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FINANCIAL HETEROGENEITY AND THE INVESTMENT CHANNEL OF MONETARY POLICY

Pablo Ottonello
Thomas Winberry

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ABSTRACT

We study the role of financial frictions and firm heterogeneity in determining the investment channel of monetary policy. Empirically, we find that firms with low default risk – those with low debt burdens and high "distance to default" – are the most responsive to monetary shocks. We interpret these findings using a heterogeneous firm New Keynesian model with default risk. In our model, low-risk firms are more responsive to monetary shocks because they face a flatter marginal cost curve for financing investment. The aggregate effect of monetary policy may therefore depend on the distribution of default risk, which varies over time.

Pablo Ottonello
Department of Economics
University of Michigan
611 Tappan Street
Ann Arbor, MI 48109
and NBER
ottonellopablo@gmail.com

Thomas Winberry
Booth School of Business
University of Chicago
5807 South Woodlawn Avenue
Chicago, IL 60637
and NBER
thomas.winberry@chicagobooth.edu

1 Introduction

Aggregate investment is one of the most responsive components of GDP to monetary shocks. Our goal in this paper is to understand the role of financial frictions in determining this investment channel of monetary policy. Given the rich heterogeneity in financial positions across firms, a key question is: which firms are the most responsive to changes in monetary policy? The answer to this question is theoretically ambiguous. On the one hand, financial frictions generate an upward-sloping marginal cost curve for investment, which dampens the response of investment to monetary policy for firms that are more severely affected by financial frictions. On the other hand, monetary policy may flatten out this marginal cost curve – for example, by increasing cash flows or improving collateral values – which amplifies the response of investment for affected firms. This latter view is the conventional wisdom in the literature, informed by applying the financial accelerator logic across firms.

We address the question of which firms respond the most to monetary policy using new cross-sectional evidence and a heterogeneous firm New Keynesian model. Our empirical work combines monetary shocks, measured using the high-frequency event-study approach, with quarterly Compustat data. We find that investment done by firms with low default risk is significantly and robustly more responsive to monetary policy than investment done by firms with high default risk. Motivated by this evidence, our model embeds a heterogeneous firm investment model with default risk into the benchmark New Keynesian environment and studies the effect of a monetary shock. In our calibrated model, firms with low default risk are more responsive to monetary policy, similar to our empirical estimates. We perform a simple calculation to show how these heterogeneous responses imply that the effect of monetary policy may become smaller when default risk in the economy is high. At the same time, we find that all firms affected by default risk in our model are *more* responsive to monetary policy than they would be in a version of our model without any default risk at all, consistent with Bernanke, Gertler and Gilchrist (1999).

Our baseline empirical specification estimates how the semi-elasticity of firm investment with respect to a monetary policy shock depends on two measures of the firm's default risk: its leverage ratio and its "distance to default" (which estimates the probability of default from the values of equity and liabilities). We control for firm fixed effects to capture permanent differences across firms and control for sector-by-quarter fixed effects to capture differences in how sectors respond to aggregate shocks. Conditional on our set of controls, leverage is negatively correlated with distance to default and credit rating, and distance to default is positively correlated with credit rating. Therefore, we view low leverage and high distance to default as proxies for low default risk.

We find that having one standard deviation lower leverage implies that a firm is approximately one-fourth more responsive to monetary policy and that having one standard deviation higher distance to default implies that the firm is one-half more responsive. These differences across firms persist for up to three years after the shock and imply large differences in accumulated capital over time. Consistent with the idea that default risk drives these heterogeneous responses, borrowing costs and the use of external finance increase by less for high-risk firms than for low-risk firms following a monetary expansion.

In order to interpret these empirical results, we embed a model of heterogeneous firms facing default risk into the benchmark New Keynesian framework. These firms invest in capital using either internal funds or external borrowing; they can default on their debt, leading to an external finance premium. There is also a group of "retailer" firms with sticky prices, generating a New Keynesian Phillips curve linking nominal variables to real outcomes. We calibrate the model to match key features of firms' investment, borrowing, and lifecycle dynamics in the micro data. Our model generates realistic behavior along non-targeted dimensions of the micro data, and the peak responses of aggregate investment, output, and consumption to a monetary policy shock are broadly in line with the peak responses estimated in the data by Christiano, Eichenbaum and Evans (2005).

We simulate a panel of firms from our calibrated model and find that firms with low measured default risk are more responsive to monetary policy, as in the data. These heterogeneous responses reflect how monetary policy directly changes the expected return on capital, which drives the response of low-risk firms, and indirectly changes cash flows and recovery values, which drive the response of the high-risk firms. Since low-risk firms are more responsive overall, our empirical results indicate that the direct effects of monetary policy dominate the indirect ones.

Finally, we quantify how changes in the distribution of default risk may alter the aggregate effect of monetary policy by fixing the firm-level response to monetary shocks while varying the initial distribution of firms. We find that a monetary shock generates an approximately 30% smaller change in the aggregate capital stock starting from a distribution with 50% less net worth than the steady state distribution. This calculation suggests a potentially important source of time-variation in monetary transmission: monetary policy is less powerful when default risk is higher.

Related Literature Our paper contributes to five strands of literature. The first studies the role of financial frictions in the transmission of monetary policy to the aggregate economy. Bernanke, Gertler and Gilchrist (1999) embed the financial accelerator in a representative firm New Keynesian model; we build on Bernanke, Gertler and Gilchrist (1999)'s framework to include firm heterogeneity. Consistent with their results, we find that the response of aggregate investment to a monetary shock is larger in our model than in a model without financial frictions at all. However, among the 99.4% of firms affected by financial frictions in our model, those with low default risk are more responsive to a monetary shock than those with high default risk, creating the potential for distributional dependence.

Second, we contribute to the literature that studies how the effect of monetary policy varies across firms by showing that firms with low default risk are more responsive to monetary policy. Other studies argue that the firm-level response also depends on size (Gertler and Gilchrist (1994)), liquidity (Jeenas (2019)), or age (Cloyne et al. (2018)). Online Appendix C shows that our results are robust to controlling for these other firm characteristics. Our results do not necessarily contradict these other studies; instead, we simply study different features of the data.

Third, we contribute to the literature which incorporates micro-level heterogeneity into the New Keynesian model. To date, this literature has focused on how household-level heterogeneity affects the consumption channel of monetary policy; see, for example, McKay, Nakamura and Steinsson (2016); Kaplan, Moll and Violante (2018); Auclert (2019); or Wong (2019). We instead explore the role of firm-level heterogeneity in determining the investment channel of monetary policy.[1] In contrast to the consumption channel, we find that both direct and indirect effects of monetary policy play a quantitatively important role in driving the investment channel. The direct effect of changes in the real interest rate are smaller for households because they have a consumption-smoothing motive which firms lack.

Fourth, we contribute to a growing literature which argues that monetary policy is less effective in recessions by suggesting that changes in the distribution of default risk are another reason monetary policy may become less effective. Tenreyro and Thwaites (2016) estimate a nonlinear time-series model and find that monetary policy shocks have a smaller impact on real economic activity in recessions than in normal times. Vavra (2013) and McKay and Wieland (2020) provide models in which monetary policy is less powerful in recessions due to changes in the distribution of price adjustment or durable expenditures.

Finally, we contribute to the literature which studies the role of financial heterogeneity in determining the business cycle dynamics of aggregate investment by introducing sticky prices and studying the effect of monetary policy shocks. Our model of firm-level investment builds heavily on Khan, Senga and Thomas (2016), who study the effect of financial shocks in a flexible price model. We extend the model to include capital quality shocks and a time-varying price of capital in order to generate variation in lenders' recovery value of capital, as in the financial accelerator literature.

Road Map Our paper is organized as follows. Section 2 provides empirical evidence that the firm-level response to monetary policy varies with default risk. Section 3 develops our heterogeneous firm New Keynesian model to interpret this evidence. Section 4 provides a theoretical characterization of the channels through which monetary policy drives investment in our model. Section 5 then calibrates the model and verifies that it is consistent with key features of the joint distribution of investment and leverage in the micro data. Section 6 uses the model to study the monetary transmission mechanism. Section 7 concludes.

[1] Reiter, Sveen and Weinke (2013) show that a model with firm heterogeneity and fixed capital adjustment costs generates a counterfactually large and short-lived response of investment to monetary policy because, conditional on adjusting, investment is extremely interest-sensitive in their model. We dampen the interest-sensitivity of investment using financial frictions and convex adjustment costs to aggregate capital. Koby and Wolf (2020) dampen the interest-sensitivity using convex adjustment costs at the firm level and find that the fixed costs generate state-dependent responses to monetary policy.

2 Empirical Results

We document that firms with low default risk – proxied by low debt burdens and high distance to default – are significantly more responsive to changes in monetary policy than other firms in the economy.

2.1 Data Description

Our sample combines monetary policy shocks with quarterly Compustat data.

Monetary Policy Shocks We measure monetary shocks using the high-frequency, event-study approach pioneered by Cook and Hahn (1989). Following Gurkaynak, Sack and Swanson (2005) and Gorodnichenko and Weber (2016), we construct our shock $\varepsilon_t^{\mathrm{m}}$ as

$$\varepsilon_t^{\mathrm{m}} = \tau(t) \times (\mathtt{ffr}_{t+\Delta_+} - \mathtt{ffr}_{t-\Delta_-}), \tag{1}$$

where t is the time of the monetary announcement, $\mathtt{ffr}_t$ is the implied Fed Funds Rate from a current-month Federal Funds future contract at time t, Δ_+ and Δ_- control the size of the time window around the announcement, $\tau(t) \equiv \frac{\tau_m^n(t)}{\tau_m^n(t)-\tau_m^d(t)}$ is an adjustment for the timing of the announcement within the month, $\tau_m^d(t)$ denotes the day of the meeting in the month, and $\tau_m^n(t)$ the number of days in the month. We focus on a window of $\Delta_- =$ fifteen minutes before the announcement and $\Delta_+ =$ forty five minutes after the announcement. Our shock series begins in January 1990, when the Fed Funds futures market opened, and ends in December 2007, in order to focus on conventional monetary policy. During this time there were 164 shocks with a mean of approximately zero and a standard deviation of 9bp.

We time aggregate the high-frequency shocks to the quarterly frequency in order to merge them with our firm-level data. We construct a moving average of the raw shocks weighted by the number of days in the quarter after the shock occurs (see Supplemental Materials A for details). Our time aggregation strategy ensures that we weight shocks by the amount of time firms have had to react to them. Table 1 indicates that these "smoothed" shocks have similar features to the original high-frequency shocks. For robustness, we also use the alternative time aggregation of simply summing all the shocks that occur within the quarter, as in Wong

Table 1
Summary Statistics of Monetary Policy Shocks

	High Frequency	Smoothed	Sum
Mean	-0.0185	-0.0429	-0.0421
Median	0	-0.0127	-0.00509
S.D.	0.0855	0.108	0.124
Min	-0.463	-0.480	-0.479
Max	0.152	0.233	0.261
Observations	164	71	72

Notes: Summary statistics of monetary policy shocks for the period 1/1/1990 to 12/31/2007. "High frequency" shocks are estimated using the event study strategy in (1). "Smoothed" shocks are time aggregated to a quarterly frequency using the weighted average described in Supplemental Materials A. "Sum" refers to time aggregating by simply summing all shocks within a quarter.

(2019). Table 1 shows that the moments of these alternative shocks do not significantly differ from the moments of the smoothed shocks, and Supplemental Materials B shows that our main results are robust to using this alternative form of time aggregation.

Firm-Level Variables We draw firm-level variables from quarterly Compustat, a panel of publicly listed U.S. firms. Compustat satisfies three key requirements for our study: it is quarterly, a high enough frequency to study monetary policy; it is a long panel, allowing us to use within-firm variation; and it contains rich balance-sheet information, allowing us to construct our key variables of interest. To our knowledge, Compustat is the only U.S. dataset that satisfies these three requirements. The main disadvantage of Compustat is that it excludes privately held firms.[2] In Section 5, we calibrate our economic model to match a broad sample of firms, not just those in Compustat.

Our main measure of investment is $\Delta \log k_{jt+1}$, where k_{jt+1} is the book value of the tangible capital stock of firm j at the end of period t. We use two measures of a firm's financial position to proxy for default risk. First, we measure leverage ℓ_{jt} as the firm's debt-to-asset ratio, where debt is the sum of short term and long term debt and assets is the book value of assets. Second, we measure the firm's distance to default dd_{jt} following Gilchrist

[2]The main attractive alternatives, covering a much broader set of firm sizes than Compustat, are the datasets constructed in Crouzet and Mehrotra (2020) (using data from the Quarterly Financial Reports) and in Dinlersoz et al. (2018) (combining data from the U.S. Census Longitudinal Business Database, Orbis, and Compustat). However, the dataset in Crouzet and Mehrotra (2020) only follows small firms for eight quarters, which limits the ability to use within-firm variation, while the dataset in Dinlersoz et al. (2018) contains data for small firms at an annual frequency.

Table 2
Summary Statistics of Firm-Level Variables

(a) Marginal Distributions

	$\Delta \log k_{jt+1}$	ℓ_{jt}	dd_{jt}	$\mathbb{1}\{\text{cr}_{jt} \geq A\}$
Mean	0.004	0.263	5.788	0.025
Median	-0.004	0.201	4.742	0.000
S.D.	0.091	0.348	5.082	0.156
95th Percentile	0.128	0.719	15.213	0.000
Observations	343276	343276	238531	343276

(b) Correlation Matrix (raw variables)

	ℓ_{jt}	dd_{jt}	$\mathbb{1}\{\text{cr}_{jt} \geq A\}$
ℓ_{jt}	1.00		
dd_{jt}	-0.39	1.00	
	(0.00)		
$\mathbb{1}\{\text{cr}_{jt} \geq A\}$	-0.02	0.20	1.00
	(0.00)	(0.00)	

p-values in parentheses

(c) Correlation matrix (residualized)

	ℓ_{jt}	dd_{jt}	$\mathbb{1}\{\text{cr}_{jt} \geq A\}$
ℓ_{jt}	1.00		
dd_{jt}	-0.28	1.00	
	(0.00)		
$\mathbb{1}\{\text{cr}_{jt} \geq A\}$	-0.01	0.05	1.00
	(0.00)	(0.00)	

p-values in parentheses

Notes: summary statistics of firm-level variables for the period 1983q3 to 2014q4. $\Delta \log k_{jt+1}$ is the change in the capital stock, ℓ_{jt} is the ratio of total debt to total assets, dd_{jt} is the firm's distance to default, and $\mathbb{1}\{\text{cr}_{jt} \geq A\}$ is an indicator variable for whether the firm's credit rating is above an A. Panel (a) computes summary statistics of these variables in our sample before winsorization, Panel (b) computes their pairwise correlations, and Panel (c) computes pairwise correlations of the residuals from the regression $x_{jt} = \alpha_j + \alpha_{st} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where $x_{jt} \in \{\ell_{jt}, \text{dd}_{jt}, \mathbb{1}\{\text{cr}_{jt} \geq A\}\}$, α_j is a firm fixed effect, α_{st} is a sector-by-quarter fixed effect, and Z_{jt-1} is a vector of firm-level controls containing sales growth, size, current assets as a share of total assets, and an indicator for fiscal quarter.

and Zakrajšek (2012). Distance to default dd_{jt} has been shown by Schaefer and Strebulaev (2008) to account well for variation in corporate bond prices due to default risk and is widely used in the finance industry. In order to validate these proxies, we correlate them with credit rating cr_{jt}, measured as S&P's long-term issue rating of the firm. Supplemental Materials A provides details of our data construction.

Panel (a) of Table 2 presents simple summary statistics of the final sample used in our analysis. The mean distance to default implies that a 6 standard deviation shock over a given year will drive the average firm to default, in line with Gilchrist and Zakrajšek (2012). We winsorize our sample at the top and bottom 0.5% of observations of investment, leverage, and distance to default in order to ensure our results are not driven by outliers.

Panel (b) of Table 2 shows the correlation structure of leverage, distance to default, and credit rating. Higher leverage is positively correlated with a smaller distance to default and a lower credit rating, indicating that higher debt burdens are associated with higher default risk. Firms with higher distance to default also have higher credit ratings, validating our interpretation of distance to default. Panel (c) of Table 2 shows that these correlations are all also true conditional on the controls in our baseline regression specification (2) below.

2.2 Heterogeneous Responses to Monetary Policy

Specification We estimate variants of the baseline empirical specification

$$\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}, \tag{2}$$

where α_j is a firm j fixed effect, α_{st} is a sector s by quarter t fixed effect, $\varepsilon_t^{\mathrm{m}}$ is the quarterly monetary policy shock, $x_{jt} \in \{\ell_{jt}, \mathrm{dd}_{jt}\}$ is the firm's leverage ratio or distance to default, $\mathbb{E}_j[x_{jt}]$ is the average value of x_{jt} for a given firm over the sample, Z_{jt-1} is a vector of controls, and e_{jt} is a residual.[3] Our main coefficient of interest is β, which measures how the semi-elasticity of investment $\Delta \log k_{jt+1}$ with respect to monetary shocks $\varepsilon_t^{\mathrm{m}}$ depends on the within-firm variation in the financial position $x_{jt} - \mathbb{E}_j[x_{jt}]$ (we discuss the rationale for using within-firm variation in financial position below). We do not estimate the specification with credit ratings $x_{jt} = \mathrm{cr}_{jt}$ because the within-firm variation in credit ratings is limited. Throughout, we cluster standard errors two ways to account for correlation within firms and within quarters.

We control for a number of factors that may simultaneously affect investment and financial position but which are outside the scope of our economic model in Section 3. The firm fixed effects α_j capture permanent differences in investment behavior across firms and the sector-by-quarter fixed effects α_{st} capture differences in how broad sectors are exposed to aggregate shocks. The vector Z_{jt-1} includes the level of the financial position x_{jt-1}, total assets, sales growth, current assets as a share of total assets, and a fiscal quarter dummy. The vector Z_{jt-1} also includes the interaction of financial position with the previous quarter's

[3]The sectors s we consider, based on SIC codes, are: agriculture, forestry, and fishing; mining; construction; manufacturing; transportation communications, electric, gas, and sanitary services; wholesale trade; retail trade; and services. We do not include finance, insurance, and real estate, and public administration.

GDP growth in order to control for differences in cyclical sensitivities across firms.[4]

Online Appendix A.1 shows that using the interaction of within-firm variation in financial position with the monetary shock $(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}}$ ensures that our results are not driven by permanent heterogeneity in responsiveness across firms. This choice is motivated by our economic model in Section 3, in which firms are ex-ante homogenous. In contrast, firms in the data may be ex-ante heterogeneous in how they respond to monetary policy according to their financial position x_{jt}. For example, firms in risky markets may be permanently more exposed to interest rate fluctuations and also permanently more likely to default. If we had instead interacted the *level* of financial position with the monetary shock $x_{jt}\varepsilon_t^{\mathrm{m}}$, then our results would be partly determined by such permanent differences in responsiveness. By demeaning financial position within firms, $(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}}$, our estimates are instead driven by how a *given* firm responds to monetary policy when it has higher or lower default risk than usual.

Results Table 3 reports the results from estimating the baseline specification (2). We perform two normalizations to make the estimated coefficient β easily interpretable. First, we standardize the firm's demeaned leverage $\ell_{jt} - \mathbb{E}_j[\ell_{jt}]$ and distance to default $\mathrm{dd}_{jt} - \mathbb{E}_j[\mathrm{dd}_{jt}]$ over the entire sample, so their units are standard deviations in our sample. Second, we normalize the sign of the monetary shock $\varepsilon_t^{\mathrm{m}}$ so that a positive value corresponds to a cut in interest rates.

The first three columns in Table 3 show that firms with lower leverage and higher distance to default are more responsive to monetary shocks $\varepsilon_t^{\mathrm{m}}$. Column (1) implies that a firm has approximately a 0.7 units lower semi-elasticity of investment to monetary policy when it is one standard deviation more indebted than it typically is in our sample. Adding firm-level controls Z_{jt-1} in Column (2) does not significantly change this point estimate; therefore, we focus on specifications with firm-level controls Z_{jt-1} for the remainder of the paper.

[4] If the monetary shock $\varepsilon_t^{\mathrm{m}}$ is truly exogenous, then this control would be unnecessary in large samples. However, we find that the largest shocks occur at the beginning of the two recessions in our small sample. Failing to incorporate this fact may bias our results if firms with different financial positions are differentially exposed to business cycle events. Online Appendix A.2 shows that controlling for differences in cyclical sensitivities strengthens the differential responses to monetary shocks, but that our results are qualitatively robust to excluding those controls as well.

Table 3
Heterogeneous Responses of Investment to Monetary Policy

	(1)	(2)	(3)	(4)	(5)
leverage × ffr shock	-0.69**	-0.57**		-0.26	-0.14
	(0.29)	(0.27)		(0.35)	(0.58)
dd × ffr shock			1.14***	1.01**	1.16**
			(0.41)	(0.40)	(0.47)
ffr shock					2.14***
					(0.61)
Observations	219402	219402	151027	151027	119750
R^2	0.113	0.124	0.141	0.142	0.151
Firm controls	no	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	no
Time clustering	yes	yes	yes	yes	yes

Notes: results from estimating $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where α_j is a firm fixed effect, α_{st} is a sector-by-quarter fixed effect, $x_{jt} \in \{\ell_{jt}, \mathrm{dd}_{jt}\}$ is leverage or distance to default, $\mathbb{E}_j[x_{jt}]$ is the average of x_{jt} for firm j in the sample, $\varepsilon_t^{\mathrm{m}}$ is the monetary shock, and Z_{jt-1} is a vector of firm-level controls containing x_{jt-1}, sales growth, size, current assets as a share of total assets, an indicator for fiscal quarter, and the interaction of demeaned financial position with lagged GDP growth. Standard errors are two-way clustered by firms and quarter. We have normalized the sign of the monetary shock $\varepsilon_t^{\mathrm{m}}$ so that a positive shock corresponds to a decrease in interest rates. We have standardized $(\ell_{jt} - \mathbb{E}[\ell_{jt}])$ and $(\mathrm{dd}_{jt} - \mathbb{E}[\mathrm{dd}_{jt}])$ over the entire sample. Column (5) removes the sector-quarter fixed effect α_{st} and estimates $\Delta \log k_{jt+1} = \alpha_j + \alpha_{sq} + \gamma \varepsilon_t^{\mathrm{m}} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}_1' Z_{jt-1} + \mathbf{\Gamma}_2' Y_{t-1} + e_{jt}$, where Y_t is a vector with four lags of GDP growth, the inflation rate, and the unemployment rate.

Column (3) shows that a firm has approximately a 1.1 unit higher semi-elasticity when it is one standard deviation further from default than usual. Column (4) shows that leverage is rendered statistically insignificant conditional on distance to default, indicating that our results are primarily driven by distance to default, which we view as our most direct measure of default risk.

