Central Bank Communication, Financial Frictions and Investment Decisions

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Abstract

I study the role of financial positions in the transmission of Fed information to investment. Central bank communication influence firms' expectations and stimulate investment, but its aggregate impact hinges on firms' financial positions. In the data, low-leverage firms invest nearly twice as much as high-leverage firms following Fed information shocks, consistent with easier access to credit markets and borrowing. To assess the aggregate implications, I augment a heterogeneous-firm model with financial frictions and default risk to include a role for Fed information. The model shows that Fed information amplifies aggregate investment volatility by around 10 percent, but its effectiveness is dampened by leverage heterogeneity, which reduces the aggregate response by about 20 percent. Moreover, while Fed communication is most powerful in recessions, its aggregate impact is dampened when credit conditions are tight. These results suggest that forward guidance is most effective when complemented by credit policy.

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1 Introduction

Central bank communication plays an important role in stimulating firms' investment decisions and aggregate demand. Since the early 1990s, the Federal Reserve has consistently used its statements and speeches to communicate expectations about future macroeconomic conditions, thereby influencing agents' beliefs about the economic outlook (Hillenbrand, 2025; Campbell et al., 2012; Nakamura and Steinsson, 2018). Because of its credibility, firms now pay close attention to the Fed's words and incorporate non-policy signals into investment decisions (Hassan et al., 2019, 2023).[1] However, the ability of firms to translate Fed information into higher investment depends critically on their financial positions. For example, high debt levels can restrict firms' access to external financing and limit their capacity to fund new investment in response to macroeconomic news. At the same time, positive news about the future can ease financial frictions by boosting expected net worth and relaxing borrowing constraints, enabling highly indebted firms to increase investment more than low-leverage counterparts (Bernanke et al., 1999b; Kiyotaki and Moore, 1997). How these opposing forces balance out at the micro level, and what they imply for aggregate transmission, remains an open question.

In this paper, I study the importance of nonfinancial firms' financial positions for the transmission of Fed information shocks—communications about the economic outlook unrelated to immediate policy changes—to aggregate investment. I begin by analyzing how firms' capital investment responds to Fed information shocks across different financial positions, using quarterly Compustat data and the identified Fed information shock series from Jarociński and Karadi (2020). I then develop a macroeconomic firm-dynamics model with financial frictions, default risk, and an explicit role for Fed information. The model illustrates and quantifies the importance of financial heterogeneity in the aggregate transmission of Fed information. Specifically, I use it to study (i) the extent to which heterogeneity in leverage influence the aggregate investment response, and (ii) how access to credit conditions the overall effectiveness of Fed information during recessions.

In the empirical analysis, I document that firms with lower leverage are, on average, more sensitive to Fed information shocks. I estimate the dynamic heterogeneous response of capital stock to the identified shocks using Jordà (2005)'s Local Projection. To capture variation across firms, I split the sample into three leverage groups based on the distribution of past leverage: low (below the 20th percentile), medium (20th to 60th percentile), and

[1] Transcripts of earnings calls reveal CEOs analyzing Fed statements to guide capital allocation, while CFO surveys rank monetary policy guidance among the most significant factors influencing strategic decisions.

high (above the 60th percentile), defined for each firm-quarter based on leverage over the preceding year. In response to a one-standard-deviation Fed information shock, low-leverage firms increase their capital stock by approximately 4.5% after two years, while medium- and high-leverage firms invest 1.5 to 2.5 percentage points less–representing a roughly 50% smaller response. Interestingly, the responses of medium- and high-leverage firms are nearly identical, suggesting that beyond a certain threshold, additional debt does not further reduce sensitivity to policy signals. These results are robust to alternative measures of financial frictions, model specifications, and proxies for Fed information.

The observed heterogeneity in investment responses can be explained by two distinct mechanisms. One hypothesis is that it reflects financial frictions: high-leverage firms, constrained by borrowing limits and default risk, cannot scale up investment when expectations improve, while low-leverage firms, with greater debt capacity, are able to expand investment when favorable conditions arise.[2] The alternative hypothesis is that low-leverage firms benefit more from positive information because they operate in more cyclical industries and experience stronger revenue growth when the economic outlook improves.[3] I find empirical evidence supporting the financial hypothesis. After a positive Fed information shock, firms across leverage groups experience similar increases in revenues and internal funds, indicating that differences in real responses do not stem from cash flow. Instead, low-leverage firms respond by issuing more debt, expanding investment, but also increasing their probability of default.

While micro-level heterogeneity offers important insights into how firms respond to exogeneous shocks, it does not directly translate into aggregate policy implications. To assess the broader relevance, I develop a structural model that quantifies the role of financial heterogeneity in the transmission of Fed information.

I extend a classical dynamic heterogeneous firm model with idiosyncratic productivity and both real and financial frictions to incorporate a role for Fed information. The economy consists of a distribution of firms that differ in productivity, capital, and debt. Firms face aggregate uncertainty regarding future aggregate productivity and the real interest rate. Firms produce a homogeneous consumption good using a decreasing-returns-to-scale technology, hire labor in a competitive market at the equilibrium wage, and invest in physical capital subject to adjustment costs. Investment is financed through a mix of internal funds, corporate bonds, and equity issuances. Corporate bonds are issued at a discount and priced

[2] This mechanism is consistent with standard theories linking financial positions and cash-liquidity to investment sensitivities (Strebulaev et al., 2012; Jeenas, 2018b).

[3] This is consistent with empirical evidence that low-leverage firms are more prevalent in sectors with higher average market betas, reflecting greater sensitivity to business cycle conditions. See, e.g., Frank and Goyal (2009), Rampini and Viswanathan (2013), and Baker and Wurgler (2002).

by risk-neutral intermediaries based on the perceived probability of default, while equity issuance entails quadratic costs. The monetary authority sets the real interest rate according to a policy rule that responds to the aggregate state of the economy. In addition, it has superior information about future aggregate productivity and communicates this to firms through a noisy public signal. Firms update their beliefs based on the signal received, which influences their expectations about future productivity, the interest rate path, and ultimately their investment and financing decisions.

I estimate the model using the Simulated Method of Moments (SMM). Parameters related to aggregate technology, preferences, and policy processes are externally calibrated to match long-run U.S. macroeconomic data, while the remaining parameters governing real and financial frictions are estimated against firm-level evidence. I target 12 quarterly moments from Compustat merged with the I/B/E/S Guidance database. These include the correlation matrix between investment, profits, debt, and CEOs' sales forecast revisions, as well as the average bond spread and the heterogeneous sensitivity of investment to changes in sales expectations across firms with different leverage levels. The estimated parameters align with the firm dynamics and corporate finance literatures, and the model provides a good overall fit, replicating firm-level covariances and heterogeneous responses to Fed information.

The model highlights two main channels through which Fed information affects the economy. At the micro level, signals about future productivity prompt firms to adjust investment and financing, but their responses differ sharply with leverage: low-leverage firms borrow and invest more readily, while highly indebted firms restrain investment because of borrowing constraints and heightened default risk. At the aggregate level, Fed signals amplify the effects of productivity shocks through two channels—an anticipation effect, as firms adjust their expectations before shocks materialize, and a reduction in uncertainty, which coordinates expectations across firms. The magnitude of this amplification depends on the degree of financial frictions in the economy, which determine how easily firms can translate improved expectations into borrowing to finance new investment.

Fed information amplifies volatility, but its effectiveness is dampened by leverage heterogeneity. On the one hand, by acting as a public signal, Fed communication makes firms' decisions more forward-looking and synchronized: investment dispersion rises by about 15 percent, firm-value growth volatility rises by more than 40 percent, and aggregate investment volatility rises by roughly 10 percent relative to a counterfactual without signals. On the other hand, leverage heterogeneity acts as a brake on transmission. Low-leverage firms expand borrowing and investment strongly in response to positive signals, while high-leverage firms remain constrained. As a result, the aggregate investment response is about 20 percent smaller than it would be if all firms behaved like low-leverage firms. Together, these findings imply that Fed information tends to amplify both firm-level volatility and aggregate responses, but its power is attenuated in economies with large shares of highly indebted firms.

Finally, Fed communication is especially powerful in recessions, when the marginal value of capital is high, but its aggregate impact depends critically on access to credit. With tight financing constraints, firms struggle to translate improved expectations into higher investment, muting the anticipation effect of Fed signals. When credit markets are looser, firms can issue more debt, and aggregate investment rises by roughly 10 percent more relative to the tight-credit case. This mechanism underscores that forward guidance and information effects are not only about coordinating expectations (Nakamura and Steinsson, 2018; Angeletos and Lian, 2018). The implication is that Fed communication is most effective in downturns when paired with policy measures that ease borrowing constraints, enabling firms to raise funds externally to finance investment.

Literature. This paper contributes to three main strands of the literature. First, this paper contributes to the literature on how the effects of monetary policy vary across firms with different balance sheet characteristics. This literature has examined excess sensitivity to monetary policy innovations using measures of firm performance and proxies for financial frictions. Gertler and Gilchrist (1994) find that small firms are more sensitive than large firms to interest rate tightening, while Bahaj et al. (2019) show that younger, more highly levered firms are most affected through employment. Closer to my paper, Ottonello and Winberry (2018) and Jeenas (2018a) analyze the role of leverage in the transmission of monetary policy to investment using Compustat data, but reach contrasting conclusions. In light of this debate, Cloyne et al. (2018) propose using dividend policy as a measure of financial frictions and find that younger, non-dividend-paying firms are more responsive in terms of investment and borrowing.[4] My paper contributes to this literature by examining the role of financial frictions in monetary policy, focusing specifically on the transmission of Fed information shocks at both the micro and macro level.

Second, this paper contributes to the growing literature on the effects of Fed information on the economy. The idea that Fed announcements can convey information about the future path of output and inflation, beyond the current and future stance of monetary policy, was first highlighted by Romer and Romer (2000) and formally modeled by Ellingsen and Söderström (2001). Subsequent work, including Campbell et al. (2012), Nakamura and

[4] Other contributions study the broader role of firm or industry heterogeneity in monetary policy transmission Gaiotti and Generale (2002), Ehrmann and Fratzscher (2004), Peersman and Smets (2005).

Steinsson (2018), Jarociński and Karadi (2020), and Andrade and Ferroni (2021), shows that information effects can contaminate traditional estimates of monetary policy shocks that rely on high-frequency identification, and can fundamentally alter conclusions about the effectiveness of monetary policy interventions.[5] My contribution to this literature is twofold. First, I show that Fed information shocks have significant effects on firm-level decisions and that financial frictions dampen the aggregate investment response. Second, I show that Fed information shocks operate primarily through the debt market and firms? capacity to borrow externally.

Finally, it contributes to the theoretical literature on the role of credit market frictions in amplifying monetary policy disturbances. In a seminal paper, Bernanke et al. (1999a) embed the financial accelerator in a representative-firm New Keynesian model with financial frictions and show that pro-cyclical firms' net worth amplifies monetary policy interventions. Ottonello and Winberry (2018) confirm this mechanism in a model with firm heterogeneity and default risk. My contribution is to show that, in the context of Fed information shocks, the aggregate effectiveness of communication depends critically on access to credit: when borrowing constraints are tight, firms cannot fully act on improved expectations, while looser credit conditions amplify the impact.

2 Empirical Analysis

This section presents the empirical results. I first describe the data and the measurement of Fed information shocks and firm-level variables. I then show that firms with high levels of leverage invest less in response to Fed information shocks. Finally, I document that this heterogeneity is primarily driven by differences in access to external finance.

2.1 Dataset and measurement

The primary source of data is the quarterly Compustat dataset, which provides comprehensive financial statement information for publicly listed companies in the U.S. and has been extensively used in prior research to assess the impact of monetary policy on capital

[5] Jarociński and Karadi (2020), Andrade and Ferroni (2021), and Miranda-Agrippino and Ricco (2018) use market-based measures of interest rate expectations and economic fundamentals, combined with sign-restriction approaches, to separate interest rate surprises. Other work employs alternative strategies: Doh et al. (2020), Handlan (2020), and Acosta (2021) apply machine-learning and text-based techniques to Fed statements; Cai et al. (2021) and Lakdawala (2019) remove information effects by controlling for differences between the Fed's information set and that of the public.

investment decisions.[6] I merge firm-level balance sheet data with a set of aggregate variables obtained from Federal Reserve Economic Data and previous literature. The final dataset includes 9,947 firms with quarterly financial information spanning from 1990-Q1 to 2019-Q4.[7] Below, I briefly outline the measurements of firm-level variables, and Fed information shocks used in the baseline specification. Additional details on the data and cleaning can be found in Appendix A.

Measurement of Fed information shocks. I measure unexpected news from the Fed regarding the future economic outlook using the Fed information shock series constructed by Jarociński and Karadi (2020). They identify these shocks by exploiting the high-frequency comovement of stock prices and interest rate expectations within a 15-minute window around Federal Open Market Committee (FOMC) announcements. When the Fed conveys positive economic news, investors anticipate stronger future earnings and expect the Fed to tighten policy gradually in response to improved growth and inflation prospects. As a result, stock prices and expected policy rates both rise. Conversely, negative Fed signals lead investors to revise down their expectations for dividends and interest rates, causing both stock prices and rate expectations to fall.[8] Figure 6 in Appendix A shows the standardized time-series for the Fed information shock sum at the quarterly level to match the frequency of the firm-level data.[9]

Measurement of firm variables. I use Compustat data to measure firms' capital investment and financial positions. To mitigate measurement error—which can obscure systematic responses in quarterly investment rates across firms—I estimate the dynamic response of capital stock accumulation to Fed information shocks, rather than the response of capital expenditures (Doms and Dunne, 1998). I calculate the capital stock $k_{i,t}$ for each firm i at the end of the quarter t using the perpetual inventory method, as is standard in the firm dynamics literature (Ottonello and Winberry, 2018; Cloyne et al., 2018).

