Monetary Policy Transmission and Firm-Level Volatility: Uncertainty Versus Risks*

Ruslana Datsenko†

This draft: January 2023
First draft: December 2021

Latest Version

Abstract

I study the role of firm-level volatility and default risk in the transmission of monetary policy to investments in fixed assets. Empirically, I find that firms facing lower volatility decrease their investments by more after increase in interest rate than firms that face higher volatility. I demonstrate that this finding is due to two channels through which volatility determines monetary policy transmission. First, volatility increases default risk which increases the price of borrowed funds. Second, volatility increases firms hesitancy to invest (real options channel). In contrast with the earlier literature, I show that the real options rather than the default risk channel matters for the transmission of monetary policy. Moreover, I demonstrate the relevance of the two channels in a heterogeneous firm model with non-convex adjustment costs and default risk. I find that the channel through which the monetary policy transmission takes place — real options or risk premium — determines whether the monetary policy increases or decreases aggregate capital relative to a model without heterogeneity, adjustment costs, and financial frictions.

Keywords: *Monetary policy, investments, volatility, uncertainty, default risk, financial constraints*

JEL Classification: *E22, E32, E43, E44, E52, G31, D25*

*I am deeply indebted to my dissertation advisors Kjetil Storesletten and Martin Blomhoff Holm, also to my host professor at the UCB Yuriy Gorodnichenko, and Marianna Kudlyak for their continuous support and invaluable guidance. I am grateful to Jon Steinsson, Emi Nakamura, James Cloyne, Benjamin Schoefer, and many others for valuable comments and helpful discussion. I am also grateful to the participants at the Oslo Macro Group, Midwest Macro Conference, and seminars at the University of California at Berkeley, University of Oslo, International Monetary Fund, Copenhagen Business School.

†PhD Student at University of Oslo, visiting student at University of Minnesota and University of California, Berkeley. Email: ruslana.datsenko@econ.uio.no

1 Introduction

Central banks play a crucial role in maintaining economic stability by adjusting interest rates, particularly in times of heightened market volatility like the 2007-2009 recession and the Covid crises. Previous studies often use volatility of stock market prices as a measure of uncertainty. Both interest rate and uncertainty are important for firm level investment dynamics. While the volatility of stock market prices is associated with uncertainty, it also correlates with a firm's risk of defaulting on loans. All else being equal, the higher the volatility of stock market prices a firm faces, the higher the default risk the firm has. The importance of default risk and financial accelerator has been studied by Bernanke, Ottonello, and show that due to the financial accelerator monetary policy has larger effect on investments. The question, however, arises: *What is a role of default risk for monetary policy transmission in the presence of high volatility?*. In this paper, I investigate the role of stock market volatility in monetary policy transmission on a firm-level investment and its connection to default risk.

Why would volatility of stock market returns matter for monetary policy transmission? There are two channels trough which volatility might be important for monetary policy. The first channel is due to association between volatility and uncertainty. When uncertainty is high firms tend to postpone their investment until market clears, i.e. *wait-and-see or real options channel*. Both uncertainty/volatility and interest rate affect options of a firm to invest. When uncertainty increases the marginal costs of investments increases and, thus, fewer firms invest and those that invest, invest less. Firms that face high volatility/uncertainty are, thus, less affected by shocks. The second channel is due to the association between market volatility and the risk of default on debt. On average firms that face higher default risk also face higher volatility. The monetary policy transmission in this case is due to *risk premium*: when volatility is high firms are perceived by lenders as riskier, and thus, charge them with extra price for risk (risk premium). Firms that face higher risk premium are less affected by monetary policy due to the flatter marginal cost curve of capital. Thus relative increase in price will not affect high risk firms by much.

Financial accelerator and interaction between uncertainty and default risk

I estimate how firms' investments respond to monetary policy shocks depending on the stock market volatility using Compustat dataset. As a measure of firm level uncertainty, I use a within firm measure of standard deviation of stock prices. As a measure of default risk, I use distance-to-default obtained from MVK model. I use high-frequency shocks to interest rate changes as a monetary policy shock, as detailed by Gürkaynak, Kısacıkoğlu, and Wright (2020). I estimate the impact of monetary policy shocks on firms' investments using a local projections approach of Jordà (2005). I evaluate firms' response over a 16-quarters horizon because the effect of monetary policy is known to propagate slowly over time (see Gertler and Karadi (2015)).

My empirical results suggest that volatility is important for monetary policy transmission and that the effect of the uncertainty channel dominates the default risk channel.

Specifically, I find that firms that face lower volatility are more affected by changes in interest rates than highly volatile firms. Firms with one standard deviation lower volatility respond to a 25 bps increase in the interest rate by approximately 1.1 percentage points more than high-volatile firms. This result is nonlinear. The average investment response is close to the response in the 20th percentile of volatility distribution. Firms in the 80th percentile of volatility distribution have a marginally positive effect; however, this effect is statistically insignificant. I also estimate that the investment response to monetary policy shocks differs depending on the default risk. Firms with one standard deviation higher distance-to-default are more affected by monetary policy by 0.8 percentage points (see also similar results in Ottonello and Winberry (2020)). When I simultaneously control for both volatility and default risk to explain the differences in investment responses to monetary policy shocks, I find that the effect of the volatility remains statistically significant, and its magnitude is unchanged. Distance-to-default's quantitative and statistical significance in predicting disparities in firms' responses diminishes considerably. These results are robust to using other measures of default risk such as age, dividend payment, leverage, liquidity, and size.

To interpret these empirical findings, I build a model with heterogeneous firms confronting default risk, partial investment irreversibility, fixed capital adjustment costs, and time-varying volatility of idiosyncratic productivity. The model allows me to compare the effect of firm-level volatility on aggregate investments in the model with and without adjustment costs, as well as in the model with and without financial frictions. Further, since volatility is endogenous in the data, I utilize the exogeneity of productivity shocks in the model. Finally, in the empirical analysis, I use publicly traded firms; in the model, I calibrate the targeted moments using data from private and public firms.

In the model, I show two channels through which volatility matters for monetary policy transmission. First, the time-varying volatility of idiosyncratic productivity introduces uncertainty. Uncertainty, in turn, introduces the wait-and-see effect or real options channel via inaction region due to non-convex adjustment costs and partial irreversibility. According to the real options channel, firms decide whether to invest. When uncertainty is high, firms tend to exercise greater caution in investing and postpone investments until the market becomes clear. Consequently, an increase in the interest rate affects the option value of the investment, forcing fewer firms that face high uncertainty to disinvest, and those that do, disinvest by less than firms that face low uncertainty. Thus, firms that face high uncertainty respond less to monetary policy.

Second, in the model, an increase in the volatility of idiosyncratic productivity increases firms' probability of default on debt and, thus, the risk premium. In this case, volatility is important for monetary policy transmission through the risk premium channel. Firms that face higher default risk face higher premium prices of the debt and, thus, are less affected by monetary policy.

I calibrate the model parameters using standard parameters in the literature; the key parameters that govern the importance of volatility are adjustment costs and investment irreversibility. I replicate the empirical results using simulated data. In the model, low-volatile firms are more affected by changes in interest rates than high-volatile firms. This varied response has implications for aggregate investment.

I find that the channel through which the monetary policy transmission takes place — real options or risk premium — determines whether the monetary policy increases or decreases aggregate capital relative to a model without heterogeneity, adjustment costs, and financial frictions. By comparing the full model to a model in which I eliminate financial frictions and adjustment costs, I see that the effect of changes in the interest rate on aggregate investment is smaller in the full model than in the representative firm benchmark. This effect stems from real options rather than default risk. While incorporating default risk only *increases* the effect of monetary policy, incorporating real options *decreases* the effect of monetary policy.

Specifically, when I remove non-convex adjustment costs and partial investment irreversibility from the full model, the resulting model shows a greater reduction in aggregate investments following an interest rate increase compared to the frictionless model. This effect is similar to the financial accelerator mechanism proposed by Bernanke, Gertler, and Gilchrist (1999), where an interest rate increase affects the firm's value and, thus, its default risk. Thus, in the model with default risk, high-risk firms are less responsive to interest rate changes than low-risk firms, yet both are more responsive than those without financial frictions. In contrast, in the model with real options, even though low-volatility firms are more affected by interest rate changes, they are less impacted than the representative firms in the frictionless model. This is because they exercise greater caution in adjusting their investments due to adjustment costs and the potential for facing higher volatility in the future. Consequently, even when volatility is low, fewer firms disinvest, and those that do disinvest do so to a lesser extent after an increase in the interest rate compared to the frictionless model.

My results suggest a potentially important source of time variation in monetary transmission: monetary policy is less powerful when uncertainty is high. In particular, I show that the interest rate is the most effective when both volatility and default risk are low. In contrast, the interest rate is the least effective when both volatility and default risk are high. This suggest that market uncertainty should be taken into account while designing monetary policy.

Literature Review. My paper contributes to several strands of the literature. First, I contribute to the literature by discussing the role of firm heterogeneity in monetary policy transmission. While earlier articles, such as Gertler and Gilchrist (1994), Oliner and Rudebusch (1996), Bernanke et al. (1999), and more recently, Ippolito, Ozdagli, and Perez-Orive (2018), and Cloyne, Ferreira, Froemel, and Surico (2018) argues that financially constrained firms are more influenced by monetary policy, Ottonello and Winberry (2020) show that it is financially unconstrained firms that are the most affected by monetary policy.[1] In this paper, I show that the effect of default risk originates from volatility. When controlling for volatility, it is the financially constrained firms that are the most affected by monetary policy.

Second, I extend the literature on the role of volatility in monetary policy transmission. Recent papers, including Fang (2022), Lakdawala and Moreland (2022), and Aastveit, Natvik, and Sola (2017), delve into the significance of uncertainty in monetary policy transmission. Lakdawala and Moreland (2022) demonstrate that monetary policy more strongly influences firms facing higher uncertainty and lower resale investment prices. My findings align with their findings, highlighting the importance of volatility in monetary policy transmission, measured using the standard deviation of stock returns. However, it remains ambiguous through which channel volatility is important for monetary policy transmission, as volatility can serve as a proxy for both default risk and uncertainty. I add to this literature by differentiating between the channels through which volatility impacts monetary policy transmission: uncertainty versus default risk. My empirical findings suggests that the uncertainty channel outweighs the default risk channel.

Third, I contribute to the literature on the significance of firm level heterogeneity in theoretical models. While Ottonello and Winberry (2020) integrate default risk and Fang (2022) introduces "real options" in distinct models, I develop a model that encompasses both channels. Moreover, in contrast to Fang (2022), I incorporate financial constraints into

[1] Examples of previous papers that have employed firm or industry heterogeneity to analyze financial imperfections and non-financial firms' responses to monetary policy shocks using various empirical approaches include Kashyap and Stein (1994), Gaiotti and Generale (2002), Ehrmann and Fratzscher (2004), Peersman and Smets (2005), Dedola and Lippi (2005), Bougheas, Mizen, and Yalcin (2006), and Cao, Hegna, Holm, Juelsrud, König, and Riiser (2023).

the model, underscoring the importance of default risk in a model with "real options". My analysis indicates that the "real options" channel supersedes the "default risk" channel.

Fourth, I contribute to the literature on the importance of lumpy adjustment costs for investment decisions. Several previous papers investigate at how aggregate shocks propagate to investments through models with non-convex adjustment costs. Caballero and Engel (1999) build a partial equilibrium model. They show that large aggregate shocks with non-convex adjustment costs may lead to a substantial change in the number of establishments undertaking capital adjustments. Khan and Thomas (2003) and Khan and Thomas (2008) generalize a partial equilibrium model with lumpy investments to the general equilibrium and show that the importance of lumpy adjustment in general equilibrium is due to external rather than internal margin. Bloom, Bond, and Van Reenen (2007), Bloom (2009), and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018) incorporate time-varying volatility into models with adjustment costs and show the importance of uncertainty for aggregate demand and productivity shocks. I add to this literature by showing the importance of lumpy adjustment costs for interest rate shocks.

Finally, I contribute to the growing literature that argues that monetary policy is less effective during recessions than during normal times by suggesting that changes in the distribution of idiosyncratic volatility are another reason that monetary policy may be less effective. Aastveit et al. (2017) show that when aggregate uncertainty is high, firms are less affected by monetary policy. Tenreyro and Thwaites (2016) estimate a nonlinear time-series model and find that monetary policy shocks have a lower impact on real economic activity during recessions than during normal times. Berger and Vavra (2013) and Wieland and Yang (2020) provide models in which monetary policy is less powerful during recessions due to changes in the distribution of price adjustments or durable expenditures.

Road map. The subsequent structure of the paper unfolds as follows: Section 2 discusses connection between volatility and distance-to-default. Section 3 delineates the data and methodology employed. Empirical evidence is presented in Section 4, followed by a model discussion in Section 5. Section **??** discusses the channels of interest rate transmission, and Section 6 offers a model calibration. Section 7 shows model results, and Section 8 offers concluding remarks.

2 Theoretical Intuition: Why Volatility Would Matter for Monetary Policy Transmission?

Uncertainty. Assume a firm model with a partial investment irreversibility and time-varying volatility. Time is discrete. A firm, indexed by i, uses capital k_{it} and labor l_{it} in its production y_{it},

$$y_{it} = e^{z_{it}} k_{it}^{\alpha} l_{it}^{\beta}, \tag{1}$$

where $\alpha + \beta < 1$, and the idiosyncratic productivity follows autoregressive processes of order 1 (AR(1)),

$$z_{it+1} = \rho z_{it} + \sigma_{t-1}\epsilon_{it} \qquad \epsilon_{it} \sim N(0,1). \tag{2}$$

I allow the variance of innovations, σ_{t-1}, to move over time according to two state Markov chains, generating periods of low and high micro-uncertainty. There are two assumptions embedded in this formulation. First, the volatility in the idiosyncratic component, z_{it}, implies that productivity dispersion across firms is time-varying. Second, given the timing assumption of σ_{t-1}, firms learn in advance that the distribution of shocks from which they will draw in the next period is changing. This timing assumption captures the notion of uncertainty that firms face about future business conditions.

The firm chooses capital and labour to maximize its value subject to low of motion of capital $k_{it+1} = i_{it} + (1-\delta)k_{it}$ and partial investment irreversibility $(p_{buy}\mathbb{1}_{i_{it}>0} + p_{sell}\mathbb{1}_{i_{it}<0}) * i_{it}$ where $p_{buy} > p_{sell}$,

$$V_A(k_{it}, l_{it}, z_{it}) = \max_{\{k_{it+1}, l_{it+1}\}_{t\geq 0}} \underbrace{e^{z_{it}} k_{it}^{\alpha} l_{it}^{\beta} - rk_{it} - wl_{it} - (p_{buy}\mathbb{1}_{i_{it}>0} + p_{sell}\mathbb{1}_{i_{it}<0}) i_{it}}_{Cash\ flow} + \beta E[V(k_{it+1}, l_{it+1}, z_{it+1})], \tag{3}$$

where r and w are cost of production.