Column (5) removes the sector-by-quarter fixed effects in order to estimate the average effect of a monetary shock:

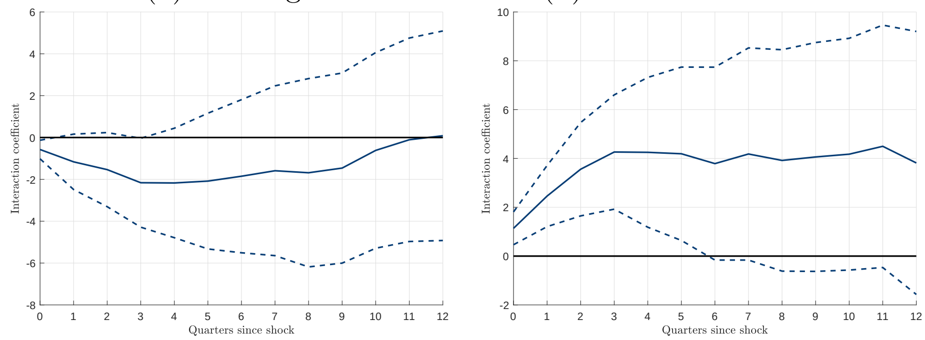
$$\Delta \log k_{jt+1} = \alpha_j + \alpha_{sq} + \gamma \varepsilon_t^{\mathrm{m}} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}_1' Z_{jt-1} + \mathbf{\Gamma}_2' Y_{t-1} + e_{jt}, \tag{3}$$

where α_{sq} is a sector s by quarter q seasonal fixed effect and Y_t is a vector with four lags of GDP growth, the inflation rate, and the unemployment rate. The average investment semi-elasticity is roughly 2.[5] Hence, our interaction coefficients in the previous columns imply an

[5] Assuming an annual depreciation rate of $\delta = 0.1$, this estimated coefficient implies that a one percentage

Figure 1: Dynamics of Differential Response to Monetary Shocks

(a) Leverage (b) Distance to Default



Notes: dynamics of the interaction coefficient between financial positions and monetary shocks over time. Reports the coefficient β_h over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_h(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \boldsymbol{\Gamma}'_h Z_{jt-1} + e_{jth}$, where all variables are defined in the notes for Table 3. Dashed lines report 90% error bands.

economically meaningful degree of heterogeneity.

Dynamics In order to estimate the dynamics of these differential responses across firms, we estimate the Jorda (2005)-style local projection of specification (2):

$$\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_h(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \boldsymbol{\Gamma}'_h Z_{jt-1} + e_{jth}, \quad (4)$$

where $h \geq 1$ indexes the forecast horizon. The coefficient β_h measures how the cumulative response of investment in quarter $t+h$ to a monetary policy shock in quarter t depends on the firm's demeaned financial position $x_{jt-1} - \mathbb{E}_j[x_{jt}]$ in quarter $t-1$. We use the cumulative change in capital on the left-hand side in order to easily assess the implications of our estimates for the capital stock itself. Online Appendix B.1 estimates a dynamic version of the specification (3) without the sector-time fixed effects α_{sth} and shows that the average firm's response is persistent, peaking two to four quarters after the shock.

Figure 1 shows that firms with low leverage and high distance to default are consistently more responsive to the shock for up to three years later. Panel (a) shows that the peak of the differences by leverage occurs after four quarters and that the differences disappear after twelve quarters. Panel (b) shows that the differences by distance to default are larger

point cut in the interest rate increases annualized investment by 20%, which is at the upper end of estimated user-cost elasticities in the literature (see, for example, Zwick and Mahon (2017)).

and significantly more persistent than for leverage. However, these long-run differences are imprecisely estimated with large standard errors, so we focus on the impact effect of the shock for the rest of the paper.

Additional Empirical Results Online Appendix B and the Supplemental Materials B contain three sets of additional empirical results. The first set of additional results contains a number of robustness checks of our main results. Online Appendix B.3 shows that the results hold when controlling for the information channel of monetary policy using Greenbook forecast revisions (following Miranda-Agrippino and Ricco (2019)) and that the results hold when we start the sample in 1994 rather than 1990. We also perform robustness checks regarding firm-level heterogeneity, including controlling for lagged investment, controlling for interactions of the monetary shock with other firm-level covariates (such as sales growth, future sales growth, size, or liquidity), and investigating other indices of financial constraints.

The second set of results includes some additional analysis of the data. First, as described above, Online Appendix B.1 estimates the dynamics of the average response to monetary policy. Second, Online Appendix B.2 shows that the heterogeneous responses are primarily driven by expansionary shocks. Third, Supplemental Materials B shows that our results hold if we measure leverage using only short term debt, only long term debt, only other liabilities, or using leverage net of liquid assets, though the estimates are less precise for individual categories of debt.

The third set of additional results, in Online Appendix C, relates our work to various strands of the existing literature. First, we show that small firms, measured using Gertler and Gilchrist (1994)'s methodology, are more responsive to monetary shocks in our sample; our results are robust to controlling for this effect. Second, we show that older firms are slightly less responsive to monetary shocks, consistent with recent work by Cloyne et al. (2018); again, our results are robust to controlling for this effect. Third, we reconcile our results with recent work by Jeenas (2019), who argues that low-leverage firms are *less* responsive to monetary policy over longer horizons. We argue that these results are largely driven by permanent heterogeneity in responsiveness, which is outside the scope of our analysis. We also show that our results are not driven by heterogeneity in liquidity across firms, which

Jeenas (2019) emphasizes. Supplemental Materials C also shows that our results are not driven by differences in firm-level sales volatility.

3 Model

We now develop a heterogeneous firm New Keynesian model in order to interpret this cross-sectional evidence and study its aggregate implications. We describe the model in three blocks: an investment block, which captures heterogeneous responses to monetary policy; a New Keynesian block, which generates a Phillips curve; and a representative household, which closes the model.

3.1 Investment Block

The investment block contains a fixed mass of heterogeneous firms that invest in capital subject to financial frictions. It builds heavily on the flexible-price model developed in Khan, Senga and Thomas (2016). Besides incorporating sticky prices, we extend Khan, Senga and Thomas (2016)'s framework in three ways. First, we add idiosyncratic capital quality shocks, which help us match observed default rates in the data. Second, we incorporate aggregate adjustment costs in order to generate time-variation in the relative price of capital, as in the financial accelerator literature (e.g., Bernanke, Gertler and Gilchrist (1999)). Third, we assume that new entrants have lower initial productivity than incumbents, which helps us match lifecycle dynamics.

Production firms Time is discrete and infinite. There is no aggregate uncertainty; in Sections 4 and 6 below, we study the transition path in response to an unexpected monetary shock. Each period, there is a fixed mass 1 of production firms. Each firm $j \in [0,1]$ produces an undifferentiated good y_{jt} using the production function $y_{jt} = z_{jt}(\omega_{jt}k_{jt})^{\theta} l_{jt}^{\nu}$, where z_{jt} is an idiosyncratic total factor productivity shock, ω_{jt} is an idiosyncratic capital quality shock, k_{jt} is the firm's capital stock, l_{jt} is the firm's labor input, and $\theta + \nu < 1$. The idiosyncratic TFP shock follows a log-AR(1) process $\log z_{jt+1} = \rho \log z_{jt} + \varepsilon_{jt+1}$, where $\varepsilon_{jt+1} \sim N(0, \sigma^2)$.

The capital quality shock is i.i.d. across firms and time and follows a truncated log-normal process with support $[-4\sigma_\omega, 0]$, where σ_ω is the standard deviation of the underlying normal distribution. This process implies that with some probability p_ω, no capital quality shock is realized ($\log \omega_{jt} = 0$), but with probability $1 - p_\omega$, capital quality is drawn from the region of a normal distribution within $[-4\sigma_\omega, 0]$. The capital quality shock also affects the value of the firm's undepreciated capital at the end of the period, $(1 - \delta)\omega_{jt}k_{jt}$. We view capital quality shocks as capturing unmodeled forces which reduce the value of the firm's capital, such as frictions in the resale market, breakdown of machinery, or obsolescence.[6]

The timing of events within each period is as follows.

(i) A mass $\overline{\mu}_t$ of new firms enter the economy. We assume that the mass of new entrants is equal to the mass of firms that exit the economy so that the total mass of production firms is fixed in each period t. Each of these new entrants draws idiosyncratic productivity z_{jt} from the time-invariant distribution $\mu^{\text{ent}}(z) \sim \log N\left(-m\frac{\sigma}{\sqrt{(1-\rho^2)}}, \frac{\sigma}{\sqrt{(1-\rho^2)}}\right)$, where $m \geq 0$ is a parameter governing the average productivity of new entrants.[7] New entrants are endowed with k_0 units of capital from the household and have no debt. They then proceed as incumbent firms.

(ii) Idiosyncratic shocks to TFP and capital quality are realized.

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

(iv) Each firm decides whether or not to default. If a firm defaults, it immediately and permanently exits the economy. In the event of default, lenders recover a fraction of the firm's capital stock (described in more detail below) and equity holders receive a zero payoff. The fraction of a defaulting firms' capital not recovered by its lenders is transferred lump-sum to households. In order to continue operation, the firm must

[6]Mechanically, the capital quality shocks allow the model to generate positive default risk for a large cross-section of firms. In our model, the value of a firm is dominated by the value of its undepreciated capital stock; without risk to this stock, our model would have the counterfactual prediction that only firms with very low net worth would have positive probability of default.

[7]The parameter m is motivated by the evidence in Foster, Haltiwanger and Syverson (2016) that young firms have persistently low levels of measured productivity.

pay back the face value of its outstanding debt, b_{jt}, and pay a fixed operating cost ξ in units of the final good.

(v) Continuing firms produce by hiring labor l_{jt} from a competitive labor market at real wage w_t. Firms sell their output to retailers (described below) in a competitive market at relative price p_t expressed in terms of the final good (which is our numeraire, described below). At this point, firms that received the i.i.d. exit shock sell their undepreciated capital and exit the economy.

(vi) Continuing firms purchase new capital k_{jt+1} at relative price q_t. Firms have two sources of investment finance, each of which is subject to a friction. First, firms can issue new nominal debt with real face value $b_{jt+1} = \frac{B_{jt+1}}{P_t}$, where B_{jt+1} is the nominal face value and P_t is the nominal price of the final good. Lenders offer a price schedule $\mathcal{Q}_t(z_{jt}, k_{jt+1}, b_{jt+1})$ for this debt (we derive this price schedule below). Second, firms can use internal finance by lowering dividend payments d_{jt} but cannot issue new equity, which bounds dividend payments $d_{jt} \geq 0$.[8]

We write the firm's optimization problem recursively. The individual state variables of a firm are its total factor productivity z and its net worth

$$n = \max_{l} p_t z(\omega k)^{\theta} l^{\nu} - w_t l + q_t(1-\delta)\omega k - b\frac{1}{\Pi_t} - \xi,$$

where $\Pi_t = \frac{P_t}{P_{t-1}}$ is realized gross inflation. Net worth n is the total amount of resources available to the firm other than additional borrowing. Conditional on continuing, the real

[8]The non-negative dividend constraint captures two key facts about external equity documented in the corporate finance literature. First, firms face significant costs of issuing new equity, both direct flotation costs and indirect costs. Second, firms issue external equity very infrequently. This specific form of the non-negativity constraint is widely used in the macro literature because it allows for efficient computation of the model in general equilibrium.

equity value $v_t(z,n)$ solves the Bellman equation[9]

$$v_t(z,n) = \max_{k',b'} n - q_t k' + \mathcal{Q}_t(z,k',b')b' + \mathbb{E}_t \left[\Lambda_{t+1} \left(\pi_d \chi^1(\hat{n}_{t+1}(z',\omega',k',b'))\hat{n}_{t+1}(z',\omega',k',b')\right.\right.$$
$$\left.\left.(1-\pi_d)\chi^2_{t+1}(z',\hat{n}_{t+1}(z',\omega',k',b'))v_{t+1}(z',\hat{n}_{t+1}(z',\omega',k',b'))\right)\right]$$
$$\text{such that } n - q_t k' + \mathcal{Q}_t(z,k',b')b' \geq 0 \tag{5}$$

where $\hat{n}_{t+1}(z',\omega',k',b') \equiv \max_{l'} p_{t+1} z'(\omega' k')^\theta (l')^\nu - w_{t+1} l' + q_{t+1}(1-\delta)\omega' k' - b' \frac{1}{\Pi_{t+1}} - \xi$ is the net worth implied by k', b', and the realization of z' and ω'; $\chi^1(n)$ and $\chi^2_t(z,n)$ are indicator variables taking the value of zero if the firm defaults, conditional on exogenously exiting and not exiting; and Λ_{t+1} is the stochastic discount factor.

Proposition 1 characterizes the decision rules which solve this Bellman equation:

***Proposition* 1.** *Consider a firm at time t that is eligible to continue into the next period, has idiosyncratic productivity z, and has net worth n. The firm's optimal decision is characterized by one of the following three cases.*

(i) ***Default****: there exists a threshold $\underline{n}_t(z)$ such that the firm defaults if $n < \underline{n}_t(z)$. These firms cannot satisfy the non-negativity constraint on dividends.*

(ii) ***Unconstrained****: there exists a threshold $\overline{n}_t(z)$ such that the firm is* ***financially unconstrained*** *if $n > \overline{n}_t(z)$. Unconstrained firms follow the "frictionless" capital accumulation policy $k'_t(z,n) = k^*_t(z)$ which solves $q_t = \mathbb{E}_t[\Lambda_{t+1} MRPK_{t+1}(z',k^*_t(z))|z]$, where $MRPK_{t+1}(z',k') = \mathbb{E}_{\omega'}[\frac{\partial}{\partial k'}(\max_{l'} p_{t+1} z'(\omega' k')^\theta (l')^\nu - w_{t+1} l' + q_{t+1}(1-\delta)\omega' k')]$ is the return on capital to the firm. Unconstrained firms are indifferent over any combination of b' and d such that they remain unconstrained for every period with probability one.*

(iii) ***Constrained****: firms with $n \in [\underline{n}_t(z), \overline{n}_t(z)]$ are* ***financially constrained****. Constrained firms' optimal investment $k'_t(z,n)$ and borrowing $b'_t(z,n)$ decisions solve the Bellman equation (5). Constrained firms also pay zero dividends because the value of*

[9] Firms which receive the exogenous exit shock have simple decision rules. Those that do not default simply sell their undepreciated capital after production. Since these firms cannot borrow, they default whenever net worth $n < 0$.

resources inside the firm, used to lower borrowing costs, is higher than the value of resources outside the firm.

Proof. See Supplemental Materials E. ■

Lenders There is a representative financial intermediary that lends resources from the representative household to firms at the firm-specific price schedule $\mathcal{Q}_t(z, k', b')$. If the firm defaults on the loan in the following period, the lender recovers a fraction α of the market value of the firm's capital stock $q_{t+1}\omega' k'$. The debt price schedule prices this default risk competitively:

$$\mathcal{Q}_t(z,k',b') = \mathbb{E}_t\left[\Lambda_{t+1}\frac{1}{\Pi_{t+1}}\left(\begin{array}{c} 1-\left(1-(\pi_d\chi^1(\hat{n}_{t+1}(z',\omega',k',b'))+(1-\pi_d)\chi^2_{t+1}(z',\hat{n}_{t+1}(z',\omega',k',b')))\right) \\ \times\left(1-\min\{\frac{\alpha q_{t+1}(1-\delta)\omega' k'}{b'/\Pi_{t+1}},1\}\right)\end{array}\right)\right], \tag{6}$$

3.2 New Keynesian Block

The New Keynesian block of the model is designed to parsimoniously generate a New Keynesian Phillips curve relating nominal variables to the real economy.

Retailers and Final Good Producer There is a fixed mass of retailers $i \in [0,1]$. Each retailer produces a differentiated variety $\widetilde{y}_{it}$ using the heterogeneous production firms' good as its only input: $\widetilde{y}_{it} = y_{it}$, where y_{it} is the amount of the undifferentiated good demanded by retailer i. Retailers set a relative price for their variety $\widetilde{p}_{it}$ but must pay a quadratic price adjustment cost $\frac{\varphi}{2}\left(\frac{\widetilde{p}_{it}}{\widetilde{p}_{it-1}}-1\right)^2 Y_t$, where Y_t is the final good. The retailers' demand curve is generated by the representative final good producer, which has production function $Y_t = \left(\int \widetilde{y}_{it}^{\frac{\gamma-1}{\gamma}}\,\mathrm{d}i\right)^{\frac{\gamma}{\gamma-1}}$, where γ is the elasticity of substitution over intermediate goods. This final good is the numeraire.

The retailers and final good producers aggregate into the familiar New Keynesian Phillips Curve:

$$\log \Pi_t = \frac{\gamma-1}{\varphi}\log\frac{p_t}{p^*} + \beta\mathbb{E}_t\log\Pi_{t+1}, \tag{7}$$

where $p^* = \frac{\gamma-1}{\gamma}$ is the steady state relative price of the heterogeneous production firm output.[10] The Phillips Curve links the New Keynesian block to the investment block through the relative price p_t. When aggregate demand for the final good Y_t increases, retailers must increase production of their differentiated goods. Because of the nominal rigidities, this force increases demand for the heterogeneous firms' goods y_{it}, which increases their relative price p_t and generates inflation through (7).

Capital Good Producer There is a representative capital good producer who produces new aggregate capital using the technology $\Phi(\frac{I_t}{K_t})K_t$, where I_t are units of the final good used to produce capital, $K_t = \int k_{jt}\,\mathrm{d}j$ is the aggregate capital stock at the beginning of the period, $\Phi(\frac{I_t}{K_t}) = \frac{\hat{\delta}^{1/\phi}}{1-1/\phi}\left(\frac{I_t}{K_t}\right)^{1-1/\phi} - \frac{\hat{\delta}}{\phi-1}$, and $\hat{\delta}$ is the steady-state investment rate.[11] Profit maximization pins down the relative price of capital as

$$q_t = \frac{1}{\Phi'(\frac{I_t}{K_t})} = \left(\frac{I_t/K_t}{\hat{\delta}}\right)^{1/\phi}. \tag{8}$$

Monetary Authority The monetary authority sets the nominal risk-free interest rate R_t^{nom} according to the Taylor rule $\log R_t^{\mathrm{nom}} = \log\frac{1}{\beta} + \varphi_\pi \log \Pi_t + \varepsilon_t^{\mathrm{m}},$ where $\varepsilon_t^m \sim N(0, \sigma_m^2)$, φ_π is the weight on inflation in the reaction function, and $\varepsilon_t^{\mathrm{m}}$ is the monetary policy shock.

3.3 Representative Household and Equilibrium

There is a representative household with preferences over consumption C_t and labor supply L_t represented by the expected utility function

$$\mathbb{E}_0 \sum_t^\infty \beta^t \left(\log C_t - \Psi L_t\right),$$

where β is the discount factor and Ψ controls the disutility of labor supply. The household owns all firms in the economy. We study perfect foresight transition paths with respect

[10] We focus directly on the linearized formulation for computational simplicity.

[11] Because the capital quality shock follows a truncated log-normal process, the steady-state investment rate is $\hat{\delta} = (1-(1-\delta)\mathbb{E}[\omega])(1+\frac{k_0\overline{\mu}}{K^*})$, where K^* is the steady-state capital stock and $\overline{\mu}$ the steady-state level of new entrants. For more details see Supplemental Materials D.

to aggregate states, so the stochastic discount factor and nominal interest rate are linked through the Euler equation for bonds, $\Lambda_{t+1} = \frac{1}{R_t^{\text{nom}}/\Pi_{t+1}}$.

An equilibrium is a set of value functions $v_t(z, n)$; decision rules $k'_t(z, n)$, $b'_t(z, n)$, $l_t(z, n)$; measure of firms $\mu_t(z, \omega, k, b)$; debt price schedule $\mathcal{Q}_t(z, k', b')$; and prices w_t, q_t, p_t, Π_t, Λ_{t+1} such that (i) all firms optimize, (ii) lenders price default risk competitively, (iii) the household optimizes, (iv) the distribution of firms is consistent with decision rules, and (v) all markets clear. Supplemental Materials D precisely defines an equilibrium of our model.

4 Channels of Monetary Transmission

Before performing the quantitative analysis, we theoretically characterize the channels through which monetary policy affects investment in our model. This exercise identifies the key sources of heterogeneous responses across firms, which motivates our calibration in Section 5.

Monetary policy experiment We study the effect of an unexpected innovation to the Taylor rule ε_t^{m} followed by a perfect foresight transition back to steady state. This approach allows for clean analytical results because there is no distinction between ex-ante expected real interest rates and ex-post realized real interest rates. We focus on financially constrained firms as defined in Proposition 1 because they make up more than 99.4% of the firms in our calibration.

Impact on decision rules The optimal choice of investment k' and borrowing b' satisfy the following two conditions:

$$q_t k' = \ n + \frac{1}{R_t(z, k', b')} b' \tag{9}$$

$$(q_t - \varepsilon_{Q,k'}(z, k', b') \frac{\mathcal{Q}_t(z, k', b') b'}{k'}) \frac{R_t^{\text{sp}}(z, k', b')}{1 - \varepsilon_{R,b'}(z, k', b')} = \frac{1}{R_t} \mathbb{E}_t \left[\text{MRPK}_{t+1}(z', k') \right] \tag{10}$$

$$+ \frac{1}{R_t} \frac{\mathbb{C}ov_t(\text{MRPK}_{t+1}(z', \omega' k'), 1 + \lambda_{t+1}(z', \hat{n}_{t+1}(z', \omega', k', b')))}{\mathbb{E}_t[1 + \lambda_{t+1}(z', \hat{n}_{t+1}(z', \omega', k', b')))]}$$

$$- \frac{1}{R_t} \mathbb{E}_{\omega'} \left[v_{t+1}^0(\omega', k', b') g_z(\underline{z}(\omega', k', b') | z) \underline{\hat{z}}_{t+1}(\omega', k', b') \right],$$

where R_t is the real risk-free rate between t and $t+1$, $R_t(z,k',b') = \frac{1}{\mathcal{Q}_t(z,k',b')}$ is the firm's implied interest rate schedule, $\varepsilon_{Qk'}(z,k',b')$ is the elasticity of the bond price schedule with respect to investment k', $R_t^{\text{sp}}(z,k',b') = R_t(z,k',b')/R_t^{\text{nom}}$ is a measure of the borrowing spread, $\varepsilon_{Rb'}(z,k',b')$ is the elasticity of the interest rate schedule with respect to borrowing, $\lambda_t(z,n)$ is the Lagrange multiplier on the non-negativity constraint on dividends, $\underline{z}_t(\omega,k,b)$ is the default threshold in terms of productivity (which inverts the net worth threshold defined in Proposition 1), $v_t^0(\omega,k,b) \equiv v_t(\underline{z}_t(\omega,k,b), \hat{n}_t(\underline{z}_t(\omega,k,b),\omega,k,b))$ is the value of the firm evaluated at the default threshold, $g_z(z'|z)$ is the density of z' conditional on z, and $\hat{\underline{z}}_{t+1}(\omega',k',b') \equiv \frac{\partial \underline{z}_{t+1}(\omega',k',b')}{\partial k'} + \frac{\partial \underline{z}_{t+1}(\omega',k',b')}{\partial b'}(q_t - \varepsilon_{Q,k'}\frac{\mathcal{Q}_t(z,k',b')b'}{k'})\frac{R_t(z,k',b')}{1-\varepsilon_{R,b'}(z,k',b')]}$. Condition (9) is the non-negativity constraint on dividends and condition (10) is the intertemporal Euler equation. The expectation and covariances in this expression are only taken over the states in which the firm does not default.

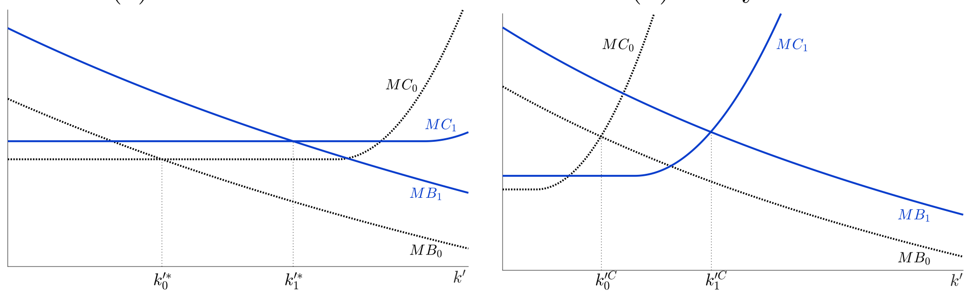
The marginal cost of capital is the product of two terms. The first term, $q_t - \varepsilon_{Q,k'}(z,k',b')\frac{\mathcal{Q}_t(z,k',b')b'}{k'}$, is the relative price of capital goods q_t net of the interest savings due to higher capital, $\varepsilon_{Q,k'}(z,k',b')\frac{\mathcal{Q}_t(z,k',b'{}'}{b}k'$. The interest savings result from the fact that, all else equal, higher capital decreases expected losses due to default to the lenders. The second term in the marginal cost of capital is related to borrowing costs, $\frac{R_t^{\text{sp}}(z,k',b')}{1-\varepsilon_{R,b'}(z,k',b')}$. A higher interest rate spread or a higher slope of that spread results in higher borrowing costs.