I measure firms' financial position using leverage, defined as the ratio of total debt to total assets. I focus on leverage for two reasons. First, it provides a clear measure of a firm's exposure to external financing, with higher leverage indicating lower net worth and potentially

[6]Compustat covers roughly 50% of U.S. business investment, making it a key source for aggregate investment dynamics.

[7]The start and end dates align with the dates of the aggregate variables in the panel, excluding the Covid-19 period.

[8]Similar identifying assumptions to isolate Fed information shocks are used by Miranda-Agrippino and Ricco (2018) and Acosta (2021); I employ alternative series for Fed information in robustness checks.

[9]See Jarociński and Karadi (2020) for additional details on the identification strategy and methodology.

tighter financial constraints. Second, leverage is strongly correlated – approximately 60% – with other indicators of financial health, such as default risk, and thus serves as a robust proxy for capturing variation in financial position that may influence how firms adjust investment in response to policy signals (Ottonello and Winberry, 2018).

In Appendix B, I use alternative proxies for financial positions, including cash liquidity, firm size, age, distance to default, and credit ratings as a robustness.

2.2 Heterogeneity of investment response

I estimate the dynamic heterogeneous response of investment to Fed information shocks using Jordà (2005)'s Local Projection as in Cloyne et al. (2018). I split firm-level observations i at time t into three leverage groups $\{g_j\}_{j=1}^{3}$ based on past leverage. For a given quarter, a firm is classified as low leverage if it falls in the bottom 20th percentile of the past-year leverage distribution, medium leverage if it lies between the 20th and 60th percentiles, and high leverage if it is above the 60th percentile. I then estimate the cumulative response of capital investment to Fed information shocks for each group using the following specification:

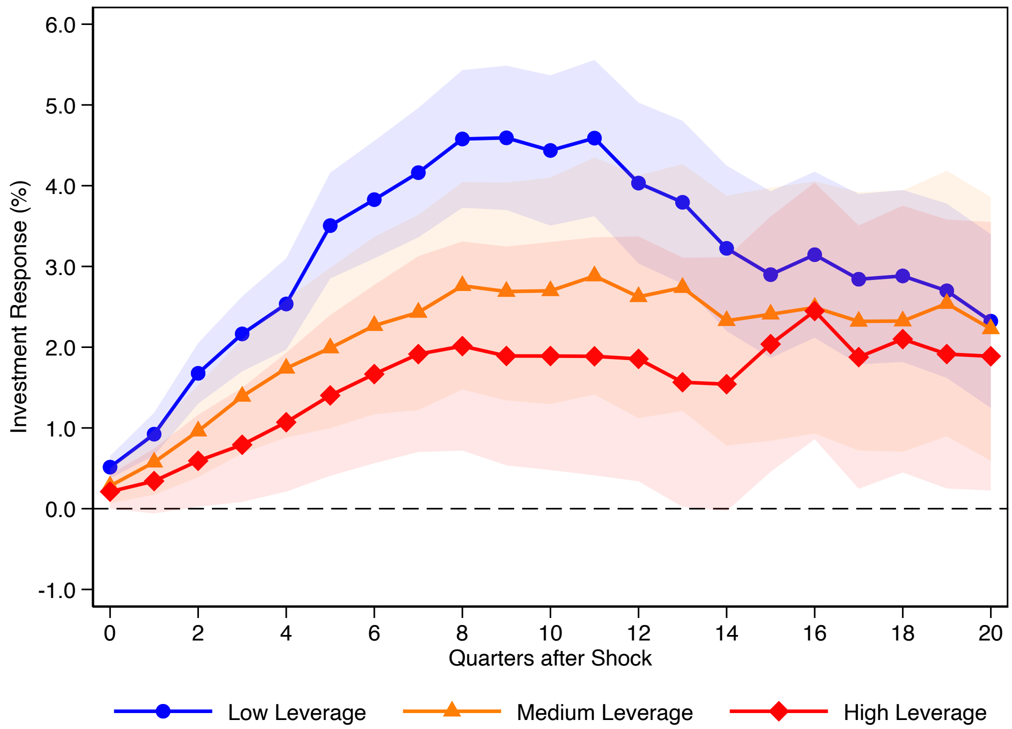
$$\Delta_h \log\left(k_{i,t+h}\right) = \alpha_{i,h} + \sum_j \beta_{h,j} \cdot \mathbb{1}[i \in g_j] \cdot \varepsilon_t^{\text{info}} + \sum_j \gamma_{h,j} \cdot \mathbb{1}[i \in g_j] + \Gamma_h' X_{i,t-1} + u_{i,t+h}, \quad (1)$$

where $\mathbb{1}[i \in g_j]$ is an indicator functions that take value 1 is a firm belongs to the leverage group j. Firm fixed effects $\alpha_{i,h}$ control for time-invariant heterogeneity, and $X_{i,t-1}$ includes lagged control variables. In the baseline specification, I control only for firm size, measured as the logarithm of total assets. Standard errors are clustered at the firm level.

Low-leverage firms serve as the baseline group. Therefore, the vector of coefficients $\beta_{h,j}$ capture the additional investment response h periods ahead for medium- and high-leverage firms relative to the low-leverage group. A significant and positive $\beta_{h,j}$ suggests that higher-leverage firms accumulate relatively more capital in response to positive information shocks compared to low-leverage firms, whereas a negative coefficient indicates a weaker response. I compute the total investment response for each group by adding $\beta_{h,j}$ to the baseline response.

Figure 1 shows that low-leverage firms are significantly more responsive to Fed information shocks than medium- and high-leverage firms. In response to a one standard deviation shock, low-leverage firms increase their capital stock by approximately 4.5% after two years. In contrast, medium- and high-leverage firms accumulate about 1.5 to 2.5 p.p. less over the same horizon, that is roughly a 50% smaller average investment response compared to low-leverage firms. Interestingly, the responses of medium- and high-leverage firms are quite similar,

Figure 1: Investment response to Fed information shock by leverage group



Notes: The figure illustrates the average cumulative response of capital accumulation to a one standard deviation Fed information shock, across firms grouped by past leverage. Firms are sorted each year based on their leverage (defined as total debt over total assets, lagged by one period) and assigned to terciles: low (bottom 20%), medium (20th-60th percentile), and high (above 60th percentile). The Fed information shock series is taken from Jarociński and Karadi (2020). Shaded areas represent 90% confidence intervals, constructed using standard errors clustered at the firm level. Labels on the y-axis are in percentage terms (i.e., 1 = 1%). Additional details on variable construction can be found in Appendix A.

suggesting that once firms cross a certain leverage threshold, further increases in leverage do not meaningfully reduce their sensitivity the shocks. These results are both quantitatively and qualitatively consistent with previous literature in monetary policy (Jeenas, 2018b; Ottonello and Winberry, 2018; Cloyne et al., 2018).

Appendix B show that the results are robust to alternative specifications and shock identification strategies. First, the main findings in Figure 1 remain stable across different model specifications and time samples. Figures 8 and 9 show that the average responses are both qualitatively and quantitatively similar when controlling for additional firm-level and macroeconomic variables, as well as when including sector-time fixed effects.[10] Figure 10

[10] I include sector-time fixed effects, defined at the one-digit SIC level, to account for variation in how firms across sectors respond to business cycle fluctuations, as in Jeenas (2018b) and Ottonello and Winberry

shows that the findings are consistent when restricting the sample to the post-1994 period–after the Fed began publicly communicating its announcements–and to the pre-crisis period ending in 2008. Second, the results are robust to alternative measures of Fed information shocks. Finally, Figure 12 shows that the main patterns hold when using different proxies for Fed information shocks (Jarociński and Karadi, 2020; Jarociński, 2024; Gürkaynak et al., 2005). Across all specifications and shock definitions, low-leverage firms consistently exhibit stronger investment responses.

Why do low-leverage firms respond more strongly to the same positive signal about future economic conditions? One possibility is that they are more exposed to macroeconomic news. As the Fed's outlook materializes, these firms may experience larger gains in revenue and cash flow, enabling them to invest more aggressively.[11] Alternatively, the heterogeneity may reflect differences in financial flexibility rather than exposure to macroeconomic conditions. Even if internal funds rise similarly across firms, low-leverage firms have greater debt capacity and can finance additional investment by borrowing or drawing down liquidity buffers. High-leverage firms, by contrast, face tighter constraints and prioritize financial stability over expanding investment. I provide empirical evidence consistent with the latter explanation.

2.3 A financial explaination of investment heterogeneity

Table 1 provide evidences that the heterogeneity in firms' investment responses to positive economic news may primarily driven by differences in firms' capacity to access external finance, rather than in their ability to generate additional revenues or internal funds. To investigate the sources of this heterogeneity, I analyze the differential responses of additional firm-level variables to Fed information shocks, using the same specification as in equation 1. I focus on two sets of outcomes capturing growth in internal and external funds, and compare their responses to Fed information shocks across low- and high-leverage firms.

Panel A shows that CEO expectations and revenue growth respond similarly to Fed information shocks across leverage groups. On average, a one standard deviation positive Fed information shock leads managers to significantly increase their quarterly revenue forecasts. Firms are expected to report an increase in sales and retained earnings of approximately 1% and 3.4%, respectively, over the subsequent year. Importantly, these responses are similar across low- and high-leverage firms. While low-leverage firms exhibit a positive adjustments

(2018). However, the results remain robust when using a more granular sector definition.

[11] This is consistent with the idea that low-leverage firms operate in more cyclical sectors and exhibit greater sensitivity to macroeconomic conditions—patterns well documented in the macro-finance and firm dynamics literature.

Table 1: Heterogeneous effect of Fed information on beliefs and growth

Panel A: CEO Expectations Revisions and Revenue Growth	(1) CEO Guidance Revision	(2) Reported Sales	(3) Retained Earnings
Effect 1 St.D. Fed Info Shock on Low Leverage Firms (p.p.)	0.88*	0.93***	3.27***
	(0.51)	(0.31)	(0.36)
Incremental Effect on High Leverage Firms (p.p)	0.42	-0.04	0.13
	(0.75)	(0.35)	(0.48)
Average Effect	0.95	0.98	3.42
Fixed Effects	Firm	Firm	Firm
Observations	2,169	301,328	276,038
Panel B: Debt and Liquidity Growth	**Debt Ratio**	**Cash-Debt Ratio**	**Distance Default**
Effect 1 St.D. Fed Info Shock on Low Leverage Firms (p.p.)	13.91***	-6.14***	-3.80***
	(1.12)	(1.34)	(0.99)
Incremental Effect on High Leverage Firms (p.p.)	-14.17***	3.42**	2.83***
	(1.13)	(1.38)	(1.07)
Average Effect	0.54	-2.65	-0.95
Fixed Effects	Firm	Firm	Firm
Observations	264,246	236,344	174,957

Notes: The table reports estimates from regressions in which the independent variable is the Fed information shock, identified using the decomposition in Jarociński and Karadi (2020). All variables are one-year cumulative change calculated using the Haltiwanger formula, with the exception of guidance revision, which is measured within the same quarter. Panel A examines CEO expectations and revenue growth. CEO guidance revision is the log difference between the final and initial sales guidance issued within the same quarter; Reported sales are nominal sales deflated by the aggregate price index. Retained earnings are retained earning as a fraction of total assets. Panel B focuses on debt and liquidity growth. Debt Ratio is total debt divided by total assets; Cash-Debt Ratio is the ratio of cash and liquid assets to total debt; Distance to Default is constructed as in Merton (1974). All regressions include firm fixed effects and control for firm size. All values are expressed in percentage points (i.e., 1 = 1%). Standard errors, clustered at the firm level, are reported in parentheses $* = 10\%$ level, $** = 5\%$ level, and $* * * = 1\%$. See Appendix A for further details.

in sales guidance, realized sales, and earnings, close to the average effect in the sample, the incremental effects for high-leverage firms are economically small and not statistically significant. This suggests that differences in expectations and realized revenue growth are unlikely to explain the observed heterogeneity in investment behavior.[12]

[12]Data on managers' expectations of firms? future revenues and earnings come from the I/B/E/S Guidance dataset.

Panel B shows a significant difference in how firms' debt and liquidity positions respond to the Fed information shock. On average, firms react to positive Fed news by increasing their reliance on external financing, with debt ratios rising by approximately 0.5 p.p. and cash ratios declining by 2.6 percent over the subsequent year. This translates into a roughly 1 p.p. decline in firms' distance-to-default measure. However, unlike in the previous panel, the responses differ significantly between leverage groups. Low-leverage firms substantially worsen their financial positions, with debt ratios increasing by approximately 14 p.p., whereas the response among high-leverage firms is essentially zero. This divergence results in notably reduced liquidity among low-leverage firms and a substantially larger increase in their probability of default. These results are consistent with the hypothesis that the primary source of heterogeneity in firms' investment responses shown in Figure 1 stems from differences in financial constraints and access to external financing rather than differences in expected or realized performance.[13]

What do these findings imply for the Fed and policymakers? While micro-level heterogeneity provides valuable insight into firm-level responses to aggregate shocks, it does not directly translate into aggregate policy prescriptions. The documented differences reflect relative sensitivities across firms, but their macroeconomic significance remains uncertain. In the next section, I introduce a structural model to quantify policy implications.

