miscellaneous Repair Services	126.40	0.09	0.70	0.13	73	0.04
Motion Pictures	679.96	0.50	3.68	0.70	1439	0.70
Amusement & Recreation Services	473.73	0.35	4.34	0.83	2398	1.17
Health Services	779.30	0.58	7.28	1.38	2864	1.40
Legal Services	155.08	0.11	0.34	0.06	26	0.01
Educational Services	418.35	0.31	3.12	0.59	696	0.34
Social Services	249.15	0.18	6.10	1.16	238	0.12
Museums, Botanical, Zoological Gardens	37.23	0.03	0.50	0.09	11	0.01
Engineering & Management Services	374.39	0.28	2.32	0.44	3339	1.63
Services, Not Elsewhere Classified	12.98	0.01	0.02	0.00	6	0.00
Non-Classifiable Establishments	3274.80	2.43	10.34	1.97	2557	1.25

B Total Factor Productivity

Table 4: TFPR in logs, Cost Share approach

SIC	Obs	mean	sd	p25	p50	p75	$\frac{p75}{p25}$	$\frac{p90}{p10}$	$\frac{p95}{p05}$	$\frac{p99}{p01}$	Skewness	Kurtosis
1	570	4.43	1.04	3.80	4.28	5.17	1.36	1.69	1.95	4.44	-0.28	4.85
2	6264	4.77	1.13	4.24	4.81	5.43	1.28	1.70	2.16	7.39	-1.08	7.47
3	971	5.73	0.95	5.11	5.87	6.45	1.26	1.55	1.78	2.19	-0.53	3.24
4	58254	4.55	0.90	4.23	4.59	4.99	1.18	1.45	1.81	5.63	-1.74	12.88
5	7053	4.19	0.73	3.77	4.09	4.48	1.19	1.45	1.66	2.80	0.28	9.81
6	4915	5.52	0.95	4.94	5.48	6.04	1.22	1.51	1.73	2.51	0.34	5.47
7	10570	4.42	0.72	4.03	4.45	4.82	1.20	1.54	1.72	2.16	0.19	4.42
8	18021	4.42	1.00	3.89	4.50	4.98	1.28	1.69	2.07	4.49	-0.58	7.27
9	11937	5.12	1.15	4.46	5.12	5.86	1.31	1.68	2.05	4.25	-0.34	6.14
Total	118555	4.62	0.98	4.15	4.61	5.11	1.23	1.60	1.95	4.61	-0.68	8.64