The marginal benefit of capital is the sum of three terms. The first term, $\frac{1}{R_t}\mathbb{E}_t\left[\text{MRPK}_{t+1}(z',k')\right]$, is the expected return on capital discounted by the real interest rate. The second term, $\frac{1}{R_t}\frac{\mathbb{C}ov_t(\text{MRPK}_{t+1}(z',\omega'k'),1+\lambda_{t+1}(z',\omega',k',b'))}{\mathbb{E}_t[1+\lambda_{t+1}(z',\omega',k',b'))]}$, captures the covariance of the return on capital with the firm's shadow value of resources. The third term captures how additional investment affects the firm's default probability and, therefore, the value of the firm. In our calibration, this term is negligible because the value of the firm close to the default threshold, $v_{t+1}^0(\omega',k',b')$, is essentially zero.

Figure 2 plots the marginal benefit and marginal cost schedules as a function of capital accumulation k'. In order to illustrate the key economic mechanisms, we compare how these curves shift following an expansionary monetary policy shock for two extreme examples of firms. These firms share the same level of productivity but the first firm has high net worth and is currently risk-free (though it is still constrained in the sense of Proposition 1), while

FIGURE 2: Response to Monetary Policy for Risk-Free and Risky Firms

(a) Risk-Free Firm (b) Risky Firm



Notes: Marginal benefit and marginal cost curves as a function of capital investment k' for firms with same productivity. Left panel is for a firm with high initial net worth and right panel is for a firm with low initial net worth. Marginal cost curve is the left-hand side of (10) and marginal benefit the right-hand side of (10). Dashed black lines plot the curves before an expansionary monetary policy shock, and solid blue lines plot the curves after the shock.

the second has low net worth and is risky constrained.

Risk-Free Firm The left panel of Figure 2 plots the two schedules for the risk-free firm. The marginal cost curve is flat when capital accumulation k' can be financed without incurring default risk, but becomes upward sloping when the borrowing required to achieve k' creates default risk and therefore a credit spread. The marginal benefit curve is downward sloping due to diminishing returns to capital. In the initial equilibrium, the firm is risk-free because the two curves intersect in the flat region of the marginal cost curve.

The expansionary monetary shock shifts both the marginal benefit and marginal cost curves. The marginal benefit curve shifts out for two reasons. First, the shock decreases the real interest rate, which decreases the firm's discount rate R_t and therefore increases the discounted return on capital. Second, the shock also changes the relative price of output p_{t+1}, the real wage w_{t+1}, and the relative price of undepreciated capital q_{t+1} due to general equilibrium effects. In our calibration, these changes increase the return on capital $\text{MRPK}_{t+1}(z, k')$ and therefore further shift out the marginal benefit curve. Third, the shock also affects the covariance term and the change in default threshold, which further shifts out the marginal benefit curve.

The marginal cost curve shifts up because the increase in aggregate investment demand increases the relative price of capital q_t. In the new equilibrium, the firm has increased its capital and remains risk-free because the marginal benefit and marginal cost curves still intersect along the flat region of the marginal cost curve.

Risky Firm The right panel of Figure 2 plots how the marginal benefit and marginal cost curves shift for the risky firm. Because this firm has low initial net worth n, it needs to borrow more than the risk-free firm to achieve the same level of investment. Hence, its marginal cost curve is upward-sloping over a larger region of net worth.

The key difference between the risky and the risk-free firm is how monetary policy shifts the marginal cost curve. As with the risk-free firm, the curve shifts up because the relative price of capital q_t increases, but there are now two additional effects. First, monetary policy increases net worth n, which decreases the amount the firm needs to borrow to finance any level of investment and therefore extends the flat region of the marginal cost curve. The increase in net worth can be decomposed according to:

$$\frac{\partial \log n}{\partial \varepsilon_t^{\mathrm{m}}} = \frac{1}{1-\nu-\theta}\left(\frac{\partial \log p_t}{\partial \varepsilon_t^{\mathrm{m}}} - \nu \frac{\partial \log w_t}{\partial \varepsilon_t^{\mathrm{m}}}\right)\frac{\iota_t(z,\omega k)}{n} + \frac{\partial \log q_t}{\partial \varepsilon_t^{\mathrm{m}}}\frac{q_t(1-\delta)\omega k}{n} + \frac{\partial \log \Pi_t}{\partial \varepsilon_t^{\mathrm{m}}}\frac{b/\Pi_t}{n}, \tag{11}$$

where $\iota_t(z,\omega k) = \max_l p_t z(\omega k)^\theta l^\nu - w_t l$. This expression (11) contains three ways that monetary policy affects cash flows. First, monetary policy affects current revenues by changing the relative price of output p_t net of real labor costs νw_t. Second, monetary policy affects the value of firms' undepreciated capital stock by changing the relative price of capital q_t. Finally, monetary policy changes the real value of nominal debt through inflation Π_t.

The second key difference in how monetary policy affects the risky firm's marginal cost curve is that it flattens the upward-sloping region, reflecting reduced credit spreads. Recall that, in the event of default, lenders recover $\alpha q_{t+1}\omega_{jt+1}k_{jt+1}$ per unit of debt; since the shock increases the relative price of capital q_{t+1}, it also increases the recovery rate, which reduces credit spreads. This channel is reminiscent of the "financial accelerator" in Bernanke, Gertler and Gilchrist (1999). Monetary policy also decreases the probability of default, but this effect is quantitatively small in our calibration.

Whether the risky firm is more or less responsive than the risk-free firm depends crucially on the size of these two shifts in the marginal cost curve. Theoretically, they may or may not be large enough to induce the risky firm to be more responsive to monetary policy than the risk-free firm. The goal of our calibration is to quantitatively discipline these shifts using our model.[12,13]

Relationship to other papers The simple framework in Figure 2 provides a powerful tool to organize various results in the existing literature. Bernanke, Gertler and Gilchrist (1999) develop a model in which firms' production functions are constant returns to scale, which results in a horizontal marginal benefit curve for investment. The level of investment is determined by the point at which this curve intersects the upward-sloping region of the marginal cost curve. Therefore, movements in the marginal cost curve have a stronger effect on how investment responds to monetary policy shocks, increasing the strength of the financial accelerator channel described above.

Jeenas (2019) develops a model in which firms face collateral constraints and a fixed cost of issuing debt but can accumulate liquid financial assets. This model implies that firms face two kinked marginal cost curves for financing investment: one corresponding to using liquid assets (which is flat until these assets are exhausted, and then becomes vertical) and another corresponding to new borrowing (which is flat – at a higher lever due an exogenous spread in borrowing costs – until firms reach the collateral constraint, at which point it becomes vertical). Optimal investment is determined by the mix of these two marginal costs curves that firms use when financing their investment. Many firms do not find it worthwhile to issue new debt, so their marginal source of investment finance is liquid assets. Therefore, firms that have more liquid assets have a larger flat region of their liquid-asset-cost curve

[12] Online Appendix B.2 shows that the heterogeneous responses to monetary policy we find in the data are primarily driven by expansionary shocks. While we do not emphasize that result due to its wide standard errors, it is potentially consistent with the analysis in Figure 2. Suppose that high-risk firms tend to position themselves at the point where their marginal cost curve just begins to be upward sloping. Then an expansionary shock will move these firms forward along the upward-sloping part – dampening their response relative to low-risk firms – while a contractionary shock will move them backward along the flat part – not dampening their response.

[13] We can use this analysis to conjecture how incorporating long-term debt would affect our results. If we were to increase the maturity of debt but hold all other parameters fixed, then we would of course decrease default probabilities (since firms will have to roll over less debt each period) and potentially flatten out the marginal cost curve. Therefore, we would also need to recalibrate the parameters in order to match the same average probability of default as in the current model. We expect that this recalibration would also imply a similar slope of the default probabilities with respect to borrowing and, therefore, a similar slope for the marginal cost curve. However, the marginal cost curve may become more responsive to monetary shocks if the resulting inflation significantly decreases the real value of long-term debt (as in Gomes, Jermann and Schmid (2016)).

Table 4
Fixed Parameters

Parameter	Description	Value
Household		
β	Discount factor	0.99
Firms		
ν	Labor coefficient	0.64
θ	Capital coefficient	0.21
δ	Depreciation	0.025
New Keynesian Block		
ϕ	Aggregate capital AC	4
γ	Demand elasticity	10
φ_π	Taylor rule coefficient	1.25
φ	Price adjustment cost	90

Notes: Parameters exogenously fixed in the calibration.

and are more responsive to monetary policy.

Cloyne et al. (2018) argue that young firms are more responsive to monetary shocks in the U.S. and the U.K. While we show in Online Appendix C.2 that age does not drive our empirical results, one can nevertheless interpret their findings through the lens of our model. One possible interpretation is that young firms face a steeper marginal cost curve than old firms, but young firms' marginal cost curves are also more sensitive to monetary policy. Another interpretation is that young firms' marginal benefit curves are themselves more responsive to monetary policy, for example if their product demand is more cyclically sensitive.

5 Parameterization

We now calibrate the model and verify that its steady state behavior is consistent with key features of the micro data.

5.1 Calibration

We calibrate the model in two steps. First, we exogenously fix a subset of parameters. Second, we choose the remaining parameters in order to match moments in the data.

Fixed Parameters Table 4 lists the parameters that we fix. The model period is one quarter, so we set the discount factor $\beta = 0.99$. We set the coefficient on labor $\nu = 0.64$. We choose the coefficient on capital $\theta = 0.21$ to imply a total returns to scale of 85%. Capital depreciates at rate $\delta = 0.025$ quarterly. We choose the elasticity of substitution in final goods production $\gamma = 10$, implying a steady state markup of 11%. This choice implies that the steady state labor share is $\frac{\gamma-1}{\gamma}\nu \approx 58\%$, close to the U.S. labor share reported in Karabarbounis and Neiman (2013). We choose the coefficient on inflation in the Taylor rule $\varphi_\pi = 1.25$, in the middle of the range commonly considered in the literature. We set the price adjustment cost parameter $\varphi = 90$ to generate a Phillips Curve slope equal to 0.1, as in Kaplan, Moll and Violante (2018). Finally, we set the curvature of the aggregate adjustment costs $\phi = 4$ following Bernanke, Gertler and Gilchrist (1999). This level of adjustment costs roughly matches the peak response of investment relative to the peak response of output estimated in Christiano, Eichenbaum and Evans (2005).

Fitted Parameters We choose the parameters listed in Table 5 to match the empirical moments reported in Table 6. The first set of parameters governs the idiosyncratic shocks (ρ, σ, and σ_ω), the second set governs the frictions to external finance (ξ and α), and the third set governs the firm lifecycle (m, k_0, and π_d). None of the statistics that we target are drawn from Compustat; later on, when we compare our model to the empirical results from Section 2, we will account for the selection of firms into Compustat.[14]

We target the dispersion of plant-level investment rates in Census micro data reported by Cooper and Haltiwanger (2006), which places discipline on the degree of idiosyncratic risk faced by firms.[15] We target a number of statistics related to firms' use of external finance. Following Bernanke, Gertler and Gilchrist (1999), we target a mean default rate of 3% as estimated in a survey of businesses by Dun and Bradstreet. We target an average firm-level

[14]At each step of the moment-matching process, we choose the disutility of labor supply Ψ to generate a steady state employment rate of 60%.

[15]We prefer to use the plant-level data from Cooper and Haltiwanger (2006), rather than firm-level data from other sources, because Cooper and Haltiwanger (2006) carefully construct measures of retirement and sales of capital to measure negative investment, which is important in our model because capital is liquid. Cooper and Haltiwanger (2006)'s sample is a balanced panel of plants that have survived at least sixteen years; to mirror this sample selection in the model, we condition on firms that have survived for twenty years, and our calibration results are robust to different choices of this cutoff.

Table 5

Fitted Parameters

Parameter	Description	Value
Idiosyncratic shock processes		
ρ	Persistence of TFP (fixed)	0.90
σ	SD of innovations to TFP	0.03
σ_ω	SD of capital quality	0.04
Financial frictions		
ξ	Operating cost	0.04
α	Loan recovery rate	0.54
Firm lifecycle		
m	Mean shift of entrants' prod.	3.12
k_0	Initial capital	0.18
π_d	Exogenous exit rate	0.01

Notes: Parameters chosen to match the moments in Table 6.

gross leverage ratio of 0.34 from the microdata underlying the Quarterly Financial Reports, as reported in Crouzet and Mehrotra (2020). We also target the share of firms with positive debt from Crouzet and Mehrotra (2020) in order to maintain a realistic distinction between gross and net leverage.[16]

The final two sets of moments are informative about firm lifecycle dynamics. We target the share of employment in firms of age less than one year, between one and ten years, and over ten years, all of which are informative about how quickly young firms grow. We also target the average exit rate and the share of firms in the economy at age one and two, which is informative about the exit rate of young firms. All of these statistics are computed from the Business Dynamics Statistics (BDS), the public-release sample of statistics aggregated from the Census' Longitudinal Business Database (LBD).

Table 6 shows that our model matches the targeted moments reasonably well despite the fact that it is overidentified. The model roughly matches the dispersion of investment rates, which captures the degree of idiosyncratic risk faced by firms. The model also matches the average default rate, but slightly overpredicts the average gross leverage ratio and underpre-

[16]We do not target credit spreads because observed credit spreads in the data are driven not only by the risk-neutral pricing of default risk, as in our model, but also by aggregate risk premia, which are outside our model. Consistent with this idea, the average annual credit spread in our model is 0.7%, compared to the 2.4% spread of BAA corporate bonds over the ten-year Treasury bond in the data.

TABLE 6
CALIBRATION TARGETS AND MODEL FIT

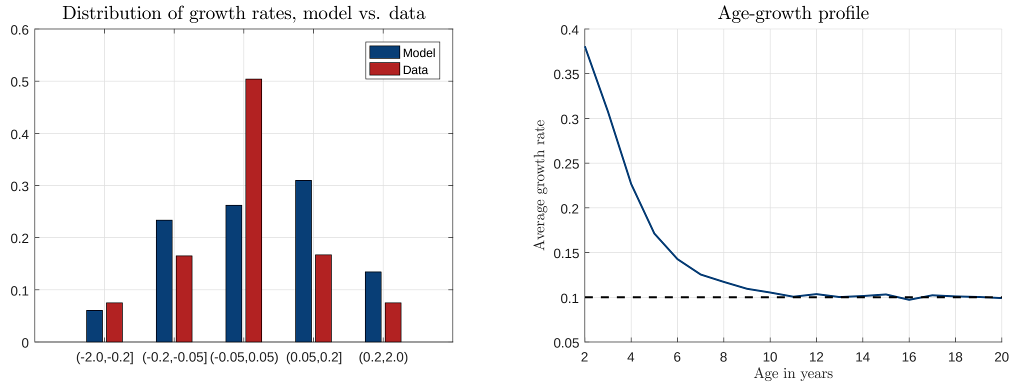
Moment	Description	Data	Model
Investment behavior (annual)			
$\sigma\left(\frac{i}{k}\right)$	SD investment rate	0.33	0.37
Financial behavior (annual)			
$\mathbb{E}\left[\text{default rate}\right]$	Mean default rate	3.0%	3.0%
$\mathbb{E}\left[\frac{b}{k}\right]$	Mean gross leverage ratio	0.34	0.49
$\text{Frac}(b>0)$	Firms w/ positive debt	0.81	0.70
Firm Growth (annual)			
N_1/N	Share of employment in age ≤ 1	0.03	0.02
N_{1-10}/N	Share of employment in age $\in(1,10)$	0.21	0.36
N_{11+}/N	Share of employment in age ≥ 10	0.76	0.62
Firm Exit (annual)			
$\mathbb{E}\left[\text{exit rate}\right]$	Mean exit rate	8.7%	8.8%
M_1/M	Share of firms at age 1	0.10	0.08
M_2/M	Share of firms at age 2	0.08	0.06

Notes: Empirical targets in the calibration. See main text for data sources.

dicts the fraction of firms with positive debt. The model matches the share of employment in young firms, but somewhat overpredicts the share of employment in 1-10 year old firms.

The calibrated parameters in Table 5 are broadly comparable to existing estimates in the literature. Idiosyncratic TFP shocks are less persistent and more volatile than measured aggregate TFP shocks, consistent with direct measurements of plant- or firm-level productivity. The calibrated loan recovery rate is 0.54, as in Khan, Senga and Thomas (2016). New entrants start with significantly lower productivity and capital than the average firm. The capital quality shock process implies that there is a $p_\omega = 0.59$ probability of receiving a zero shock $\log \omega_{jt} = 0$. Online Appendix D contains a formal discussion of identification using the local elasticities of moments with respect to parameters as well as the elasticities of estimated parameters with respect to moments (computed using the tools from Andrews, Gentzkow and Shapiro (2017)). The financial frictions in our calibrated model affect nearly all firms in the stationary distribution. Using the classification from Proposition 1, 52.8% of firms are risky constrained, 47.5% of firms are risk-free constrained, and 0.6% of firms are unconstrained.

FIGURE 3: Firm Lifecycle Dynamics, Model vs. Data



Notes: Panel (a) plots a histogram of the distribution of quarterly growth rates in the model vs. the data. In the model, we measure the firm's growth rate as $\frac{l_{jt+1}-l_{jt}}{0.5(l_{jt+1}+l_{jt})}$ where l_{jt} is employment. "Data" is the empirical distribution of quarterly establishment growth rates in the Business Employment Dynamics (BED) data, reported in Davis et al. (2010). Panel (b) plots the average firm-level growth rate as a function of age in steady state. We add 0.1 to the model's growth profile to account for the fact that our model does not feature trend growth. We exclude the first year of growth since firms in our model are born significantly below optimal scale; the average growth rate in year 1 is nearly 1.

5.2 Financial Heterogeneity in the Model and the Data

Online Appendix D analyzes firms' decision rules in steady state and identifies two key sources of financial heterogeneity across firms. The first source is lifecycle dynamics; firms are born below their optimal scale, i.e. $k_0 < k^*(z)$, and need to grow their capital stock. These young firms initially borrow in order to accumulate capital, increasing their risk of default and therefore borrowing costs. The second source of financial heterogeneity is TFP shocks z; a positive shock increases the firm's optimal scale $k^*(z)$, which again induces debt-financed capital accumulation. We show that firms more affected by these financial frictions have a positive "marginal propensity to invest" out of net worth.

The lifecycle dynamics of firms in our model are in line with the key features of the data emphasized by the firm dynamics literature. Panel (a) in Figure 3 compares the distribution of firm growth rates in steady state to the establishment-level data from the Business Employment Dynamics (BED) data, reported in Davis et al. (2010). The model matches the empirical distribution of growth rates fairly well except for the large mass of growth rates within $(-0.05, 0.05)$ in the data. This discrepancy is driven by the fact that 15% of firms have growth rates of exactly zero; these observations likely correspond to small, non-growing establishments, which are outside our model. Panel (b) in Figure 3 shows that the model produces a negative correlation between age and growth, as in the data (and comparable to the model in Clementi and Palazzo (2016)).

Online Appendix D and Supplemental Materials F further analyze the behavior of the model in steady state and compares it to the data. First, we further analyze the lifecycle dynamics of firms. Second, we show that the joint distribution of investment and leverage rates in our model is comparable to Census and Compustat data. Finally, we compare our model's sample of public and private firms to the data.

6 Quantitative Monetary Policy Analysis

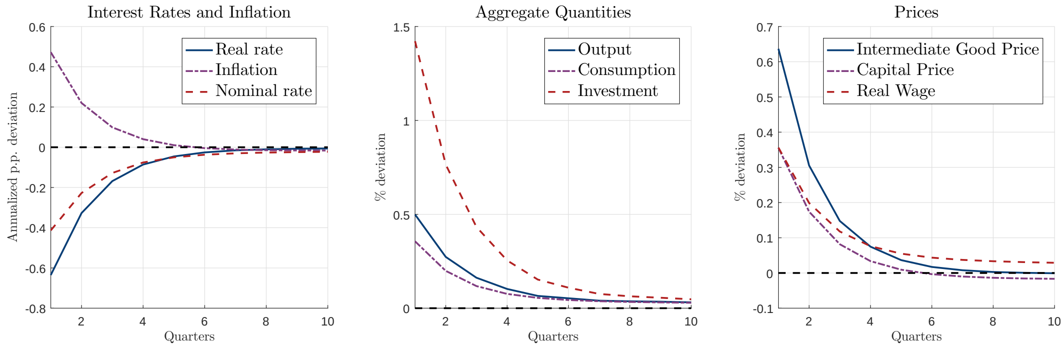
We now quantitatively analyze the effect of a monetary policy shock $\varepsilon_t^{\mathrm{m}}$. Section 6.1 begins the analysis by computing the aggregate impulse responses to an expansionary shock in our calibrated model. Section 6.2 then studies the heterogeneous effects of monetary policy across firms and shows that, consistent with the empirical results from Section 2, firms with high default risk are less responsive to monetary policy. Finally, Section 6.3 performs a simple calculation to show that the aggregate effect of monetary policy may depend on the distribution of default risk across firms.

The economy is initially in steady state and unexpectedly receives a $\varepsilon_0^{\mathrm{m}} = -0.0025$ innovation to the Taylor rule which reverts to 0 according to $\varepsilon_{t+1}^{\mathrm{m}} = \rho_m \varepsilon_t^{\mathrm{m}}$ with $\rho_m = 0.5$. We compute the perfect foresight transition path of the economy as it converges back to steady state.

6.1 Aggregate Response to Monetary Policy

Figure 4 plots the responses of key aggregate variables to this expansionary shock. The shock lowers the nominal interest rate and, because prices are sticky, also lowers the real interest rate. The lower real interest rate stimulates investment demand by shifting out the marginal benefit of investment, as discussed in Section 4. It also stimulates consumption demand from the household due to the standard intertemporal substitution. The higher aggregate demand for goods changes other prices in the economy, further shifting the marginal benefit and marginal costs curves for investment. Overall, investment increases by approximately

Figure 4: Aggregate Responses to Expansionary Monetary Shock



Notes: Aggregate impulse responses to a $\varepsilon_0^{\mathrm{m}} = -0.0025$ innovation to the Taylor rule which decays at rate $\rho_m = 0.5$. Computed as the perfect foresight transition in response to a series of unexpected innovations starting from steady state.

1.4%, consumption increases by 0.4%, and output increases by 0.5%. These magnitudes are broadly in line with the peak effects of monetary policy shocks estimated in Christiano, Eichenbaum and Evans (2005); for a similarly-sized change in the nominal interest rate, they find that investment increases by approximately 1%, consumption increases by 0.2%, and output increases by 0.5%.[17]

6.2 Heterogeneous Responses to Monetary Policy

Model-Implied Regression Coefficients In order to directly compare our model to the data, we simulate a panel of firms in response to a monetary shock and estimate our empirical specification (2) on the simulated data:[18] $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$. We account for the sample selection into Compustat by conditioning on firms that have survived at least seven years, which is around the median time to IPO reported in Wilmer et al. (2017). Online Appendix D shows that the behavior of the model's public firms vs. private firms compares fairly well to the data along certain dimensions. We assume

[17] Our model does not generate the hump-shaped aggregate responses emphasized by Christiano, Eichenbaum and Evans (2005). We could do so by incorporating adjustment costs to investment rather than capital. However, in order to be consistent with the hump-shaped responses of consumption and employment, we would also need to add habit formation and potentially labor adjustment costs. While interesting, this extension is outside the scope of this paper, whose goal is to focus on the role of financial heterogeneity in monetary transmission using an otherwise basic New Keynesian model.