3 Quantitative Model

I develop a dynamic model with heterogeneous firms and both real and financial frictions to quantify the implications of firm-level investment heterogeneity for monetary policy. The model retains the core elements of a standard neoclassical framework with firm heterogeneity and risky debt, but incorporates informational asymmetry between firms and the central bank about the future state of the economy.[14]

The key agents in the model are firms that differ in their idiosyncratic productivity. Firms accumulate capital through investment financed by internal cash flow, corporate bonds, and equity issuance (Gomes, 2001). Real frictions stem from capital adjustment costs, while financial frictions arise due to an equity financing premium and default risk. Firms face

[13]These results align with theoretical predictions from the corporate finance literature, which suggest that firms highly value financial stability and may refrain from fully exploiting investment opportunities if doing so risks their financial position (Whited, 1992; Gomes, 2001).

[14]In contrast to previous literature, which primarily studies firms' investment sensitivity to interest rate shocks (Ottonello and Winberry, 2018; Jeenas, 2018a; Koby and Wolf, 2020), my analysis emphasizes the role of Fed communication policy and the associated risks for the aggregate economy.

uncertainty about the future aggregate state, which directly affects their output, as well as uncertainty about the real interest rate, which influences both their continuation value and borrowing costs. In this environment, the central bank influences the real interest rate and provides unbiased signals to firms about the future aggregate state of the economy.

I briefly outline the model setup below. To simplify notation, I omit the time subscript t and use $'$ to denote future values. Uppercase letters denote aggregate or common variables, while lowercase letters indicate idiosyncratic firm-level variables.

3.1 Heterogeneous firms

Time is discrete and the horizon is infinite. In each period, there is a unit mass of firms with a well-defined distribution Γ, owned by a continuum of identical households. Each firm produces a homogeneous consumption good y using capital k and labor n within a technology that exhibits decreasing returns to scale.[15] Firms' production is influenced by firm-specific productivity z and the overall state of the economy A:

$$y = Azk^{\alpha}n^{\nu}, \qquad \alpha + \nu \leq 1 \tag{2}$$

Firm-specific productivity evolves according to a Markov process in logs, given by:

$$\log z' = \rho_z \log z + \sigma_z \varepsilon_z', \qquad 0 \leq \rho_z < 1, \quad \varepsilon_z' \sim \mathcal{N}(0,1) \tag{3}$$

Similarly, the aggregate state of the economy follows a Markov process in logs, given by:

$$\log A' = \rho_A \log A + \sigma_A \varepsilon_A', \qquad 0 \leq \rho_A < 1, \quad \varepsilon_A' \sim \mathcal{N}(0,1) \tag{4}$$

The terms $\varepsilon_z'$and ε_A' represent shocks to firm-specific productivity and the aggregate state, respectively.[16] In each period, firms observe their idiosyncratic productivity, the current aggregate state of the economy, and a signal about future aggregate productivity sent by the monetary authority. Given that they form expectations about future aggregate states. I denote with Ω the information set of the firms and intermediaries in the economy.

At the beginning of each period, firms can endogenously default on their existing debt b before making investment, labor, or financing decisions. If a firm defaults, its assets, net of deadweight default costs, are recovered by financial intermediaries, and the firm restarts with

[15]The assumption of decreasing returns to scale ensures that firms do not grow indefinitely, allowing for an optimal firm size.

[16]Similar representation of the aggregate economic state A is in Senga et al. (2017).

an initial stock of capital, $k_{\min}$, and zero debt after one period. A firm strategically defaults if the value of continuing operations is lower than the expected value of restarting in the next period.

If a firm decides to not default, it hires labor in a competitive labor market at the equilibrium wage W, invest in new capital stock k', and determine their external financing needs. Capital stock evolves according to:

$$k' = (1-\delta)k + i, \qquad \delta < 1 \tag{5}$$

where i represents the amount of new gross investment in capital stock, δ is the deprectiation rate. The price of investment is fixed and normalized to one. In addition, firms face quadratic adjustment costs whenever they invest in or divest capital:

$$\Phi\left(k, i\right) = \frac{c_0}{2}\left(\frac{i}{k}\right)^2 k, \qquad c_1 \geq 0 \tag{6}$$

The presence of quadratic adjustment costs slows convergence to the optimal firm size implied by decreasing returns to scale and productivity.[17]

Firms finance new investments using both internal and external funds. Internal financing, represented by cash-on-hand from production and operations, is preferred due to the absence of transaction costs. In contrast, external financing is costly and includes the issuance of corporate bonds, b', sold at a discounted price, $\mathcal{Q}$, and equity issuances. The price of debt, $\mathcal{Q}$, is firm-specific and determined in equilibrium by a financial intermediary. Debt is preferred over equity financing because of a tax advantage.[18] The corporate tax rate is denoted by τ.

The amount of dividends paid to shareholders after paying taxes, issuing debt and investing in new capital is:

$$d = (1-\tau)\left[Azk^{\alpha}n^{\nu} - Wn - \Phi(k,i)\right] - i + \mathcal{Q}\cdot b' - b + \tau\left[(R-1)b + \delta k\right] \tag{7}$$

where R is the risk-free rate set by the monetary authority. If $d > 0$, the firm distributes positive dividends to its shareholders; if $d < 0$, it indicates that the firm is raising external funds by issuing new equity. However, equity issuance is costly and is only used when the investment opportunities justify the additional cost, making it infrequent in the model. The

[17]The inclusion of adjustment costs benefits the model in two ways: it allows for imperfect correlation between firm size and idiosyncratic shocks by smoothing investment decisions, and it introduces a forward-looking element by linking investment to expected marginal-Q, which is absent without real frictions.

[18]Because of tax advantage, Modigliani-Miller's theorem does not hold and firms choose to finance investment by issuing debt over equity.

cost incurred by firms when raising external equity is given by:

$$\mathcal{H}(d) = (a_0 + a_1|d|)\,\mathbb{1}_{d<0}, \qquad a_0, a_1 \geq 0 \tag{8}$$

The cost of external finance is zero when the firm distributes dividends, but becomes positive and increasing in the amount of new equity issued when the firm raises funds from shareholders, consistent with the empirical findings in Altınkılıç and Hansen (2000).[19] The equity payout to shareholders is equal to the dividends net of the equity issuance cost.

3.2 Financial intermediary

There is a risk-neutral financial intermediary owned by households. The financial intermediary transfers household deposits to firms in the form of zero-coupon bonds. When a firm defaults on its debt b, the lender seizes firms' assets less any deadweight default costs,so that total recovery per unit of debt, $\mathcal{R}(k, b)$, is:

$$\mathcal{R}(k, b) = \alpha(1-\delta)\frac{k}{b} \tag{9}$$

The parameter α is the exogenous recovery rate of the firm's capital stock, which has a liquidation value of $(1-\delta)k$. Thus, the fraction $1-\alpha$ represents the deadweight loss per unit of depreciated capital.

Since the financial intermediary is risk-neutral, the lender requires an expected return equal to the risk-free rate. Thus, the price of debt is derived from the lender's zero-profit condition, accounting for less-than-full recovery in default:

$$\mathcal{Q} \cdot \mathbb{E}(R' \mid \Omega) = \mathbb{E}\Big[\mathcal{R}(k', b') \cdot \mathbb{1}_{\mathrm{D}} + \mathbb{1}_{\mathrm{ND}} \mid \Omega\Big] \tag{10}$$

where $\mathbb{1}_{\mathrm{D}}$ is an indicator function that takes value 1 if default occurs, 0 otherwise; conversely for $\mathbb{1}_{\mathrm{ND}}$. The expectations are taken with respect to the information set Ω.

Aggregate uncertainty about future states affects debt pricing in two ways. First, an increase in expectations about the future state of the economy can reduce borrowing costs by lowering default risk and increasing recovery rates in the event of default. Second, an increase in expectations about future interest rates can raise borrowing costs. The interplay between these two forces is crucial for matching the heterogeneity in responses to Fed information shocks observed in the data.

[19]This structure of equity issuance costs is common in the corporate finance literature.

3.3 Monetary authority

A monetary authority sets the real interest rate R and communicates private information about the future aggregate state of the economy through a signal, $\mathcal{S}$. I model monetary policy as a process for the real interest rate, allowing the policy rate to correlate with the aggregate state of the economy as follows:

$$\log R' - \bar{R} = \rho_i \log R + \phi_a \log A' + \varepsilon_r', \quad \varepsilon_r' \sim N(0, \sigma_r^2) \tag{11}$$

where $\bar{R}$ is the stationary real interest rate, and ϕ_a captures the policy response to deviations in the aggregate state. The real interest rate may change endogenously when the central bank observes shifts in the aggregate state, or exogenously through monetary policy shocks, ε_r', which temporarily deviate from the systematic rule.[20]

The monetary authority has perfect foresight about the future state of the economy, A', and at the beginning of every period it send with some probability an unbiased signal $\mathcal{S}$ about A' to the firms, subject to a certain amount of noise:

$$\mathcal{S} = \log A' + \varepsilon_S, \quad \varepsilon_S' \sim \mathcal{N}(0, \sigma_S^2) \tag{12}$$

The precision of the signal is exogenous, and the cost of acquiring this information is zero for all the firms. This structure is consistent with the setting in the empirical analysis: a positive signal about A', would lead to an upward revision in firms' beliefs about the future state of the economy, which in turn raise their expectations about future firms' profitability and policy rates, reflecting anticipated policy adjustments by the central bank in response to improved economic prospects.[21]

3.4 Firms' problem and equilibrium

The timing of the model is the following. At the beginning of every period, a firm observes its idiosyncratic and aggregate states (z, k, b, A, R) and the signal $\mathcal{S}$ about the future aggregate state of the economy A'.

Bayesian updating Given the observed aggregate states and the signal $\mathcal{S}$, firms and the financial intermediary update their beliefs about A', and future real interest rate R'. The

[20] Wang et al. (2022) consider a similar representation of the monetary policy rule in a model with bank heterogeneity and market power.

[21] See Jarociński and Karadi (2020) for a discussion.

posterior distribution of future realization of A' after receiving the signal is:

$$\log A' \mid \mathcal{S}, A \sim \mathcal{N}\left(\rho_A \log A + \mathcal{K}(\mathcal{S} - \rho_A \log A), \sigma_A^2(1-\mathcal{K})\right) \tag{13}$$

where $\mathcal{K} = \frac{\sigma_A^2}{\sigma_A^2+\sigma_S^2}$ captures the weight firms put on the signal. Equation 14 reflects how the signal adjusts the firms' initial beliefs about A'. A more precise signal (smaller σ_S relative to σ_A) gives more weight on the signal on the updated expectations, and leads to a narrower posterior distribution.

Similarly, the updated belief about the future state of the economy influences agents' expectations about the future real interest rate, R'. Since the real interest rate is directly linked to the expected state of the economy through the monetary policy rule, the posterior belief about R' is conditional on the updated information about A':

$$\log R' | \mathcal{S}, R \sim \mathcal{N}\left(\bar{R} + \rho_r \log R + \phi_a\left(\rho_a \log A + \mathcal{K}(\mathcal{S} - \rho_A \log A)\right), \phi_a^2 \sigma_A^2(1-\mathcal{K}) + \sigma_r^2\right) \tag{14}$$

This posterior distribution of future interest rates incorporates both the initial expectations and the revised beliefs about the future rates, which are updated based on the new information about the future state of the economy received through the signal. The variance of the posterior captures the remaining uncertainty, which includes both residual uncertainty about A' and the noise in the future interest rates.

A positive signal about A' has two effects on managers. First, it raises expectations about the state of the economy (first-order effect). Second, it reduces uncertainty about future aggregate states (second-order effect). The first effect can be positive or negative for the economy depending on the current aggregate state, whereas the effect on uncertainty is always positive. The magnitude of these effects is governed by the precision of the signal, σ_S, which I treat as exogenous and estimate to match firm-level data.[22]

Dynamic problem Given the observed idiosyncratic and aggregate state of the economy and firms' beliefs, each firm chooses whether to default, as well as its investment and financing policies, to maximize the future stream of cash flows for its shareholders. The firm's problem can be written recursively. Denote by $(s; S)$ the set of idiosyncratic and aggregate states, and with f^{post} the posterior density of next-period aggregate states given the Fed's signal; the value of the firm conditional to the signal sent by the monetary authority is given by:

$$V(s; S) = \max\left[V_D(s; S), V_{ND}(s; S)\right] \tag{15}$$

[22]Figure 14 in Appendix C provide a graphical representation of those effects on conditional expectations.

Here $V_D(s;S)$ represents the value of the firm if it defaults, while $V_{ND}(s;S)$ represents the value of the firm if it does not default. The region where $V_D(s;S) > V_{ND}(s;S)$ defines the states in which the firm strategically defaults.
The value of a firm that default is:

$$V_D(s;S) = \frac{1}{R}\int_{S'}\int_{z'} f^{post}\left(S'|S\right) f\left(z'\right) V\left(z', k_{min}, 0; S'\right) \tag{16}$$

When a firm defaults, its assets k net of deadweight costs, are seized by lenders during a reorganization period with no production. The firm then restarts with zero debt and a k_{min} of assets. The continuation value from not defaulting is determined recursively as:

$$V_{ND}(s,S) = \max_{k',b',n}\left\{d - \mathcal{H}\left(d\right) + \frac{1}{R}\int_{S'}\int_{z'} f^{post}\left(S'|S\right) f\left(z'|z\right) V'\left(\varepsilon', S'|\varepsilon\right)\right\} \tag{17}$$

where d is from equation 7, $\mathcal{H}\left(d\right)$ is the cost function from equation 8, the expectations are taken with respect to the Bayesian-updated probabilities. The price of debt is derived from the zero-profit condition in equation 10 given firms' policy functions.