Under these assumptions, increase in volatility of productivity shocks will lead to increase in volatility of market capitalization and, thus, volatility of asset prices:

$$\sigma_{\epsilon} \uparrow \rightarrow \sigma_{V_A} \uparrow . \tag{4}$$

Channel of interest rate transmission: Inaction region. The effect of monetary policy on investments depends on the inaction region. This model yields a region of inaction due to the partial investment irreversibility. Firms only invest when business conditions are sufficiently good and only disinvest when they are sufficiently bad. When uncertainty is higher, these thresholds move out: firms become more cautious in responding to business conditions. To provide some graphical intuition, Figure 1 plots the inaction region for high and low-volatile firms. The red (dashed) lines represent inaction region when uncertainty is high, and the blue (solid) line represents inaction region when uncertainty is low. In these regions, the real-option value of waiting is worth more than the investment returns. Outside the inaction region, investment will occur according to the optimal values of i.

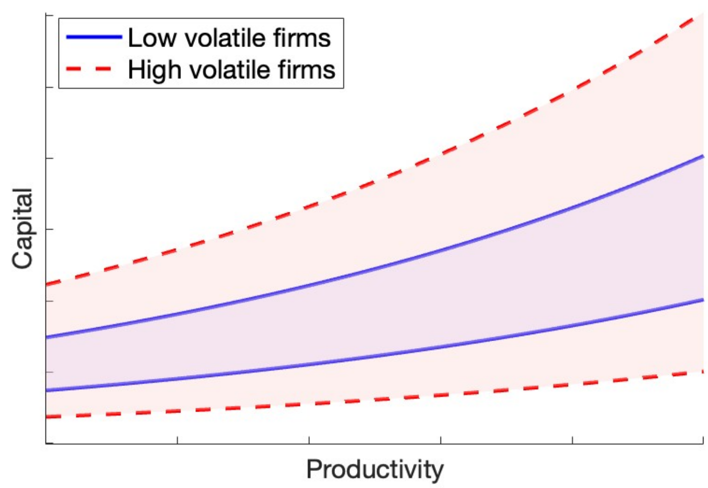

Figure 1: Inaction region

When interest rate increases, the inaction region shifts downwards, making some firms opt out/in from/to the region of inaction. Figure 2 displays how the inaction region shifts for firms that face high and low volatility when the interest rate rises.

Panel (a) shows the effects on low-volatility firms. The red region represents the inaction region before the interest rate change, while the blue part indicates the region after the rate increase. When the interest rate increases, some firms move out of the original inaction area (red), and others move into the new inaction area (blue).

Panel (b) depicts a similar trend but for high-volatility firms. These firms have a broader inaction region, implying that fewer firms will transition into or out of the region. This, in turn, means that fewer firms will adjust capital, and thus, when volatility is high, fewer firms are affected by changes in the interest rate.

Defaul Risk. Volatility of market capitalization σ_{V_A} is important in the derivation of default risk in Merton (1974) model. To derive distance-to-default (DD), I use a variant of

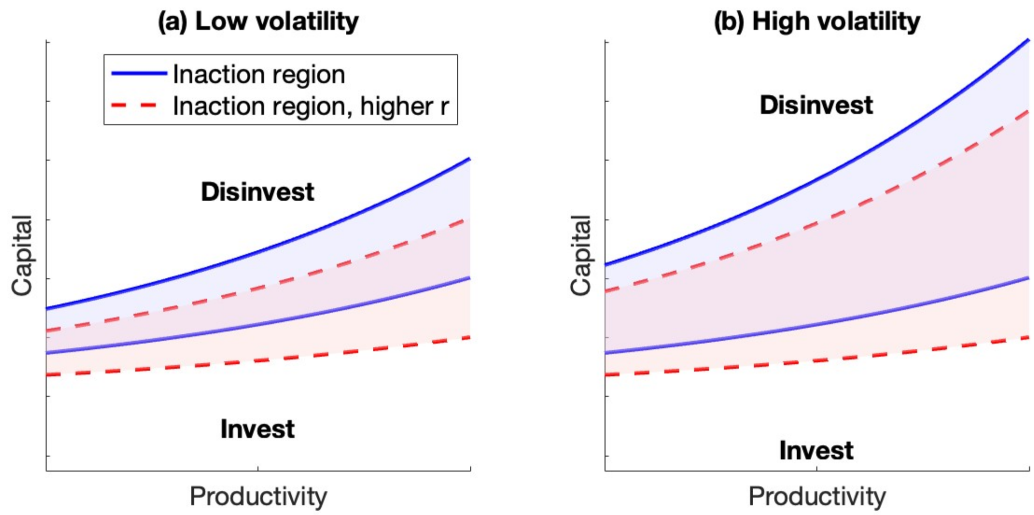

Figure 2: Inaction region: increase in interest rate

the Merton (1974) model, i.e. KMV model. The model considers that the firm's equity is treated as a call option on the underlying value of the firm's assets, with a strike price equal to the face value of a firm's zero-coupon bond debt maturing in T.

In the model the firm's value, V_A, is assumed to follow the geometric Brownian motion, with an expected return of μ_{V_A} and volatility of σ_{V_A},

$$dV_A = \mu_{V_A} dt + \sigma_{V_A} dW. \tag{5}$$

According to the Black-Scholes-Merton option-pricing framework the value of the firm equity then satisfies:

$$E = V\Phi(\delta_1) - e^{-rt} D\Phi(\delta_2), \tag{6}$$

where r denotes the instantaneous risk free interest rate, $\Phi()$ is the cumulative standard normal distribution function, and

$$\delta_1 = \frac{\ln\left(\frac{V_A}{D}\right) + (r + 0.5\sigma_{V_A}^2)T}{\sigma_{V_A}\sqrt{T}}, \quad \text{and} \quad \delta_2 = \delta_1 - \sigma_{V_A}\sqrt{T}.$$

The resulting solution of the Merton DD model can be used to calculate the firm-specific DD over the one year horizon as

$$DD = \frac{log\left(\frac{V_A}{D}\right) + (\mu_{V_A} - \frac{1}{2}\sigma_{V_A}^2)(T-t)}{\sigma_{V_A}\sqrt{T-t}}, \tag{7}$$

where D is firm's debt and T is a time to debt maturity, in this context, default occurs when the numerator in equation (7) is negative. In effect DD measures the number of standard deviations the log of the value of assets to debt ratio must deviate from its mean for default to occur.

While the volatility of assets, σ_{V_A} is unobserved, the equation (6) underpins the link between the volatility of the firms value and the volatility of its equity σ_E. In particular it follows from the Ito's lemma that

$$\sigma_E = \frac{E}{V}\frac{\partial E}{\partial V_A}\sigma_{V_A}, \tag{8}$$

Under the Black-Scholes-Merton option-pricing framework $\frac{\partial E}{\partial V_A} = \Phi(\delta_1)$. Thus the relation between the volatility of the firms value and the volatility of its equity is given by:

$$\sigma_E = \frac{E}{V}\Phi(\delta_1)\sigma_{V_A}. \tag{9}$$

In equation (7), distance-to-default depends on the volatility of stock returns through the volatility of assets. Thus, the distance-to-default depends on the volatility of productivity shocks. In particular, an increase in the volatility of productivity shocks will increase the volatility of the firm value and thus decrease the distance-to-default,

$$\sigma_\epsilon \uparrow \rightarrow \sigma_{V_A} \uparrow \rightarrow DD \downarrow . \tag{10}$$

Risk premium. The monetary policy transmission is contingent upon the marginal costs and benefits of capital. Specifically, low-risk firms tend to have a flatter marginal cost curve for capital. As a result, these firms are less susceptible to shifts in monetary policy, as documented in previous literature (see by bernanke and Ottonello and Winberry (2020)).

Figure 3 shows how marginal costs and benefits change when the interest rate increases. Low-risky firms face a flatter marginal cost curve than high-risky firms; this will cause those firms to be more reactive to monetary policy.

In the model, the volatility dynamics, which can vary over time, further complicate this relationship. Even without adjustment costs, volatility remains a crucial factor in monetary policy transmission due to its significant impact on default risk.

3 Data and Measurements

In this section, I describe data measurements and methods of providing empirical results. In Subsection 3.1, I describe monetary policy shocks that I use in the empirical

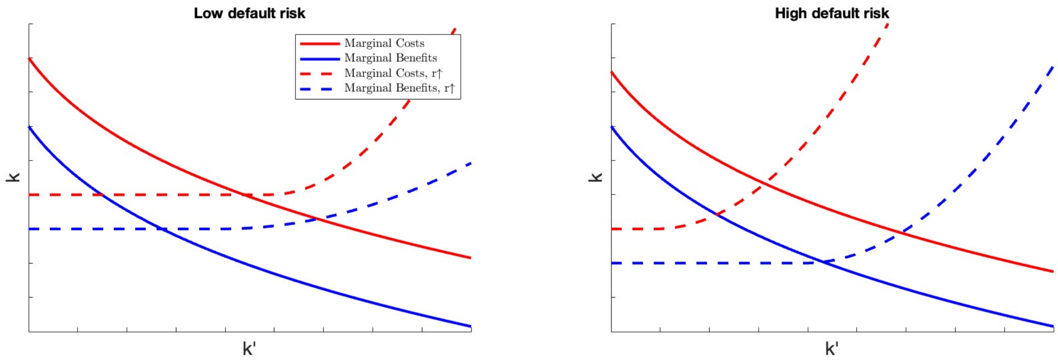

Figure 3: Marginal costs and benefits

analysis. In Subsection 3.2, I describe firm-level variables that I use, with a particular focus on the measurement of default risk and volatility.

3.1 Monetary Policy Shocks

To identify monetary policy shocks, I follow the methods described by Cook and Hahn (1989) and, more recently, by Kuttner (2001) and Gorodnichenko and Weber (2016). They use high-frequency data from the Fed's policy instrument around the time of Federal Open Market Committee (FOMC) meetings combined with an event study approach. Specifically, they investigate fluctuations in the federal fund's futures within a narrow 30-minute time window surrounding FOMC press releases. They operate under the assumption that, within these time frames, any relevant shock is most likely attributable to changes in monetary policy, denoted as η_t^{MP}:

$$\eta_t^{MP} = \frac{D}{D-t}(ff_{t+\delta t^+} - ff_{t-\delta t^-}), \tag{11}$$

where t is the time when the FOMC issues an announcement, $ff_{t+\delta t^+}$ is the fed funds futures rate shortly after t, $ff_{t-\delta t^-}$ is the FED funds futures rate just before t, and D is the number of days in the month. The $\frac{D}{D-t}$ term adjusts for the fact that the federal funds futures settle on the average effective overnight federal funds rate. For a better understanding of the shock construction, see Gürkaynak et al. (2020).

To construct quarterly measures of monetary policy shocks from the high-frequency series for η_t^{MP}, I sum up high-frequency shocks within any quarter t. This yields a measure, ε_t^{MP}, of the monetary shock in that quarter:

$$\varepsilon_t^{MP} = \sum \eta_t^{MP}. \tag{12}$$

Table 1 presents summary statistics for monetary policy shocks across three categories. The data reflects 137 monetary policy shocks based on daily observations. However, when these shocks are aggregated to a quarterly duration and periods of the Great Recession are excluded, the total observations decrease to 56. The mean value of these shocks hovers near zero, with the minimum and maximum values ranging between -0.00431 and 0.00261, respectively. Within this dataset, 29 shocks are expansionary, and 21 are contractionary. These shocks help delineate between the contractionary and expansionary effects of monetary policy. It's essential to note that these numbers don't sum up to the total monetary policy shocks because zero-valued shocks are not included.

Statistics	High frequency	Summed	Expansion	Contraction
Mean	−0.015	−0.021	−0.080	0.053
Std dev	0.091	0.107	0.109	0.064
Min	−0.463	−0.431	−0.431	0.006
Max	0.152	0.261	−0.005	0.261
# of obs	137	56	29	21

Table 1: Summary statistics of monetary policy shocks

3.2 Firm-Level Variables

I use firm-level variables from Compustat, which offers a panel of publicly listed U.S. firms. Compustat satisfies three key requirements for my study: it is quarterly, providing a high enough frequency to study monetary policy; it spans a long duration, allowing me to leverage within-firm variation; and it contains comprehensive balance-sheet information, enabling me to construct the primary variables of interest. To my knowledge, Compustat is the only U.S. dataset that meets these three criteria.

I measure capital as a book value of the tangible capital stock, $log(k_{it})$, of firm i at the end of period t. The main independent variable of interest is *volatility*. I define volatility as a standard deviation of daily stock returns over each quarter. Consistent with prior literature, such as Cloyne et al. (2018), Gertler and Gilchrist (1994), Ottonello and Winberry (2020), and Jeenas (2019), I use age, size, distance-to-default, leverage, and liquidity, as possible proxies for firms' financial constraints. *Age* is defined as the number of years since a firm's inaugural appearance in Compustat. Following Cloyne et al. (2018), I categorize firms into young and old based on the median age in the sample; firms with ages below this median are classified as young. *Size* is represented by the book value of the firm's total assets. I define the *distance-to-default* using the methodology outlined in Ottonello and Winberry (2020), which is grounded in the Merton (1974) model. I define *leverage* as debt to total assets ratio and *liquidity* as deposits and short-term investments to total assets ratio. For a more comprehensive understanding of variable definitions and sample selection, please consult Appendix A and B.

Summary statistics. Table 2 provides an overview of the summary statistics of the main variables of interest. Standard deviations and means shown in Table 2 are taken to standardize variables (after demeaning with firm-specific means).

	Mean	Median	Std dev
Capital change	0.008	-0.002	0.092
Volatility	0.039	0.033	0.023
Distance-to-default	5.477	4.514	4.577
Size	5.468	5.303	1.977
Liquidity	0.180	0.084	0.214
Leverage	0.211	0.172	0.206

Table 2: Descriptive statistics

The primary independent variables I focus on are volatility and distance-to-default. Within the sample, stock return volatility vary between 0.008 and 0.120, with the mean and median values closely aligned. The average distance-to-default is 5.477, with a median of 4.514. A firm defaults when the distance-to-default becomes negative. Given that the average is 5.477 and the standard deviation is 4.577, it suggests that firms begin to default just one standard deviation beyond the mean.