[18] In the model, we use time fixed effects rather than sector-time fixed effects because our model does not contain multiple sectors. In addition, we do not include the subset of control variables Z_{jt} which are outside our model, such as fiscal quarter.

Table 7
Empirical results, model vs. data

	Standardized		Not Standardized	
	Data (1)	Model (2)	Data (3)	Model (4)
demeaned leverage × ffr shock	-0.57^{**}	-1.30	-3.12^{**}	-6.84
	(0.29)		(1.47)	
Firm controls	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
R^2	0.12	0.58	0.12	0.58

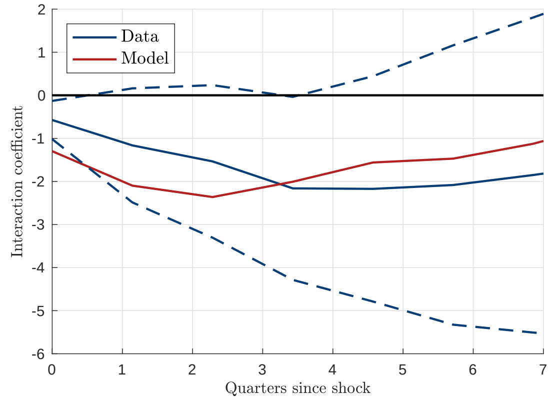
Notes: Column (1) show the results from running the specification $\Delta \log k_{jt} = \alpha_j + \alpha_{st} + \beta(\ell_{jt-1} - \mathbb{E}_j[\ell_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where all variables are defined in the notes for Table 3. Column (2) estimates this empirical specification on the simulated data. In the model, we use time fixed effects rather than sector-time fixed effects and we do not include the subset of control variables Z_{jt} which are outside our model, such as fiscal quarter. The sample period is four quarters before the monetary shock through ten quarters after the shock. To mirror the sample selection into Compustat, we condition on firms that have survived at least seven years. Columns (3) and (4) do not standardize $\ell_{jt} - \mathbb{E}_j[\ell_{jt}]$.

that the high-frequency shocks $\varepsilon_t^{\mathrm{m}}$ that we measure in the data are the innovations to the Taylor rule in the model. We estimate the regressions using data from one year before the shock to ten quarters after the shock.

We estimate the empirical specification (2) using leverage ℓ_{jt} as the measure of financial position x_{jt} for two main reasons. First, it is not obvious how to map our model to measured distance to default because measured distance to default is based on the volatility of firms' equity values, which are partly driven by equity risk premia due to aggregate shocks. Second, there is a tight relationship between leverage and default risk in the model. This relationship occurs because there is a monotonic relationship between leverage and net worth (shown in Figure 24 in Supplemental Materials F), and firms only default when net worth falls below the default threshold $\underline{n}_t(z)$.

Columns (1) and (2) of Table 7 shows that high-leverage firms are less responsive to monetary policy in the model, as in the data. In the data, a firm with one standard deviation more leverage than the average firm has an investment semi-elasticity that is approximately -0.57 percentage points lower than the average firm; in the model, that firm has an approximately -1.47 lower semi-elasticity (which is just outside the 95% confidence interval of the empirical estimate). The R^2 of the regression is lower in the data than in the model, indi-

Figure 5: Dynamics of differential responses, model vs. data



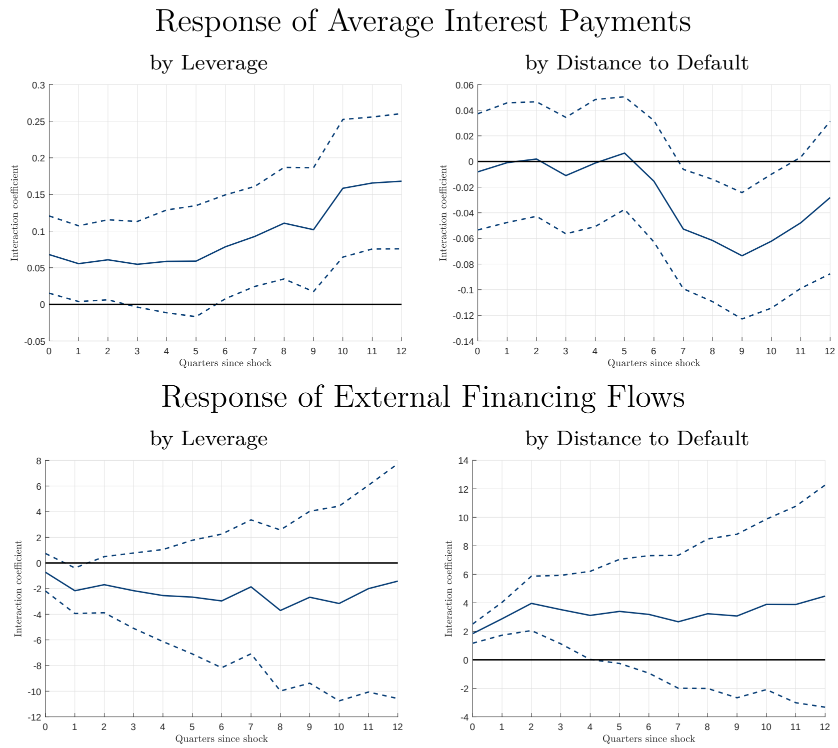
Notes: dynamics of the interaction coefficient between leverage and monetary shocks. Reports the coefficient β_h over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_h(\ell_{jt-1} - \mathbb{E}_j[\ell_{jt}])\varepsilon_t^{\text{m}} + \mathbf{\Gamma}_h' Z_{jt-1} + \mathbf{\Gamma}_{2h}'(\ell_{jt-1} - \mathbb{E}_j[\ell_{jt}])Y_{t-1} + e_{jt}$, where all table notes from Columns (1) and (2) of Table 7 apply. Dashed lines report 90% error bands.

cating that the data contain more unexplained variation than the model. Columns (3) and (4) estimate the same regression except that they do not standardize the leverage variable (so that the magnitudes of the coefficients can be interpreted as a reduced-form elasticity of the responsiveness with respect to leverage). The coefficient increases by roughly an order of four in both the model and the data, consistent with the fact that the dispersion of leverage in our model is similar to the data.

Figure 5 shows that the dynamics of the differential responses of investment are persistent in the model, consistent with the data. In this figure, we estimate the local projection (4) on our model-simulated data using standardized leverage. Quantitatively, the model's differences mostly stay within the data's 90% confidence interval up to eight quarters after the shock.

These heterogeneous responses indicate that high-leverage firms are positioned on the upward-sloping part of their marginal cost curve from Figure 2, and that the shifts in that curve are quantitatively dominated by the shift out in the marginal benefit curve. This mechanism has two implications for the data, both of which are confirmed in Figure 6. First, the top panel shows that firms with high default risk – either those with high leverage or low distance to default – see an increase in their borrowing costs relative to firms with low default risk. In the data, we measure borrowing costs as average interest payments

Figure 6: Testable Implications of Model Mechanism for the Data



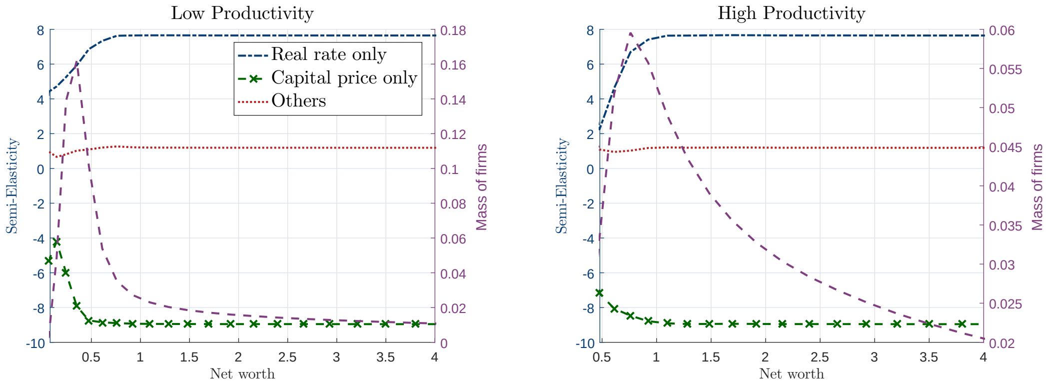
Notes: Reports the coefficient β_h from $y_{jt+h} = \alpha_{jh} + \alpha_{sth} + \beta_h(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}'_h Z_{jt-1} + e_{jth}$, where y_{jt+h} is either the average interest rate in period $t+h$ or the external financing flows between periods $t+h$ and t, and all notes from Columns (1) and (2) of Table 7 apply. Dashed lines report 90% error bands.

relative to lagged liabilities; therefore, the response of interest payments after eight to ten quarters (which is approximately the average maturity of debt in Compustat) most closely corresponds to interest payments on new borrowing in our model.[19]

The second implication of our model's mechanism is that low-risk firms can afford to access more external finance following a monetary shock; Figure 6 shows that this implication also holds in the data. We define external financing flows as the sum of the change in total debt plus the change in total equity, scaled by assets. We then estimate the dynamic empirical specification (4) with this measure of financing flows on the left-hand side. We include equity because it is a source of external finance for firms in the data. Figure 6 shows

[19]The borrowing costs of high-leverage firms also rise relative to the borrowing costs of low-leverage firms in our model, but the quantitative magnitude of this spread is smaller than in the data. However, the marginal cost curve in the model is determined by both measured spreads and the shadow value of the net worth ($\lambda_t(z,n)$ from Section 4). We do not compare the quantitative implications of the model to the data because our model is not calibrated to match credit spreads, the empirical response of credit spreads to monetary policy are contaminated by changes in risk premia, and credit spreads do not directly correspond to the shadow value $\lambda_t(z,n)$.

FIGURE 7: Decomposition of Semi-Elasticity of Capital to Monetary Policy Shock



Notes: Semi-elasticity of capital in response to monetary shock and the initial distribution of firms. "Real rate only" refers to feeding in the path of the real interest rate R_t but keeping all other prices fixed at steady state. "Capital price only" refers to feeding in the path of the relative price of capital q_t but keeping all other prices fixed at steady state. "Others" refers to feeding in all other prices but keeping the real rate and capital price fixed at steady state. Dashed purple line is the initial distribution of firms. Left panel plots for low level of idiosyncratic productivity z. Right panel plots for high level of idiosyncratic productivity z.

that, in the data, firms with low leverage or high distance to default access more external finance following a monetary shock.

Decomposition of Channels Driving Heterogeneous Responses In order to better understand the sources of these heterogeneous responses across firms, we now decompose the channels through which monetary policy affects firms' investment into three different channels. First, we compute the "direct effect" of monetary policy by feeding in the path of the real interest rate R_t and hold all other prices fixed at steady state. Second, we feed in the series of the relative price of capital q_t but keep all other prices fixed. Finally, we feed in all other prices in the model – the relative price of output p_t, the real wage w_t, and inflation Π_t – but keep the real interest rate R_t and relative price of capital q_t fixed. Figure 7 plots the semi-elasticity of investment to each of these series in the initial period of the shock, conditional on a particular level of idiosyncratic TFP.

The results in Figure 7 indicate that the heterogeneous responses in our model are driven by the fact that firms with high default risk face a steeper marginal cost curve for financing investment. The decrease in the real interest rate shifts out the marginal benefit curve in Figure 2; firms with higher default risk – which, in Figure 7, have low net worth – are less responsive to this change because they have a steeper marginal cost curve. The increase in the relative price of capital has two offsetting effects. On the one hand, it makes new capital more expensive and therefore shifts the marginal cost curve up for all firms; on the other hand, it increases the recovery rate of lenders in the event of default, which flattens out the marginal cost curve for firms with low net worth. On net, the former force outweighs the latter, but firms with low net worth are more strongly affected by the latter. Finally, the increase in all other prices also shifts out the marginal benefit curve by increasing the revenue product of capital; once again, this effect is offset for low net worth firms by their steeper marginal cost curve.[20]

The fact that both the direct and indirect effects play a quantitatively important role in driving the investment channel of monetary policy contrasts with Auclert (2019)'s and Kaplan, Moll and Violante (2018)'s decomposition of the consumption channel. In the context of a household's consumption-savings problem, they find that the contribution of the direct effect of lower real interest rates is small relative to the indirect general equilibrium effects of higher labor income. In our model, direct interest rate effects are stronger because firms are more price-sensitive than households. In fact, without any financial frictions at all, the partial equilibrium elasticity of investment with respect to interest rates would be nearly infinite (see Koby and Wolf (2020) for a discussion of the role of interest-elasticities in heterogeneous firm macro models). In contrast, households are less price sensitive because of consumption-smoothing motives, so these direct effects are less important.

6.3 Aggregate Implications of Financial Heterogeneity

In this subsection, we illustrate two ways in which financial heterogeneity matters for understanding the aggregate transmission mechanism. We first show that the aggregate effect of a given monetary shock may be smaller when the initial distribution of firms features higher default risk. Nevertheless, we show that the aggregate effect of monetary policy is *larger* in our model than in a comparable version of the model without any financial frictions (which collapses to a representative firm).

[20]The changes in these other prices also increase net worth by increasing cash flow and increasing the relative value of undepreciated capital, which moves firms along the x-axis of Figure 7.

Table 8
Aggregate Response Depends on Initial Distribution

(everything rel. to steady state)	**Bad Distribution**	**Medium distribution**
Avg. capital response	0.67	0.84
Avg. net worth	0.48	0.75
Frac. risky constrained	1.37	1.17

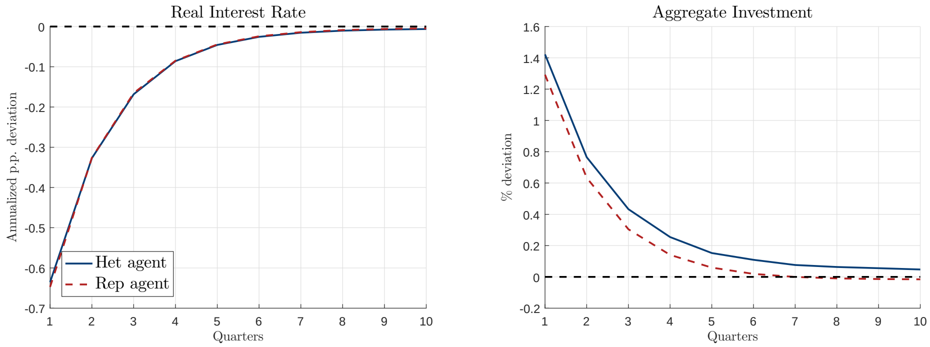
Notes: Dependence of aggregate response on initial distribution. We compute the change in aggregate capital for different initial distributions as described in the main text. “Bad distribution” corresponds to $\widehat{\omega} = 1$ and “Medium distribution” corresponds to $\widehat{\omega} = 0.5$.

State Dependence of Aggregate Transmission In order to illustrate the quantitative scope for state dependence, we fix the semi-elasticity of capital with respect to monetary policy as a function of firms' state variables and vary the initial distribution of firms. We vary the initial distribution of firms $\mu(z,n)$ by taking the weighted average of two reference distributions. The first reference distribution is the steady-state distribution $\mu^*(z,n)$. The second reference distribution $\widetilde{\mu}(z,n)$ assumes that the conditional distribution of net worth for every level of productivity is equal to the distribution of net worth conditional on a low realization of productivity in steady state. We then compute the initial distribution as a weighted average of these two reference distributions, $\mu(z,n) = \hat{\omega}\widetilde{\mu}(z,n) + (1-\hat{\omega})\mu^*(z,n)$.

Table 8 shows that the average response of capital accumulation is 33% smaller starting from the low net-worth distribution $\widetilde{\mu}(z,n)$ than starting from the steady state distribution $\mu^*(z,n)$. In that distribution, average net worth is 52% lower and there are 37% more risky constrained firms in the low-net worth distribution than in the steady state distribution. Placing a weight $\hat{\omega} = 0.5$ on the steady state distribution increases the aggregate capital response, but it is still 16% below the response starting from steady state.

These results suggests a potentially powerful source of time-variation in the aggregate transmission mechanism: monetary policy is less powerful when net worth is low and default risk is high. Of course, a limitation of this analysis is that we have varied the initial distribution exogenously. The natural next step in this analysis is to incorporate various business cycle shocks into our model and study the shapes of the distributions that actually arise in equilibrium. We also emphasize that aggregate state dependence is an implication of the micro-level behavior of our model and has not been validated using aggregate time-series

Figure 8: Aggregate Impulse Responses in Full Model vs. Rep Firm Model



Notes: "Het agent" refers to calibrated heterogeneous firm model from the main text. "Rep agent" refers to a version of the model in which the heterogeneous production sector is replaced by a representative firm with the same production function and no financial frictions.

evidence.[21]

Comparison to Frictionless Model We now compare our full model to a model in which we eliminate financial frictions. We do so by removing the non-negativity constraint on dividends; in this case, the investment block of the model collapses to a financially unconstrained representative firm (see Khan and Thomas (2008) Appendix B). Figure 8 shows that the impact effect of monetary policy on investment is larger in our full model than in the representative firm benchmark. Hence, despite the fact that 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 expansionary monetary policy increases firms' net worth.

7 Conclusion

In this paper, we have argued that financial frictions dampen the response of investment for firms with high default risk. Our argument had two main components. First, we showed in the micro data that firms with high leverage or low credit ratings invest significantly less than

[21] Tenreyro and Thwaites (2016) provide time-series evidence that monetary shocks are less powerful in recessions, which is broadly consistent with the implication of our model to the extent that firm-level net worth falls in recessions. However, it is difficult to estimate the contribution of default risk alone in driving this result given that the changes in the distribution are slow-moving and highly correlated with other relevant factors in the time series.

other firms following a monetary policy shock. Second, we built a heterogeneous firm New Keynesian model with default risk that is quantitatively consistent with these empirical results. In the model, monetary policy stimulates investment through a combination of direct and indirect effects. High-risk firms are less responsive to these changes because their marginal cost of investment finance is steeper than that of low-risk firms. The aggregate effect of monetary policy is primarily driven by these low-risk firms, which suggests a novel form of state dependence: monetary policy may be less powerful when default risk in the economy is higher.

Our results may be of independent interest to policymakers who are concerned about the distributional implications of monetary policy across firms. An often-discussed goal of monetary policy is to provide resources to viable but credit constrained firms. Many policymakers' conventional wisdom, built on the financial accelerator mechanism, suggests that constrained firms will significantly increase their capital investment in response to expansionary monetary policy. Our results imply that, instead, expansionary policy will stimulate the less risky firms in the economy to invest.

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Online Appendix for "Financial Heterogeneity and the Investment Channel of Monetary Policy" by Pablo Ottonello and Thomas Winberry

A Empirical Specification

This appendix justifies the choices in our baseline empirical specification (2). Subsection A.1 clarifies the type of permanent heterogeneity in responsiveness for which our specification controls by using only within-firm variation in financial position. Subsection A.2 shows that our results are qualitatively robust, but quantitatively weaker, if we do not control for differences in cyclical sensitivities across firms.

A.1 Controlling for Permanent Heterogeneity in Responsiveness

We discuss how our estimator controls for permanent heterogeneity in responsiveness using a simple example. Suppose the data generating process is

$$y_{jt} = \alpha_j + \lambda_t + \beta_j \varepsilon_t + \gamma x_{jt} \varepsilon_t + e_{jt} \tag{12}$$

where y_{jt} is an outcome of interest, ε_t is an aggregate shock, x_{jt} is a firm characteristic, $\beta_j = b\mathbb{E}_j[x_{jt}]$ is a permanent characteristic that controls the responsiveness of y_{jt} to ε_t, and e_{jt} is an exogenous error term. In the main text, the outcome of interest y_{jt} is investment, the firm characteristic x_{jt} is financial position, and the aggregate shock ε_t is a monetary policy shock. The assumption $\beta_j = b\mathbb{E}_j[x_{jt}]$ implies that the average value of the firm's financial position is proportional to the permanent heterogeneity in responsiveness β_j. The coefficient of interest to be estimated is γ, which measures how changes in the characteristic x_{jt} affect the response of y_{jt} to the aggregate shock ε_t.

We assume that the aggregate shock ε_t is exogenous and homoskedastic given the entire sample of x_{jt}, which we denote $\mathbf{x}$. That is, we assume (i) $\mathbb{E}[\varepsilon_t|\mathbf{x}] = 0$ and (ii) $\mathbb{E}[\varepsilon_t^2|\mathbf{x}] = \sigma^2$, though we can relax (i) to be conditioned only on the values of $\mathbf{x}$ up to date t in the discussion below. Our interpretation of this condition is that the particular aggregate shock

ε_t accounts for a vanishingly small proportion of the variation in x_{jt}. In our context, this assumption is consistent with the idea that monetary policy shocks account for a small fraction of fluctuations.

Demeaning the data generating process (12) within firm j gives $\widehat{y}_{jt} \equiv y_{jt} - \mathbb{E}_j[y_{jt}] = (\lambda_t - \mathbb{E}_j[\lambda_t]) + \beta_j\varepsilon_t + \gamma x_{jt}\varepsilon_t + e_{jt}$, which uses the facts that $\mathbb{E}_j[e_{jt}] = 0$ for all j, $\mathbb{E}_j[\varepsilon_t] = 0$ for all j, and $\mathbb{E}_j[x_{jt}\varepsilon_t] = \mathbb{E}_j[x_{jt}\mathbb{E}_j[\varepsilon_t|\mathbf{x}]] = 0$. As usual, one can estimate the time fixed effect $(\lambda_t - \mathbb{E}_j[\lambda_t])$ with time dummies, so we drop this term from the discussion going forward. Using the fact that $\beta_j = b\mathbb{E}_j[x_{jt}]$, we now have

$$\widehat{y}_{jt} = b\overline{x}_j\varepsilon_t + \gamma x_{jt}\varepsilon_t + e_{jt} \tag{13}$$

where $\overline{x}_j = \mathbb{E}_j[x_{jt}]$.

The typical within-firm fixed effects estimator will be biased due to an omitted variable problem. It estimates the misspecified model $\widehat{y}_{jt} = gx_{jt}\varepsilon_t + \nu_{jt}$. From (13), the residual ν_{jt} includes $b\overline{x}_j\varepsilon_t$, which is correlated with $x_{jt}\varepsilon_t$ in the cross-section of firms. Therefore, the estimator of g will not converge to the coefficient of interest γ. Intuitively, a high value of x_{jt} in the cross section may influence how the firm responds to the aggregate shock through the coefficient of interest γ or through the permanent responsiveness $b\overline{x}_j$.

Our estimator solves the omitted variable problem by making the regressor orthogonal to the omitted terms. From (13), we have $\widehat{y}_{jt} = \gamma(x_{jt} - \overline{x}_j)\varepsilon_t + (\gamma + b)\overline{x}_j\varepsilon_t + e_{jt}$. Our estimator omits the second term, $(\gamma + b)\overline{x}_j\varepsilon_t$, from the regression. However, this procedure will still yield consistent estimates of γ if $\mathbb{E}[(x_{jt} - \overline{x}_j)\varepsilon_t \times \overline{x}_j\varepsilon_t] = 0$. Our assumption of a homoskedastic shock ensures that this condition holds. Intuitively, a high value of $x_{jt} - \overline{x}_j$ will only influence how the firm responds to the aggregate shock through the coefficient of interest γ because its variation is relative to the permanent differences proxied by $\overline{x}_j$.