Table 5: TFPR Innovations based on Cost Share approach

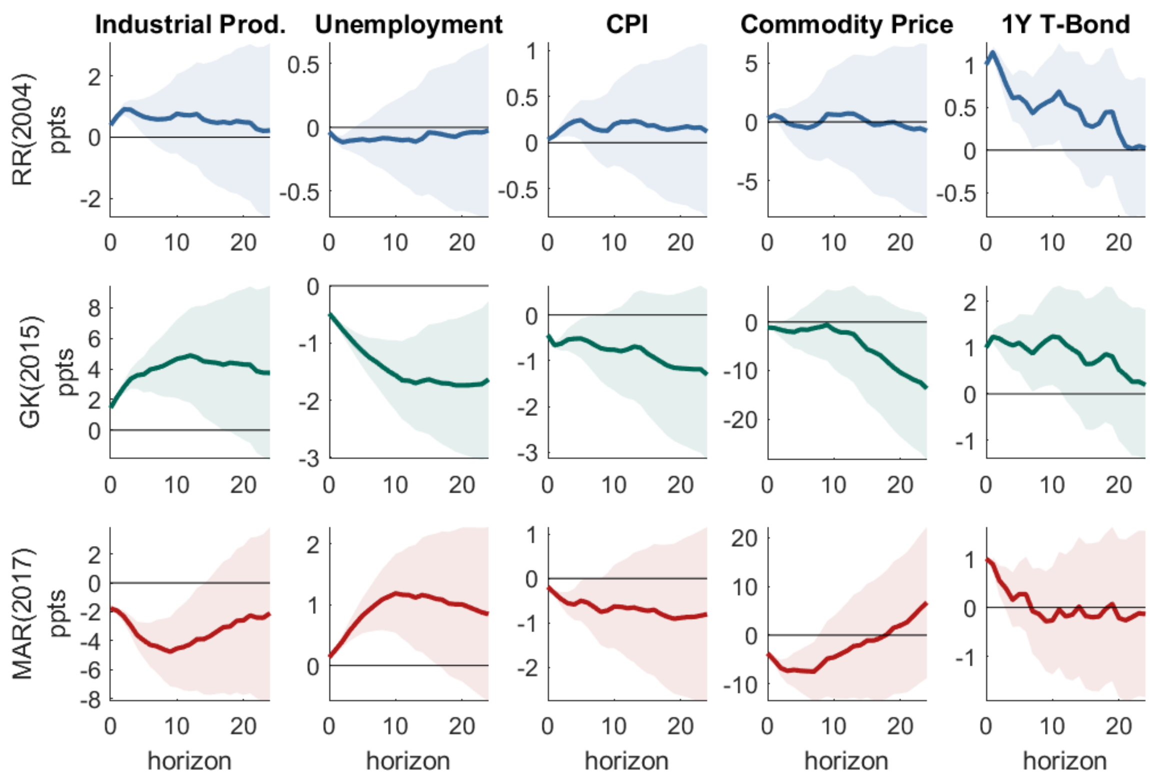
SIC	Obs	mean	sd	p25	p50	p75	$p_{75}-p_{25}$	$p_{90}-p_{10}$	$p_{95}-p_{05}$	$p_{99}-p_{01}$	skewness	kurtosis
1	453	0.00	0.38	-0.14	0.00	0.16	0.30	0.71	1.06	2.19	-1.98	25.81
2	4908	0.00	0.46	-0.17	0.01	0.18	0.35	0.82	1.24	2.63	-0.99	19.08
3	804	0.00	0.30	-0.16	0.00	0.16	0.32	0.63	0.87	1.63	-0.53	9.59
4	48197	0.00	0.38	-0.09	0.00	0.10	0.19	0.51	0.85	2.29	-1.24	41.21
5	5773	0.00	0.22	-0.06	0.00	0.07	0.13	0.30	0.50	1.28	0.17	65.57
6	3936	0.00	0.24	-0.08	0.00	0.09	0.17	0.40	0.61	1.28	-0.37	41.24
7	8912	0.00	0.16	-0.05	0.00	0.06	0.11	0.26	0.38	0.82	-5.23	167.07
8	13427	0.00	0.36	-0.10	0.01	0.11	0.21	0.53	0.87	2.07	-2.39	56.02
9	9523	0.00	0.39	-0.12	0.00	0.13	0.25	0.62	0.98	2.34	-1.03	26.69
Total	95933	0.00	0.35	-0.09	0.00	0.10	0.19	0.49	0.82	2.09	-1.43	43.99

C Alternative Monetary Policy Shocks

The figure below compares monthly aggregate responses to three distinct monetary policy shock series. The first, RR (Romer and Romer (1989)) identifies periods in which policy was tightened in a plausibly exogeneous way by examining FOMC meeting minutes, the so-called "narrative identification". GK

(Gertler and Karadi (2015)) creates a proxy for structural monetary policy shocks by examining the reaction of Fed Funds Futures to policy annoucement events within a tight window, the "high frequency" identification. The final series, MAR (Miranda-Agrippino and Ricco (2017)) accounts for the fact that the central bank's and agents' information sets are not identical, so policy changes induce direct effects, as well as signaling effects - agents learn more about the state of the economy from the central banks policy choices.