Equilibrium An equilibrium in the model is a set of policy functions, k', b', a default policy, df, firm value function V, and a distribution of firms Γ, such that: i) firms' value functions and defualt choices are consistent with Equation 15, 16 and 17; ii) firms that continue to operate choose k' and b' to solve Equation 17; iii) financial intermediaries price debt according to the zero-profit condition in Equation 10; iv) the distribution Γ is consistent with the idiosyncratic and aggregate stochastic processes and firms'policy functions.

Solving the model involves addressing two challenges. First, computing expectations and beliefs require observing the signal sent by the monetary authority which depends on both the realization of future aggregate productivity A', unknown at time t, and the draw of a noise shock ε_S. Directly incorporating these variables would expand the state space by two dimensions, making the problem computationally intractable at high precision. To overcome this, I assume the Fed observes the true value of A' one period in advance and communicates it through a noisy signal. Firms, unaware that the Fed is perfectly informed, rationally treat the signal as containing noise when forming expectations.[23] With this assumption, I can discretize the signal state using the same grid as for A, and discretize agents' posterior

[23]Without this assumption, firms would recognize that the monetary authority observes A' directly, and the signal would be interpreted as fully revealing. In that case, there would be no role for noise in shaping firms' expectations.

beliefs using the entropy-based algorithm of Farmer and Toda (2017) before solving the firms' problem. This approach preserves the key informational frictions driving firm behavior, while maintaining tractability and precision. Second, firms negotiate with a competitive lender to determine the cost of debt, which depends on their current state and decisions regarding capital and debt. Solving the model requires knowing the firm's value in order to compute a default threshold, which itself depends on the cost of debt. To address this, I use a standard nested "loop-within-a-loop" method following the algorithm in Strebulaev et al. (2012). Further details on this procedure are provided in Appendix C.

4 Estimation

I calibrate a subset of model parameters based on prior literature, while parameters related to real and financial frictions are estimated via Simulated Method of Moments (SMM) to match a set of micro moments observed in the data at quarterly frequency.

Calibrated parameters. Table 2 reports the set of parameters calibrated externally. The long-run risk-free rate R is set to 4% annually, consistent with the average 1-year Treasury yield. Capital and labor elasticities ($\alpha = 0.25$, $\nu = 0.50$) follow Bloom et al. (2018), and the depreciation rate δ is calibrated to 10% annually. The corporate tax rate τ is set to 20%, based on effective rates reported in (CBO) (2017). Finally, the probability of arrival of a Fed signal about future productivity, p_S, is calibrated to 88%, which corresponds to the empirical frequency of revisions in real GDP growth in the Fed's Greenbook forecasts.[24]

To calibrate the aggregate processes for total factor productivity (TFP) and the real interest rate, I estimate a VAR(1) system using quarterly U.S. data. I construct utilization-adjusted TFP by accumulating quarterly changes in the detrended TFP series from Basu and Kimball (2005), and estimate its persistence ρ_A and innovation volatility σ_A from an AR(1) regression. I then estimate the real interest rate process as a function of its lag and predicted TFP, identifying the persistence ρ_R, volatility σ_R, and sensitivity to productivity news ϕ_A, calibrated to match U.S. time series moments. The estimated parameters are: $\rho_A = 0.921$, $\sigma_A = 0.110$, $\rho_R = 0.851$, $\sigma_R = 0.006$, and $\phi_A = 0.008$.

Simulated Method of Moments. Table 3 reports the values of the 9 remaining parameters estimated using the Simulated Method of Moments (SMM), and target moments. I target 12

[24]Specifically, I use real-time GDP revision data from the Fed Greenbook forecasts and construct a binary indicator equal to one whenever the absolute revision in projected real GDP growth exceeds 0.1 percentage points. The frequency of this indicator over the sample period is 88%.

Table 2: Calibrated parameters

Parameter	Description	Value	Target
R	LR risk-free rate	1.040	Avg. 1Y T-bill (FRED)
δ	Depreciation rate	0.100	Bloom et al. (2018)
α	Capital elasticity	0.250	Bloom et al. (2018)
ν	Labor elasticity	0.500	Bloom et al. (2018)
τ	Corporate tax rate	0.200	(CBO) (2017), effective rates
p_s	Fed signal probability	0.880	Greenbook GDP revision frequency
ρ_A	TFP persistence	0.921	Persistence detrended TFP-Util.
σ_A	TFP shock std. deviation	0.110	Volatility detrended TFP-Util.
ρ_R	Rate rule persistence	0.851	Persistence of interest rate
σ_R	Rate shock std. deviation	0.006	Volatility of interest rate
ϕ_A	Rate sensitivity to TFP	0.008	Comovement: rate and TFP

Notes: The table reports the calibrated parameters of the model, along with their descriptions, values, and empirical targets. The parameters governing technology and monetary policy processes are calibrated to match empirical properties of U.S. macroeconomic time series. The persistence and volatility of TFP are calibrated using utilization-adjusted total factor productivity from Basu and Kimball (2005). The monetary policy rule parameters are calibrated based on the estimated autocorrelation and conditional volatility of the real interest rate, as well as its co-movement with productivity innovations. The parameters are joinlty-calibrated.

empirical moments from quarterly Compustat data merged with I/B/E/S Guidance, spanning 1990-2018 and covering 60,319 firm-quarters from about 12,520 firms. Specifically, I target the correlation matrix among investment, profits, debt, and CEOs' sales forecast revisions, the OLS coefficient on the interaction between debt and CEOs' sales forecast revisions in predicting investment, and the aggregate average bond spread.

I choose the optimal model parameter vector, θ, to make simulated model moments close to data moments. I estimate the optimal vector of parameters $\hat{\theta}_{\text{SMM}}$ such that:

$$\hat{\theta}_{\text{SMM}} = \theta : \min_{\theta} \quad \Big(m(\tilde{x} \mid \theta) - m(\tilde{x})\Big) W \Big(m(\tilde{x} \mid \theta) - m(\tilde{x})\Big)', \tag{18}$$

where $m(\tilde{x})$ is the data moment vector and $m(\tilde{x} \mid \theta)$ is the simulated model moment vector. I use the asymptotically efficient weighting matrix W, cluster standard errors by firm with the asymptotic formulas in Hansen and Lee (2019). I generate simulated data on 3,000 firms for 150 periods with a burn-in-period of 75 periods from the model for a given set of parameters. I compute the equivalent model moments from the simulated data and compare them to the true moments in the data. In estimating Equation (18), I use the particle swarm stochastic search algorithm.

Table 3: Estimated parameters and moments

A. Estimated parameters	Symbol	Estimate	Std. Error
Persistence of idiosyncratic productivity	ρ_z	0.8282	0.0032
Std. deviation of idiosyncratic productivity	σ_z	0.1161	0.0031
Quadratic adjustment cost	c_1	2.7868	0.0620
Fixed equity issuance cost	a_1	0.0530	0.0151
Linear equity issuance cost	a_2	0.0817	0.0268
Recovery rate	γ	0.2500	0.0121
Fixed operating cost	ϕ	0.0137	0.0009
Std. deviation of aggregate Fed signal	σ_S	0.2425	0.0101
Std. deviation of noise in earnings	σ_π	0.3151	0.0147
B. Targeted moments	**Data**	**Std. Error**	**Model**
Std. deviation of investment	0.1346	0.0039	0.0949
Correlation of investment, profits	0.0951	0.0187	0.3087
Correlation of investment, debt	0.0325	0.0164	0.5481
Correlation of investment, sales forecast revision	0.0212	0.0060	0.0937
Std. deviation of profits	0.4600	0.0137	0.5572
Correlation of profits, debt	-0.0480	0.0198	0.2543
Correlation of profits, sales forecast revision	0.0325	0.0129	0.0768
Std. deviation of debt	0.1842	0.0049	0.2153
Correlation of debt, sales forecast revision	0.0178	0.0071	0.1322
Std. deviation of sales forecast revision	0.0586	0.0047	0.0898
Coeff. of debt x sales forecast revision on investment	-0.1062	0.1144	-0.4246
Average Bond Spread	0.0259	0.0064	0.0020

Notes: Panel A reports SMM parameter estimates using efficient moment weighting. Panel B reports data moments from Compustat merged with the I/B/E/S Guidance dataset, spanning 1990-2018, covering 12,520 firms and 60,319 firm-quarters. Model moments are computed from a simulated panel of 3,000 firms over 150 periods, with a 75-period burn-in. Standard errors are clustered at the firm level, except for the bond spread, which is clustered over time.

Identification. While the targeted moments are standard in the literature for identifying the key parameters of financial and real frictions, two moments are especially informative for pinning down the noise in firms' earnings expectations, σ_π. First, the correlation between investment and CEOs' forecast revisions is informative about how strongly managers adjust real activity in response to informational signals. A higher correlation implies that revisions are relatively precise and managers react strongly; conversely, when forecast revisions are noisy, the correlation weakens. Second, the volatility of forecast revisions is highly informative for σ_π. Greater noise in signals increases the dispersion of managers' expectations about future sales, thereby raising the dispersion of CEOs' sales forecast revisions. Together, these moments allow me to discipline the amount of informational noise required for the model to match the empirical joint distribution of investment, financing, and managerial expectations.

Baseline Estimates. Panel A of Table 3 summarizes the estimated parameters and their standard errors. Idiosyncratic productivity is highly persistent, with $\rho_a = 0.828$, and has a standard deviation of $\sigma_a = 11.6\%$, values consistent with the firm dynamics literature. The quadratic adjustment cost parameter is $c_1 = 2.78$, while fixed and linear equity issuance costs, a_1 and a_2, are 5% and 8%, respectively, in line with Hennessy and Whited (2007). The debt loss parameter $\gamma = 0.25$, implying that intermediaries recover only 25% of firms' capital stock in the event of firms' default. Fixed operating costs, ϕ, are equal to 1.3%, and the standard deviation of noise in the aggregate Fed signal is $\sigma_S = 0.24$. Finally, the model requires a substantial amount of earnings noise to match quarterly moments, with $\sigma_\pi = 31\%$, which is consistent with the estimates in Bordalo et al. (2024).

Model fit. Panel B of Table 3 presents the data moments, their standard errors, and the simulated moments. Despite the model being nonlinear and overidentified, the estimation achieves an overall good fit. The model replicates the signs of all key covariances and closely matches the volatility of investment, debt, and CEOs' sales expectation revisions. It also captures the lower sensitivity of investment to Fed information shocks for highly leveraged firms, as observed in the micro data.[25] A few moments remain more difficult to match, in particular the average bond spread—typically hard to replicate without introducing additional frictions—and the correlation between profits and debt, which is positive in the model but much weaker in the data at a quarterly frequency. This discrepancy arises because, in the model, investment and debt are tightly linked, whereas in the data quarterly fluctuations in profits and debt are only weakly correlated.

5 Model mechanisms

I outline the main mechanisms of the model that guide the interpretation of the quantitative results in the next section. I first examine firms' responses to Fed news at the micro level, and then analyze how Fed signals shape the aggregate response to shocks.

[25] In estimation, I target the heterogeneous effect of Fed information using investment one period ahead, which is smaller in the data and has a higher standard deviation, since most of the average and heterogeneous responses materialize only with a multi-year lag.

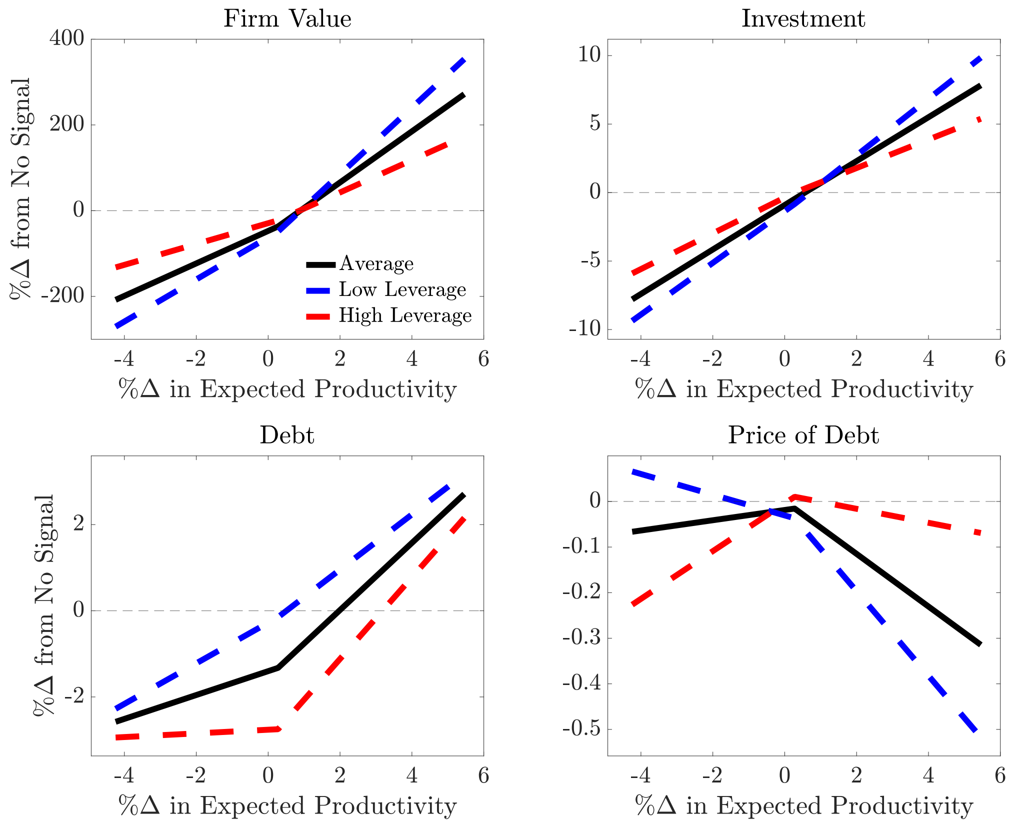
5.1 Firm-level response to Fed news

Figure 2 shows the average firm-level responses in investment, debt, market value, and bond prices, plotted against the expected percentage change in future productivity following a Fed signal. A signal from the monetary authority shifts firms' expectations about aggregate productivity, prompting adjustments in investment, borrowing, and default decisions. The magnitude of the effect depends on firms' leverage positions at the time of the announcement. To highlight this heterogeneity, I report the overall average response for the entire distribution along with separate averages for low-leverage firms (leverage below median) and high-leverage firms (leverage above median). All variables are expressed as percentage deviations from their means in the conditional stationary distribution without any signal.