This simple example makes clear that the standard fixed effects estimator will yield biased estimates of the coefficient of interest γ if there are permanent differences in how firms respond to the aggregate shock ε_t. Table 9 shows that this is the case in our application; it estimates the standard specification $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta x_{jt-1}\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$. These results are qualitatively consistent with our main results in the sense that firms with lower

Table 9
Heterogeneous Responses, Not Demeaning Financial Position

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
leverage × ffr shock	-1.00***	-0.80***			-0.79***	-0.80*	-0.71
	(0.32)	(0.29)			(0.29)	(0.41)	(0.45)
$\mathbb{1}\{\text{cr\_}jt \geq A\}\times$ ffr shock			1.64		1.36		
			(1.36)		(1.39)		
dd × ffr shock				0.91*		0.53	0.71
				(0.52)		(0.52)	(0.54)
ffr shock							2.08***
							(0.59)
Observations	219402	219402	219402	151027	219402	151027	119750
R^2	0.113	0.124	0.120	0.141	0.124	0.142	0.151
Firm controls	no	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	yes	yes	no
Time clustering	yes	yes	yes	yes	yes	yes	yes

Notes: results from estimating variants of the baseline specification $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta x_{jt-1}\varepsilon_t^{\text{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where all variables are defined as in the main text or in the notes for Table 3. We have standardized leverage ℓ_{jt} and distance to default dd_{jt} over the entire sample, so their units are in standard deviations relative to the mean. Column (7) removes the sector-quarter fixed effect α_{st} and estimates $\Delta \log k_{jt+1} = \alpha_j + \alpha_{sq} + \gamma\varepsilon_t^{\text{m}} + \beta x_{jt-1}\varepsilon_t^{\text{m}} + \mathbf{\Gamma}_1' Z_{jt-1} + \mathbf{\Gamma}_2' Y_{t-1} + e_{jt}$, where Y_t is a vector with four lags of GDP growth, the inflation rate, and the unemployment rate.

leverage or higher distance to default are more responsive to monetary policy. However, these differences are smaller and less precisely estimated, indicating that permanent heterogeneity in responsiveness is quantitatively relevant in our sample. Table 9 also shows that firms with a higher credit rating are more responsive to changes in monetary policy. We did not include that variable in the main text because the within-firm variation in credit rating is limited.

A.2 Role of Differences in Cyclical Sensitivities Across Firms

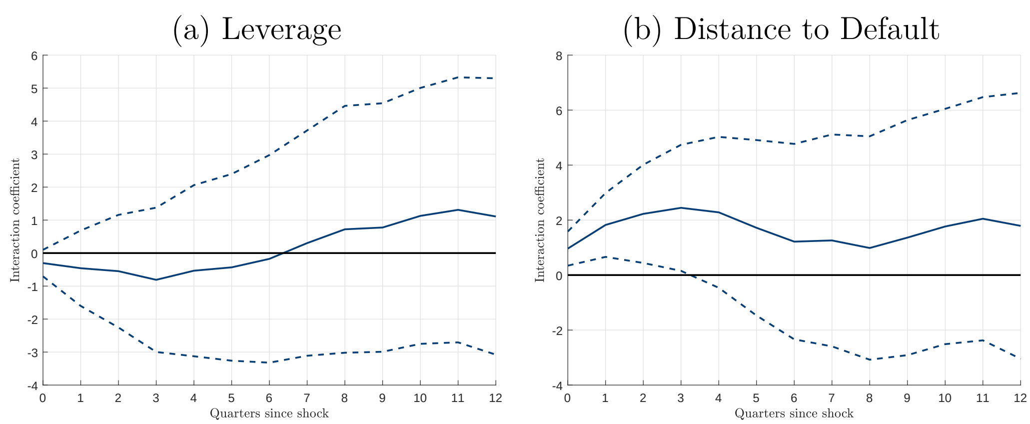
Our baseline specification (2) controls for the interaction between the firm's financial position ($x_{jt-1} - \mathbb{E}_j[x_{jt}]$) and lagged GDP growth in order to control for differences in cyclical sensitivities across firms. Our motivation for this choice is that the largest shocks in our sample occur at the beginning of the two recessions, so we want to ensure that our heterogeneous responses to monetary policy are not driven by differences in cyclical sensitivities across firms. Table 10 shows that excluding this control does not significantly affect the differential responses by distance to default, showing that our main results are robust to this

Table 10
Main Results, Not Controlling for Differences in Cyclical Sensitivities

	(1)	(2)	(3)	(4)
leverage × ffr shock	-0.30		-0.09	-0.07
	(0.24)		(0.32)	(0.51)
dd × ffr shock		0.96**	0.91**	1.11***
		(0.38)	(0.35)	(0.41)
ffr shock				2.14***
				(0.61)
Observations	219402	151027	151027	119750
R^2	0.124	0.141	0.142	0.151
Firm controls	yes	yes	yes	yes
Time sector FE	yes	yes	yes	no
Time clustering	yes	yes	yes	yes

Notes: results from estimating $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where all variables are defined as in the main text or in the notes for Table 3 except that Z_{jt-1} does not include the interaction of lagged GDP growth with demeaned financial position.

Figure 9: Dynamics, Not Controlling for Differences in Cyclical Sensitivities

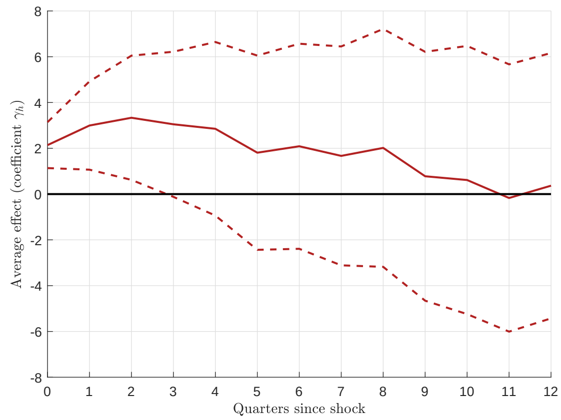


Notes: dynamics of the interaction coefficient between financial positions and monetary shocks over time. Reports the coefficient β_h over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_h(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}'_h Z_{jt-1} + e_{jt}$, where all variables are defined as in the main text or in the notes for Table 3 except that Z_{jt-1} does not include the interaction of lagged GDP growth with demeaned financial position.

concern. However, the differential responses by leverage become significantly weaker.

Figure 9 plots the dynamics of the differential responses from specification (2) without controlling for differential responses to GDP growth. Not controlling for these differences makes the long-run differences somewhat smaller and substantially increases the standard errors, suggesting that differences in cyclical sensitivities confounds inference about the mon-

FIGURE 10: Average Investment Response to Monetary Shock



Notes: results from estimating (14) from the text. Standard errors are two-way clustered by firms and time. Dashed lines report 90% error bands. We have normalized the sign of the monetary shocks $\varepsilon_t^{\mathrm{m}}$ so that a positive shock is expansionary corresponds to a decrease in interest rates.

etary shock. In any event, Figure 9 makes clear that our conclusion that long-run dynamics are imprecisely estimated is not due to controlling for differences in cyclical sensitivities.

B Additional Empirical Results

B.1 Dynamics of Average Effect of Monetary Policy

We estimate the specification

$$\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \gamma_h \varepsilon_t^{\mathrm{m}} + \beta_h (X_{jt-1} - \mathbb{E}_j[X_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}'_{1h} Z_{jt-1} + \mathbf{\Gamma}'_{2h} Y_{t-1} + e_{jt}, \quad (14)$$

where, as before, Y_t is a vector with four lags of GDP growth, the inflation rate, and the unemployment rate and X_{jt} is a vector of financial positions (leverage and distance to default). Figure 10 shows that the average response to monetary policy, γ_h, is hump-shaped and fairly persistent up to three years after the shock. However, these long-run effects are imprecisely estimated and not statistically significant three quarters after the shock and later. We have also found that these long-run effects are somewhat sensitive to the set of aggregate controls Y_{t-1}. Therefore, in the main text, we focus on the heterogeneous responses across firms, which are robustly estimated across a number of specifications.

Table 11
Expansionary vs. Contractionary Shocks

	(1)	(2)	(3)	(4)
leverage × ffr shock	-0.57**			
	(0.27)			
leverage × pos ffr shock		-0.61**		
		(0.28)		
leverage × neg ffr shock		-0.44		
		(0.93)		
dd × ffr shock			1.14***	
			(0.41)	
dd × pos ffr shock				1.34**
				(0.53)
dd × neg ffr shock				0.41
				(0.87)
Observations	219402	219402	151027	151027
R^2	0.124	0.124	0.141	0.141
Firm controls	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes

Notes: results from estimating variants of the baseline specification described in the main text and in the notes for Table 3. Columns (2) and (4) contain separate interactions for expansionary and contractionary shocks.

B.2 Expansionary vs. Contractionary Shocks

Table 11 separately estimates heterogeneous responses for expansionary and contractionary shocks. Although the heterogeneous responses by leverage or distance to default are only significant for expansionary shocks, the differences between the two are at best marginally significant. This result is largely due to the fact that there are relatively few observations of contractionary shocks in our sample, generating large standard errors.

B.3 Robustness Checks

Controlling for the information channel of monetary policy One concern about our monetary shocks $\varepsilon_t^{\mathrm{m}}$ is that the FOMC announcements on which they are based also release information about the future path of economic activity (see, for example, Nakamura and Steinsson (2018)). Table 12 show that our results are not driven by this information channel of monetary policy. Following Miranda-Agrippino and Ricco (2019), we control for information using the Greenbook forecast revisions between concurrent FOMC announce-

Table 12
Controlling for Greenbook Forecast Revisions

	(1)	(2)	(3)	(4)	(5)	(6)
leverage × ffr shock	-0.69**		-0.88**		-0.98***	
	(0.27)		(0.33)		(0.32)	
dd × ffr shock		1.18***		0.90*		0.86*
		(0.41)		(0.48)		(0.47)
Observations	219402	151027	219402	151027	219402	151027
R^2	0.124	0.141	0.124	0.141	0.124	0.141
Firm controls	yes	yes	yes	yes	yes	yes
Forecast rev controls	GDP	GDP	GDP Inflation	GDP Inflation	GDP Inflation Unemployment	GDP Inflation Unemployment

Notes: Results from estimating the baseline specification (2), including as controls in the interaction between our variable of interest, $x_{jt-1} - \mathbb{E}_j[x_{jt}]$, and forecast revisions of output growth, inflation, and unemployment in FOMC announcements.

Table 13
Controlling for Greenbook Forecasts

	(1)	(2)	(3)	(4)	(5)	(6)
leverage × ffr shock	-0.91***		-0.62*		-0.62	
	(0.28)		(0.31)		(0.43)	
dd × ffr shock		1.22***		1.12***		1.04*
		(0.43)		(0.39)		(0.56)
Observations	219402	151027	219402	151027	219402	151027
R^2	0.124	0.141	0.124	0.141	0.124	0.141
Firm controls	yes	yes	yes	yes	yes	yes
Forecast rev controls	GDP	GDP	GDP Inflation	GDP Inflation	GDP Inflation Unemployment	GDP Inflation Unemployment

Notes: Results from estimating the baseline specification (2), including as controls in the interaction between our variable of interest, $x_{jt-1} - \mathbb{E}_j[x_{jt}]$, and forecasts of output growth, inflation, and unemployment in FOMC announcements.

ments. Our main results are robust to including this control. In addition, Table 13 shows that our results are also robust to controlling for the level of the forecasts.

Results hold in the post-1994 sample Another concern is that our monetary shocks may become less powerful after the Fed began making formal policy announcements in 1994. Columns (1)-(3) of Table 14 show that our main results concerning heterogeneous responses continue to hold in the post-1994 sample. A potential concern about this later sample is that the Fed announcements contain more information revelation than in the past. Consistent with that concern, Columns (4)-(6) of Table 14 show that the results become stronger when

TABLE 14
POST-1994 ESTIMATES

	(1)	(2)	(3)	(4)	(5)	(6)
leverage × ffr shock	-0.71**		-0.28	-0.84**		-0.22
	(0.35)		(0.50)	(0.34)		(0.50)
dd × ffr shock		1.13**	1.01**		1.35***	1.24***
		(0.44)	(0.44)		(0.45)	(0.46)
Observations	174274	118496	118496	174274	118496	118496
R^2	0.138	0.154	0.155	0.138	0.154	0.155
Firm controls	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes	yes	yes
Controls Greenbook Forecast Revisions	no	no	no	yes	yes	yes

Notes: results from estimating variants of $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where all variables have been defined in the main text and the notes to Table 3. Columns (1)-(3) show the results of estimating our baseline model using with only data after 1994. Columns (4)-(6) include in the vector of firm-level controls Z_{jt-1} the interaction between our variable of interest, $x_{jt-1} - \mathbb{E}_j[x_{jt}]$, and forecast revisions of output growth in FOMC announcements.

we control for Greenbook forecast revisions of GDP growth (similarly to above).

Results robust to controlling for lagged investment Eberly, Rebelo and Vincent (2012) show that lagged investment is a powerful predictor of current investment in a balanced panel of large firms in Compustat. Motivated by this finding, Table 15 shows that our main results continue to hold when we control for lagged investment. In addition, the top panel of Figure 11 shows that the dynamics of these differential responses are also persistent to controlling for lagged investment.

Unlike Eberly, Rebelo and Vincent (2012), the R^2 of our regressions does not significantly increase when we control for lagged investment. The bottom panel of Figure 11 suggests that the main reason for this difference is that we use quarterly data while Eberly, Rebelo and Vincent (2012) use annual data. It shows that the R^2 of the regression increases as we take longer-run changes in capital on the left-hand side. In addition, Eberly, Rebelo and Vincent (2012) use a balanced panel of only large firms, while we use an unbalanced panel of all firms.

Table 15
Lagged Investment

	(1)	(2)	(3)	(4)
leverage × ffr shock	-0.39		-0.17	-0.07
	(0.27)		(0.36)	(0.59)
$\Delta \log k_{jt}$	0.20***	0.15***	0.14***	0.15***
	(0.01)	(0.01)	(0.01)	(0.01)
dd × ffr shock		0.88**	0.80**	0.66*
		(0.38)	(0.37)	(0.37)
Observations	219402	151027	151027	119750
R^2	0.159	0.159	0.160	0.169
Firm controls	yes	yes	yes	yes
Time sector FE	yes	yes	yes	no
Time clustering	yes	yes	yes	yes

Notes: results from estimating variants of the baseline specification $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \rho \Delta \log k_{jt} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where all variables are defined as in the main text or in the notes for Table 3. Standard errors are two-way clustered by firms and quarters. We have normalized the sign of the monetary shock $\varepsilon_t^{\mathrm{m}}$ so that a positive shock is expansionary (corresponding to a decrease in interest rates). We have standardized within-firm leverage $(\ell_{jt} - \mathbb{E}[\ell_{jt}])$ and within-firm distance to default $(\mathrm{dd}_{jt} - \mathbb{E}[\mathrm{dd}_{jt}])$ over the entire sample, so their units are in standard deviations relative to the mean.

C Comparison to Existing Empirical Literature

In this subsection, we relate our findings to empirical studies documenting heterogeneous responses across firms with different size, age, and liquidity. Subsection C.1 replicates the results of Gertler and Gilchrist (1994) regarding firm size in our sample and shows that including their measure of size does not affect our results. Subsection C.2 replicates the results of Cloyne et al. (2018) regarding firm age and shows that including their measure of age also does not affect our results. Subsection C.3 reconciles our results with recent work by Jeenas (2019).

C.1 Relation to Gertler and Gilchrist (1994) and firm size

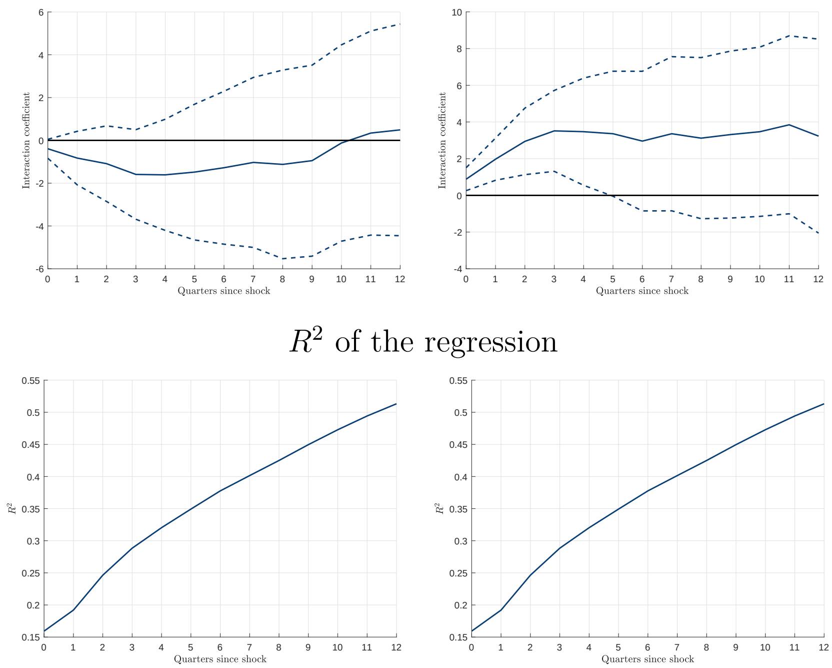
Gertler and Gilchrist (1994) showed that small firms' sales and inventory holdings were more sensitive to monetary contractions. In this subsection, we replicate their results in our sample and show that firm size does not affect our main findings. Following Gertler and Gilchrist (1994), we identify a small firm if their average sales over the past ten years is below the

Figure 11: Dynamics Controlling by Lagged Investment

(a) Leverage (b) Distance to Default

Interaction coefficient

R^2 of the regression



Notes: dynamics of the interaction coefficient between financial positions and monetary shocks over time. Reports the coefficient β_h over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \rho\Delta \log k_{jt} + \beta_h(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}'_h Z_{jt-1} + e_{jt}$, where all variables are defined in the main text and notes to Table 3.

30^{th} percentile of the distribution.[22] We then estimate our baseline dynamic model (4) using this measure of size as the financial position x_{jt}.

Figure 12 replicates the spirit of Gertler and Gilchrist (1994)'s results for investment in our sample. Panel (a) measures monetary contractions as the Romer and Romer (1990) dates in our version of Gertler and Gilchrist (1994)'s time period 1972-1989. It shows that small firms cut investment by more than large firms following a monetary contraction. Panel (b) shows that these results also hold using our measure of monetary shocks $\varepsilon_t^{\mathrm{m}}$ in our time period 1990-2007, although the estimates are only marginally statistically significant.[23]

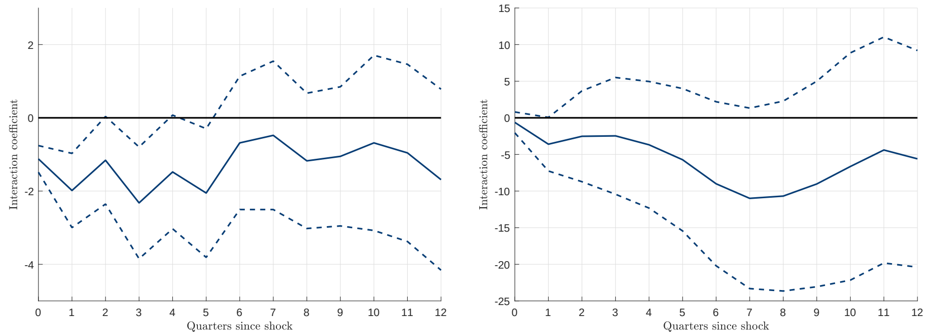
Figure 13 shows that our main results are unaffected by controlling for Gertler and

[22] These results are similar if we use five or twenty year averages.

[23] Our findings here are consistent with the analysis in Crouzet and Mehrotra (2020).

Figure 12: Dynamics of Differential Responses to Monetary Shocks by Size

(a) Period 1972–1989 (b) Period 1990–2007



Notes: dynamics of the interaction coefficient between size and monetary shocks. Reports the coefficient β_h over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_h size^s_{jt-1}\varepsilon^{\mathrm{m}}_t + \boldsymbol{\Gamma}'_h Z_{jt-1} + e_{jth}$, where $size^s_{jt}$ is a measure of firm size taking the value of one if firm j is "large" in period t and zero otherwise (see main text for definition) and all other variables defined in the main text or notes to Table 3, except that Z_{jt-1} additionally includes the variable $size^s_{jt-1}$. Monetary shocks in panel (a) correspond to the Romer and Romer (1990) dates.

Gilchrist (1994)'s measure of size using the local projection:

$$\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_{1h}(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon^{\mathrm{m}}_t + \beta_{2h} size^s_{jt-1}\varepsilon^{\mathrm{m}}_t + \boldsymbol{\Gamma}'_h Z_{jt-1} + e_{jth}. \tag{15}$$

Panel (a) reports results for $x_{jt} = \ell_{jt}$ and panel (b) reports results for $x_{jt} = \mathrm{dd}_{jt}$. In both cases, the dynamics of the differential response β_{1h} are virtually identical to the main text.[24] This occurs because size and our measures of financial position are largely uncorrelated in our sample. Hence, we view our work as simply focusing on a different feature of the data than Gertler and Gilchrist (1994).

C.2 Relation to Cloyne et al. (2018) and firm age

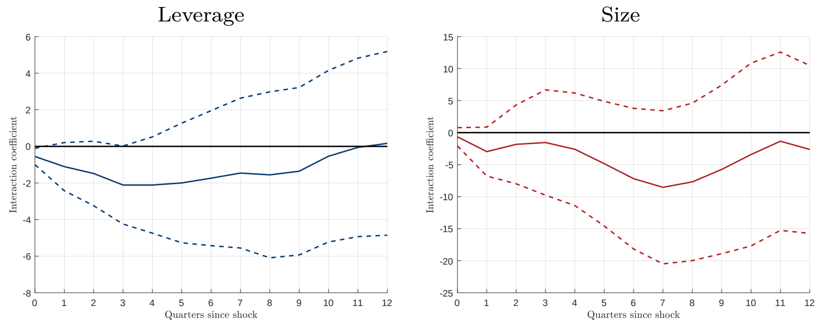
Recent work Cloyne et al. (2018) argues that younger firms are more responsive to monetary policy in both the U.S. and the U.K. In this subsection, we replicate the spirit of their results in our sample and show that they do not affect our main results. Following Cloyne et al. (2018), we measure age as time since incorporating, which is available from Datastream.

Figure 14 replicates the spirit of Cloyne et al. (2018)'s results and show that our main

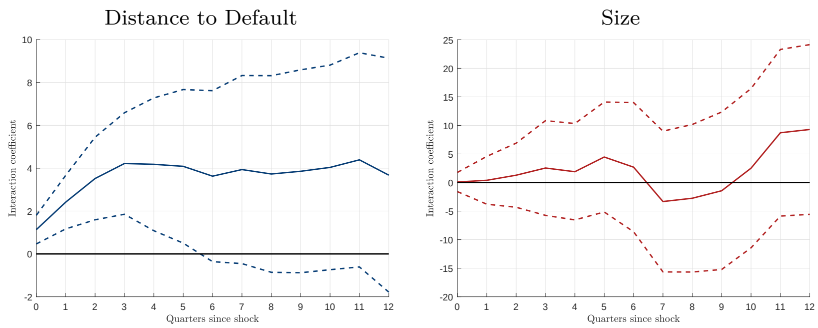
[24] This result is robust to measuring size with capital or total assets instead of sales.