In particular I am interested in how firms withing different percentiles of volatility and distance-to-default distribution respond to monetary policy transmission. I categorize firms into four bins based on the median values of volatility and distance-to-default distributions. First, I split firms based on their volatility distribution: firms above the median are classified as "high volatile", and those below the median are "low volatile". Similarly, based on the distance-to-default distribution, firms are subdivided into "high default risk" (above the median) and "low default risk" (below the median). I then cross these bins of volatility and default risk. Specifically, low-volatile firms with a high distance-to-default are driven by volatility, while high-volatile firms with a high distance-to-default are driven by leverage.

		Low distance-to-default	High distance-to-default
		Mean	
Low volatility	leverage	0.486	−0.277
	volatility	−0.492	−0.624
	distance-to-default	−0.581	0.778
High volatility	leverage	0.441	−0.303
	volatility	0.755	0.496
	distance-to-default	−0.745	0.611

Table 3: Demeaned and standardized: Means within bins

Table 3 presents the means of volatility, leverage, and distance-to-default within these four bins. My primary focus is on firms with a high distance-to-default but varying volatility levels. Table 3 shows that firms with a high distance-to-default demonstrate similar means of leverage, regardless of whether they exhibit high or low volatility. Specifically, firms with a distance-to-default and low volatility tend to have lower leverage, yet they experience above-average volatility. Conversely, firms with a high distance-to-default and high volatility typically have lower leverage while exhibiting below-average volatility. When the distance-to-default is below the firm's average, there's a tendency for firms to increase leverage.

Measurements. As I have already noted I demean regressors using firm specific mean and then standardize using means and standard deviations from Table 2. In particular I use following measures of regressors:

$$\hat{x}_{it} = \frac{\tilde{x}_{it} - \mu(x)}{\sigma_x}, \tag{13}$$

where $\mu(x)$ is a mean over a whole sample of a regressor x, and σ_x is a sample standard deviation. These values are displayed in Table 2. $\tilde{x}_{it}$ is a regressor demeaned using a firm specific mean $\mu(x_i)$,

$$\tilde{x}_{it} = x_{it} - \mu(x_i). \tag{14}$$

I call $\hat{x}_{it}$ the within-firm measure. It eliminates permanent heterogeneity and shows how a variable fluctuates around its mean. I also define $\hat{\sigma}$ as the within-firm measure of the volatility.

Tables 4 provides correlations between demeaned and not demeaned main variables of interest. In the first column of Table 4, I report correlations of variables that are not demeaned using firm-specific mean $Corr(\sigma, .)$, while the second column reports within firm measures of the volatility, i.e. demeaned using firm specific mean $Corr(\hat{\sigma}, \hat{.})$.

	$Corr(\sigma, .)$	$Corr(\hat{\sigma}, \hat{.})$
Default	-0.531	-0.395
Size	-0.500	-0.135
Age	-0.352	-0.062
Liquidity	0.118	-0.070
Leverage	0.050	0.143

Table 4: Correlations

The first column of Table 4 shows a correlation of not demeaned variables. Volatility has a moderate correlation with distance-to-default (-0.531), size (-0.500), and age (-0.352). It weakly correlates with liquidity (0.118) and is uncorrelated with other proxies for financial constraints, such as leverage (0.050). After subtracting the firm-specific mean from variables before standardizing, volatility becomes uncorrelated with age (0.062), liquidity (-0.070), and size (-0.135) while keeping its correlation with distance-to-default (-0.395).

While, on average, within the firm, measures of volatility and default risk are moderately and negatively correlated at the level -0.395, correlation itself is different for firms. Heterogeneity in correlation allows me to study firms that are within different percentiles of volatility and distance-to-default distribution and interaction between those percentiles. In particular, I am interested in how firms that face low volatility versus firms that face low volatility and high distance-to-default respond to monetary policy shocks. To show how volatility and distance-to-default evolve over time for firms that are low and highly correlated, I present Figure 4. In the figure, I plot within firm measures of volatility and distance-to-default over the years for two firms that have low and high correlations between volatility and default risk.

4 Results

In this subsection, I provide empirical results. Subsection 4.1 shows the estimated average effect of monetary policy on investments and serves as a baseline. Subsection 4.3

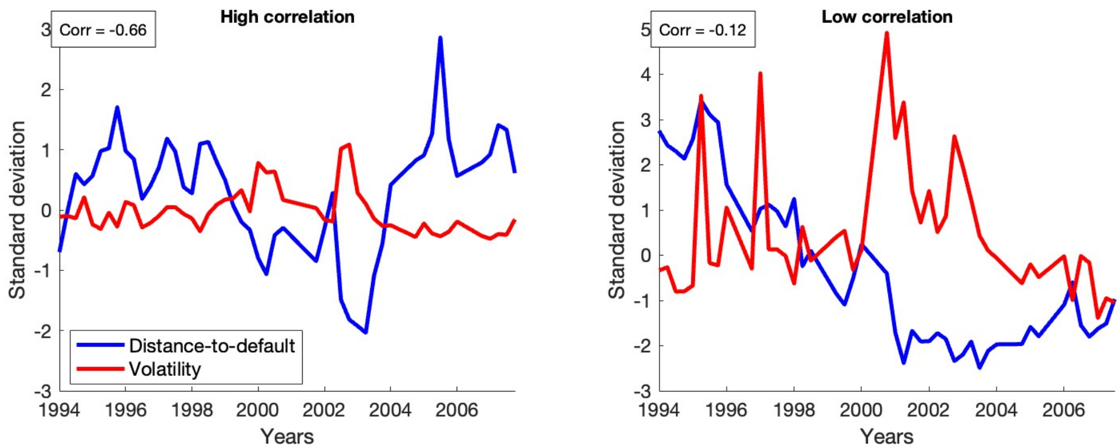

Figure 4: Volatility and distance-to-default over time

investigates the importance of heterogeneity in volatility and default risk for monetary policy transmission.

4.1 Average Effect

Before presenting the impulse response functions (IRFs) across the various groups, it is useful to report the average impact of the monetary policy shocks on firm-level investments. This will provide a benchmark against which I can evaluate the contribution of the response by volatility and default risk.

Empirical specification. To estimate the effect of monetary policy on firms' investments, I use the local projection method described in Jordà (2005). In particular, I estimate equation:

$$\Delta k_{it} = log(k_{it+h}) - log(k_{it-1}) = \alpha_{ih} + \eta_{sqh} + \beta_h \epsilon_t^m + \delta_h^{'} X_{it-1} + \zeta_h^{'} Z_{it-1} + e_{it}, \qquad (15)$$

where $h \geq 0$ indexes the forecast horizon. k_{it+h} is a capital of firm i in period $t+h$, and k_{it} is a capital in period t. $log(k_{it+h}) - log(k_{it-1})$ is a log change in capital. α_{ih} captures firm fixed effect, and η_{sqh} captures industry, s, quarter, q, fixed effect. The coefficient β_h measures the cumulative response of investment in quarter $t+h$ to a monetary policy shock ϵ_t^m in quarter t. X_{it-1} is a set of firm-level control variables (age, volatility, distance-to-default, leverage, liquidity, sales growth, current to total assets ratio, and four lags of the dependent variable). Z_{it-1} is a set of aggregate control variables (inflation, unemployment rate, change in GDP, and 12 lags of the monetary policy shocks).

Figure 5 displays the coefficient β^h estimated from equation (15). It specifically illus-

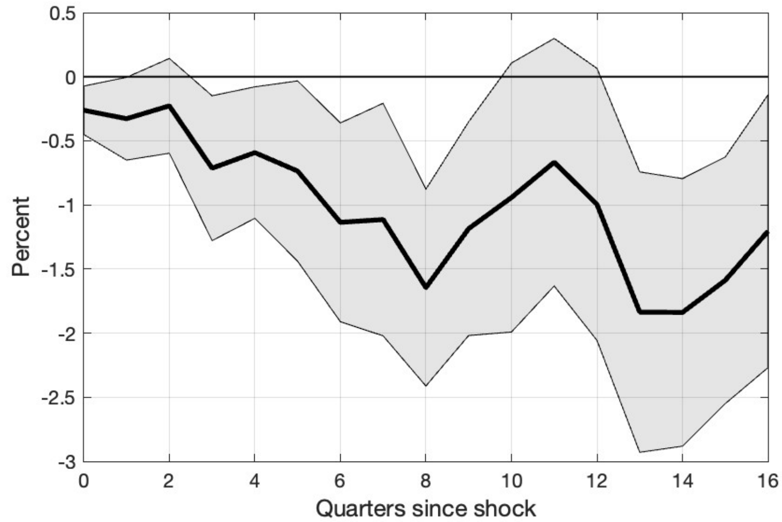

Figure 5: Average effect

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (15) where all variables are defined in Section 3. Filled lines report 95% error bands. Standard errors are clustered on time and firm ID.

trates the average effect of an unexpected 25 basis points (bps) increase in the interest rate on firms' fixed capital investments. The effect of the interest rate increase on investments is hump-shaped, with its peak occurring in the second year (or the 8th quarter). A 25 bps unexpected increase in the interest rate leads to a decline in investments on average by approximately 1 percent. This result is similar to the findings of Cloyne et al. (2018) and Ottonello and Winberry (2020), who show that a 25 bps unexpected increase in the interest rate reduces investments on average by about 1 percent.

4.2 Heterogeneous Investment Responses

In this subsection, I provide empirical results to answer two main questions. First, I show that volatility is important for monetary policy transmission. I then show that firms that face high default risk are less affected by monetary policy.[2] Finally, I show that controlling for volatility, the importance of default risk diminishes, while volatility remains an essential factor for monetary policy transmission.

Empirical specification. To estimate the marginal effects of volatility and distance-to-default on the investment response to monetary policy shocks, I modify the equation (15).

[2]Similar results are shown in Ottonello and Winberry (2020)

Specifically, I introduce an interaction term between either within firm measures of volatility or distance-to-default, denoting $\hat{x}_{it-1}$, and monetary policy shocks. Furthermore, I replace the term η_{sqh}, which controls for the industry-quarter fixed effect, with η_{sth} to control for the industry-year-quarter fixed effect. Consequently, any variables collinear with the time-fixed effect, such as monetary policy shocks, its lags, and other aggregate controls like inflation, GDP change, and unemployment rate, are omitted. The final equation that I estimate is as follows:

$$log(k_{it+h}) - log(k_{it}) = \alpha_{ih} + \eta_{sth} + \beta_h \hat{x}_{it-1}\epsilon_t^m + \nu_h \hat{x}_{it-1} + \delta_h^{'} X_{it-1} + e_{it}. \tag{16}$$

Heterogeneity Due to Volatility. Figure 6 shows estimated coefficient β^h from estimating the specification described in the equation (16). In particular, firms with low volatility are more responsive to the monetary policy shock for up to three years after the shock. The peak of the differences by volatility occurs after four quarters. Firms with one standard deviation lower volatility are more affected by monetary policy by about 1.1 percentage points.

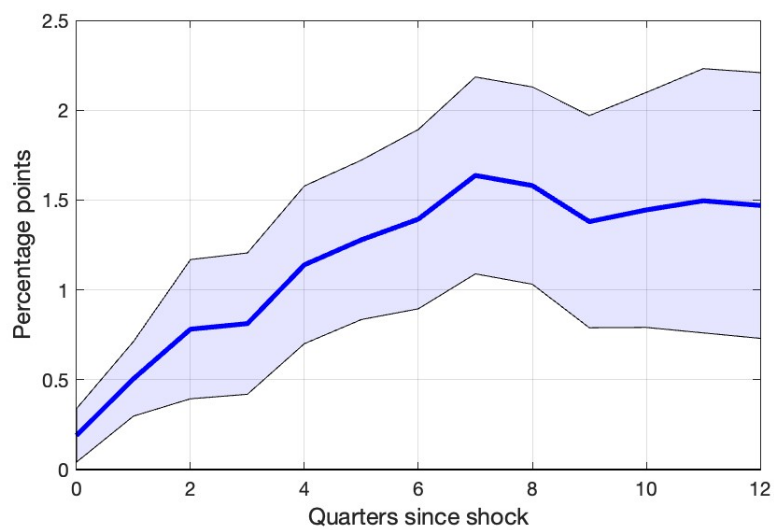

Figure 6: Effect of volatility

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (16) where all variables are defined in Section 3. Filled lines report 95% error bands. Standard errors are clustered on time and firm ID.

It is important to note that volatility is a within-firm measure. Thus, the most affected firms by monetary policy are those that face lower volatility than their mean.

Non-linearities. A remaining question is: while Figure 6 shows that the volatility explains variation in the firm investment response to monetary policy, it is unclear whether the marginal effect of varying the volatility is monotonic. To explore the quantitative relevance of heterogeneity in the volatility of the firm investment response to monetary policy, I present the implied average responses for firms in the 20th percentile and the 80th percentile of the volatility distribution. The marginal effects I document in Figure 6 are large, implying that the investment response to monetary policy differs across firms. Figure 7 shows the implied average investment responses in the 20th and 80th percentile of the volatility distribution.

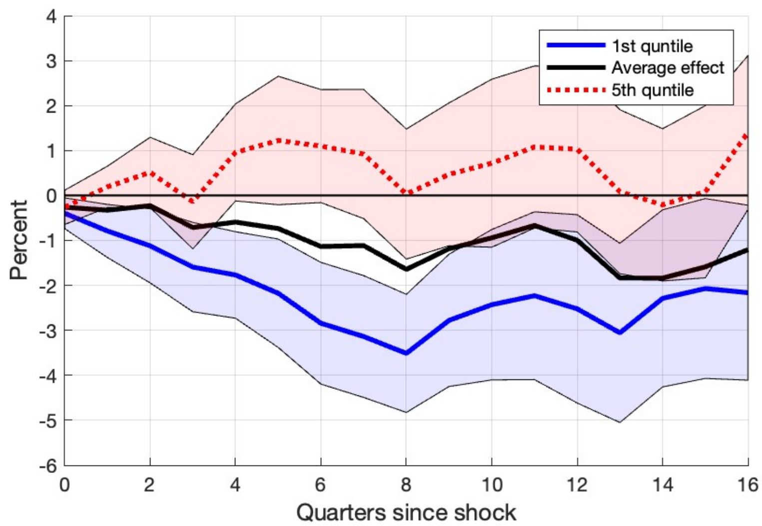

Figure 7: Volatility by percentiles

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (15) where all variables are defined in Section 3. Filled lines report 95% error bands. Standard errors are clustered on time and firm ID.