In response to a positive signal about future economic conditions, firms expect productivity to rise and increase investment while issuing more debt. The anticipated improvement raises the marginal value of capital, encouraging firms to invest more even though current cash-on-hand remains unchanged. As a result, firms finance new investment by relying more heavily on external borrowing, thereby raising debt and equity issuances. Financial intermediaries adjust the pricing of debt accordingly. On the one hand, improved future prospects lower default risk, leading to higher bond prices and more favorable borrowing conditions. On the other hand, a stronger economic outlook is associated with expectations of future interest rate increases, which reduce bond prices and raise borrowing costs. The net effect on debt pricing is therefore ambiguous and depends on the relative strength of these two opposing forces. Finally, on average, firm value increases.

The average response of investment and debt depends on the existing level of firm leverage at the time of the announcement. Highly leveraged firms are less sensitive to Fed information because they benefit less from improvements in financial conditions. This occurs for two reasons. First, raising additional debt increases the likelihood of future default. Second, taking on more debt today implies higher repayments tomorrow, which raises the probability of needing external equity financing in the future Strebulaev et al. (2012).[26] In contrast, firms with low leverage can expand investment without substantially increasing their debt exposure or the likelihood of equity issuance. As a result, low-leverage firms respond more strongly to Fed information, increasing debt issuance more than their high-leverage counterparts.

Figure 2: Firm policy over Fed signal shock



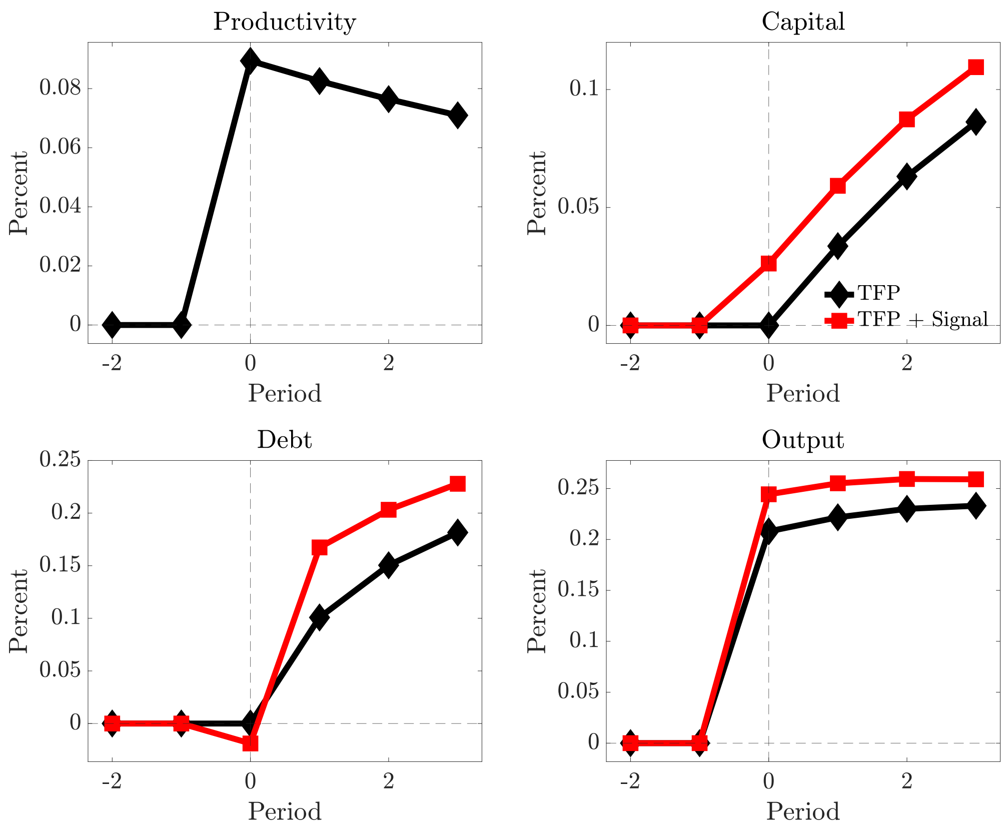
Notes: The solid black line shows the average policy function response to a Fed signal about future macroeconomic conditions. The dotted red lines correspond to high-leverage firms, while the solid blue lines represent low-leverage firms. All policy functions are expressed in percentage deviations from their average values in the conditional stationary distribution without a signal and are plotted against the expected change in future productivity. The top row of the figure displays the responses of firm value and investment rate, while the bottom row shows the responses of debt and the cost of debt. Firm value and debt are scales by firm capital stock. All policy functions are weighted using the erogidic distribution of non-defaulting firms in the steady state without signal.

5.2 Aggregate response to Fed information

Figure 3 shows the aggregate responses of investment, debt, and output to a TFP shock, both anticipated and unanticipated by the monetary authority. I estimate the response of aggregate outcomes to a Fed information shock by computing generalized impulse response functions (GIRFs) to a positive TFP shock, following the methodology of Koop et al. (1996). I compare two scenarios: (i) the economy experiences a surprise TFP shock with no signal

[26] The presence of costly equity issuance introduces a forward-looking component into firms' debt choices, which limits their willingness to issue debt to finance new investment.

Figure 3: Impulse response to a TFP shock and Fed signal



Notes: The figure shows the generalized impulse response functions (GIRFs) to a positive TFP shock, following the methodology of Koop et al. (1996). The solid black line reports the average policy function response to a surprise TFP shock with no signal from the central bank, while the red line shows the case in which firms receive a signal about future productivity one period in advance. All policy functions are expressed as percentage deviations from their average values in the conditional stationary distribution without a signal and are plotted against the expected change in future productivity. Results are based on simulations of 1,000 independent economies, each consisting of 1,000 firms over 150 periods. The economy is in aggregate steady state before the shock occurs.

from the monetary authority, and (ii) firms receive a signal from the central bank one period before the TFP shock occurs. The difference between these responses captures the impact of Fed communication on aggregate dynamics. To average idiosyncratic shocks, for each scenario, I simulate 1,000 independent economies, each consisting of 1,000 firms simulated over 150 periods, and average the outcomes.[27]

The amplification effect of the TFP shock in Figure 3 due to Fed information arises from two forces: an anticipation effect, reflecting expected improvements in future economic conditions, and a reduction in uncertainty about the future outlook. Without the Fed's

[27]Details on the algorithm are in Appendix C.

signal, firms respond only once the positive TFP shock actually materializes. At that point, the marginal value of capital rises and firms begin accumulating more capital. Output increases due to higher productivity and continues to grow endogenously as investment in capital expands. With improved borrowing conditions, firms optimally expand investment, financing it with a combination of internal resources and external borrowing, so that debt gradually increases. When the Fed signals a future positive TFP shock, firms? expectations of productivity rise and uncertainty about the outlook declines immediately at the time of the announcement. Firms anticipate higher productivity and optimally increase investment in new capital stock right away. Since no additional cash is received at the time of the announcement, firms must rely more on external funds to finance this new investment. Firms with low leverage can raise debt aggressively because their borrowing costs are low, while high levergaged firms may find optimally to limit new borrowing or repay debt as their financial conditions improve with falling default risk. As a result, aggregate debt may not rise immediately at the time of the announcement, since the additional borrowing by low-leverage firms is offset by the more cautious behavior of constrained firms.

The strength of this amplification depends on two factors. First, the cost of raising external funds, which reflects the degree of financial frictions in the economy. When borrowing is expensive or constrained, firms cannot easily translate improved expectations into higher investment, limiting the impact of Fed information. Conversely, when credit is relatively cheap and accessible, firms can expand investment more aggressively in response to a signal. Second, firms' willingness to invest depends on the state of the business cycle. During recessions, when the marginal product of capital is high, firms have stronger incentives to accumulate capital in response to favorable news, whereas in booms the return to additional investment is lower. The interaction of these forces is important for interpreting the quantitative results presented in the next section.

6 Quantitative implications

I use the model to quantify the aggregate impact of Fed information and financial frictions. First, I examine how Fed information contributes to aggregate volatility. Second, I estimate the role of financial heterogeneity in its transmission. Third, I discuss the policy implications of Fed communication in the presence of financial frictions.

6.1 Impact on aggregate volatility

Table 4 shows that Fed information increases the volatility of investment and firm value growth at both the firm and aggregate levels. I simulate a panel of 1,000 firms over 150 periods under two scenarios. In the first scenario (baseline), the Fed learns about the future state of the economy and sends noisy signals to firms, whereas in the second scenario (counterfactual), Fed signals are removed and expectations are formed solely from prior beliefs.[28] I then compare the volatility of investment, firm-value growth, and bond prices at both the firm and aggregate level. Firm-level volatility is the overall standard deviation of each variable across the firm-time panel, whereas aggregate volatility is the time-series standard deviation of the corresponding aggregate variables.

Table 4: Quantitative impact of Fed information on volatility

	(1)	(2)	(3)=(1)-(2)
Panel A. Firm-level volatility	Baseline	Counterfactual	Difference
Investment	10.459	9.034	1.425
Value growth	16.449	11.435	5.015
Bond prices	0.033	0.024	0.009
Panel B. Aggregate volatility	Baseline	Counterfactual	Difference
Investment	4.764	4.326	0.438
Value growth	14.062	6.983	7.079
Bond prices	0.009	0.008	0.001

Notes: This table reports the standard deviation of investment, firm value growth, and credit spreads under both baseline and counterfactual scenarios. Panel A shows the overall standard deviation of firm-level outcome variables in the simulated panel, while Panel B shows the standard deviation of the aggregate series computed as cross-sectional averages. Column (1) reports results from the baseline model, which corresponds to the original simulation, while Column (2) reports the counterfactual scenario without Fed signals. Column (3) reports the difference between the baseline and counterfactual.

Forward-looking policy signals make firms' decisions anticipate future economic shocks. By shifting expectations and reducing uncertainty, Fed communication induces firms to respond more aggressively and immediately to future shocks, generating larger micro-level fluctuations that translate into heightened aggregate volatility. The quantitative effects are sizable. At the micro level, investment becomes more dispersed across firms, with the standard deviation rising by roughly 15% relative to the counterfactual, while firm-value growth volatility increases by more than 40%. These heightened fluctuations carry over to

[28] In the baseline scenario, the probability that the Fed sends a signal is 88%, consistent with the calibration.

the macro economy: aggregate investment volatility rises by about 10%, and the volatility of aggregate firm-value growth nearly doubles compared with a counterfactual without Fed information. The effect on bond prices is instead negligible at both micro and macro level.

The findings align with theories that view public signals as coordination devices (Bergemann et al., 2015; Veldkamp, 2006; Xue and Zheng, 2021), which emphasize that shared information makes agents' beliefs move together and strengthens their collective response to aggregate shocks. Consistent with this view, my results suggest that Fed communication, while reducing uncertainty about the future, also induces more synchronized and forceful reactions to news, thereby amplifying real and financial volatility across firms.

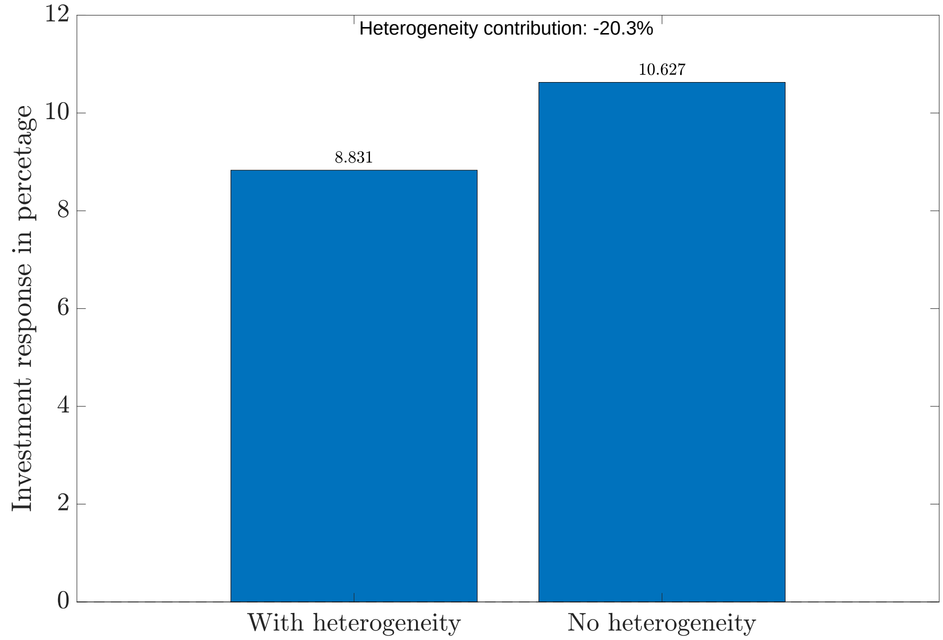
6.2 Contribution of the heterogeity in aggregate response

Figure 4 shows that heterogeneity in leverage dampens the aggregate effect of Fed information on investment by about 20%. To quantify this, I use the simulated firm panel from Table 4 and estimate firm-level regressions of investment on a Fed signal dummy interacted with leverage. The baseline coefficient captures the response of a low-leverage firm, while the interaction term measures how sensitivity varies with leverage. I then aggregate these micro elasticities using the cross-sectional distribution of leverage in the simulated panel. This mapping yields two comparable objects: the aggregate impulse response with heterogeneity, and a counterfactual response in which all firms react as if leverage were irrelevant. The difference between the two isolates the contribution of leverage heterogeneity to the aggregate response.