Figure 13: Joint Dynamics of Financial Position and Size

(a) Leverage and Size



(b) Distance to Default and Size



Notes: dynamics of the interaction coefficient between financial position monetary shocks and between size and monetary shocks. Reports the coefficients β_{1h} and β_{2h} over quarters h from

$$\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_{1h}(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \beta_{2h} size_{jt-1}^{s} \varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}_h' Z_{jt-1} + e_{jt},$$

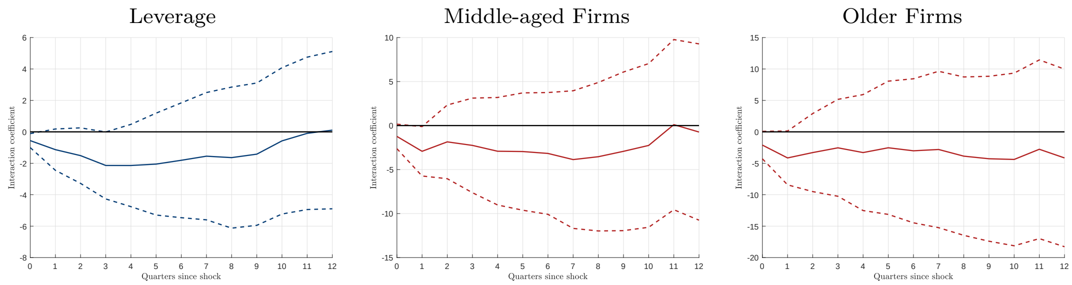
where here $size_{jt}^{s}$ is a measure of firm size taking the value of one if firm j is "large" in period t and zero otherwise (see main text for definition) and all other variables defined in the main text or notes to Table 3, except that Z_{jt-1} additionally includes the variable $size_{jt-1}^{s}$. Panel (a) runs our baseline specification with leverage $x_{jt} = \ell_{jt}$. Panel (b) runs our preferred specification with distance to default $x_{jt} = \mathrm{dd}_{jt}$.

findings are robust to controlling for age. Following Cloyne et al. (2018), we classify firms as "young" (whose age since incorporation is less than fifteen years), "middle aged" (between fifteen and fifty years), and "older" (more than fifty years). Panel (a) shows that, conditional on the interaction between leverage and the monetary shock, middle-aged and old firms are less responsive to monetary shocks as in Cloyne et al. (2018).[25] However, panel (b) shows that the differences by age largely disappear once we control for the interaction between distance to default and the monetary shock. In both cases, the interaction with financial position is similar to our results in the main text. We view these findings as reflecting the

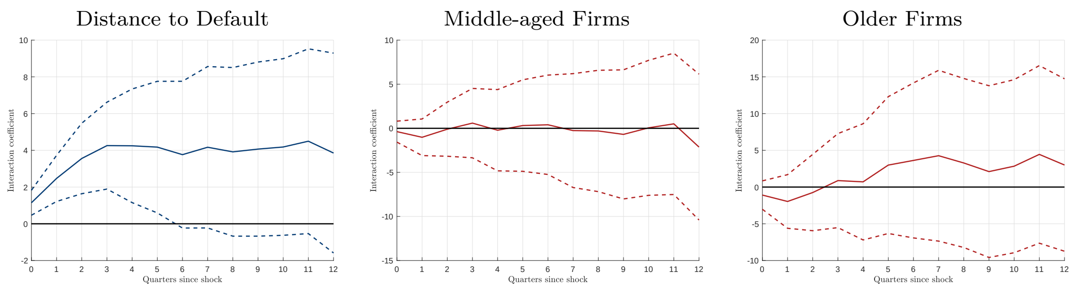
[25]These differences are not statistically significant for most horizons in our specification and sample. A potentially important difference between our specifications is that Cloyne et al. (2018) measure monetary policy shocks with a VAR approach and use the high-frequency shocks as an instrumental variable.

Figure 14: Joint Dynamics of Financial Position and Age

(a) Leverage and Age



(b) Distance to Default and Age



Notes: dynamics of the interaction coefficient between financial positions and monetary shocks and between age and monetary shocks. Reports the coefficients β_{1h} and $\boldsymbol{\beta}_{2h}$ over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_{1h}(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \boldsymbol{\beta}_{2h}' age_{jt}\varepsilon_t^{\mathrm{m}} + \boldsymbol{\Gamma}_h' Z_{jt-1} + e_{jt}$, where $age_{jt} \equiv [middleage_{jt} \;\; oldage_{jt}]'$ is a vector with two dummy variables measuring firm age (see main text for definition), and all other variables defined in the main text or notes to Table 3, except that Z_{jt-1} additionally includes the vector age_{jt}. Dashed lines report 90% error bands. Panel (a) runs our baseline specification with leverage $x_{jt} = \ell_{jt}$. Panel (b) runs our preferred specification with distance to default $x_{jt} = \mathrm{dd}_{jt}$.

fact that we analyze a different dimension of the data than Cloyne et al. (2018).

C.3 Relation to Jeenas (2019) and firm liquidity

In this subsection, we relate our findings to recent work by Jeenas (2019) along two dimensions. First, we show that the differences between our estimated dynamics are accounted for by permanent heterogeneity in responsiveness across firms. Second, we show that our results are not driven by differences in liquidity across firms.

Dynamics We begin by replicating Jeenas (2019)'s results in our sample. For reference, Panel (a) of Figure 15 plots the dynamics of the interaction of within-firm leverage and the monetary shock $(\ell_{jt-1} - \mathbb{E}_j[\ell_{jt}])\varepsilon_t^{\mathrm{m}}$ from the local projection

$$\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_h(\ell_{jt-1} - \mathbb{E}_j[\ell_{jt}])\varepsilon_t^{\mathrm{m}} + \boldsymbol{\Gamma}_h' Z_{jt-1} + e_{jth}, \tag{16}$$

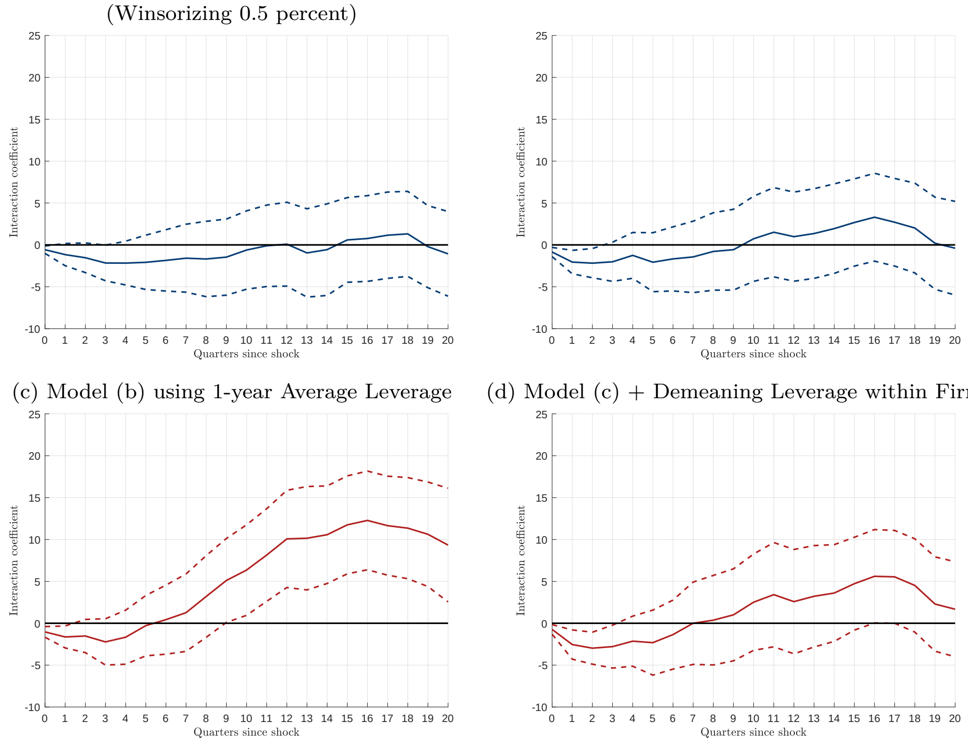
which simply extends Figure 1 from the main text out to twenty quarters. Jeenas (2019)'s specification differs from ours in two key ways. First, Jeenas (2019) drops observations in the top 1% of the leverage distribution while we winsorize the top 0.5%.[26] Second, Jeenas (2019) computes the interaction between the monetary shock and the firm's average leverage over the past four quarters, $\widehat{\ell}_{jt-1}$, rather than the within-firm variation in the stock of leverage in the past quarter, $\ell_{jt} - \mathbb{E}_j[\ell_{jt}]$. Panel (d) applies these two operations and recovers the spirit of Jeenas (2019)'s result: high-leverage firms become substantially more responsive to the shock after approximately four quarters. Quantitatively, this point estimate implies that four years after a one percentage point expansionary shock, a firm with one standard deviation more leverage than the average firm increases its capital stock by over ten percentage points more than the average firm.

The remaining panels of Figure 15 decompose the effect of these two differences between our specifications on the estimated dynamics. Panel (b) shows that Jeenas (2019)'s more aggressive trimming of high-leverage observations has an insignificant effect on the estimated dynamics. In this panel, we estimate our baseline specification (16) after dropping observations in the top 1% of the leverage distribution and find that high-leverage firms are not statistically significantly more responsive to monetary policy.

Panel (c) shows that sorting firms by the average of their past four quarters of leverage $\widehat{\ell}_{jt-1}$ accounts for the difference between our results. In this panel, we re-estimate our dynamic specification (16) after dropping the top 1% of leverage observations and replacing the within-firm variation in last quarter's stock of leverage $\ell_{jt} - \mathbb{E}_j[\ell_{jt}]$ with Jeenas (2019)'s moving average $\widehat{\ell}_{jt-1}$. The moving average eliminates high-frequency variation in leverage within a firm, implying that the estimated dynamics are more strongly driven by permanent heterogeneity across firms. Consistent with this idea, Panel (d) shows that using only within-firm variation in averaged leverage $\widehat{\ell}_{jt-1} - \mathbb{E}_j[\widehat{\ell}_{jt}]$ renders the long-horizon dynamics smaller and insignificant, largely consistent with our baseline specification. We prefer our specification because it maps more directly into our economic model in which heterogeneity in leverage is driven by ex-post realizations of idiosyncratic shocks and lifecycle dynamics

[26] We winsorize the top 0.5% rather than drop the top 1% because the most highly indebted firms are the most likely to have substantial default risk, which is our object of interest.

Figure 15: Comparison of Our Dynamic Results to Jeenas (2019)



(a) Baseline Model (Winsorizing 0.5 percent)

(b) Model (a) + Trimming top 1 percent

(c) Model (b) using 1-year Average Leverage

(d) Model (c) + Demeaning Leverage within Firm

Notes: dynamics of the interaction coefficient between leverage and monetary shocks over time. Reports the coefficient β_h over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_h(\ell_{jt-1} - \mathbb{E}_j[\ell_{jt}])\varepsilon_t^{\text{m}} + \mathbf{\Gamma}_h' Z_{jt-1} + e_{jt}$, where all variables are defined in the main text or the notes to Table 3. Panel (b) drops the top 1% of the observations in the leverage variable used in the particular forecasting horizons. Panel (c) applies this operation and replaces demeaned leverage $\ell_{jt-1} - \mathbb{E}_j[\ell_{jt}]$ with the firm's average leverage over the last four quarters, $\widehat{\ell}_{jt-1}$. Panel (d) estimates this specification using only within-firm variation in averaged leverage $\widehat{\ell}_{jt-1} - \mathbb{E}[\widehat{\ell}_{jt}]$.

across firms. We focus our analysis of the model on the heterogeneous responses upon impact, which are robustly estimated in both our specification and Jeenas (2019) and survive the litany of robustness checks in this Online Appendix and the Supplemental Material.[27]

Heterogeneous Responses Not Driven by Liquidity Jeenas (2019) argues that the

[27] An additional difference between our specification and Jeenas (2019)'s is that we control for differences in cyclical sensitivities while Jeenas (2019) does not. We include these controls because we have found that there are significant differences in long-run cyclical sensitivities and that GDP growth is correlated with monetary shocks over these horizons in our sample. Online Appendix A.2 shows that excluding these controls does not affect the point estimates in our specification but does increase the standard errors. We have also found that excluding these controls does not strongly affect the point estimates or standard errors in Jeenas (2019)'s baseline specification with averaged leverage $\widehat{\ell}_{jt}$. Excluding these controls slightly increases the responsiveness of firms with high demeaned average leverage $\widehat{\ell}_{jt} - \mathbb{E}_j[\widehat{\ell}_{jt}]$, but the difference from Panel (d) in Figure 15 is small and not statistically significant.

dynamics of heterogeneous responses by leverage documented above are driven by differences in liquidity across firms. Figure 16 shows that our results are not driven by liquidity once we use within-firm variation as in our main specification (2). We estimate the local projection

$$\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_{1h}(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \beta_{2h}(y_{jt-1} - \mathbb{E}_j[y_{jt}])\varepsilon_t^{\mathrm{m}} \quad (17)$$
$$+ \mathbf{\Gamma}'_h Z_{jt-1} + e_{jth},$$

where $y_{jt} - \mathbb{E}_j[y_{jt}]$ is the within-firm variation in liquidity. Panel (a) shows that the point estimate of the leverage dynamics are similar to those presented in the main text, although the standard errors are wider given the correlation between leverage and liquidity. Panel (b) shows that the dynamics of distance to default are strongly and significantly positive, as in the main text. In that case, the dynamics of liquidity are always statistically insignificant, suggesting that default risk is the primary source of heterogeneous responses across firms when using within-firm variation.

D Analysis of Calibrated Model

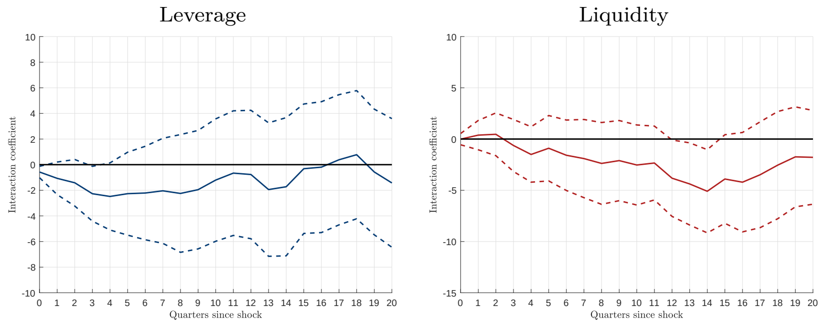
In this appendix, we analyze firms' decision rules in our calibrated steady state and show that the financial heterogeneity in our model is broadly comparable to that in the data.

D.1 Identification of Fitted Parameters

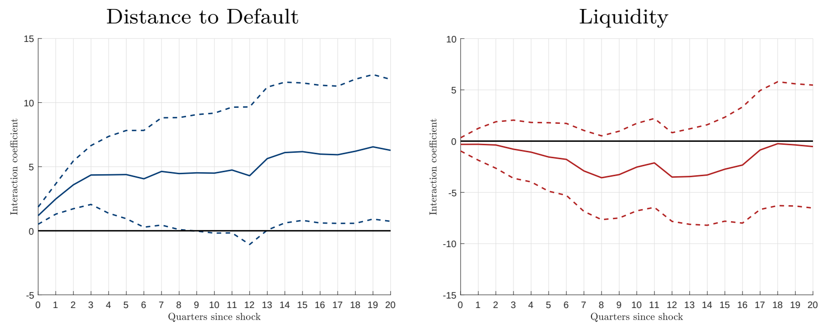
Figure 17 reports information to help assess the sources of identification in our calibration exercise. The top panel reports the local elasticities of targeted moments with respect to the parameters chosen in our calibration, computed at the estimated parameters. The patterns that emerge are intuitive. For example, increasing the volatility of productivity shocks σ increases the dispersion of investment rates across firms but decreases default rates and leverage ratios (because it makes right-tail positive outcomes more likely). In contrast, increasing the volatility of capital quality shocks makes left-tail negative outcomes more likely and therefore increases default rates (consistent with our discussion in Footnote 6). Increasing the operating cost ξ or decreasing lenders' recovery rates α tightens the financial

Figure 16: Joint Dynamics of Financial Position and Liquidity

(a) Leverage and Liquidity



(b) Distance to Default and Liquidity

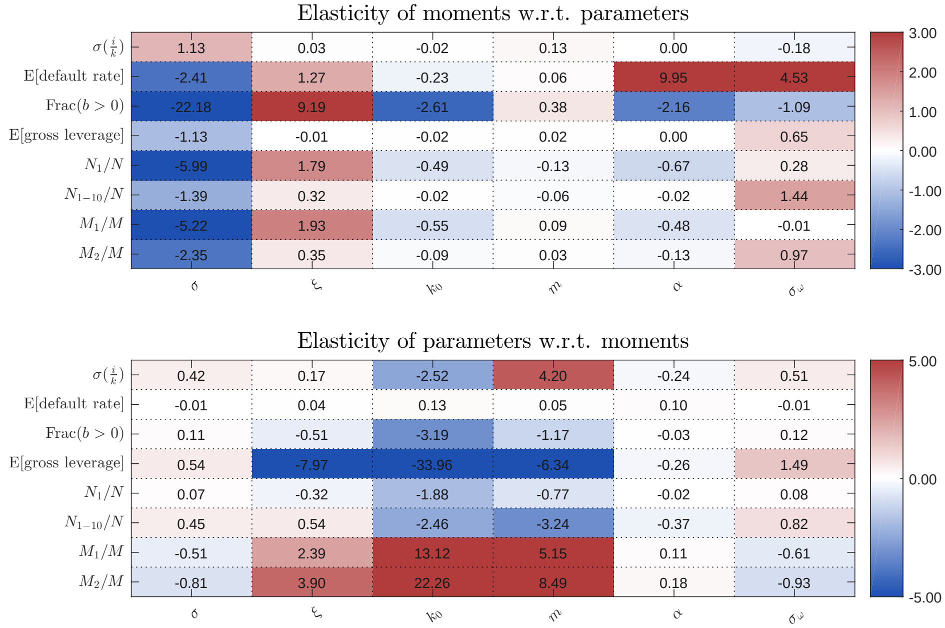


Notes: the coefficients β_{1h} and β_{2h} over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_{1h}(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \beta_{2h}(y_{jt-1} - \mathbb{E}_j[y_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}'_h Z_{jt-1} + e_{jt}$, where $y_{jt} - \mathbb{E}_j[y_{jt}]$ is the within-firm variation in liquidity and all other variables are defined in the main text or the notes to Table 3, except that Z_{jt-1} additionally includes the variable $y_{jt} - \mathbb{E}_j[y_{jt}]$. We have also standardized demeaned liquidity $y_{jt} - \mathbb{E}_j[y_{jt}]$ over the entire sample.

constraints and leads to higher default rates among firms. Finally, increasing the initial size of new firms k_0 makes default less likely.

The bottom panel of Figure 17 plots the inverse of the mapping in the top panel, i.e., it plots the local elasticities of estimated parameters with respect to moments as in Andrews, Gentzkow and Shapiro (2017). This inverse mapping clarifies how variation in targeted moments would influence estimated parameter values, taking into account the joint dependencies across moments in the data. An important limitation of this exercise is that the relevant size of the variation in the moments is not clear; nevertheless, we believe it contains additional useful information. For example, it shows that the dispersion of investment rates across firms is a particularly informative moment for all parameters, especially those governing the lifecycle of young firms. This result may be surprising in light of the top panel, which shows that the dispersion of productivity shocks is the only parameter that strongly

Figure 17: Sources of Identification



Notes: top panel computes the local elasticities of moments (rows) with respect to parameters (columns) at the estimated parameter values. Bottom panel computes the local elasticities of estimated parameters (columns) to moments (rows) computed as in Andrews, Gentzkow and Shapiro (2017).

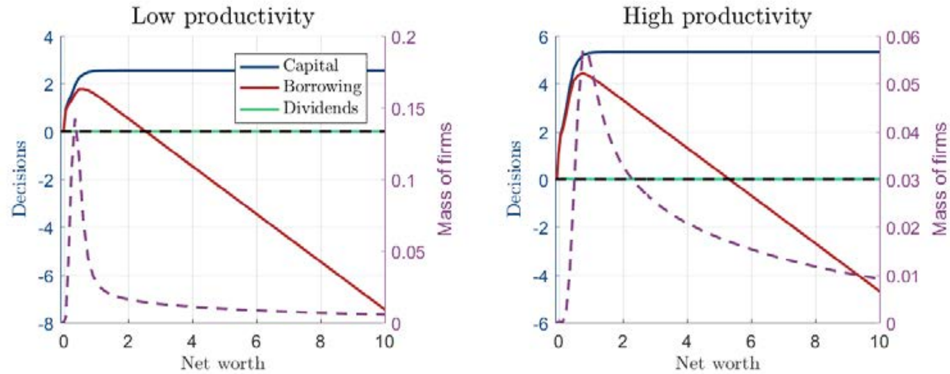
influences the dispersion of investment rates; it is nonetheless an influential moment because changing the productivity process changes other moments, and therefore other parameter estimates, as well.

D.2 Firm Dynamics

Firms' Decision Rules Figure 18 plots the investment, borrowing, and dividend payment decisions of firms. Firms with net worth n below the default threshold $\underline{n}_t(z)$ do not operate. Once firms clear this default threshold, they lever up to increase their capital to its optimal scale $k_t^*(z)$. Once capital is at its optimal level $k_t^*(z)$, firms use additional net worth to pay down their debt until they reach the unconstrained threshold $\overline{n}_t(z)$. Only unconstrained firms pay positive dividends.

The curvature in the policy functions over the region with low net worth n reflects the role of financial frictions in firms' decisions. Without frictions, all non-defaulting firms would borrow the amount necessary to reach the optimal scale of capital $k_t^*(z)$. However, firms with low net worth n would need to borrow a substantial amount in order to do so, increasing

Figure 18: Steady State Decision Rules



Notes: Left panel plots decision rules and stationary distribution of firms conditional on idiosyncratic productivity one standard deviation below the mean. Right panel plots the same objects conditional on productivity one standard deviation above the mean. The left y-axis measures the decision rules (capital accumulation, borrowing, and dividend payments) as a function of net worth n. The right y-axis measures the stationary distribution of firms (dashed purple line).

their risk of default and therefore borrowing costs. Anticipating these higher borrowing costs, firms with low net worth n accumulate capital below its optimal scale.

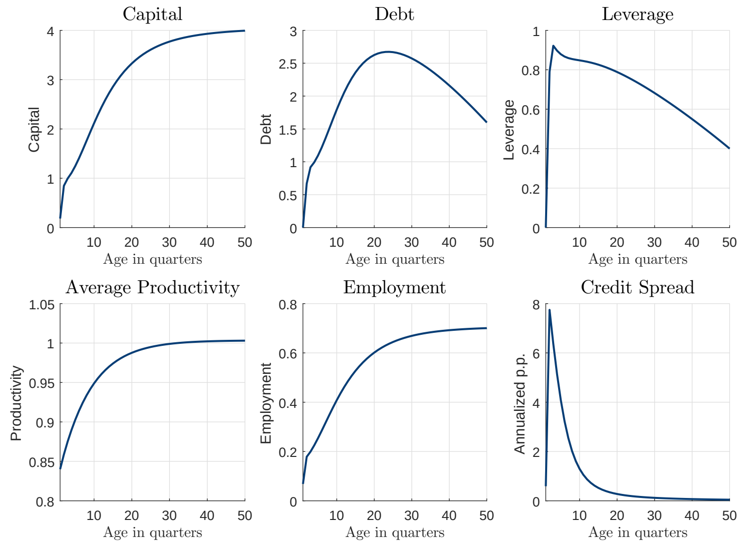
The right axis of Figure 18 plots the stationary distribution of firms. 51.8% of firms pay a risk premium, i.e., are "risky constrained." These firms are in the region with curved policy functions described above. 47.5% of firms are constrained but do not currently pay a risk premium, i.e., are "risk-free constrained." These firms have achieved their optimal scale of capital $k_t^*(z)$ and have linear borrowing policies. The remaining 0.6% of firms are unconstrained.