Figure 10: Comparison of monetary policy shock series 1979m1 to 2014m12



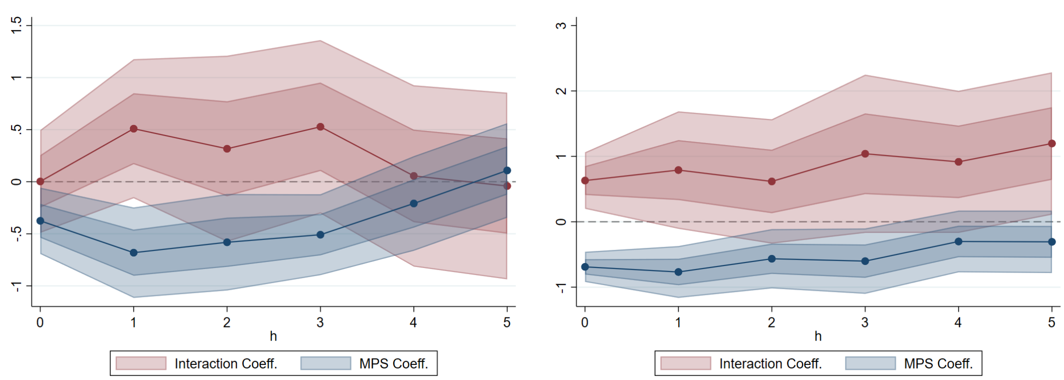
The above figure shows that only the MAR shock series induces changes in the macroeconomy consistent with economic theory, i.e. jointly depresses economic activity in the decline in industrial production, and increase in the unemployment rate, a deflationary reaction of consumer prices and commodity prices, and the shock only induces a very short-lived response from short-term interest rates. The RR shocks present what might be dubbed output and price puzzles, and the decay of the response to the 1 year treasury bill rate is much slower. GK shocks conversely present problematic responses of output and unemployment, while prices seem to conform more to what one would expect.

D Annualized Monetary Policy Shock

In our baseline analysis we use the higher frequency quarterly Compustat dataset. However this means we cannot examine employment responses. Below we switch to annual data, and aggregate the monetary policy shocks within a calendar year. Responses remain qualitatively similiar, even if not always statistically significant. This is rationalized with a substantial loss of observations due to time aggregation.

Figure 11: Investment and Hiring Response to Monetary Policy Shock, Annual Responses, Fixed Volaility Interaction

(a) Investment (b) Hiring

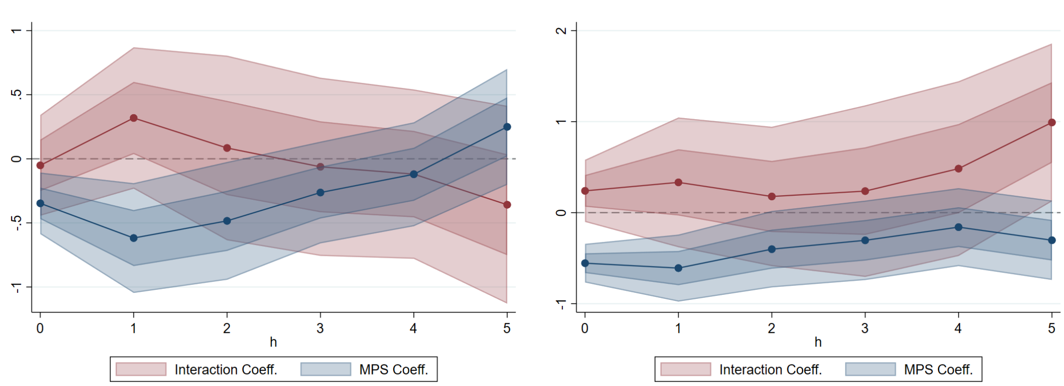


Average response of investment and employment at horizon h (in years) to a 100 bpts monetary policy shock.

We see a slower hump-shaped IRF profile for investment, while employment reacts most on impact. In both factors sectoral volatility of TFPR innovations dampens the reaction to monetary policy shocks given the MPS an volatility interaction coefficietions have opposite signs over most of the horizon.

Figure 12: Investment and Hiring Response to Monetary Policy Shock, Annual Responses, Time-varying Volaility Interaction

(a) Investment (b) Hiring



Average response of investment and employment at horizon h (in years) to a 100 bpts monetary policy shock.