The dampening effect of Fed information on aggregate investment stems from the more muted response of high-leverage firms. Low-leverage firms react strongly to positive signals because they can expand borrowing and finance new capital at relatively low risk. High-leverage firms, by contrast, face tighter borrowing constraints and higher expected costs of default or equity issuance, which limit their willingness to scale up investment even when the outlook improves. As a result, the aggregate response is smaller than it would be if all firms behaved like the median leverage firm. The contribution of heterogeneity is therefore negative: differences in leverage across firms act as a brake on the transmission of Fed communication to the real economy.

This finding complements recent evidence that financial frictions shape the real effects of central bank communication. Prior work emphasizes the amplification role of balance sheets in traditional monetary policy shocks (Bernanke et al., 1999b; Kiyotaki and Moore, 1997). Here, the mechanism operates through information: when the Fed improves expectations, only

Figure 4: Contribution to aggregate investment response of the heterogeneity



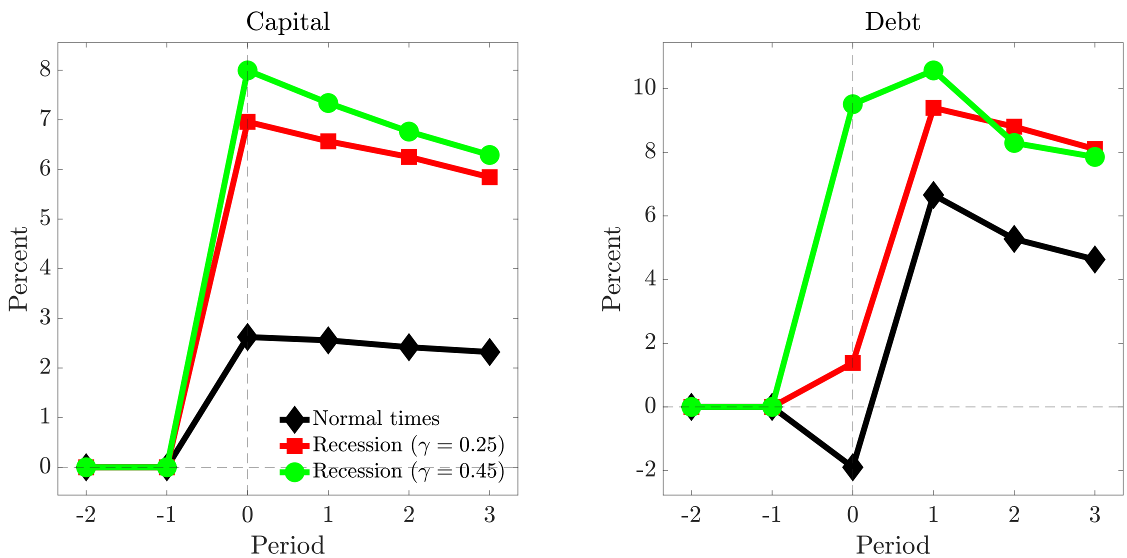
Notes: The Figure compares the aggregate investment response to Fed information under two scenarios. The first bar ("With heterogeneity") shows the aggregate response of investment when firms differ by leverage, using the cross-sectional distribution from the simulated panel. The second bar ("No heterogeneity") shows the counterfactual response if all firms reacted as the median leverage firm. The gap between the two bars isolates the dampening contribution of leverage heterogeneity to the aggregate effect of Fed communication.

firms with healthy balance sheets can translate this into higher investment. The implication for monetary policy is that the effectiveness of forward guidance or information shocks is state-dependent, being stronger in recoveries or among firms with low leverage. From a policy perspective, this suggests that the aggregate impact of Fed communication may be limited in highly indebted corporate sectors, underscoring the importance of firm heterogeneity for understanding the transmission of non-monetary policy tools.

6.3 How does access to credit affect Fed information?

The effectiveness of Fed information depends critically on credit conditions. In recessions, the marginal value of capital is high, so the informational content of Fed signals is especially valuable in guiding investment. At the same time, recessions are also periods when firms face tighter borrowing conditions, which may limit their ability to act on improved expectations. As a result, limited access to external finance can dampen the effectiveness of Fed information in period of recession or recovery.

Figure 5: Effectiveness of Fed information in recession



Notes: The figure illustrates the impact of Fed information under three scenarios. The black line reports the aggregate effect of Fed information in normal times. The red line shows the case in which firms receive a signal about future productivity one period in advance, starting from a recessionary state with tight credit conditions ($\gamma = 0.25$). The green line depicts the corresponding response when credit markets are looser ($\gamma = 0.45$). All results are based on generalized impulse response functions (GIRFs) following the methodology of Koop et al. (1996).

To quantify the effect, I re-estimate the GIRFs from Figure 3 under the assumption that the economy is first subjected to a sequence of negative TFP shocks that push it into a temporary recession. Starting from this recessionary state, I then compute the GIRFs to a positive TFP shock under two alternative credit market assumptions: (i) the baseline calibration with $\gamma = 0.25$, and (ii) a looser credit regime with $\gamma = 0.45$. For each case, I measure the contribution of Fed information by taking the difference between the GIRF with both the TFP shock and the Fed signal and the GIRF with only the TFP shock.[29]

Figure 5 shows that good news about the future are particularly effective in recessions, but tighter access to financial markets can dampen their overall impact. When financing constraints are tight ($\gamma = 0.25$), firms face higher costs of external funding and limited ability to leverage expected future gains into current investment. As a result, the anticipation effect of Fed communication is muted: although expectations about future productivity improve, firms cannot fully translate those expectations into immediate investment. By contrast, when

[29]Previous literature has studied the effects of monetary policy in recessions relative to normal times, without accounting for the potential confounding role of Fed information (Koby and Wolf, 2020; Ottonello and Winberry, 2018).

access to credit is easier ($\gamma = 0.45$), firms respond more aggressively to Fed signals, and aggregate investment rises by roughly 10% more. This amplification arises because looser credit conditions enable firms to borrow more to finance investment, which is reflected in higher debt issuance at the time of the announcement.

Overall this finding show that the power of Fed communication depends not only on its ability to coordinate expectations, as highlighted by Nakamura and Steinsson (2018) and Angeletos and Lian (2018), but also on whether firms can act on those expectations. In recessions, when the marginal value of capital is high, forward-looking signals are particularly valuable, yet tight credit conditions often prevent firms from converting improved outlooks into investment. By contrast, when borrowing constraints are relaxed, firms respond more aggressively to Fed signals, financing new projects through debt issuance and amplifying the aggregate impact. The policy implication is that forward guidance and Fed communication are most powerful in downturns when paired with measures that ease borrowing constraints, allowing firms to leverage improved prospects into real economic recovery.

7 Conclusion

Central bank communication has become an increasingly important tool for shaping expectations and guiding the economy. Unlike traditional policy moves, information shocks work through beliefs about future conditions, making their effectiveness dependent on firms' ability to translate improved expectations into real investment. Understanding how financial frictions influence its transmission is therefore central for both theory and policy.

This paper shows that the transmission of Fed information to investment depends critically on firms' financial positions. In the data, low-leverage firms respond much more strongly to Fed information shocks, expanding investment through additional borrowing, while high-leverage firms remain constrained. A structural model with financial frictions and default risk rationalizes this heterogeneity and highlights its aggregate implications.

At the aggregate level, Fed communication amplifies the effects of productivity shocks by aligning expectations and reducing uncertainty, but leverage heterogeneity dampens the overall response. Aggregate investment rises less than it would in an economy dominated by low-leverage firms. Moreover, the power of Fed information is highly state-dependent. In recessions, when the marginal value of capital is high, forward guidance can be especially potent?but only if firms have access to credit markets that allow them to act on improved expectations.

Taken together, my results suggest that forward guidance is most effective when complemented by policies that ease borrowing constraints. In highly indebted corporate sectors or during credit crunches, Fed communication alone may fall short of stimulating real activity, whereas in environments with healthier balance sheets and accessible credit markets, its impact on recovery is amplified.

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Appendix

A Construction of the dataset and cleaning

A.1 Firm-level variables on Compustat

I construct the firm-level variables in the Compustat database as follows. I measure capital stock as the book value of capital. I use the perpetual inventory method to calculate the capital value for each firm i at a time t. I measure the initial value of firm i's capital stock as the earliest available entry of $ppegtq_{i,t}$, and then iteratively construct $k_{i,t}$ from $ppentq_{i,t}$ as:

$$k_{i,t+1} = k_{i,t} + ppentq_{i,t+1} - ppentq_{i,t}$$

Investment rate is the ratio of the variation of capital stock on the past value of capital $k_{i,t-1}$, and the average Q is the sum of the market value of the firm *mkval* net of Common/Ordinary Equity *ceqq*, total assets atq and investment tax credit *txditcq*, divided by *atq*.

I use several measures of financial frictions. My benchmark measure is leverage, defined as the ratio of current liabilities ($dlcq_{i,t}$) and long-term debt ($dlttq_{i,t}$) to total assets ($atq_{i,t}$). Additional measures are included for robustness. Cash holdings are measured as the ratio of cash and short-term investments ($cheq_{i,t}$) to total assets ($atq_{i,t}$). Credit rating corresponds to the S&P domestic long-term issuer credit rating ($spcsrc_{i,t}$). I classify firms into three groups based on ratings lagged by two quarters: firms with *spcsrc* between A+ and A- are assigned a value of 2; those rated between B+ and B- are assigned a value of 1; and all others are assigned a value of 0. Firm size is constructed following Gertler and Gilchrist (1994). For each firm i, I calculate the moving average of sales over the past ten years. In each quarter t, firm i is classified as a large firm (value 0) if its average sales are above the 30th percentile of that year's distribution, and as a small firm (value 1) if below the threshold.

Finally, I construct a sectoral dummies following Ottonello and Winberry (2018): (i) agriculture, forestry and fishing: sic < 999; (ii) mining: sic $\in [1000, 1499]$; (iii) construction: sic $\in [1500, 1799]$; (iv) manufacturing: sic $\in [2000, 3999]$; (v) transportation, communications, electric, gas, and sanitary services: sic $\in [4000, 4999]$; (vi) wholesale trade: sic $\in [5000, 5199]$; (vii) retail trade: sic $\in [5200, 5999]$; (viii) services: sic $\in [7000, 8999]$.

I deflate capital stock, sales, and total assets using the implied price index of gross value added in the U.S. non-farm business sector. To control for outliers in the regressors, I trim the variables, leverage, cash holdings, total assets at the 1% top-level and sales growth at the 1% top and bottom level as standard in the main reference literature. I transform all regressors in logarithm before the estimation.

A.2 Sample selections

The sample period is 1990Q1 to 2018Q4. I perform the following cleaning steps:

i) I keep only US-based firms, $fic_{i,t} =$"USA".

ii) To avoid firms with strange production functions, drop regulated utilities and financial companies, I drop all firm-quarters for which the 4-digit sic code is in the range [4900,5000) or [6000,7000).

iii) To get rid of years with extremely large values for acquisitions to avoid the influence of large mergers, I drop all firm-quarters for which the value of acquisitions $acq_{i,t}$ is greater than 5% of total assets $atq_{i,t}$.

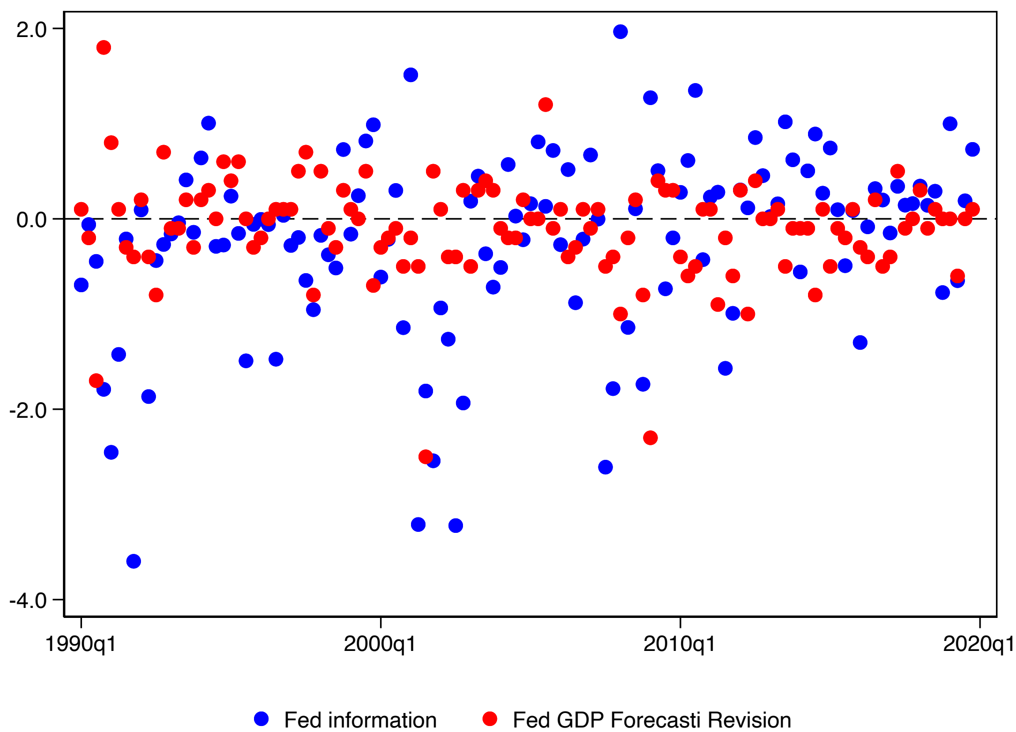
iv) I drop all firm-quarters for which the measurement of Total Assets $atq_{i,t}$, Sales $saleq_{i,t}$, Property, Plant and Equipment (Net) $ppentq_{i,t}$, Cash and Short-Term Investments $cheq_{i,t}$, Debt in Current Liabilities $dlcq_{i,t}$, Total Long-Term Debt $dlttq_{i,t}$, Total Inventories $invtq_{i,t}$ are missing or negative.

v) I drop all firm-quarters before a firm's first observation of Property, Plant, and Equipment (Gross) $ppegtq_{i,t}$.