I highlight two observations. First, the average effect of monetary policy on investments stems entirely from the low volatile firms. High-volatile firms do not show any statistically significant results. Second, I find a non-linear effect of volatility. In particular, firms within the 40th and 60th percentile of volatility distribution respond similarly to the 20th percentile.

Heterogeneity Due to Default risk. In Figure 6, I show the heterogeneity in firms' investment responses to monetary policy, which varies with their volatility levels. This heterogeneity could arise from two potential channels: uncertainty and default risk.

Figure 8 shows the coefficient β_h obtained from estimating equation (16), where I interact within the measure of distance-to-default with monetary policy shocks. Obtained

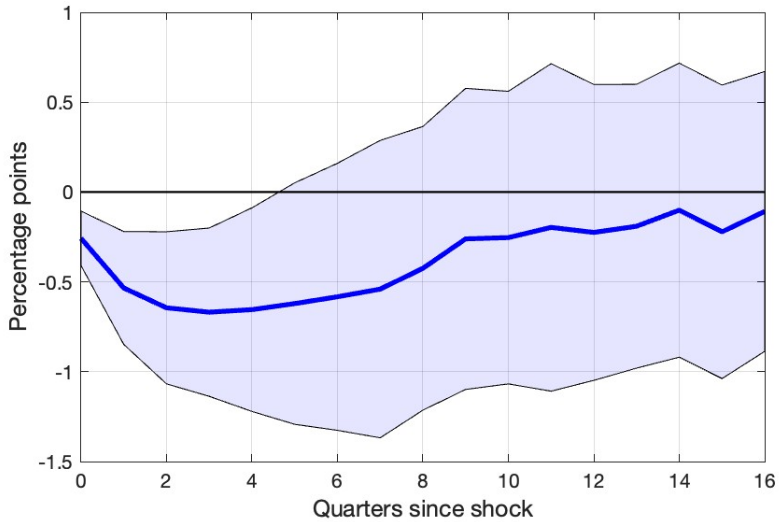

Figure 8: Effect of default risk

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (16) where all variables are defined in Section 3. Filled lines report 95% error bands. Standard errors are clustered on time and firm ID.

results are shown in Figure 8 and are similar to the results represented by Ottonello and Winberry (2020). Specifically, firms that face one standard deviation higher distance-to-default are more affected by monetary policy by about 0.7 percentage points. The peak of the difference by distance-to-default occurs after two quarters, and the marginal effect lasts for about five quarters.

There are two things to note. First, the marginal effect of volatility is higher than that of the default risk. Second, the timing of peak estimates is different. This could be because the variation in distance-to-default depends on both the inverse debt-to-leverage ratio and volatility.

4.3 What Drives Volatility: Default Risk Versus Uncertainty?

Default risk versus volatility. To understand whether the effect of monetary policy stems from volatility or default risk, I adjust the equation (16) by adding both distance-to-default, volatility, and their interactions with monetary policy shocks in the same regression. Figure 9 shows the obtained coefficient from the three regressions: controlling for the marginal effect of distance-to-default and volatility in the same regression (blue lines) and coefficients from Figures 6 and 8 (red lines).

Panel (a) shows the coefficients on the interaction term between volatility and monetary

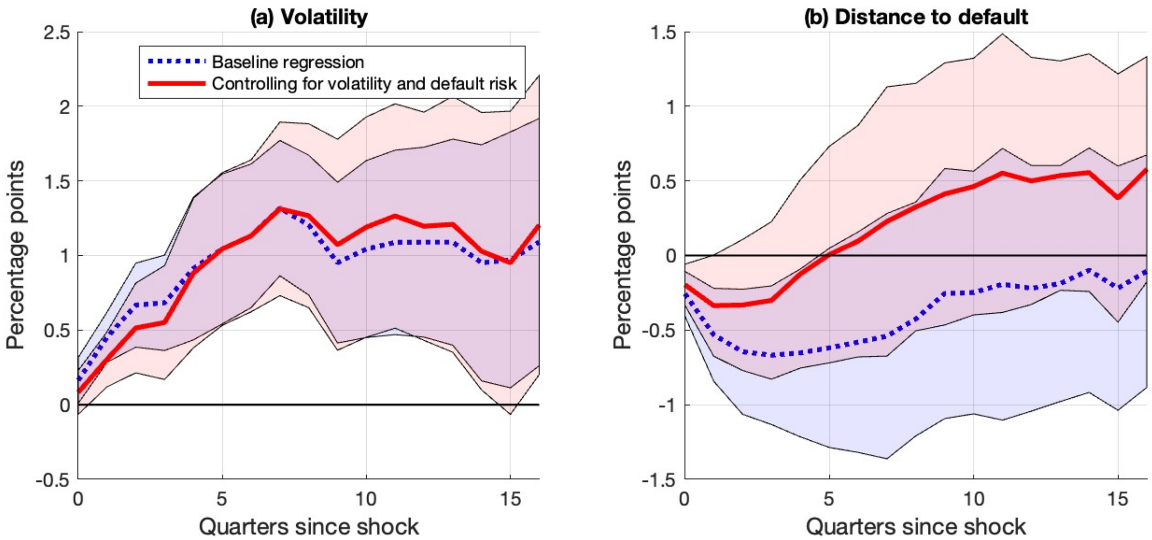

Figure 9: Volatility versus distance-to-default

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (16) where all variables are defined in Section 3. Filled lines report 95% error bands. Standard errors are clustered on time and firm ID.

policy. The red line represents the coefficient obtained from equation (16). Meanwhile, the blue line represents the coefficient of the interaction term between volatility and monetary policy shocks controlling for the marginal effect of distance-to-default. Notably, even with slightly wider confidence intervals — attributed to the correlation between volatility and distance-to-default — the marginal effect of volatility on the investment response to monetary policy shocks retains its statistical significance without weakening.

Panel (b) depicts the coefficient on the interaction term between distance-to-default and monetary policy. The red line shows the coefficient while excluding the marginal effect of volatility. Conversely, the blue line incorporates this marginal effect. Importantly, this reveals that when accounting for the marginal effect of volatility, the influence of distance-to-default on the investment response to monetary policy shocks decreases and loses its statistical significance.

To further investigate the source of the marginal effect of volatility, I categorize firms into four bins based on the median values of volatility and distance-to-default distributions. First, I split firms based on their volatility distribution: firms above the median are classified as "high volatile", and those below the median are "low volatile". Similarly, based on the distance-to-default distribution, firms are subdivided into "high default risk" (above the median) and "low default risk" (below the median). I then cross these bins of volatility and default risk. Specifically, low-volatile firms with a high distance-to-default are driven by volatility, while high-volatile firms with a high distance-to-default are driven by leverage.

To provide empirical investigation, I adjust the equation (15) by including interactions between bins of volatility, distance-to-default, and monetary policy shocks. In particular, I estimate the equation:

$$log(k_{it+h}) - log(k_{it}) = \alpha_{ih} + \eta_{sth} + \sum_{q=1}^{Q} \beta_h^q \mathbb{1}_{[\hat{x}_{it-1} \in q]} \varepsilon_t^{MP} + \sum_{q=1}^{Q} \alpha_h^q \mathbb{1}_{[\hat{x}_{it-1} \in q]} + \zeta_h^{'} Z_{it-1} + e_{it}, \quad (17)$$

where $\mathbb{1}_{[\hat{x}_{it-1} \in q]}$ represents a dummy variable that equals to one if distance-to-default and volatility are in specific bins. The coefficient β_h now measures the average response of investment in quarter $t + h$ to a monetary policy shock in quarter t for different bins of volatility and distance-to-default.

Figure 10 illustrates the outcomes of the regression when analyzing firms across different groups. The figure corroborates observations from Figure 9. Specifically, only firms that face low volatility, independent of their default risk, are affected by monetary policy.

While Figure 10 shows that there are differences in response to monetary policy over low volatile firms with high vs low default probability, the question remain whether differences between two groups - low volatile firms with low distance-to-default and low volatile firms with high distance-to-default - is statistically significant. To provide this exercise, I adjust equation (17) by incorporating time fixed effect. I also set firms that are in the group of low distance-to-default and high volatility as a base group.

Figure 11 shows results of the regression. Panel (a) of the figure reveals that firms that are within low distance-to-default and low volatility group are more affected by monetary policy shocks by 2 percentage points than firms that are within low distance-to-default and high volatility group. Similarly panel (b) shows that firms that are within high distance-to-default and low volatility group are more affected by monetary policy shocks by 1.5 percentage points than firms that are within low distance-to-default and high volatility group. Panel (c) shows that firms that there are no statistically significant difference in monetary policy effect on firms that are within high distance-to-default and high volatility group and firms that are within low distance-to-default and high volatility group. This results reinforces results in Figures (10) and (9) that shows that it is firms with low volatility independently whether they face high or low default risk are more affected by monetary policy shocks.

Robustness. I discuss several robustness exercises for the marginal effects in Appendix C.

In the Appendix C.1, I control for business cycles and volatility cycles. Table 6 shows correlations between firm-level volatility and distance-to-default with aggregate variables, such as inflation, the unemployment rate, the change in GDP, and the volatility index

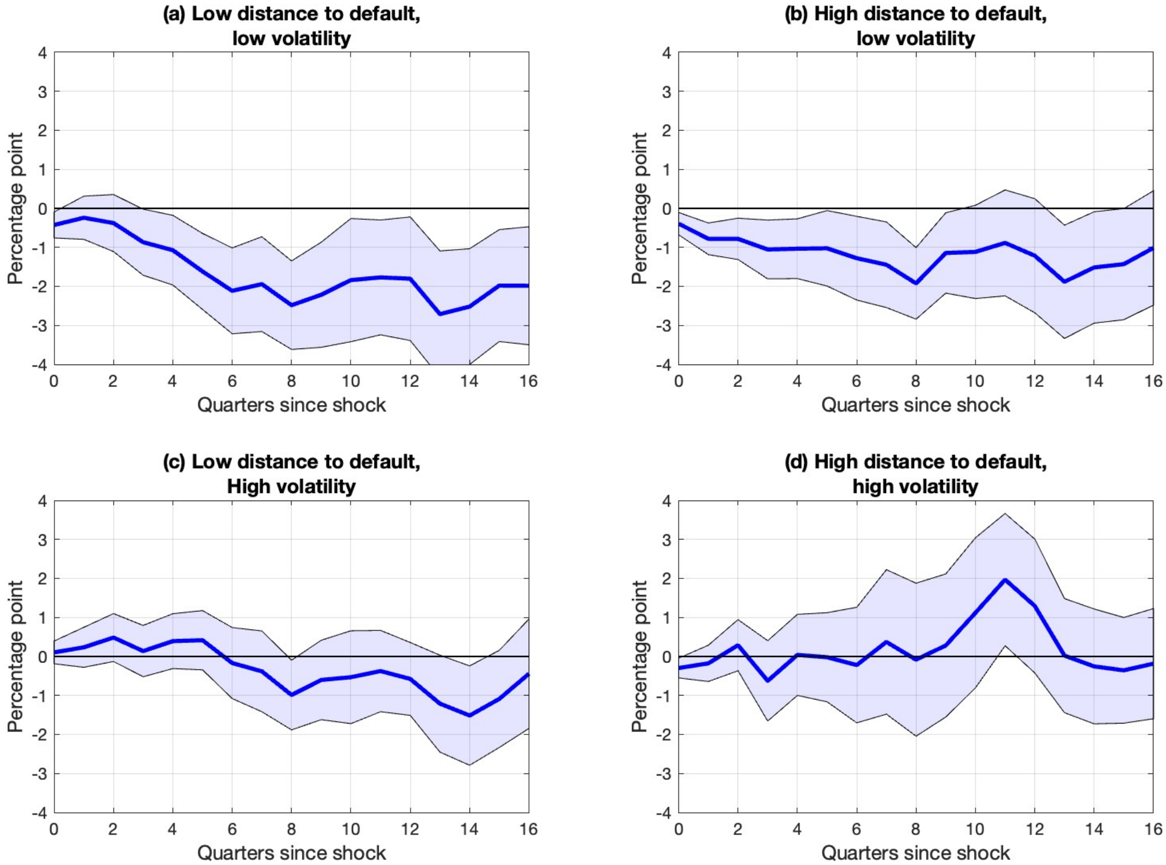

Figure 10: Volatility vs distance-to-default: by groups

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (15) where all variables are defined in Section 3. Filled lines report 95% error bands. Standard errors are clustered on time and firm ID.

(VIX). The table shows that volatility and distance-to-default correlate with the VIX index the most. In addition, previous papers (for example Aastveit et al. (2017) and Fang (2022)) show that aggregate volatility matters for monetary policy transmission.

This it is important to show whether distance-to-default is affected by aggregate volatility. To provide this estimation, I control for the interactions between VIX and distance-to-default or VIX and volatility in the regression. Results are depicted in Figure 17. Panel (a) displaces results for volatility, where in the blue line, I show baseline regression from Figure 6. The red line shows the results from regression with the interaction between VIX and volatility. The results are similar. Panel (b) displaces similar results for default risk, where the red line shows the results from the baseline regression. In contrast, the blue line shows the regression results, including the interaction between distance-to-default and VIX. The

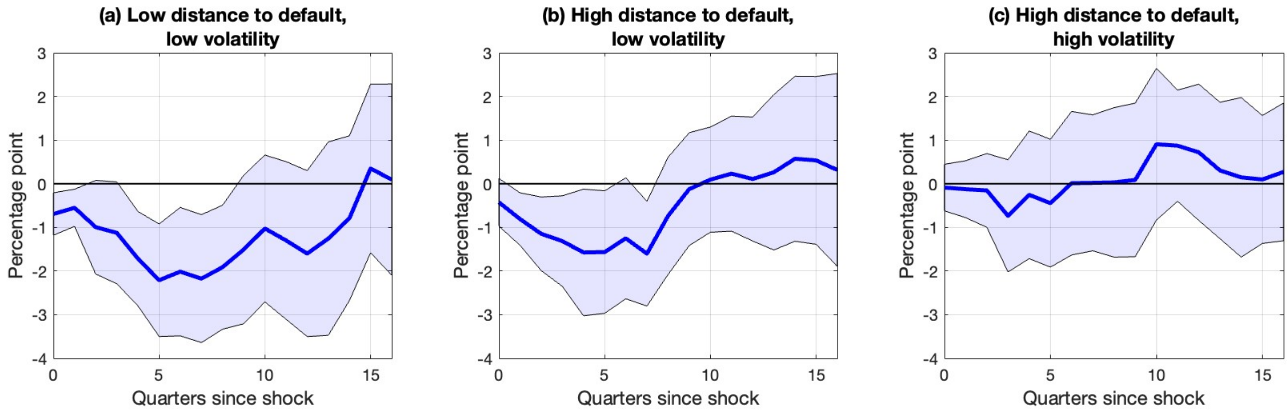

Figure 11: Volatility vs distance-to-default: Difference in means

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (15) where all variables are defined in Section 3. Filled lines report 95% error bands. Standard errors are clustered on time and firm ID.

marginal effect of default risk is diminished and becomes statistically insignificant.