Figure 18 makes clear that there are two key sources of financial heterogeneity in the model. First, reading the graphs from left to right captures heterogeneity due to lifecycle dynamics; young firms accumulate debt in order to reach their optimal level of capital $k_t^*(z)$ and then pay down that debt over time. Second, moving from the left to the right panel captures heterogeneity due to idiosyncratic productivity shocks; a positive shock increases the optimal scale of capital $k_t^*(z)$, again leading firms to first accumulate and then decumulate debt.[28,29]

[28] A third source of financial heterogeneity is the capital quality shocks, which simply generate variation in firms' net worth n.

[29] Buera and Karmakar (2018) study how the aggregate effect of an interest rate shock depends on these two sources of heterogeneity in a simple two-period model.

Figure 19: Lifecycle Dynamics in Model



Notes: Average capital, debt, leverage, productivity, employment, and credit spread conditional on age in steady state.

Lifecycle Dynamics Figure 19 plots the dynamics of key variables over the firm lifecycle. New entrants begin with a low initial capital stock k_0 and, on average, a low draw of idiosyncratic productivity z. As described above, young firms take on new debt in order to finance investment, which increases their default risk and credit spreads. Over time, as firms accumulate capital and productivity reverts to its mean, they reach their optimal capital stock $k_t^*(z)$ and begin paying down their debt.

D.3 Cross-Sectional Distribution of Investment and Leverage

Table 16 shows that our model is broadly consistent with key features of the distributions of investment and leverage not targeted in the calibration. The top panel analyzes the distribution of investment rates in the annual Census data reported by Cooper and Haltiwanger (2006). We present the corresponding statistics in our model for a selected sample – conditioning on firms that survive at least twenty years to mirror the selection into the LRD – and in the full sample. Although we have calibrated the selected sample to match the dispersion of investment rates, the mean and autocorrelation of investment rates in the selected sample are also reasonable. The mean investment rate in the full sample is higher than the selected sample because the full sample includes young, growing firms.

Table 16
Investment and Leverage Heterogeneity

Moment	Description	Data	Model (selected)	Model (full)
Investment heterogeneity (annual LRD)				
$\mathbb{E}\left[\frac{i}{k}\right]$	Mean investment rate	12.2%	13.9%	28.4%
$\sigma\left(\frac{i}{k}\right)$	SD investment rate (calibrated)	33.7%	36.7%	48.3%
$\rho\left(\frac{i}{k}, \frac{i}{k}_{-1}\right)$	Autocorr investment rate	0.06	-0.14	-0.14
Joint investment and leverage heterogeneity (quarterly Compustat)				
$\rho\left(\frac{b}{k}, \frac{b}{k}_{-1}\right)$	Autocorr leverage ratio	0.94	0.96	0.96
$\rho\left(\frac{i}{k}, \frac{b}{k}\right)$	Corr. of leverage and investment	-0.08	-0.08	-0.01
Average Indebtedness of Firms (quarterly Compustat)				
$\mathbb{E}[\frac{\max\{b,0\}}{k+\max\{-b,0\}}]$	Mean gross leverage	0.27	0.34	0.49
$\mathbb{E}[\frac{b}{k+\max\{-b,0\}}]$	Mean net leverage	-0.04	0.13	0.32
$\text{Frac}(b > 0)$	Fraction with positive debt	0.85	0.59	0.70

Notes: Statistics about the cross-sectional distribution of investment rates and leverage ratios in steady state. Data for investment heterogeneity are drawn from Cooper and Haltiwanger (2006). Model (selected) for investment heterogeneity corresponds to firms alive for longer than twenty years in a panel simulation, time aggregated to the annual frequency. Model (full) corresponds to the full sample of firms in a panel simulation, time aggregated to the annual frequency. Data for joint investment and leverage heterogeneity and the average indebtedness of firms drawn from quarterly Compustat data. Model (selected) for these panels corresponds to firms alive for longer than seven years in a panel simulation. Model (full) corresponds to the full sample of firms in a panel simulation.

Compustat Firms in the Model and the Data We account for the sample selection into Compustat by conditioning on firms that have survived for at least seven years. According to Wilmer et al. (2017), the median time to IPO has ranged from roughly six to eight years over the last decade.[30] The bottom panels of Table 16 shows that the model-implied distribution of investment rates and leverage ratios in Compustat is aligned with the data. Leverage is highly autocorrelated and weakly correlated with investment in both the model and the data. The model roughly captures both the mean gross and net leverage in Compustat, as well as the fraction of firms with positive debt.

Table 17 compares public and private firms in our model to the data along three key dimensions. First, public firms are substantially larger than private firms in our model; however, our model comes nowhere close to the size gap observed in the data. An important reason for this discrepancy is that, in the data, many firms are born small and never grow;

[30]Our results are robust to sensitivity analysis around this cutoff.

Table 17
Public vs. private firms in the model and data

	Data	Model
$\frac{\mathbb{E}[n\|\text{public}]}{\mathbb{E}[n\|\text{private}]}$	62	1.68
$\frac{\mathbb{E}[age\|\text{public}]}{\mathbb{E}[age\|\text{private}]}$	2.18	6.60
$\frac{\sigma(\frac{1}{2}\frac{n_{jt}-n_{jt-1}}{n_{jt}+n_{jt-1}}\|\text{public})}{\sigma(\frac{1}{2}\frac{n_{jt}-n_{jt-1}}{n_{jt}+n_{jt-1}}\|\text{private})}$	0.65	0.62

Notes: comparison of public and private firms. "Public" firms in the model are those who reach seven years old (the median time to IPO in Wilmer et al. (2017)). $\frac{\mathbb{E}[n|\text{public}]}{\mathbb{E}[n|\text{private}]}$ computes the average size of firms measured by employment; data comes from Dinlersoz et al. (2018) Table 3. $\frac{\mathbb{E}[age|\text{public}]}{\mathbb{E}[age|\text{private}]}$ computes the average age; data comes from Dinlersoz et al. (2018) Table 3. $\frac{\sigma(\frac{1}{2}\frac{l_{jt}-l_{jt-1}}{l_{jt}+l_{jt-1}}|\text{public})}{\sigma(\frac{1}{2}\frac{l_{jt}-l_{jt-1}}{l_{jt}+l_{jt-1}}|\text{private})}$ computes the dispersion of growth rates; data comes from Davis et al. (2006) Figure 2.5.

therefore, there is a large mass of permanently small firms which is outside of our model.[31] Second, public firms are older than private firms in both our model and the data; the gap is larger in our model since we select firms based solely on age. Finally, the dispersion of growth rates is smaller among public firms in both the model and data. In our model, private firms' growth rates are more disperse since they are more strongly affected by financial frictions.

[31] Gavazza, Mongey and Violante (2018) use permanent heterogeneity in returns to scale to match this group of permanently small firms. We have solved a related version of our model in which there are two types of firms: one with low returns to scale, which reach their optimal size relatively quickly, and another with the returns to scale of our baseline model. This model generates a skewed size distribution, as in the data, but by construction does not directly affect the behavior of the large "Compustat" firms in our model. In addition, these small firms make up a small share of aggregate investment and are therefore unlikely to have a substantial influence on aggregate dynamics.

Supplemental Materials for "Financial Heterogeneity and the Investment Channel of Monetary Policy" by Pablo Ottonello and Thomas Winberry

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, Whited, 1992; Gomes, 2001; Eisfeldt and Rampini, 2006; Clementi and Palazzo, 2019).

Variables

1. *Investment*: defined as $\Delta \log(k_{jt+1})$, where k_{jt+1} denotes the capital stock of firm j at the end of period t. For each firm, we set the first value of k_{jt+1} to be the level of gross plant, property, and equipment (`ppegtq`, item 118) in the first period in which this variable is reported in Compustat. From this period onwards, we compute the evolution of k_{jt+1} using the changes of net plant, property, and equipment (`ppentq`, item 42), which is a measure 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 we estimate its value using a 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. We only consider investment spells with 40 quarters or more in order to precisely estimate fixed effects.

2. *Leverage*: defined as the ratio of total debt (sum of `dlcq` and `dlttq`, items 45 and 71) to total assets (`atq`, item 44).

3. *Net leverage*: defined as the ratio of total debt minus net current assets (`actq`, item 40, minus `lctq`, item 49) to total assets.

4. *Distance to default*: Following Merton (1974) and Gilchrist and Zakrajšek (2012), we define this variable as $dd \equiv \frac{\log(V/D)+(\mu_V-0.5\sigma_V^2)}{\sigma_V}$, where V denotes the total value of the

firm, μ_V the annual expected return on V, σ_V the annual volatility of the firm's value, and D firm's debt.[32] To estimate the firm's value V, we follow an iterative procedure, based on Gilchrist and Zakrajšek (2012) and Blanco and Navarro (2017):

i. 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`).

ii. 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, $\Delta \log V$.

iii. Obtain a new estimate of V for every day of the 250-day moving window from the Black-Scholes-Merton option-pricing framework $E = V\Phi(\delta_1) - e^{-rT} D\Phi(\delta_2)$, where $\delta_1 \equiv \frac{\log(V/D)+(r+0.5\sigma_V^2)T}{\sigma_V^2\sqrt{T}}$, and $\delta_2 \equiv \delta_1 - \sigma_V\sqrt{T}$, where r is the daily one-year constant maturity Treasury-yield (data source: Federal Reserve Board of Governors H.15 Selected Interest Rates release).

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

5. *Real sales growth*: measured as log-differences in sales (`saleq`, item 2) deflated using the BLS implicit price deflator.

6. *Size*: measured as the log of total real assets, deflated using the BLS implicit price deflator.

7. *Liquidity*: defined as the ratio of cash and short-term investments (`cheq`, item 36) to total assets.

8. *Cash flow*: measured as EBIT divided by capital stock.

9. *Dividend payer*: defined as a dummy variable taking a value of one in firm-quarter observations in which the firm paid dividends to preferred stock of the company (constructed using `dvpq`, item 24).

10. *Sectoral dummies*. We consider the following sectors: (i) agriculture, forestry, and fishing: `sic` < 999; (ii) mining: `sic` $\in [1000, 1499]$; (iii) construction: `sic` $\in [1500, 1799]$; (iv)

[32] We measure the face value of debt D as the sum of the firm's short-term debt (`dlcq`, item 45) and one-half of long-term debt (`dlttq`, item 71), following Gilchrist and Zakrajšek (2012) and a common practice by credit rating agencies (Moody's/KMV).

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` $\in [7000, 8999]$.

Sample Selection Our empirical analysis excludes (in order of operation):

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

2. Firms not incorporated in the United States.

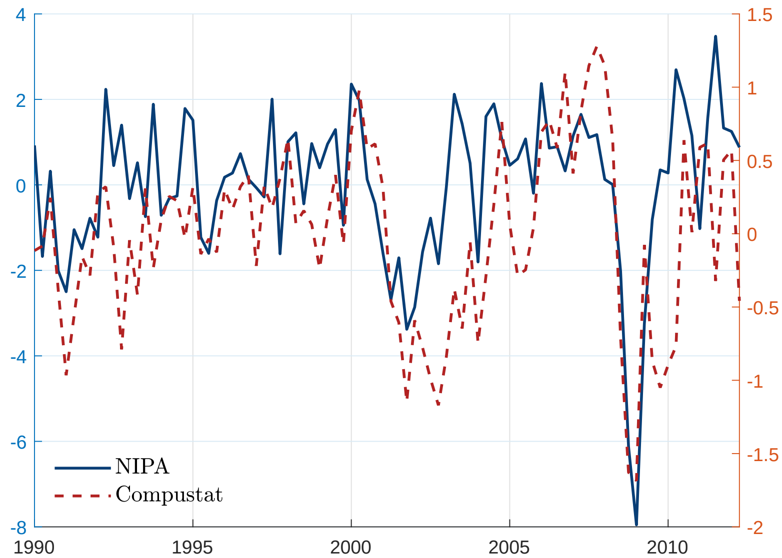
3. Firm-quarter observations that satisfy one of the following conditions, aimed at excluding extreme observations:

   i. Negative capital or assets
   ii. Acquisitions (constructed based on `aqcy`, item 94) larger than 5% of assets.
   iii. Investment rate is in the top and bottom 0.5% of the distribution.
   iv. Investment spell is shorter than 40 quarters.
   v. Net current assets as a share of total assets higher than 10 or below -10.
   vi. Leverage higher than 10 or negative.
   vii. Quarterly real sales growth above 1 or below -1.
   viii. Negative sales or liquidity

Because our empirical analysis relates firms' investment in a period with its financial positions in the previous period, we exclude not only firm-quarter observations satisfying the exclusion criteria above but also those in their subsequent quarter. We start the sample in 1983q3, when the data on acquisitions (variable `aqcy`) becomes available.[33] After applying these sample selection operations, we winsorize observations of leverage and distance to default at the top and bottom 0.5% of the distribution.

[33] For the empirical analysis in Appendix C.1, which measures differential responses to monetary shocks by size for the 1972-1989, we do not apply the restriction above based on acquisitions because the variable `aqcy` is not available.

Figure 20: Aggregate Investment: NIPA vs. Compustat



Notes: comparison of aggregate NIPA investment to aggregated Compustat investment. NIPA investment measured as log nonresidential fixed investment and aggregated Compustat investment measured as average $\Delta \log k_{jt}$ across firms. Figure reports the cyclical component (in percentage points) using an HP filter with smoothing parameter $\lambda = 1600$.

Figure 20 plots the cyclical component the average firm-level investment from our Compustat data to nonresidential fixed investment from NIPA. Both series exhibit similar business cycle patterns, with a correlation of 53%. Our aggregated Compustat time series also behaves similarly to NIPA investment in response to an identified monetary shock estimated using the external-instruments VAR model in Gertler and Karadi (2015) (results are available upon request).

B Additional Empirical Results

Other Controls for Cyclical Sensitivity While our baseline specification controls for aggregate conditions using GDP growth, Table 18 shows that the results are robust to using either inflation or the unemployment rate instead.

Results driven by effect of monetary shocks on short rates Table 19 shows that the differential responses across firms are primarily driven by how monetary policy affects the overall level of interest rates rather than long rates in particular. Following Gurkaynak,

Table 18
Controlling for Differences in Cyclical Sensitivities

	(1)	(2)	(3)	(4)	(5)	(6)
leverage × ffr shock	-0.57**		-0.53*		-0.30	
	(0.27)		(0.27)		(0.24)	
dd × ffr shock		1.14***		1.17***		0.97**
		(0.41)		(0.40)		(0.38)
leverage × dlog gdp	-0.12**		-0.13**			
	(0.05)		(0.05)			
dd × dlog gdp		0.09		0.07		
		(0.12)		(0.12)		
leverage × dlog cpi			-0.12			
			(0.09)			
dd × dlog cpi				-0.13		
				(0.15)		
leverage × ur					0.00	
					(0.00)	
dd × ur						-0.00
						(0.00)
Observations	219402	151027	219402	151027	219402	151027
R^2	0.124	0.141	0.124	0.141	0.124	0.141
Firm controls	yes	yes	yes	yes	yes	yes

Notes: results from estimating variants of the baseline specification $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta_y(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}_1' Z_{jt-1} + \mathbf{\Gamma}_2'(x_{jt-1} - \mathbb{E}_j[x_{jt}])Y_{t-1} + e_{jt}$, where Y_{t-1} is a vector of aggregate variables containing combinations of GDP growth (dlog gdp), the inflation rate (dlog cpi), and the unemployment rate (ur) and all other variables are defined in the main text or the notes to Table 3. Columns (1) and (2) include only GDP growth in Y_{t-1} (as our baseline specification), columns (3) and (4) include GDP growth and the inflation rate, while columns (5) and (6) include the unemployment rate and the inflation rate.

Sack and Swanson (2005), we decompose monetary policy announcements into a "target" component that affects the level of the yield curve and a "path" component that affects the slope of the yield curve. The table shows that only the interactions of financial position with the target component are statistically significant.

Alternative Time Aggregation Table 20 shows that our baseline results hold when we time-aggregate the high-frequency shocks by taking the simple sum within the quarter, rather than the weighted sum in the main text.

Results not driven by other firm-level covariates Table 21 shows that our main results are not driven by differences in firms' sales growth, realized future sales growth, size,

Table 19
Target vs. Path Decomposition

	(1)	(2)	(3)	(4)
leverage × ffr shock	-0.57**			
	(0.27)			
leverage × target shock		-0.84*		
		(0.43)		
leverage × path shock		-0.65		
		(1.19)		
dd × ffr shock			1.14***	
			(0.41)	
dd × target shock				1.46*
				(0.73)
dd × path shock				0.19
				(1.83)
Observations	219402	214032	151027	147588
R^2	0.124	0.125	0.141	0.142
Firm controls	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes

Notes: results from estimating variants of the baseline specification $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta_y (x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where all variables are defined in the main text or the notes to Table 3. Columns (2) and (4) run separate interactions of financial position x_{jt} with the target and path component of interest rates, as defined in Campbell et al. (2012).

or liquidity. It expands the baseline specification using within-firm variation as:[34]

$$\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta_y (x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \beta_z z_{jt-1}\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt},$$

where z_{jt-1} is lagged sales growth, realized future sales growth in one year, lagged size, or lagged liquidity. In each case, the coefficients on leverage ℓ_{jt-1} and distance to default dd_{jt-1} remain stable. Hence, firm-level shocks or characteristics that are correlated with these additional variables do not drive the heterogeneous responses by default risk that we document in the main text.

Other indices of financial constraints less powerful We have interpreted our measures of financial position as primarily proxying for default risk across firms. Consistent with this interpretation of the data, Table 22 shows that other measures of financial position that

[34] The results for the baseline specification (2) are very similar.

Table 20
Alternative Time Aggregation

	(1)	(2)	(3)	(4)
leverage × ffr shock (sum)	-0.61***		-0.53**	-0.53
	(0.18)		(0.23)	(0.40)
dd × ffr shock (sum)		0.88***	0.68**	0.80**
		(0.28)	(0.29)	(0.33)
ffr shock (sum)				0.95**
				(0.47)
Observations	222174	153113	153113	121399
R^2	0.123	0.140	0.141	0.149
Firm controls	yes	yes	yes	yes
Time sector FE	yes	yes	yes	no
Time clustering	yes	yes	yes	yes

Notes: results from estimating variants of the baseline specification $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where all variables are defined in the main text or the notes to Table 3. We time-aggregate the monetary shock by simply summing the high-frequency shocks that occur in a given quarter. Column (4) removes the sector-quarter fixed effect α_{st} and estimates $\Delta \log k_{jt+1} = \alpha_j + \alpha_{sq} + \gamma \varepsilon_t^{\mathrm{m}} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}_1' Z_{jt-1} + \mathbf{\Gamma}_2' Y_{t-1} + e_{jt}$, where Y_t is a vector with four lags of GDP growth, the inflation rate, and the unemployment rate.

Table 21
Interaction With Other Firm-Level Covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
leverage × ffr shock	-0.58**		-0.59**		-0.57**		-0.62**	
	(0.27)		(0.29)		(0.27)		(0.26)	
dd × ffr shock		1.14***		1.18***		1.17***		1.18***
		(0.41)		(0.42)		(0.41)		(0.41)
sales growth × ffr shock	-0.18	0.04						
	(0.24)	(0.26)						
future sales growth × ffr shock			-0.34	-0.62				
			(0.42)	(0.54)				
size × ffr shock					0.39	0.65		
					(0.29)	(0.40)		
liquidity × ffr shock							-0.25	-0.33
							(0.29)	(0.35)
Observations	219402	151027	208624	144731	219402	151027	219278	150947
R^2	0.124	0.141	0.128	0.144	0.124	0.141	0.126	0.142
Firm controls	yes	yes	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes	yes	yes	yes	yes

Notes: results from estimating variants of the baseline specification $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta_y(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \beta_z z_{jt-1}\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where z_{jt-1} is the firm's lagged sales growth, future sales growth, size, or liquidity, and all other variables are defined in the main text or the notes to Table 3, except that Z_{jt-1} additionally includes the variable z_{jt-1}.

Table 22

Interaction With Other Measures of Financial Positions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
leverage × ffr shock	-0.57**		-0.57**		-0.57**		-0.62**	
	(0.27)		(0.27)		(0.27)		(0.26)	
dd × ffr shock		1.17***		1.12***		1.14***		1.18***
		(0.41)		(0.40)		(0.41)		(0.41)
size × ffr shock	0.39	0.65						
	(0.29)	(0.40)						
cash flows × ffr shock			0.02	-0.33				
			(0.43)	(0.60)				
$\mathbb{1}\{\text{dividends} > 0\}\times$ ffr shock					0.33	0.24		
					(0.59)	(0.64)		
liquidity × ffr shock							-0.25	-0.33
							(0.29)	(0.35)
Observations	219402	151027	217900	149949	219182	150902	219278	150947
R^2	0.124	0.141	0.130	0.145	0.125	0.141	0.126	0.142
Firm controls	yes	yes	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes	yes	yes	yes	yes

Notes: results from estimating variants of the baseline specification
$\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta_y(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\text{m}} + \beta_z z_{jt-1}\varepsilon_t^{\text{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where z_{jt-1} is the firm's lagged size, cash flows, dividend payments, and liquid assets, and all other variables are defined in the main text or the notes to Table 3, except that Z_{jt-1} additionally includes the variable z_{jt-1}.

are less closely associated with default risk – size, cash flows, dividend payments, and available liquid assets – do not generate statistically significant differential responses to monetary policy. However, the point estimates do indicate that larger firms, dividend-paying firms, and firms with less liquid assets are more responsive to monetary shocks.

Results stronger when instrument financial position with past financial position One concern about our measures of financial position x_{jt} is that they contain measurement error. Table 23 corrects for this measurement error by instrumenting financial position x_{jt} with the financial position in the previous year x_{jt-4}. The heterogeneous responses are stronger in this specification, consistent with measurement error generating attenuation bias in our baseline specification in the main text.

Heterogeneous responses for different measures of leverage Table 24 decomposes leverage into various types of debt and shows that our results hold for each of these types of

Table 23

Instrumenting Financial Position with Past Financial Position

	(1)	(2)	(3)	(4)	(5)	(6)
leverage × ffr shock	-0.61*	-0.68*	-1.17**			
	(0.34)	(0.37)	(0.45)			
dd × ffr shock				1.18**	1.30**	1.05
				(0.52)	(0.57)	(0.80)
Observations	219402	216913	212948	147498	143925	138084
R^2	0.020	0.019	0.018	0.024	0.023	0.017
Firm controls, Time-Sector FE	yes	yes	yes	yes	yes	yes
Instrument	1q lag	2q lag	4q lag	1q lag	2q lag	4q lag

Notes: IV results from estimating the baseline specification $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta_y (x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where all variables are defined in the main text or the notes to Table 3. Within-firm financial position $x_{jt} - \mathbb{E}_j[x_{jt}]$ is instrumented with the past quarter, past two quarters or past four quarters financial position.

debt.[35] In addition, the table shows that our results hold when use leverage net of current assets.

C Comparison to Firm Volatility Literature

In this subsection, we explore the empirical link between firm-level volatility and the response to monetary policy. Our motivation is a growing strand of literature that has argued that firm-level volatility is an important determinant of how those firms respond to shocks (see, e.g., Vavra (2013) or Bloom et al. (2018)). Indeed, one can view volatility as a proxy for default risk, since all else equal firms with more volatile cash flows will default more frequently. We measure volatility vol_{jt} as the standard deviation of the firm's year-on-year sales growth over the past twenty quarters.[36]

Panel (a) of Figure 21 shows that firms with more volatile sales growth are less responsive

[35] This decomposition sheds light on the role of the "debt overhang" hypothesis in driving our results. Under this hypothesis, equity holders of highly leveraged firms capture less of the return on investment; since equity holders make the investment decision, they will choose to invest less following the monetary policy shock. However, because investment is long lived, this hypothesis would predict much stronger differences by long-term debt. We find that this is not the case; if anything, the differences across firms are stronger for debt due in less than one year.