After computing the yearly moving averages for leverage and liquid asset ratios but before estimating (1), I drop all firms observed between 1990Q1-2016Q4 for less than 40 quarters.

A.3 Time-series of the Fed information shocks

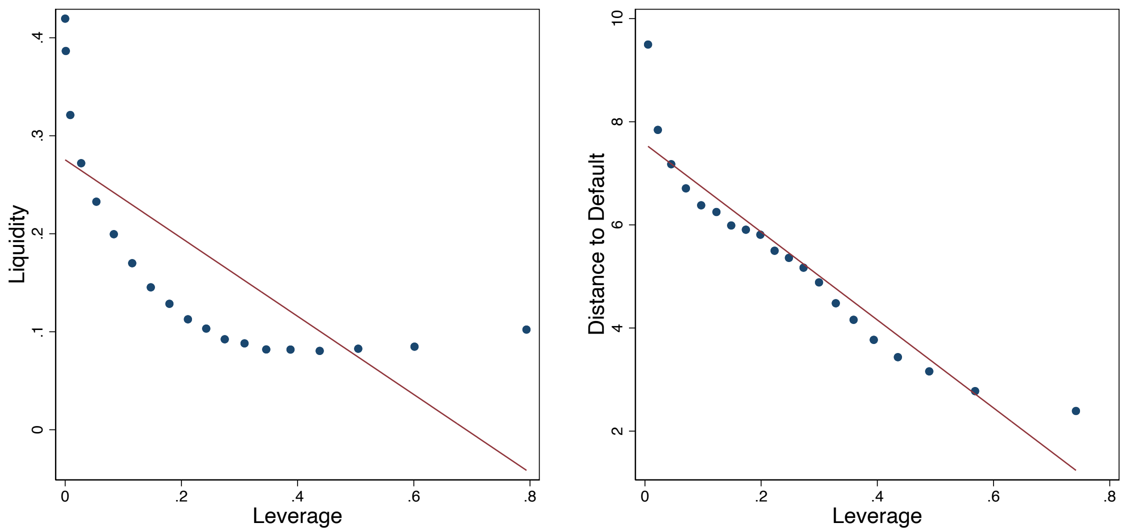
Figure 6: Fed information shocks vs. Fed GDP forecast revision



Notes: The figure shows the time-series of Fed information shocks identified following Jarociński and Karadi (2020) approach and the Fed Real GDP forecast revisions 2-periods ahead. All the macro data series for the identification, and the time series of the shocks are available in their replication file.

A.4 Firm leverage, distance to default and cash in the data

Figure 7: Relationship between firms' leverage and other financial variables

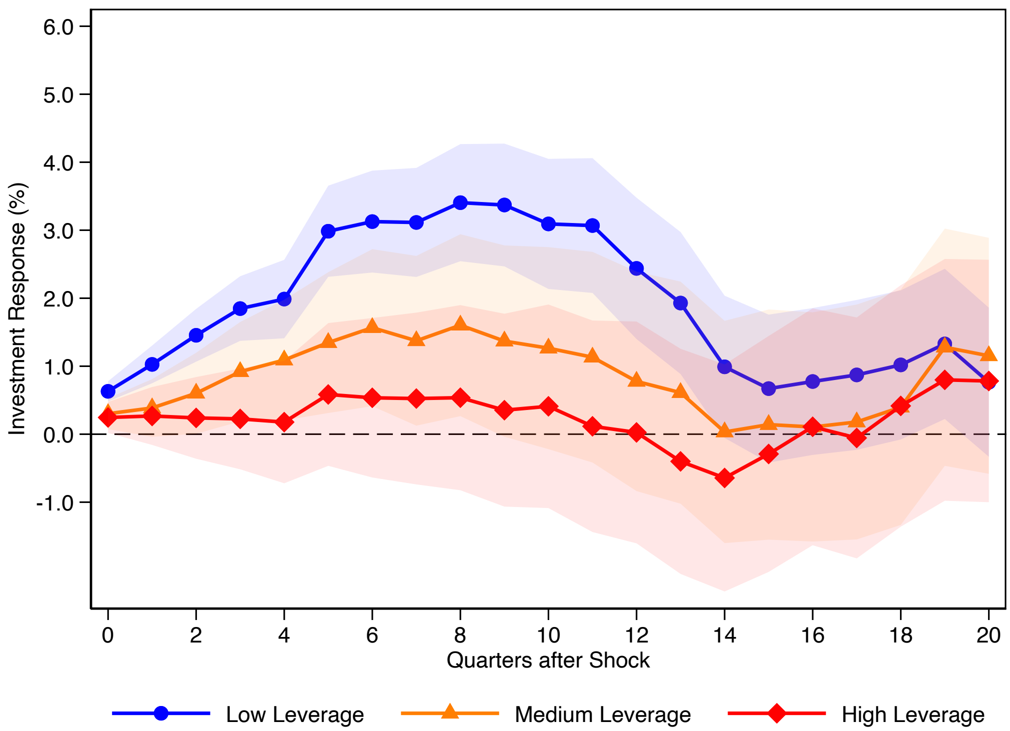


Notes: The figure illustrates the relationship between leverage, liquidity and distance to default in the data. Leverage is calculated as the ratio of debt in current liabilities ($dlcq_{i,t}$) and long-term debt ($dlttq_{i,t}$) to shareholder equity (i.e., total assets minus liabilities), averaged within the year. The distance to default is estimated for each firm in Compustat, following the procedure outlined in Merton (1974). A value of distance to default above 3 indicates that a firm faces a low or zero probability of default, while a value lower than 3 may suggest a higher probability of default. Liquidity is cash available divided by total assets.

B Additional results and robustness

B.1 Average response by leverage with extended controls

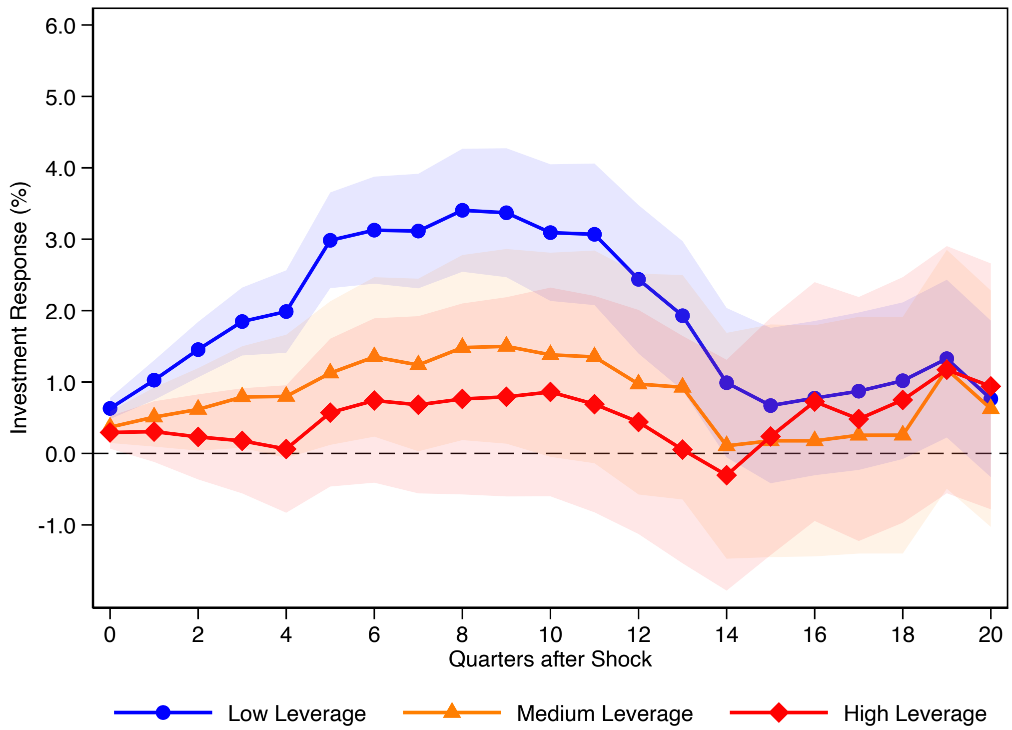
Figure 8: Investment response to $\varepsilon_t^{\text{info}}$ by leverage group with extended controls



Notes: The figure illustrates the average cumulative response of capital accumulation to a one standard deviation Fed information shock, across firms grouped by past leverage. The specification includes firm-level controls (lagged firm size, liquidity changes, and market valuation), as well as macroeconomic controls (four lags of GDP growth, inflation, interest rates, and a time trend). Firms are sorted each quarter based on their leverage (defined as total debt over total assets, lagged by one year) and assigned to terciles: low (bottom 20%), medium (20th-60th percentile), and high (above 60th percentile). The Fed information shock series is taken from Jarociński and Karadi (2020). Shaded areas represent 90% confidence intervals, constructed using standard errors clustered at the firm level. Labels on the y-axis are in percentage terms (i.e., 1 = 1%). Additional details on variable construction can be found in Appendix A.

B.2 Average response by leverage adding sector-time FEs

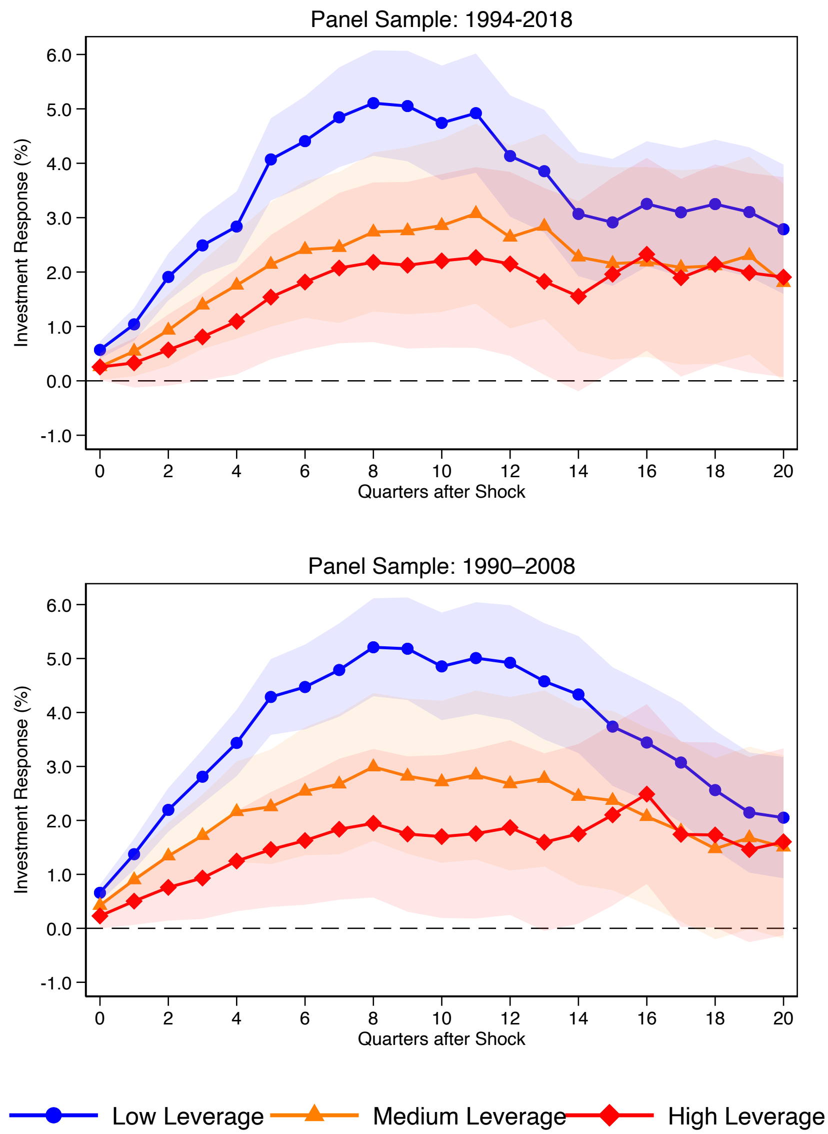
Figure 9: Investment response to $\varepsilon_t^{\text{info}}$ by leverage group controlling for sector-time FE



Notes: The figure illustrates the average cumulative response of capital accumulation to a one standard deviation Fed information shock, across firms grouped by past leverage. The estimation includes sector-time fixed effects (defined at the one-digit SIC level) and firm-level controls for lagged firm size, liquidity changes, and market valuation. Because the inclusion of sector-time fixed effects absorbs the average response of the baseline group (low-leverage firms), I estimate this baseline response in a separate specification without sector-time fixed effects as in figure 8. The total responses for the medium- and high-leverage groups are then computed by summing the interaction terms from the main regression with the separately estimated low-leverage response. Firms are sorted each quarter into terciles based on their leverage (defined as total debt over total assets, lagged by one year): low (bottom 20%), medium (20th-60th percentile), and high (above the 60th percentile). The Fed information shock series is taken from Jarociński and Karadi (2020). Shaded areas represent 90% confidence intervals, constructed using standard errors clustered at the firm level. Labels on the y-axis are in percentage terms (i.e., 1 = 1%). Additional details on variable construction can be found in Appendix A.