Figure 16 shows results where I include interaction terms between volatility and distance-to-default with aggregate measures of change in GDP to control for business cycles. Panel (a) displaces results for volatility, where in the blue line, I show baseline regression from 6. The red line shows regression results from the estimation of the regression with the interaction between change in GDP and volatility. Panel (b) shows results for default risk, where the blue line shows the results from the baseline regression, while the red line shows the results, including the interaction between distance-to-default and change in GDP in the regression. Results for both volatility and default risk are similar before and after controlling for the business cycles.

In Appendix C.2, I use different shock series that Gorodnichenko and Weber (2016) and different period than 1994 - 2007. In particular, I use the target and the path monetary policy shocks developed by Gürkaynak et al. (2020) from 1994 to 2018 and orthogonal shocks developed by Swanson (2023) from 1988 to 2018. As seen from Figures 18, 20, my results are robust to the other identification of shocks and period. I also show that the marginal effect of both volatility and default risk are due to changes in interest rate (Figure 18) rather than forward guidance (Figure 19).

In Appendix C.3, I control for the effect of financial constraint by augmenting baseline estimation of equation (15) with age, size, liquidity, leverage, the ratio of current assets to total assets, and sales growth, along with their interactions with monetary policy shocks. Figure 21 illustrates the effects of volatility and distance-to-default when controlling for other proxies of financial constraints and their interactions with monetary policy shocks.

The impact of volatility is observed to be slightly diminished compared to the uncontrolled model. Nevertheless, this effect remains statistically significant.

In Appendix C.4, I replicate Figure 21 by using the volatility of firm assets from equation (7) instead of the volatility of firm returns to assess. Figure 22 shows similar results to Figures 9 and 21, i.e., controlling for volatility the effect of default risk diminishes.

5 Model

I now show a heterogeneous firm model to interpret this cross-sectional evidence and study its aggregate implications.

Firm. Time is discrete and infinite. Each firm i produces good y_{it} using production function $y_{it} = e^{z_{it}} k_{it}^{\alpha}$, where z_{it} is an idiosyncratic productivity, k_{it} is a capital stock, and $\alpha < 1$. The capital stock k_{it} follows the law of motion $k_{it+1} = (1 - \delta)k_{it} + i_{it}$, where δ is the depreciation rate of capital and i_{it} is investments made by the firm at year t. The firm faces non-convex capital adjustment costs and partial investment irreversibility. In addition, firms can save and borrow in one period bond, b_{it}, with price of $q_{it}(d(z_{it+1}, k_{it+1}, b_{it+1}, \sigma_t))$.

The timing of events within each period is as follows:

(i) With probability π_d each firm receives an i.i.d. exit shock and must exit the economy after producing.

(ii) Each firm decides whether or not to default. The firm defaults if it cannot satisfy a non-negativity constraint on its dividends, i.e., $D < 0$. If a firm defaults, it immediately and permanently exits the economy. To continue operation, the firm must pay back the face value of its outstanding debt, b_{it}, and pay the fixed operating cost, ζ.

(iii) Continuing firms decide whether to adjusts its capital k_{it+1} and pay its rental price on existing capital of r. Firms have two sources of investment finance, each subject to friction. First, firms can issue short-term debt, denoted as b, which operates under a one-period contract framework. However, firms face collateral constraints and cannot save or borrow more their output, $b_{it+1} \leq y_{it}$.

Lenders offer a price schedule $q_{it+1}(d(z_{it+1}, k_{it+1}, b_{it+1}, \sigma_t))$ for this debt. If the firm defaults on the loan in the following period, the lender recovers a fraction ν of the market value of the firm's capital stock $(1 + r) * k_{it+1}$. The debt price schedule prices this default risk competitively:

$$q_{it+1}(d(z_{it+1},k_{it+1},b_{it+1},\sigma_t)) = \beta E\left[\Big(1-d(z_{it+1},k_{it+1},b_{it+1},\sigma_t)\Big)\left(1-\min\left\{\frac{\nu(1+r)*k_{it+1}}{b_{it+1}}\right\}\right)\right],$$

where $d(z_{it+1},k_{it+1},b_{it+1},\sigma_t)$ is an indicator function and takes a value of 1 if a firm defaults and zero otherwise.

Second, firms can use internal finance by lowering dividend payments D_{it} but cannot issue new equity, which bounds dividend payments $D_{it} \geq 0$.

Fixed adjustment costs. When a firm adjusts its capital, it incurs a cost proportional to F of its current capital k_{it}. This implies that firms making larger capital adjustments face higher fixed capital adjustment costs. The firm can, however, make small adjustments for the value of λ without incurring any costs, i.e: $\mathbb{1}_{|i_{it}|>\lambda}F * k_{it}$.

Secondary market for capital. I assume that there is a secondary market for capital where firms face iceberg costs for selling capital. This assumption implies that the price of buying new p_{buy} capital is larger than the price of selling capital p_{sell} and is reminiscent to partial irreversibility: $(p_{buy}\mathbb{1}_{i_{it}>0} + p_{sell}\mathbb{1}_{i_{it}<0}) * i_{it}$.

The stochastic process for volatility. I assume that productivity z_{it} follows an AR(1) process with time-varying volatility:

$$z_{it} = \rho z_{it-1} + \sigma_{t-1}\epsilon_{it} \qquad \epsilon_{it} \sim N(0,1). \tag{18}$$

The stochastic volatility process σ_t is assumed, for simplicity, to follow two-point Markov chains:

$$\sigma_t \in \{\sigma_L, \sigma_H\}, \qquad \text{where} \qquad Pr(\sigma_{t+1} = \sigma_j | \sigma_t = \sigma_k) = \pi^{\sigma}_{jk}. \tag{19}$$

Dividends. I write the firm's optimization problem recursively. The state variables of a firm are its productivity, capital, debt, and volatility. The dividend of a firm is expressed as:

$$D_{it} = e^{z_{it}}k_{it}^{\alpha} - \mathbb{1}_{|i_{it}|>\lambda}F * k_{it} - (p_{buy}\mathbb{1}_{i_{it}>0} + p_{sell}\mathbb{1}_{i_{it}<0}) * i_{it} - b_{it} + q_{it+1}b_{it+1} - \zeta,$$

subject to:

$$\begin{aligned} k_{it+1} &= (1-\delta)k_{it} + i_{it} \\ z_{it} &= \rho z_{it-1} + \sigma_{t-1}\epsilon_{it} \qquad \epsilon_{it} \sim N(0,1). \end{aligned} \tag{20}$$

Conditional on continuing, the value of the firm $v_t^c(z,n)$ solves the Bellman equation:

$$v^c(z,k,b,\sigma) = \max_{\{k',b'\}_{t\geq 0}} \quad D + \beta E[V(z',k',b',\sigma')],$$

subject to equation (20), where $v(z',k',b',\sigma') = \max(v^c(z',k',b',\sigma'),0)$.

6 Calibration

The model period is one quarter, allowing me to use evidence on establishment-level investment to select the parameters. I choose the parameters listed in column 3 of Table 5 to match the targeted moments reported in column 1 of Table 5. I first choose parameters to obtain aggregate moments as in the data. I then set parameters that govern the importance of uncertainty. Lastly, I set parameters that govern the frictions to external finance.

Parameters that govern the average values. The discount factor $\beta = 0.9091$ is set to imply an annual steady-state interest rate of 10 percent. Capitals share α is then set to 1/3, targeting the average annual capital-to-output ratio of 2.353 as in the data, and the depreciation rate is selected on the level of 0.05 annual to match an average investment-to-capital ratio of 6 percent as in Cooley and Prescott (2020).

Parameters that govern the importance of uncertainty. The parameters that govern the importance of uncertainty are parameters that govern idiosyncratic productivity $(\rho, \sigma, \rho_\sigma)$ and adjustment costs (p, F, λ).

I target the dispersion of plant-level investment rates in Census microdata reported by Cooper and Haltiwanger (2006), which places discipline on the degree of idiosyncratic risk firms face. There is little agreement about the persistence of the idiosyncratic shock process ρ and volatility of idiosyncratic shocks σ.[3] I use the ratio of $\sigma_l/\sigma_h = 0.24$ and persistence of 0.96 quarterly ($0.85^{1/4}$) as in the İmrohoroğlu and Tüzel (2014) to match the data on the volatility of plant-level investment rates reported by Cooper and Haltiwanger (2006). I set $\rho_\sigma = 0.7$ estimating it from Compustat datatset.

I also target the percentage of firms in inaction. Constructing their own plant capital series using data on retirements and investment from the Longitudinal Research Database (LRD), Cooper and Haltiwanger (2006) provided a detailed set of time-averaged moments on plants'

[3] Compare, for example, the values in Comin and Philippon (2005) to those of Cooper and Haltiwanger (2006). Asker, Collard-Wexler, and De Loecker (2014) found for the Census microdata, the dispersion of TFPR shocks ranges from 0.1 - 10th percentile to 1.4 - 90th percentile, with a persistence coefficient ranging from 0.65 to 0.94 with a median of 0.85.

investment rates. They defined any plant with an investment rate (ratio of investment to capital) less than 1 percent in absolute value as inactive. They show that investment inactivity is relatively rare, occurring among only 8 percent of plants on average. To target the percentage of firms in inaction, I set fixed capital adjustment costs F to 0.05 and free adjustment region parameter is set to 0.01 Following Khan and Thomas (2008). Following Bloom (2009) I set investment resale price to $p = 0.66$.

Parameters that govern the frictions to external finance. I set value of the borrowing constraint and fixed costs of operation to target two statistics related to firms' use of external finance. First to target a mean default rate of 3 % as in Ottonello and Winberry (2020), I set fixed costs of operation on the level of 0.05. To target an average firm-level gross leverage ratio of 0.34 from the microdata underlying the Quarterly Financial Reports, as reported in Crouzet and Mehrotra (2020), I set borrowing constraint on the level of 0.8. I set recovery value ν to 0.54 following Ottonello and Winberry (2020).

Target	Data	Model	Parameter	Value
Average investment rate	0.060	0.062	Depreciation, δ	0.05
Return to capital	0.100	0.100	Discount factor, β	0.9091
Output to capital ratio	2.353	1.648	Capital coefficient, α	1/3
Mean leverage	0.340	0.231	Borrowing constraint, γ	0.800
Default rate	0.030	0.041	Fixed costs of operation, ζ	0.050
St. dev. of inv rate	0.337	0.446	Standard deviation of TFP shocks, σ	(0.032, 0.145)
			Persistence of TFP, ρ	0.840
Firms in inaction	0.300	0.351	Free adjustment region, λ	0.01
			Fixed capital adjustment costs, F	0.060

Table 5: Parameters and targeted moments (annual)

Table 5 shows targeted data momenta and model moments. According to the table, the model underpredicts output to capital ratio, and mean leverage. The model also slightly overpredicts standard deviation of investment rates.

7 Quantitative Analysis of Interest Rate Shock

I now analyze the effect of changes in interest rate ϵ on firms' investments. Section 7.1 studies the importance of distribution of volatility and default risk for investments response. I show that, consistent with the empirical results from Section 4, firms with high volatility are less responsive to interest rate changes independently of default risk. In section 7.2 I compute the aggregate impulse responses to an increase in interest rate in the calibrated model. I compare my full model to the representative firm model.

The economy is initially in a stochastic steady state and unexpectedly receives a shock to the steady state interest rate $\epsilon = 0.0025$, which reverts to 0 according to $\epsilon_{t+1} = \rho_m \epsilon$ with $\rho_m = 0.6$. I compute the transition path of the economy as it converges back to the steady state.

7.1 Aggregate Response to the Interest Rate shocks

In this subsection, I show how changes in the interest rates affect aggregate investments for different volatility and distance to default distributions. First, I show how low versus high volatile firms are affected by a 25 bps change in interest rate in the full model. Second, I show the effect on high versus low default risk firms. Lastly, I show that firms that face lower volatility are more affected by changes in interest rate independently of default risk, as in the data shown in Section 3.

To show how the implications of different distribution of volatility and default risk. I use simulated data from the model. I aggregate capital by summing a capital over all firm.

Volatility: Impulse Response Functions. To produce the impulse response function for high and low-volatile firms, I subdivide simulated data obtained from the full model into high and low-volatile firms. High-volatile firms are firms that face high volatility, and low-volatile firms are firms that face low volatility during the period preceding the shock.

Figure 12 depicts the investment responses of firms with different volatility exposures to a 25 bps interest rate shift. The blue line represents firms facing low volatility, which, on average, reduces investments by approximately 2.1 percent. Conversely, the red line highlights the behavior of firms when volatility is high, showing an average investment reduction of about 0.9 percent. Notably, low-volatility firms are more sensitive to interest rate changes, demonstrating a 1.2 percentage point greater effect.

Distance-to-default: Impulse Response Functions. To produce the impulse response function for high and low probability of default, I subdivide simulated data obtained from the full model into high and low default risk firms based on their median. High-risk firms are firms that face a probability of default above the median, and low-risk firms are firms that face a probability of default below the median in the period preceding the shock.