[36] Many papers measure volatility using the dispersion in firm- or establishment-level TFP rather than sales growth. We cannot construct firm-level TFP because our dataset does not contain observations of employment.

TABLE 24
DECOMPOSITION OF LEVERAGE

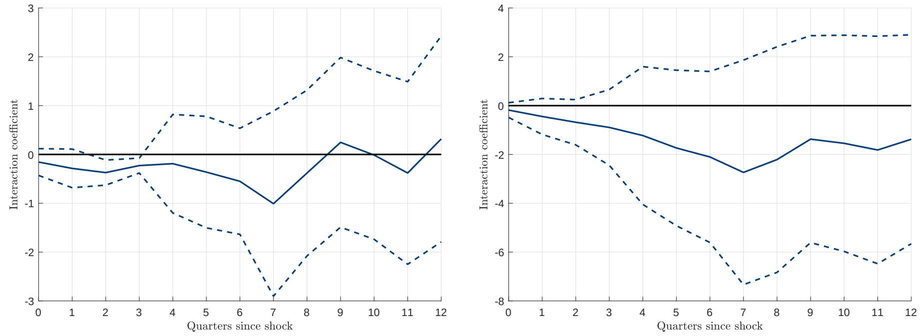
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
leverage × ffr shock	-0.57**						
	(0.27)						
net leverage × ffr shock		-0.56*					
		(0.29)					
ST debt × ffr shock			-0.33		-0.39		
			(0.29)		(0.29)		
LT debt × ffr shock				-0.16	-0.30		
				(0.24)	(0.24)		
other liabilities × ffr shock						-0.16	
						(0.26)	
liabilities × ffr shock							-0.56*
							(0.28)
Observations	219402	219402	219402	219402	219402	219393	219393
R^2	0.124	0.125	0.124	0.121	0.125	0.124	0.126
Firm controls	yes	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes	yes	yes	yes

Notes: results from estimating variants of the baseline specification
$\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\text{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where all variables are defined in the main text or the notes to Table 3. “Leverage” refers to leverage constructed as in the main text. “Net leverage” is leverage net of current assets. “Short term debt” is current debt (coming due in less than one year) divided by total assets. “Long term debt” is total debt minus current debt divided by total assets. “Other liabilities” is other liabilities divided by total assets. “Liabilities” is total debt plus other liabilities divided by total assets. Standard errors are two-way clustered by firms and quarters.

to monetary policy. Quantitatively, the estimates imply that a firm with one standard deviation higher volatility has an approximately 0.5 units lower semi-elasticity of investment with respect to monetary policy. Panel (b) shows that these differential responses are larger if we measure volatility over the past forty quarters rather than the past twenty.

However, Panel (a) of Figure 22 shows that these heterogeneous responses by volatility become insignificant once we control for heterogeneity in distance to default. We therefore conclude that the differences by volatility are in fact driven by differences in default risk, consistent with our model. Panel (b) shows that controlling for leverage has a smaller effect on the heterogeneous responses by volatility.

Figure 21: Dynamics of Differential Responses to Monetary Shocks by Volatility



Notes: dynamics of the interaction coefficient between firm's sales volatility and monetary shocks and between size and monetary shocks. Reports the coefficients β_h over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_h \text{vol}_{jt-1}\varepsilon_t^{\text{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jth}$, where vol_{jt} is the standard deviation of the firm's year-on-year sales growth over the past five or ten years, and all other variables are defined in the main text or the notes to Table 3, except that Z_{jt-1} additionally includes the variable vol_{jt-1}. We have standardized volatility vol_{jt}, so their units are in standard deviations relative to the mean.

D Equilibrium Definition

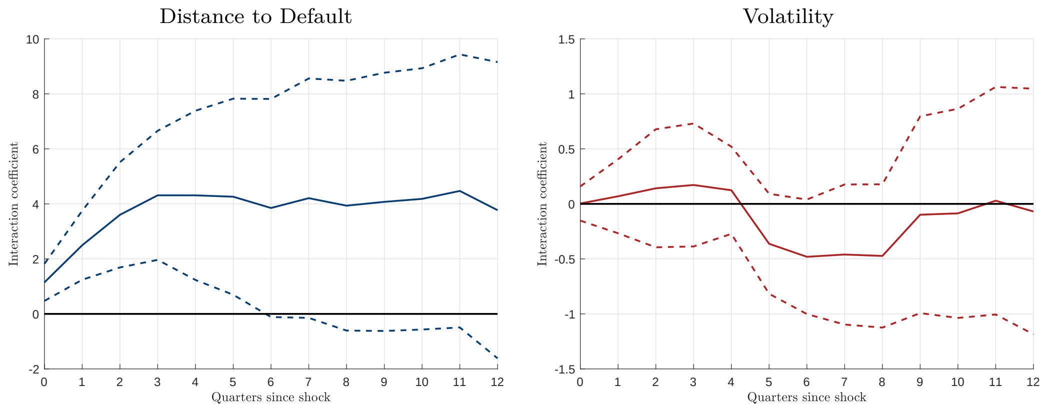
Distribution of Firms We need to derive the evolution of the distribution of firms in order to precisely define an equilibrium. The distribution of firms in production is composed of incumbents who do not default and new entrants who do not default. Mathematically, this distribution $\hat{\mu}_t(z,n)$ is given by

$$\begin{aligned}\hat{\mu}_t(z,n) = & \int \left(\pi_d \chi^1(n_t(z,\omega,k,b)) + (1-\pi_d)\chi_t^2(z, n_t(z,\omega,k,b))\right) \mathrm{d}\mu_t(z,\omega,k,b) \\ & + \overline{\mu}_t \int \left(\pi_d \chi^1(n_t(z,\omega,k_0,0)) + (1-\pi_d)\chi_t^2(z, n_t(z,\omega,k_0,0))\right) g(\omega)\mathrm{d}\omega \mathrm{d}\mu^{\text{ent}}(z),\end{aligned} \quad (18)$$

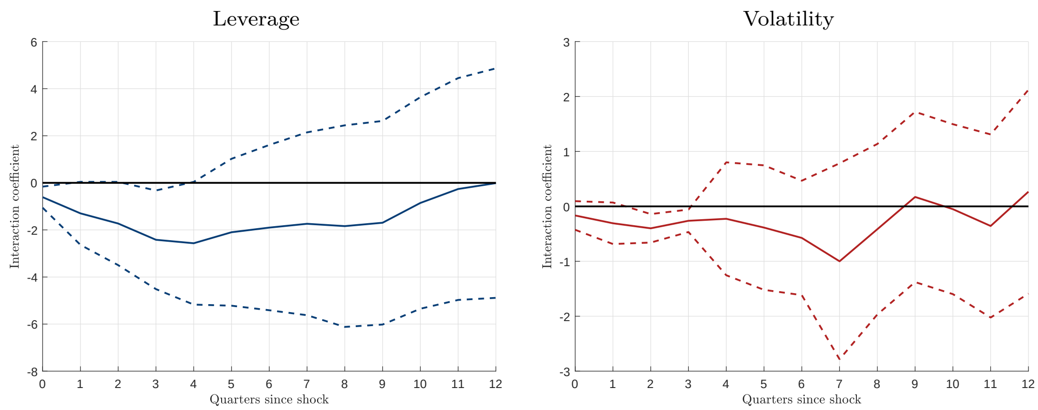
where $n_t(z,\omega,k,b) = \max_l p_t z(\omega k)^\theta l^\nu - w_t l + q_t(1-\delta)\omega k - b - \xi$ is the implied net worth n of a firm with state (z,ω,k,b) and $g(\omega)$ is the p.d.f. of capital quality shocks.

FIGURE 22: Joint Dynamics of Financial Position and Volatility

(a) Distance to Default and Volatility



(b) Leverage and Volatility



Notes: dynamics of the interaction coefficient between financial positions and monetary shocks and between volatility and monetary shocks. Reports the coefficients β_{1h} and β_{2h} over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_{1h}(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \beta_{2h}\mathrm{vol}_{jt-1}\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}'_h Z_{jt-1} + e_{jt}$, where vol_{jt} is the standard deviation of the firm's year-on-year sales growth over the past five or ten years and all other variables are defined in the main text or the notes to Table 3, except that Z_{jt-1} additionally includes the variable vol_{jt-1}. Panel (a) runs our baseline specification with leverage $x_{jt} = \ell_{jt}$. Panel (b) runs our preferred specification with distance to default $x_{jt} = \mathrm{dd}_{jt}$.

The evolution of the distribution of firms $\mu_t(z, \omega, k, b)$ is given by

$$\begin{aligned}\mu_{t+1}(z', \omega', k', b') = &\int (1-\pi_d)\chi_t^2(z, n_t(z, \omega, k, b))1\{k_t'(z, n_t(z, \omega, k, b)) = k'\} \\ &\times \mathbb{1}\{\frac{b_t'(z, n_t(z, \omega, k, b))}{\Pi_{t+1}} = b'\}p(\varepsilon|e^{\rho \log z + \varepsilon} = z')g(\omega')\mathrm{d}\varepsilon \mathrm{d}\mu_t(z, \omega, k, b) \\ &+ \overline{\mu}_t \int (1-\pi_d)\chi_t^2(z, n_t(z, \omega, k_0, 0))1\{k_t'(z, n_t(z, \omega, k_0, 0)) = k'\} \\ &\times \mathbb{1}\{\frac{b_t'(z, n_t(z, \omega, k_0, 0))}{\Pi_{t+1}} = b'\}p(\varepsilon|e^{\rho \log z + \varepsilon} = z')g(\omega')\mathrm{d}\varepsilon \mathrm{d}\mu^{\text{ent}}(z),\end{aligned} \tag{19}$$

where $p(\varepsilon|e^{\rho \log z + \varepsilon} = z')$ denotes the density of draws ε such that $e^{\rho \log z + \varepsilon} = z'$.

Equilibrium Definition An **equilibrium** of this model is a set of $v_t(z, n)$, $k_t'(z, n)$, $b_t'(z, n)$, $n_t(z, n)$, $\mathcal{Q}_t(z, k', b')$, Π_t, Y_t, q_t, $\mu_t(z, \omega, k, b)$, $\hat{\mu}_t(z, n)$, Λ_{t+1}, w_t, C_t, and I_t such that

(i) Production firms optimization: $v_t(z, n)$ solves the Bellman equation (5) with associated decision rules $k_t'(z, n)$, $b_t'(z, n)$, and $n_t(z, n)$.

(ii) Financial intermediaries price default risk according to (6).

(iii) New Keynesian block: Π_t, p_t, and q_t satisfy (7) and (8).

(iv) The distribution of firms in production $\hat{\mu}_t(z, n)$ satisfies (18) and the distribution $\mu_t(z, \omega, k, b)$ evolves according to (19).

(v) Household block: the stochastic discount factor is given by $\Lambda_{t+1} = \beta \frac{C_{t+1}^{-\sigma}}{C_t^{-\sigma}}$. The wage must satisfy $w_t = \Psi C_t$. The stochastic discount factor and nominal interest rate are linked through the Euler equation for bonds, $1 = \mathbb{E}_t \left[\Lambda_{t+1} \frac{R_t^{\text{nom}}}{\Pi_{t+1}} \right]$.

(vi) Market clearing: aggregate investment is implicitly defined by $K_{t+1} = \Phi \left(\frac{I_t}{K_t} \right) K_t + (1 - \delta)\mathbb{E}[\omega]K_t - (1-(1-\delta)\mathbb{E}[\omega])k_0\overline{\mu}_t$, where $K_t = \int k \mathrm{d}\mu_t(z, \omega, k, b)$. Aggregate consumption is defined by $C_t = Y_t - I_t - \xi$.[37]

[37] We normalize the mass of firms in production to 1, so ξ is the total resources lost from the fixed operating costs.

E Proof of Proposition 1

We prove Proposition 1 in steady state; extending the proof to include transition dynamics is straightforward. To clarify the economic mechanisms, we work with a simple version of the model that abstracts from capital-quality shocks ($\sigma_\omega = 0$), has zero recovery value of debt ($\alpha = 0$), and has no exogenous exit shocks ($\pi_d = 0$). The proof in the full model follows the same steps with more complicated notation.

Default Threshold As discussed in the main text, firms only default when they have no feasible choice which satisfies the non-negativity constraint on dividends, i.e., there is no (k', b') such that $n - k' + \mathcal{Q}(z, k', b')b' \geq 0$. Define the default threshold $\underline{n}(z) = \min_{k',b'} k' - \mathcal{Q}(z, k', b')b'$. Note that the largest feasible dividend payment of a firm is $n - \underline{n}(z)$. If $n \geq \underline{n}(z)$, then $\arg\min_{k',b'} k' - \mathcal{Q}(z, k', b')b'$ is a feasible choice and the firm will not default. On the other hand, if $n < \underline{n}(z)$, then $d \leq 0$ for all (k', b'), violating feasibility.

With this notation in hand, the Bellman equation of a continuing firm in this simple case is

$$v(z, n) = \max_{k',b'} n - k' + \mathcal{Q}(z, k', b')b' + \beta \mathbb{E}\left[v(z', \hat{n}(z', k', b'))\mathbb{1}\{n' > \underline{n}(z')\}|z, k', b'\right] \text{ s.t. } d \geq 0, \tag{20}$$

where $\underline{n}(z')$ is the default threshold.

Although the continuation value is kinked at the default point, it is never optimal for a firm to choose this point (see Clausen and Strub (2020) and the discussion in Arellano et al. (2016)). Hence, the first order conditions are necessary at the optimum.

Unconstrained Firms Define the *unconstrained capital accumulation rule* $k^*(z)$ as

$$k^*(z) = \underset{k'}{\text{argmax}} -k' + \beta \mathbb{E}\left[\iota(z', k') + (1 - \delta)k'|z\right],$$

where $\iota(z, k) = \max_l zk^\theta l^\nu - wl$. After some algebra, one can show that the expression in the main text solves this maximization problem (extending the expression to the full model).

We will now fully characterize the decision rules for firms that can afford the unconstrained capital accumulation rule and have zero probability of default in all future states. We first claim that such a firm is indifferent over any choice of debt b' which leaves the firm unconstrained. To show this, note that since the firm has no default risk it borrows at the risk-free rate $\frac{1}{\beta}$. In this case, the first order condition for borrowing b' is $\beta = \beta$, which is obviously true for any value of b'.

Following Khan, Senga and Thomas (2016), we resolve this indeterminacy by defining the *maximum borrowing policy* $b^*(z)$ as the maximal borrowing b' the firm can do while having zero probability of default in all future states.[38] To derive the maximum borrowing policy $b^*(z)$, first note that if the firm if the firm invests $k^*(z)$ and borrows $b^*(z)$ in the current period, its dividends in the next period are

$$\iota(z', k^*(z)) + (1-\delta)k^*(z) - b^*(z) - \xi - k^*(z') + \beta b^*(z'),$$

for a given realization of z'. The requirement that the firm has zero probability of default in all future states then implies that

$$b^*(z) = \min_{z'} \iota(z', k^*(z)) + (1-\delta)k^*(z) - k^*(z') + \beta b^*(z').$$

Hence, $b^*(z)$ is the largest amount of borrowing the firm can do and be guaranteed to satisfy the non-negativity constraint on dividends.[39]

By construction, if a firm can follow the unconstrained capital accumulation policy $k^*(z)$ and the maximum borrowing policy $b^*(z)$ while satisfying the non-negativity constraint on dividends in the current period, it will also satisfy the non-negativity constraint in all future periods. Moreover, following $k^*(z)$ is indeed optimal for such firms because it solves the associated first-order condition of these firms. Hence, a firm is *unconstrained* and follows these decision rules if and only if $d = n - k^*(z) + \beta b^*(z) > 0$, i.e.,

$$n > \overline{n}(z) \equiv k^*(z) - \beta b^*(z).$$

[38] Khan, Senga and Thomas (2016) refer to this object as the "minimum savings policy."

[39] To derive this expression, first re-arrange the non-negativity constraint on dividends conditional on a realization of the future shocks as an inequality with b' on the left-hand side. This results in a set of inequalities for each possible realization of the future shocks. The min operator ensures that all of these inequalities are satisfied.

Constrained Firms Consider again the constrained Bellman equation (20). We will show that firms with $n \in [\underline{n}(z), \overline{n}(z)]$ pay zero dividends. Invert the default threshold $\underline{n}(z)$ so that the firm defaults if $z' < \underline{z}(k', b')$. The Bellman equation (20) can then be written as

$$v(z,n) = \max_{k',b'} n - k' + \mathcal{Q}(z,k',b')b' + \beta \int_{\underline{z}(k',b')}^{\overline{z}} v(z', \hat{n}(z',k',b'))g_z(z'|z)\mathrm{d}z' \text{ s.t. } d \geq 0, \quad (21)$$

where $\overline{z}$ is the upper bound of the support of z.

Letting $\lambda(z,n)$ be the Lagrange multiplier on the $d \geq 0$ constraint, the first order condition for b' is

$$(1+\lambda(z,n))(\mathcal{Q}(z,k',b') + \mathcal{Q}_3(z,k',b')b') =$$
$$\beta\left[\int_{\underline{z}(k',b')}^{\overline{z}} (1+\lambda(z',\hat{n}(k',b')))g_z(z'|z)\mathrm{d}z' + v^0(k',b')g_z(\underline{z}(k',b')|z)\frac{\partial \underline{z}(k',b')}{\partial b'}\right],$$

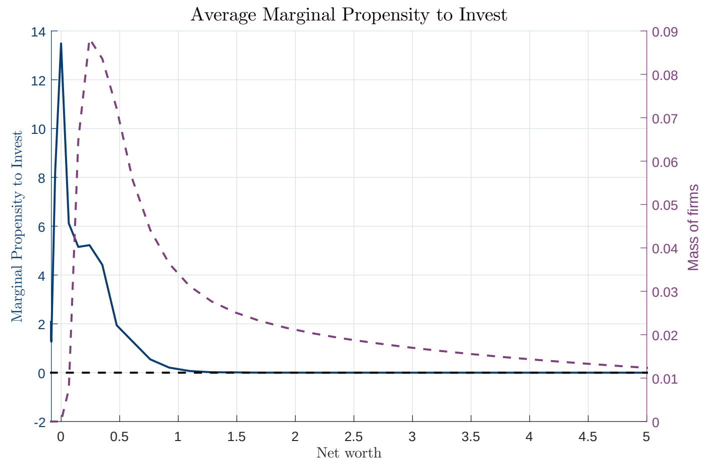
where $\mathcal{Q}_3(z,k',b')$ is the derivative of the debt price schedule with respect to b'. The left hand side of this expression measures the marginal benefit of borrowing. The marginal resources the firm receives by borrowing is the debt price, adjusting for the fact that the marginal cost of borrowing changes on existing debt. The firm values those marginal resources using the Lagrange multiplier. The right hand side of this expression measures the discounted marginal cost of borrowing. In states of the world in which the firm does not default, it must give up one unit of resources, which it values using the next period's Lagrange multiplier. In addition, marginal borrowing implies that the firm defaults in additional future states.

Note that the debt price schedule is $\mathcal{Q}(z,k',b') = \beta\int_{\underline{z}(k',b')}^{\overline{z}} g_z(z'|z)\mathrm{d}z'$, which implies that $\mathcal{Q}_3(z,k',b') = -\beta g_z(\underline{z}(k',b')|z)\frac{\partial \underline{z}(k',b')}{\partial b'}$. Plugging this into the first order condition gives

$$\beta(1+\lambda(z,n))\left[\int_{\underline{z}(k',b')}^{\overline{z}} g_z(z'|z)\mathrm{d}z' - g_z(\underline{z}(k',b')|z)\frac{\partial \underline{z}(k',b')}{\partial b'}\right] =$$
$$\beta\left[\int_{\underline{z}(k',b')}^{\overline{z}} (1+\lambda(z',\hat{n}(z',k',b')))g_z(z'|z)\mathrm{d}z' + v^0(k',b')g_z(\underline{z}(k',b')|z)\frac{\partial \underline{z}(k',b')}{\partial b'}\right]. \quad (22)$$

We will now show that constrained firms set $d = 0$. We do so by contradiction: suppose that a constrained firm sets $d > 0$, implying that $\lambda(z,n) = 0$. First consider a firm that has zero probability of default in the next period, i.e., $\underline{z}(k',b') = \underline{z}$ and $\frac{\partial \underline{z}(k',b')}{\partial b'} = 0$. In this case,

Figure 23: Effect of Net Worth Transfer



Notes: solid blue line plots the "marginal propensity to invest" out of a positive net worth transfer, i.e., $\frac{k(z,n+\Delta)-k(z,n)}{\Delta}$ as a function of net worth n. We average over idiosyncratic productivity shocks z using the ergodic distribution. Dashed purple line plots the stationary distribution of firms.

the first order condition (22) can be simplified to

$$0 = \int_{\underline{z}}^{\overline{z}} \lambda(z', k', b') g_z(z'|z) \mathrm{d}z'.$$

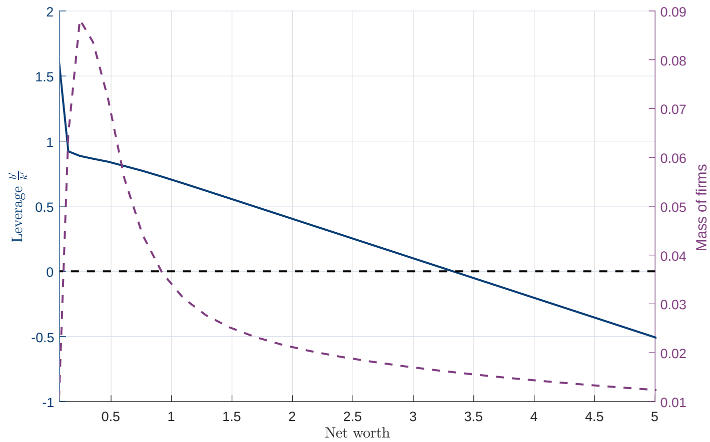
Since the firm is constrained, $\lambda(z', k', b') > 0$ for some positive mass of realizations of z', leading to a contradiction.

Now consider a firm that has some positive probability of default, implying that $\underline{z}(k', b') > \underline{z}$ and $\frac{\partial \underline{z}(k',b')}{\partial b'} > 0$. In this case, the first order condition (22) can be rearranged to

$$0 = \int_{\underline{z}(k',b')}^{\overline{z}} \lambda(z', k', b') g_z(z'|z) \mathrm{d}z' + \frac{\partial \underline{z}(k', b')}{\partial b'} g_z(\underline{z}(k', b')|z)(b' + v(z', k', b')),$$

where $v(z', k', b') = v(z', n')$ for the n' implied by (z', k', b'). By construction, risky constrained firms engage in strictly positive borrowing $b' > 0$. This implies that the right hand side is strictly greater than zero, leading to a contradiction.

FIGURE 24: Relationship between leverage and net worth



Notes: firms' optimal leverage choice $\frac{b'(z,n)}{k'(z,n)}$ as a function of net worth in steady state. We average over idiosyncratic productivity z using its ergodic distribution.

F Additional Analysis of Calibrated Model

Figure 23 plots the response of firm-level investment to an exogenous increase in net worth n. We measure the response using the "marginal propensity to invest" $\frac{k(z,n+\Delta)-k(z,n)}{\Delta}$, which computes the fraction of the net worth transfer Δ used for investment. Consistent with the discussion above, firms with low net worth exhibit a positive response because they are below their optimal scale $k^*(z)$; in fact, firms with very low net worth invest more than one-for-one because higher net worth decreases their default probabilities, allowing them to borrow more externally. The marginal propensity to invest then falls to zero once the firm reaches its optimal scale $k^*(z)$.

Figure 24 shows that there is a strong a monotonic relationship between firms' leverage and net worth in our model. Given that firms only default when net worth is below the threshold $\underline{n}(z)$, this figure implies that there is a monotonically increasing relationship between leverage and default risk in our model.