Figure 13 depicts the investment responses of firms with different probabilities of default to a 25 bps interest rate shift. The blue line represents firms facing low default prob-

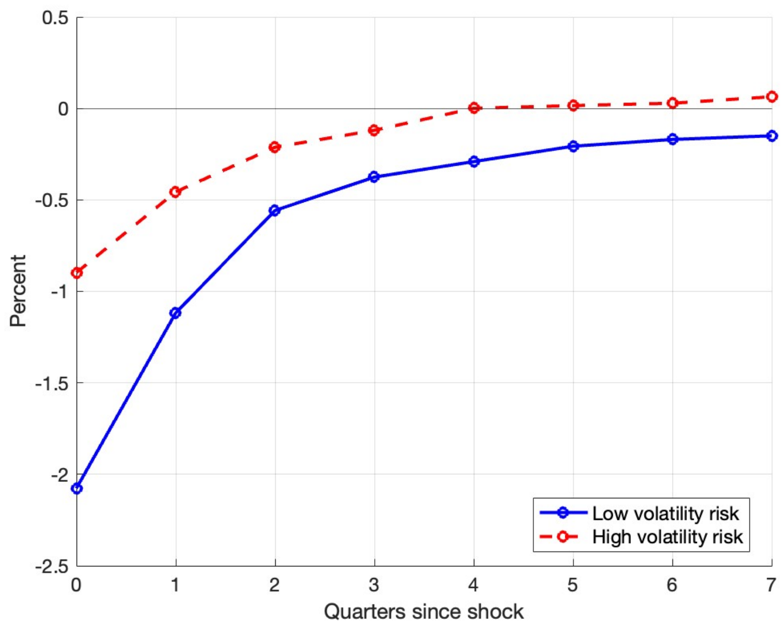

Figure 12: Volatility

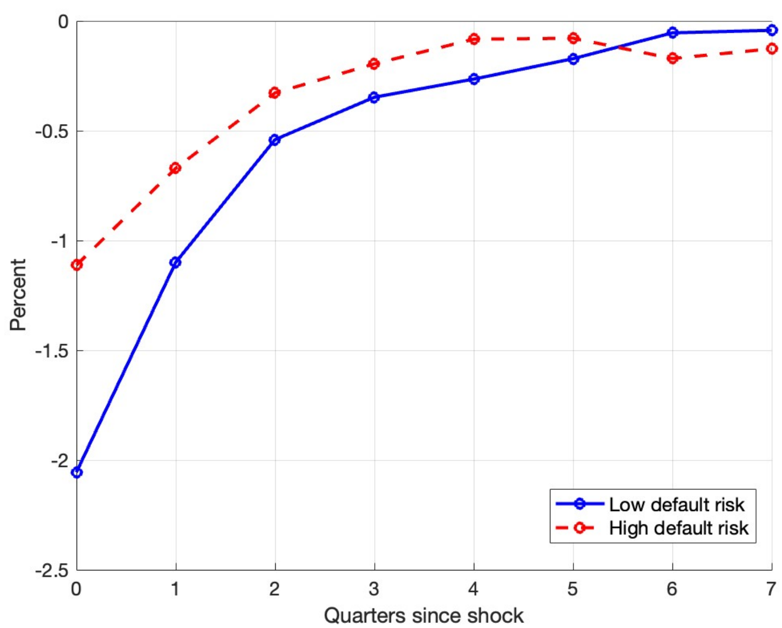

Figure 13: Default risk

ability, which, on average, reduces investments by approximately 2.1 percent. Conversely, the red line highlights the behavior of firms with a high probability of default, showing an average investment reduction of about 1.1 percent. Notably, firms with a low probability of default are more sensitive to interest rate changes, demonstrating about a 1 percentage point greater effect. It is important to note that there are striking similarities in the response for high versus low default probabilities and high versus low volatility.

Distance-to-default and volatility: Impulse Response Functions. To produce the impulse response function for high and low probability of default vs high and low volatility, I interact volatility and default probabilities from two previous cases. I obtain four groups with different volatility and default probabilities.

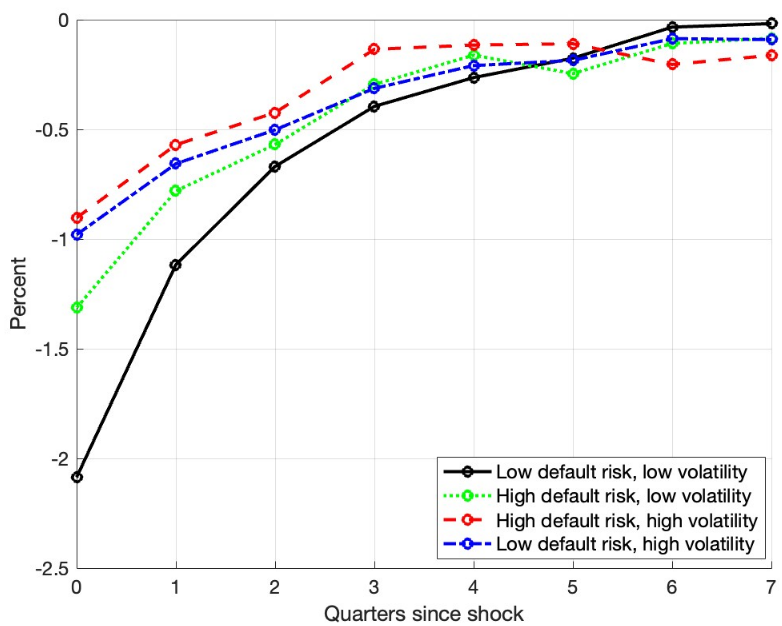

Figure 14: Volatility and default risk

Figure 14 depicts the investment responses of firms with differing volatility and default risk probability exposures to a 25 bps interest rate shift. The figure shows the impulse response function for four groups based on their volatility and default probabilities. As in the data, the figure shows that firms facing low volatility are more affected by changes in interest rates than firms that face high volatility.

7.2 Aggregate Implications

In this subsection, I illustrate two ways financial heterogeneity matters for understanding the aggregate transmission mechanism. I show that the aggregate effect of a given interest rate shock is smaller in a model that incorporates real options than in a comparable version of the model without any frictions.

Figure 15 plots the responses of average investments to a 25 bps increase in interest rate. Overall, investment decreased by approximately 1.6 %. These magnitudes align with the peak effects of monetary policy shocks estimated in Ottonello and Winberry (2020). They find that investment decreases by about 1.4 % using monetary shock as a 0.25 % change to the Taylor rule.

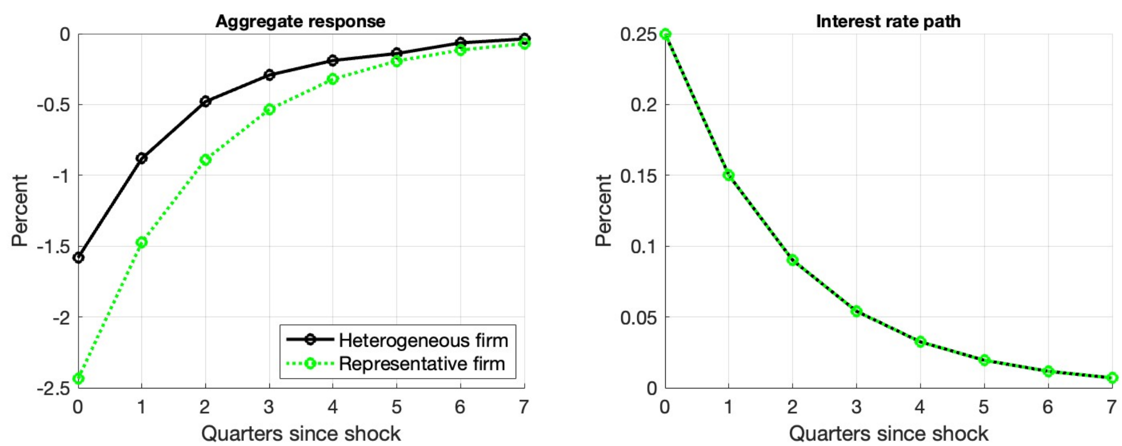

Figure 15: Aggregate response

I now compare the full model to one in which I eliminate financial frictions and adjustment costs. In this case, the model collapses to a representative firm. Figure 15 shows that the effect of an increase in interest rate on investment is smaller in the full model than in the representative firm benchmark. This effect stems entirely from real options. While incorporating default risk *increases* the effect of monetary policy, incorporating "real option" *decreases* its effect. Ottonello and Winberry (2020) show that even though risky constrained firms are less responsive than risk-free constrained firms, both types of constrained firms are more responsive than in a model without financial frictions because contractory monetary policy decreases firms' net worth. The opposite holds true for the model with real options. Even though low-volatile firms are more affected by changes in interest rates, they are less affected than the representative firm model due to firms' caution about the possibility of high volatility: the wait-and-see effect.

8 Conclusion

This paper examines the relationship between firm-level volatility and how firms adjust their investments in response to interest rate changes. I show several main findings.

First, I showed in the micro-level data that firms that face high volatility are significantly less affected than low-volatile firms following a contractory monetary policy shock. Second, I showed that the importance of volatility stems from uncertainty and is predominant in the significance of the default risk.

Lastly, I developed a heterogeneous firm model incorporating capital adjustment costs and default risk, reflecting the empirical observations. In this model, changes in interest rates affect investment through two primary channels: real options and risk premium. When classifying firms based on volatility and default risk, it becomes evident that low-volatility firms, irrespective of their default risk, show greater sensitivity to interest rate shocks. This effect is due to the real options. This variation in responses contributes significantly to the aggregate investment outcome.

Comparing the full model to a representative firm benchmark reveals that the immediate effect of interest rate changes on aggregate investment appears less pronounced in the full model. Interestingly, while the inclusion of default risk amplifies the effect of monetary policy, introducing real options mitigates it. Ottonello and Winberry (2020) found that risky and constrained firms, despite being less responsive than risk-free constrained ones, are more reactive than in models excluding financial frictions. Conversely, in the model featuring real options, low-volatile firms, despite being more affected by interest rate changes, remain more reserved in their investment adjustments due to potential future volatility and inherent adjustment costs. As a result, fewer firms modify their investments, and those that do, do so more conservatively after interest rate shifts than in models without these frictions.

These findings hold significant relevance for policymakers keen on understanding the nuanced effects of monetary policy across firms. A primary objective of monetary policy often centers around influencing investment behavior. Previous research shows that firms that face high default risk are less affected by monetary policy shocks. However, my research challenges this notion and implies that, instead, the channel of monetary policy is due to uncertainty and not default risk. This shows the importance of policy to affect the volatility of asset prices.

References

Knut Are Aastveit, Gisle James Natvik, and Sergio Sola. Economic uncertainty and the influence of monetary policy. *Journal of International Money and Finance*, 76:50–67, 2017.

John Asker, Allan Collard-Wexler, and Jan De Loecker. Dynamic inputs and resource (mis) allocation. *Journal of Political Economy*, 122(5):1013–1063, 2014.

David Berger and Joseph S Vavra. Volatility and pass-through. Technical report, National Bureau of Economic Research, 2013.

Ben S Bernanke, Mark Gertler, and Simon Gilchrist. The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics*, 1:1341–1393, 1999.

Nicholas Bloom. The impact of uncertainty shocks. *Econometrica*, 77(3):623–685, 2009.

Nicholas Bloom, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J Terry. Really uncertain business cycles. *Econometrica*, 86(3):1031–1065, 2018.

Nick Bloom, Stephen Bond, and John Van Reenen. Uncertainty and investment dynamics. *The review of economic studies*, 74(2):391–415, 2007.

Spiros Bougheas, Paul Mizen, and Cihan Yalcin. Access to external finance: Theory and evidence on the impact of monetary policy and firm-specific characteristics. *Journal of Banking & Finance*, 30(1):199–227, 2006.

Ricardo J Caballero and Eduardo MRA Engel. Explaining investment dynamics in us manufacturing: a generalized (s, s) approach. *Econometrica*, 67(4):783–826, 1999.

J. Cao, T. Hegna, Martin B. Holm, R. Juelsrud, T. König, and M. Riiser. The investment channel of monetary policy: Evidence from norway. *Working paper*, 2023.

Gian Luca Clementi and Berardino Palazzo. Investment and the cross-section of equity returns. *The Journal of Finance*, 74(1):281–321, 2019.

James Cloyne, Clodomiro Ferreira, Maren Froemel, and Paolo Surico. Monetary policy, corporate finance and investment. Working Paper 25366, National Bureau of Economic Research, December 2018. URL http://www.nber.org/papers/w25366.

Diego Comin and Thomas Philippon. The rise in firm-level volatility: Causes and consequences. *NBER macroeconomics annual*, 20:167–201, 2005.

Timothy Cook and Thomas Hahn. The effect of changes in the federal funds rate target on market interest rates in the 1970s. *Journal of Monetary Economics*, 24(3):331–351, 1989. ISSN 0304-3932. doi: https://doi.org/10.1016/0304-3932(89)90025-1. URL https://www.sciencedirect.com/science/article/pii/0304393289900251.

Thomas F Cooley and Edward C Prescott. Economic growth and business cycles. In *Frontiers of business cycle research*, pages 1–38. Princeton University Press, 2020.

Russell W Cooper and John C Haltiwanger. On the nature of capital adjustment costs. *The Review of Economic Studies*, 73(3):611–633, 2006.

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

Luca Dedola and Francesco Lippi. The monetary transmission mechanism: evidence from the industries of five oecd countries. *European Economic Review*, 49(6):1543–1569, 2005.

Michael Ehrmann and Marcel Fratzscher. Taking stock: Monetary policy transmission to equity markets. *Journal of Money, Credit and Banking*, pages 719–737, 2004.

Andrea L Eisfeldt and Adriano A Rampini. Capital reallocation and liquidity. *Journal of monetary Economics*, 53(3):369–399, 2006.

Min Fang. Lumpy investment, fluctuations in volatility and monetary policy. In *Lumpy Investment, Fluctuations in Volatility and Monetary Policy: Fang, Min.* [Sl]: SSRN, 2022.

Eugenio Gaiotti and Andrea Generale. Does monetary policy have asymmetric effects? a look at the investment decisions of italian firms. *Giornale degli economisti e annali di economia*, pages 29–59, 2002.

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

Mark Gertler and Peter Karadi. Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1):44–76, 2015.

Simon Gilchrist and Egon Zakrajšek. Credit spreads and business cycle fluctuations. *American economic review*, 102(4):1692–1720, 2012.

Joao F Gomes. Financing investment. *American Economic Review*, 91(5):1263–1285, 2001.

Yuriy Gorodnichenko and Michael Weber. Are sticky prices costly? evidence from the stock market. *American Economic Review*, 106(01):165–199, 2016.

Refet S Gürkaynak, Burçin Kısacıkoğlu, and Jonathan H Wright. Missing events in event studies: Identifying the effects of partially measured news surprises. *American Economic Review*, 110(12):3871–3912, 2020.

Ayşe İmrohoroğlu and Şelale Tüzel. Firm-level productivity, risk, and return. *Management Science*, 60(8):2073–2090, 2014.

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

Priit Jeenas. Monetary policy shocks, financial structure, and firm activity: A panel approach. *Working paper*, 2019.

Òscar Jordà. Estimation and inference of impulse responses by local projections. *American economic review*, 95(1):161–182, 2005.

Anil K Kashyap and Jeremy C Stein. Monetary policy and bank lending. In *Monetary policy*, pages 221–261. The University of Chicago Press, 1994.

Aubhik Khan and Julia K Thomas. Nonconvex factor adjustments in equilibrium business cycle models: do nonlinearities matter? *Journal of monetary economics*, 50(2):331–360, 2003.

Aubhik Khan and Julia K Thomas. Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics. *Econometrica*, 76(2):395–436, 2008.

Kenneth N Kuttner. Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of Monetary Economics*, 47(3):523–544, 2001.

Aeimit Lakdawala and Timothy Moreland. Firm-level uncertainty and the transmission of monetary policy. *Available at SSRN 4255980*, 2022.

Robert C Merton. On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance*, 29(2):449–470, 1974.

Stephen D Oliner and Glenn D Rudebusch. Monetary policy and credit conditions: Evidence from the composition of external finance: Comment. *The American Economic Review*, 86 (1):300–309, 1996.

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

Gert Peersman and Frank Smets. The industry effects of monetary policy in the euro area. *The Economic Journal*, 115(503):319–342, 2005.

Eric T Swanson. The macroeconomic effects of the federal reserve's conventional and unconventional monetary policies. 2023.

Silvana Tenreyro and Gregory Thwaites. Pushing on a string: Us monetary policy is less powerful in recessions. *American Economic Journal: Macroeconomics*, 8(4):43–74, 2016.

Toni M Whited. Debt, liquidity constraints, and corporate investment: Evidence from panel data. *The journal of finance*, 47(4):1425–1460, 1992.

Johannes F Wieland and Mu-Jeung Yang. Financial dampening. *Journal of Money, Credit and Banking*, 52(1):79–113, 2020.

Appendices

A Data Construction

This subsection describes the firm-level variables used in the empirical analysis of the paper based on quarterly Compustat data. The definition of the variables and sample selection follow standard practices in the literature (see, for example, Clementi and Palazzo (2019), Ottonello and Winberry (2020), Cloyne et al. (2018), Jeenas (2019), and earlier works of Whited (1992), Gomes (2001), Eisfeldt and Rampini (2006)).

Variables:

1. *Investment*: defined as $\Delta log(k_{it+1})$, where k_{it+1} denotes the capital stock of firm i at the end of period t. For each firm, I set the first value of k_{it+1} to be the level of gross plant, property, and equipment (*ppegtq*) in the first period in which this variable is reported in Compustat. From this period onwards, I compute the evolution of k_{it+1} using the changes of net plant, property, and equipment (*ppentq*), which is a measure of net investment with significantly more observations than *ppegtq* (net of depreciation). If a firm has a missing observation of *ppentq* located between two periods with non-missing observations, I estimate its value using linear interpolation with the values of *ppentq* right before and after the missing observation; if two or more consecutive observations are missing, we do not do any imputation. Following Ottonello and Winberry (2020), I only consider investment spells with 40 quarters or more to estimate fixed effects precisely.

2. *Distance-to-default*: Following Merton (1974), I estimate equation 7 using compustat dataset by an iterative procedure, based on Gilchrist and Zakrajšek (2012) and Blanco and Navarro (2017):

   - Set an initial value for the firm value equal to the sum of firm debt and equity, $V = E + D$, where E is measured as the firm's stock price times the number of shares (data source: CRSP).
   - Estimate the mean and variance of return on firm value over a 250-day moving window. The return on firm value is measured as the daily log return on assets, $\Delta log(V)$.
   - Obtain a new estimate of V for every day of the 250-day moving window from the Black-Scholes-Merton option-pricing framework $E = V\Phi(d_1) - e^{-rT}D\Phi(d_2)$, where $d_1 = log(V/D)+(r+0.5\sigma V_2)T$, and $d_2 = d_1-\sigma\sqrt{T}$, where r is the daily one-

year constant, $\sigma V_2\sqrt{T}21V$ maturity Treasury-yield (data source: Federal Reserve Board of Governors H.15 Selected Interest Rates release).

- Iterate on steps [ii.] and [iii.] until convergence.

3. *Volatility*: standard deviation of daily stock returns over a quarter.

4. *Age*: Number of years from the first time Compustat appeared in the sample.

5. *Leverage*: defined as the ratio of total debt (sum of *dlcq* and *dlttq*) to total assets (*atq*).

6. *Real sales growth*: measured as log-differences in sales (*saleq*) deflated using the BLS implicit price deflator.

7. *Size*: measured as the log of total real assets (*atq*), deflated using the BLS implicit price deflator.

8. *Liquidity*: defined as the ratio of cash and short-term investments (*cheq*) to total assets (*atq*).

9. *Cash flow*: measured as EBIT (*oiadpq*).

10. *Dividend payer*: defined as a dummy variable taking a value of one in firm-quarter observations in which the firm paid dividends.

11. *Sectoral dummies.* I consider the following sectors: (i) agriculture, forestry, and fishing: $sic < 999$; (ii) mining: $sic \in [1000, 1499]$; (iii) construction: $sic \in [1500, 1799]$; (iv) manufacturing: $sic \in [2000, 3999]$; (v) transportation, communications, electric, gas, and sanitary services: $sic \in [4000, 4999]$; (vi) wholesale trade: $sic \in [5000, 5199]$; (vii) retail trade $sic \in [5200, 5999]$; (viii) services: $sic \in [7000, 8999]$;

B Sample Selection

The primary sample in my research incorporates monetary policy shocks and quarterly Compustat data from 1994 to 2007. My empirical analysis excludes the following:

1. Firms in finance, insurance, and real estate sectors (sic [6000, 6799]), utilities (sic [4900, 4999]), nonoperating establishments (sic = 9995), and industrial conglomerates (sic = 9997).

2. Firms not incorporated in the United States.

3. Firm-quarter observations that satisfy one of the following conditions aimed at excluding extreme observations:
    - Negative capital, total assets, sales, liquidity, or leverage.
    - Acquisitions (constructed based on *aqcy*, item 94) larger than 5% of assets.
    - Investment rate is in the top and bottom 0.5% of the distribution.
    - Volatility is in the top of 2% of the distribution.
    - Liquidity that is higher than one and leverage higher than 10.
    - Quarterly real sales growth above one or below minus one.

After applying these sample selection operations, I winsorize observations of regressors at the top and bottom 0.5% of the distribution.

C Robustness

C.1 Aggregate Cycles

Table 6 presents the correlations between firm-level (demeaned within a firm-specific mean and standardized) volatility measures, distance-to-default, and various macroeconomic variables. Notably, the correlations between the volatility index (VIX) and both distance-to-default and idiosyncratic volatility are moderate, with values of -0.3489 and 0.3477, respectively. However, the correlation of these metrics with other macro variables like inflation, unemployment rate, and GDP changes is considerably weaker.

	VIX	ΔCPI	UR	ΔGDP
ΔCPI	-0.526	1.000		
UR	0.151	-0.219	1.000	
ΔGDP	-0.464	0.283	-0.268	1.000
Distance-to-default	-0.348	0.122	-0.076	0.164
Volatility	0.347	-0.186	0.017	-0.152

Table 6: Correlations between micro and macro variables

C.2 Other Monetary Policy Shocks

In Section 4, I present the main results derived from the monetary policy shocks as estimated by Gorodnichenko and Weber (2016) for 1994 to 2007. For a more comprehensive

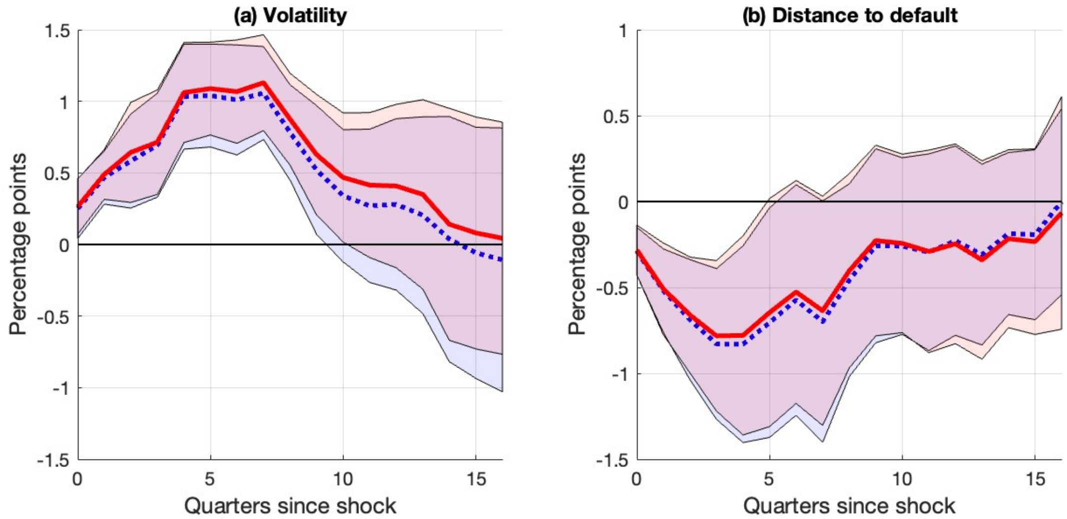

Figure 16: Business cycles, idiosyncratic volatility, and distance-to-default

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (16) where all variables are defined in the Section 3. Filled lines report 95% error bands. Standard errors are clustered on time and firm ID.

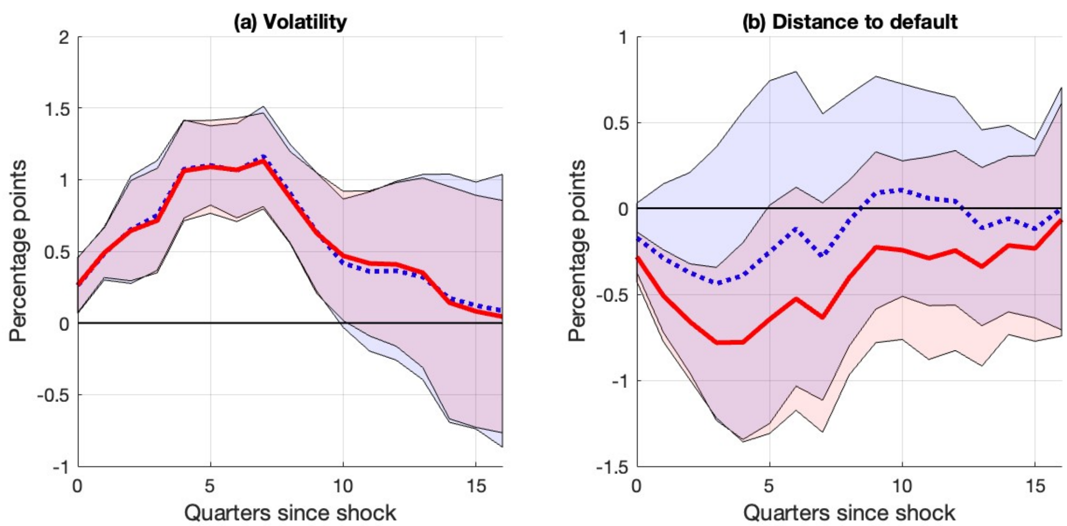

Figure 17: Aggregate volatility, idiosyncratic volatility, and distance-to-default

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (16) where all variables are defined in the Section 3. Filled lines report 95% error bands. Standard errors are clustered on time and firm ID.

analysis in this subsection, I extend the data coverage from 1994 to 2018, integrating the target and path shocks as detailed by Gürkaynak et al. (2020). This categorization is based on target shocks — linked to interest rate changes — and path shocks, which relate to forward guidance. As a further robustness measure, I also incorporate shocks from Swanson (2023) from 1988 to 2018. The outcomes of this analysis are depicted in Figures 18, 19, and 20.

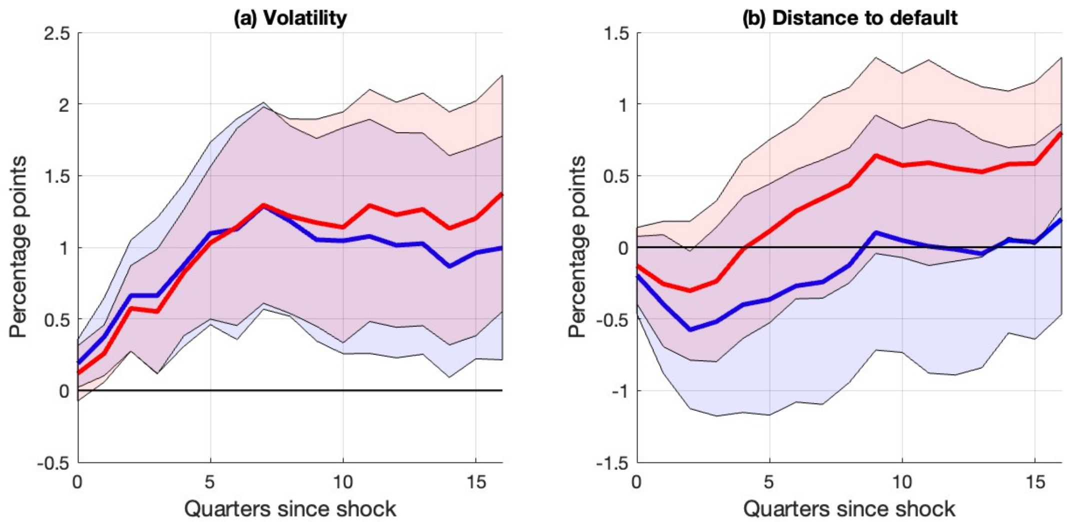

Figure 18: Target: Volatility vs default risk

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (16) where all variables are defined in Section 3. Filled lines report 95% error bands. Standard errors are cluster on time and firm ID.

In particular, Figures 18, 19 shows impulse response functions using Gürkaynak et al. (2020) shocks over the period of 1994 - 2018. Figure 18 shows impulse response to the target shocks (due to interest rate changes). It displays similar results for volatility to Figure 9, but slightly lower results for distance-to-default. The implications are, however, similar: controlling for volatility, the importance of distance-to-default diminishes.

Figure 19 shows impulse response functions to the path shocks (due to forward guidance). It shows statistically insignificant results for both volatility and default risk. In addition, results for default risk are the opposite: monetary policy shocks due to forward guidance imply that firms that have a lower distance-to-default (high default risk) are more affected by monetary policy.

Figure 20, shows impulse response functions using Swanson (2023) shocks throughout

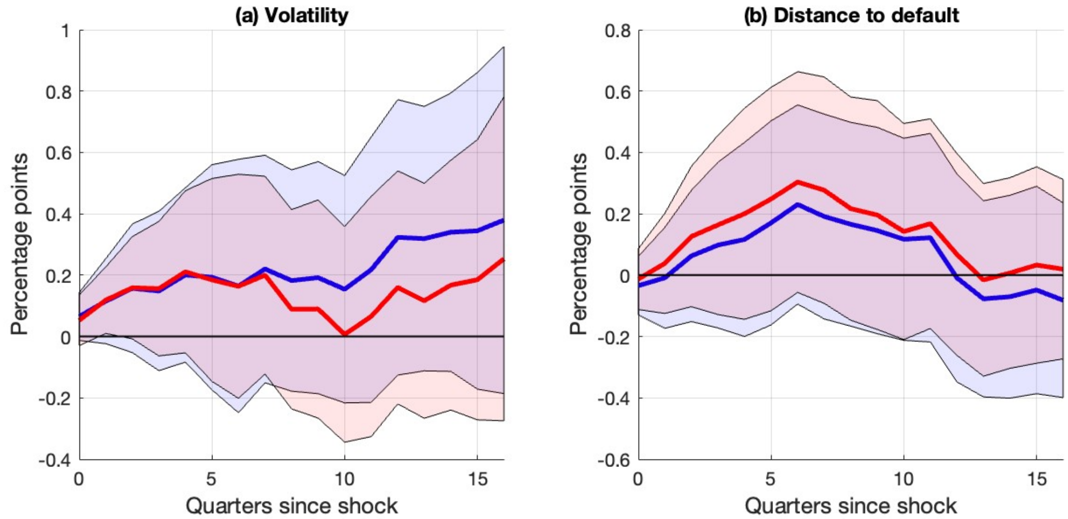

Figure 19: Path: Volatility vs default risk

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (16) where all variables are defined in the Section 3. Filled lines report 95% error bands. Standard errors are cluster on time and firm ID.

1988 - 2018. It displays similar results for volatility to Figure 9, but slightly lower results for distance-to-default. The implications are, however, similar: controlling for volatility, the importance of distance-to-default diminishes.

C.3 Controlling for Financial Constraint

In this subsection, I relate my findings to empirical studies documenting heterogeneous responses across firms with different sizes Gertler and Gilchrist (1994), age and dividend payment Cloyne et al. (2018), liquidity Jeenas (2019), and leverage Ottonello and Winberry (2020).

Panel (a) shows the coefficients on the interaction term between volatility and monetary policy. The blue line represents the coefficient obtained from equation (16). Meanwhile, the red line represents the coefficient of the interaction term between volatility and monetary policy shocks controlling for the marginal effect of distance-to-default, size, age and dividend payment, liquidity, and leverage. Notably, even with slightly wider confidence intervals — attributed to the correlation between volatility and distance-to-default — the marginal effect of volatility on the investment response to monetary policy shocks retains its statistical significance without weakening.

Panel (b) depicts the coefficient on the interaction term between distance-to-default

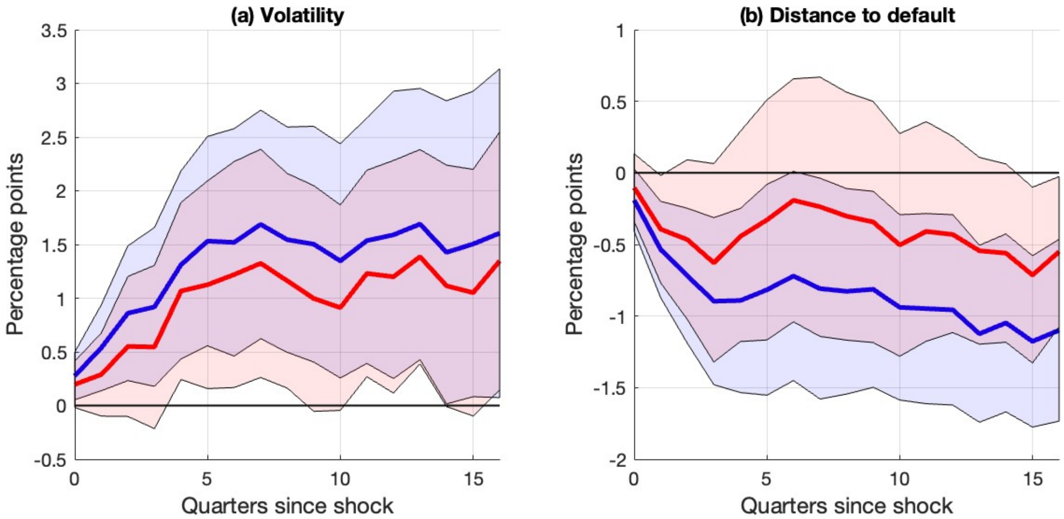

Figure 20: Volatility vs default risk

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (16) where all variables are defined in the Section 3. Filled lines report 95% error bands. Standard errors are cluster on time and firm ID.

and monetary policy. The blue line shows the coefficient while excluding the marginal effect of volatility, size, age and dividend payment, liquidity, and leverage. Conversely, the red line incorporates these marginal effects. Importantly, the figure reveals that when accounting for these marginal effects, the influence of distance-to-default on the investment response to monetary policy shocks decreases and loses its statistical significance.

C.4 Other measures of volatility

In this subsection, I explore alternative measures for volatility. Specifically, I examine the volatility of an asset (firm value), represented as σ_{V_A}, derived from equation 7.

In particular, I run a similar regression as in C.3; both lines, though, include all regressors discussed in C.3 in addition to the monetary policy interaction term. The regression results are displayed in Figure 22. Panel (a) of the figure shows the effect of monetary policy through volatility, while Panel (b) shows the effect of monetary policy through volatility. The red (solid line), however, shows the effect before including the interaction between default risk/volatility and monetary policy shock. In contrast, the blue (dashed) line shows the effect of monetary policy after including these interactions. As can be seen from the figure, my results are robust to using the volatility of firm value rather than the volatility of stock prices.

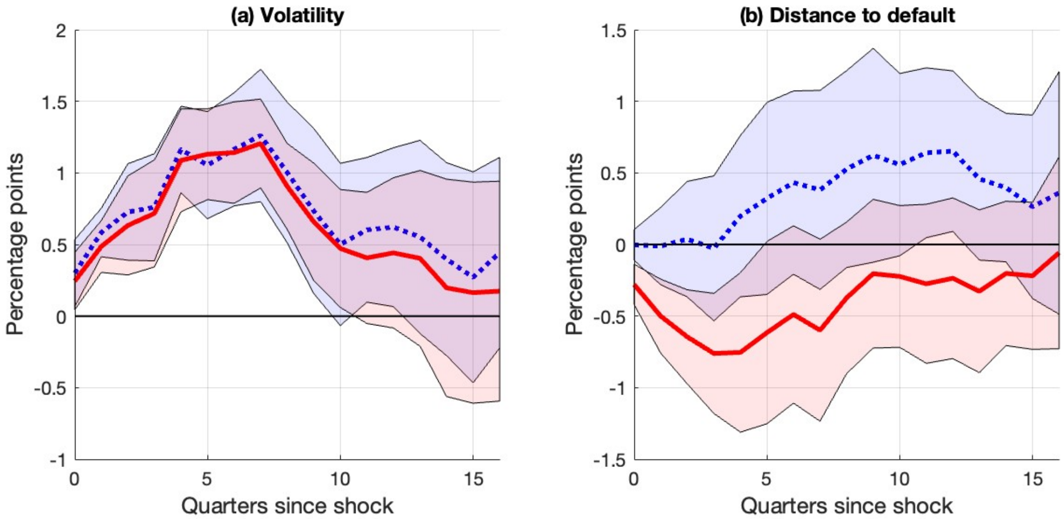

Figure 21: Financial constraint

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (16) where all variables are defined in the Section 3. Filled lines report 95% error bands. Standard errors are cluster on time and firm ID.

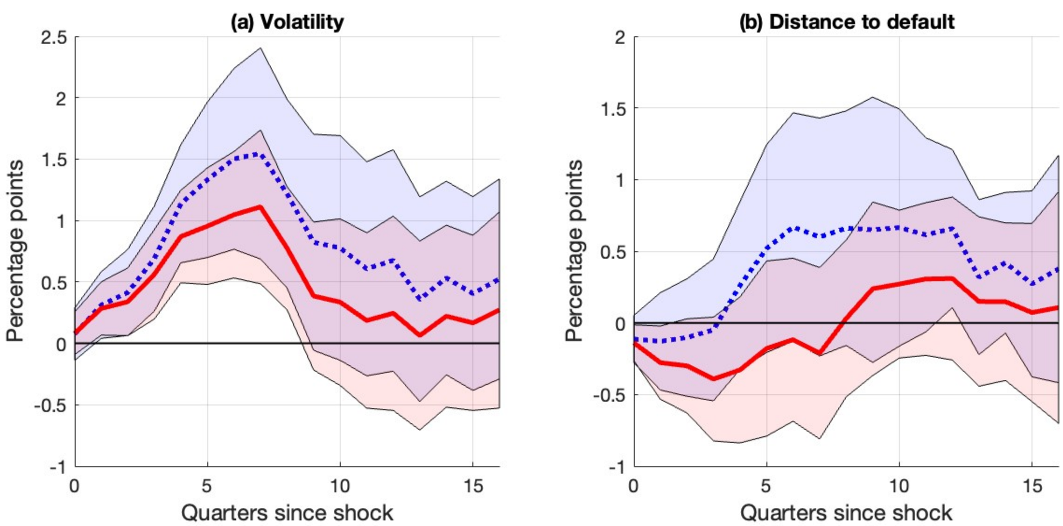

Figure 22: Other proxies for volatility: single interaction

Notes: dynamic effect of monetary shocks over time. Reports the coefficient β_h over quarters h from equation (16) where all variables are defined in the Section 3. Filled lines report 95% error bands. Standard errors are cluster on time and firm ID.

D Additional model results

In this section, I provide additional results for the model. Because the monetary policy transmission is due to adjustment costs and not default risk, I consider a model with adjustment costs and partial irreversibility only (excluding defaultable debt). In subsection D.1, I show the importance of fixed adjustment costs and partial irreversibility. In subsection D.2, I show the importance of large shocks to the interest rate.

D.1 Capital adjustment costs and partial irreversibility

In this subsection, I show the importance of fixed capital adjustment costs and partial irreversibility. In particular Figure 23 shows impulse response functions for all costs and partial irreversibility and non-convex costs only.

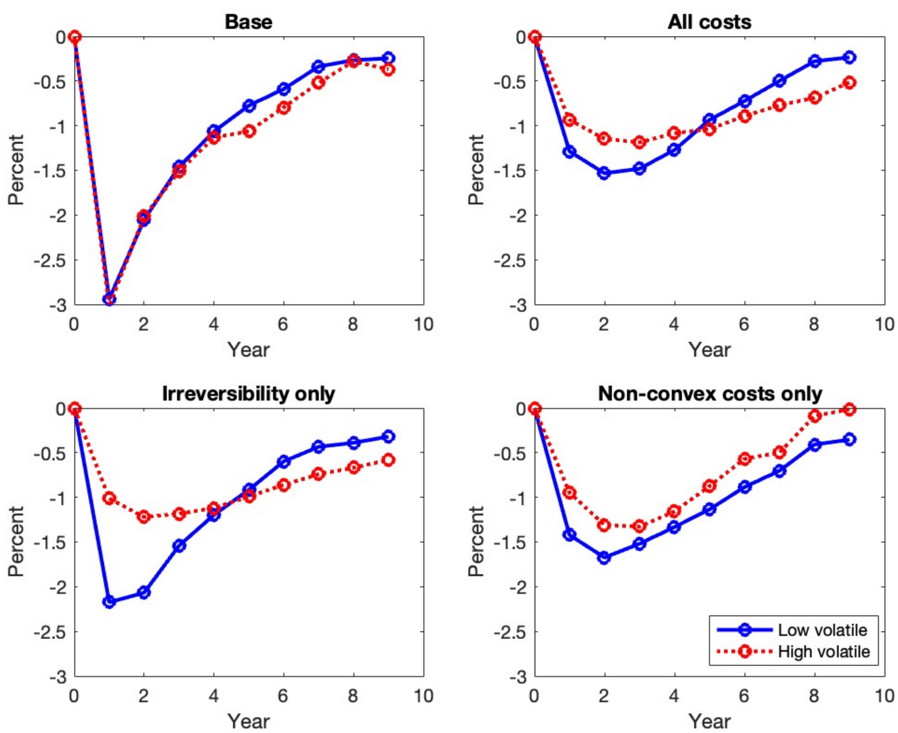

Figure 23: Adjustment costs

D.2 Interest rate shocks

In this subsection, I show the importance of larger shocks in particular Figure 24 shows impulse response functions to 1 percentage point change in interest rate instead of 25 bps. The figure shows that when shocks are larger the gap between high and low volatile firms diminishes.

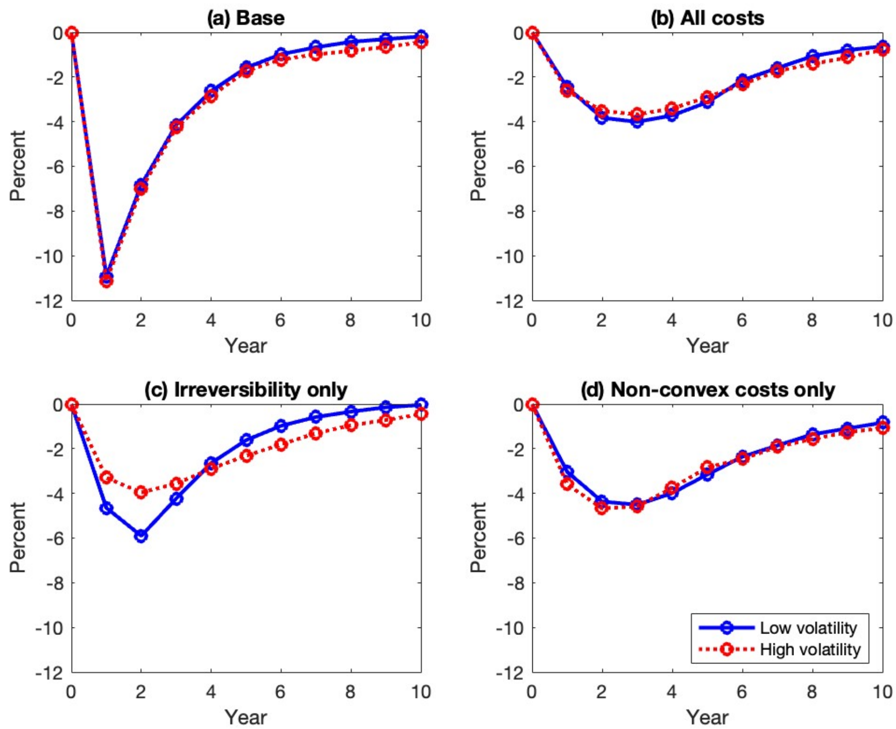

Figure 24: Interest rate shocks