B.3 Robustness to different time-samples

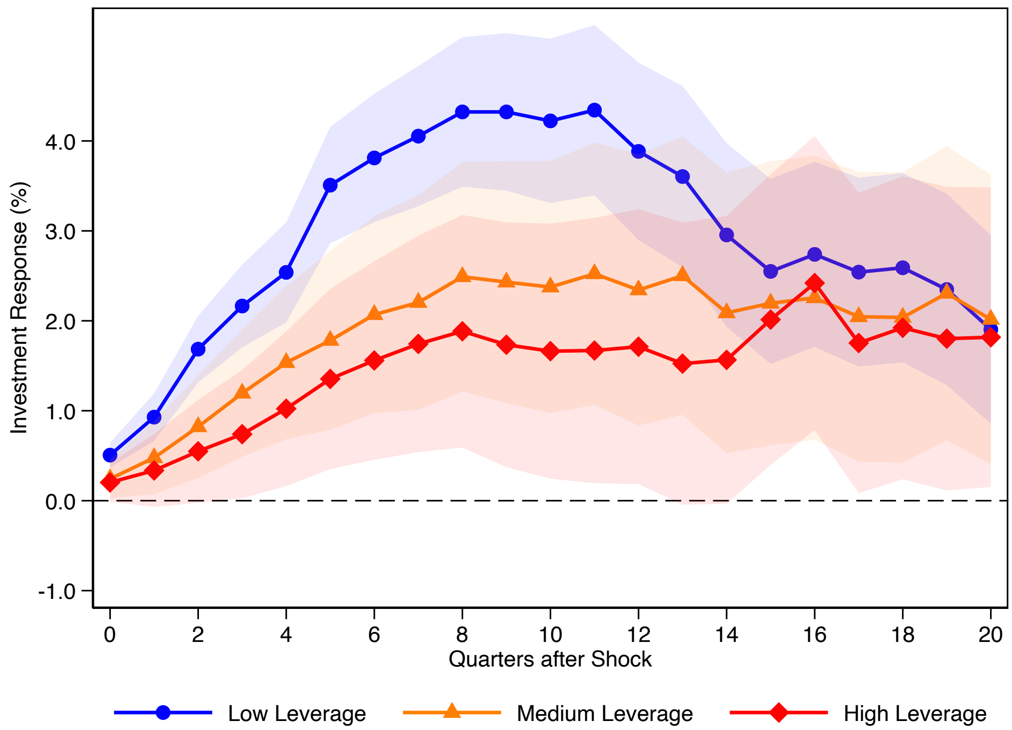
Figure 10: Investment response to $\varepsilon_t^{\text{info}}$ by leverage group and different time sample



Notes: The figure illustrates the average cumulative response of capital accumulation to a one standard deviation Fed information shock, across firms grouped by past leverage. The top panel shows the response for the sample period 1994-2018, while the bottom panel covers 1990-2008. The specification follows that used in the main text. Firms are sorted each quarter into terciles based on their leverage (defined as total debt over total assets, lagged by one year): low (bottom 20%), medium (20th-60th percentile), and high (above the 60th percentile). The Fed information shock series is taken from Jarociński and Karadi (2020). Shaded areas represent 90% confidence intervals, constructed using standard errors clustered at the firm level. Labels on the y-axis are in percentage terms (i.e., 1 = 1%). Additional details on variable construction can be found in Appendix A.

B.4 Controlling for heterogeneity in firm size and total assets

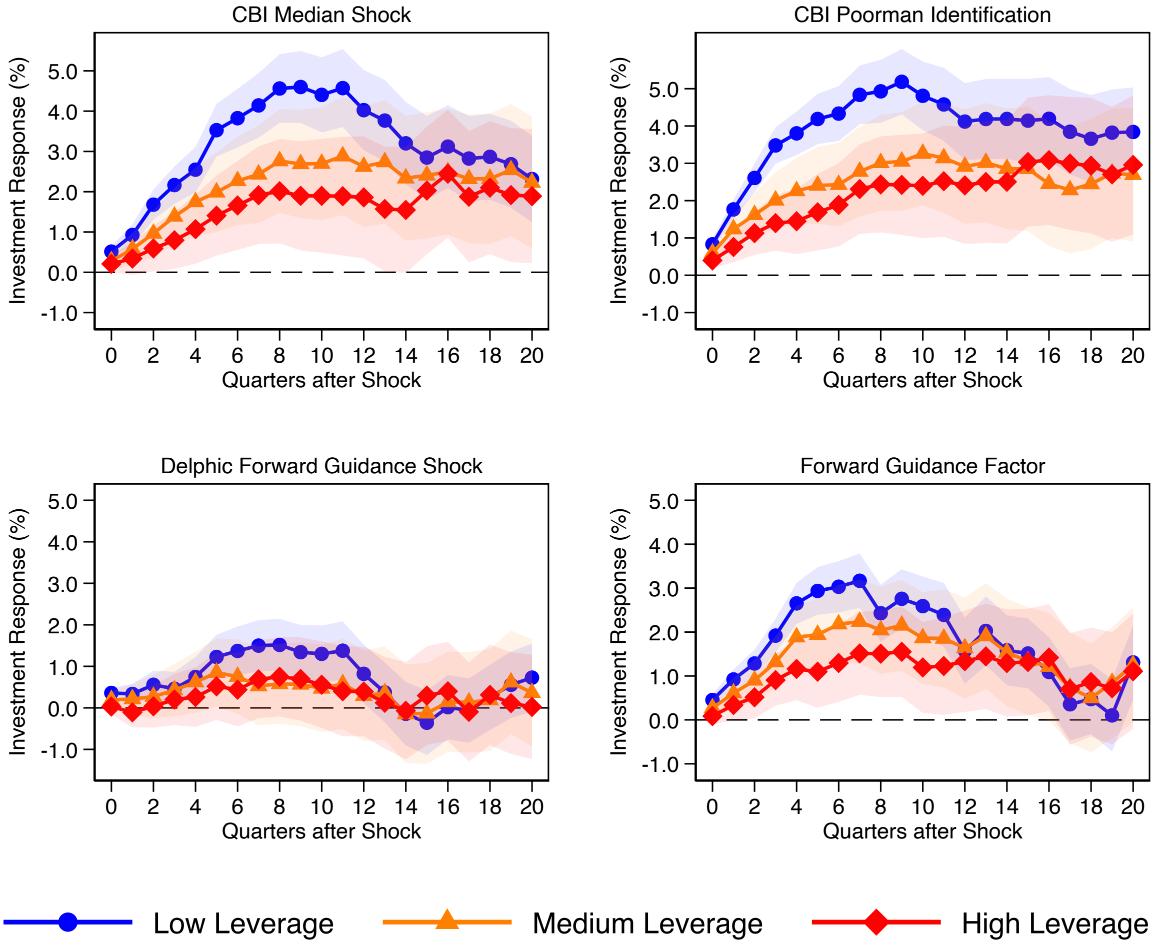
Figure 11: Investment response to $\varepsilon_t^{\text{info}}$ by leverage group



Notes: The figure illustrates the average cumulative response of capital accumulation to a one standard deviation Fed information shock, across firms grouped by past leverage. I control for lagged firm size and allowing the shock's effect to vary with firm size. This ensures that observed heterogeneity is not driven by systematic differences in scale across firms. The specification follows that used in the main text. Firms are sorted each quarter into terciles based on their leverage (defined as total debt over total assets, lagged by one year): low (bottom 20%), medium (20th-60th percentile), and high (above the 60th percentile). The Fed information shock series is taken from Jarociński and Karadi (2020). Shaded areas represent 90% confidence intervals, constructed using standard errors clustered at the firm level. Labels on the y-axis are in percentage terms (i.e., 1 = 1%). Additional details on variable construction can be found in Appendix A.

B.5 Robustness to different Fed information shock identification

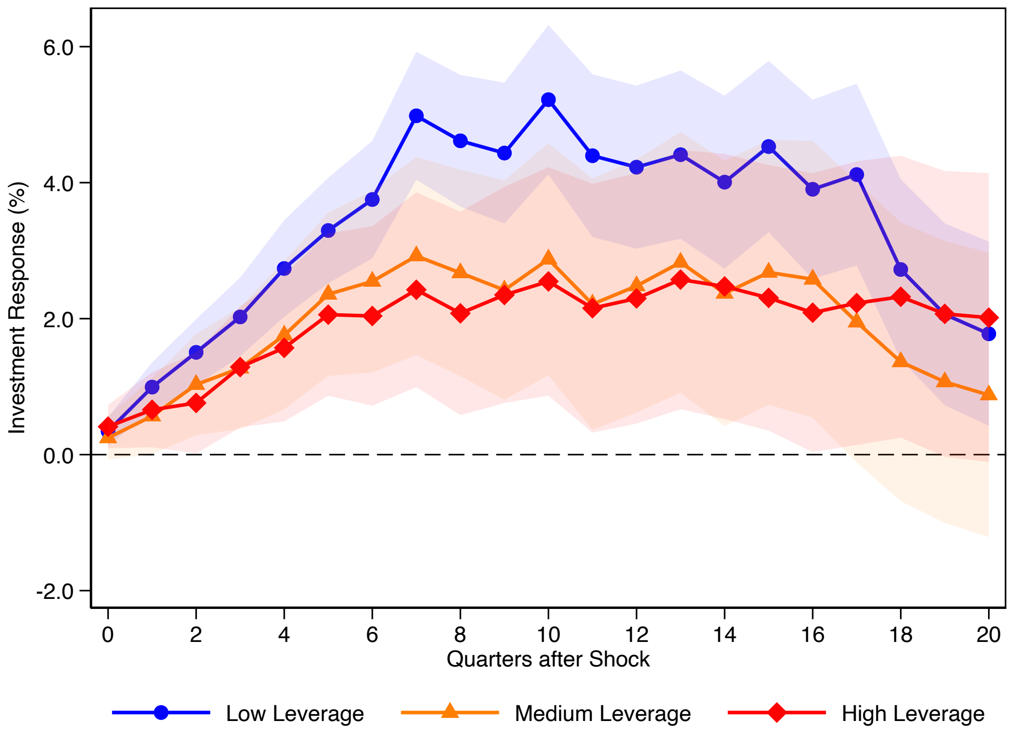
Figure 12: Investment response to $\varepsilon_t^{\text{info}}$ by leverage group for different shocks



Notes: The figure illustrates the average cumulative response of capital accumulation to the quarter FED RGDP forecast revision, across firms grouped by past leverage. I control for lagged firm size and allowing the shock's effect to vary with firm size. This ensures that observed heterogeneity is not driven by systematic differences in scale across firms. The specification follows that used in the main text. Firms are sorted each quarter into terciles based on their leverage (defined as total debt over total assets, lagged by one year): low (bottom 20%), medium (20th-60th percentile), and high (above the 60th percentile). The Fed information shock series is taken from Jarociński and Karadi (2020). Shaded areas represent 90% confidence intervals, constructed using standard errors clustered at the firm level. Labels on the y-axis are in percentage terms (i.e., 1 = 1%). Additional details on variable construction can be found in Appendix A.

B.6 Result using Fed Forecast Revision as measure of Fed info

Figure 13: Investment response to the Fed's 2-quarter-ahead RGDP expectation revision



Notes: This figure shows the investment response by leverage group to the Fed's 2-quarter-ahead revision in real GDP expectations. The Fed expectation revision is constructed as the change in the Fed forecast for real GDP two quarters ahead within the same quarter, comparing the last available forecast to the first one released during that quarter. Real Firms are sorted each quarter into terciles based on their leverage (defined as total debt over total assets, lagged by one year): low (bottom 20%), medium (20th-60th percentile), and high (above the 60th percentile). Shaded areas represent 90% confidence intervals, constructed using standard errors clustered at the firm level. Labels on the y-axis are in percentage terms (i.e., 1 = 1%). Additional details on variable construction can be found in Appendix A.

C Quantitative model

C.1 Solution algorithm

This section details the computational procedure used to solve the model. The algorithm is performed conditional on each realization of the observed signal. That is, for each value of the signal, I independently solve for firm policies, value functions, default behavior, and the stationary distribution. I solve the model using value function iteration combined with grid search over the firm's control variables. To compute the stationary distribution of firms over the idiosyncratic state space, I use the non-stochastic simulation method (Young, 2010).

I discretize the firm-level state space over three variables: aggregate state A and R, idiosyncratic productivity z, capital k, and leverage b. The continuous AR(1) process for the aggregate idiosyncratic states are approximated using the Tauchen method Tauchen (1986), with $N = [3, 3, 5]$ grid points. The grid for capital k contains 51 non-uniformly spaced points over the interval $(0, k^{\max}]$, with a higher density at lower capital levels. The leverage ratio b/k is defined over 31 uniformly spaced points in the interval $[0, 1]$, with greater density at low leverage values.

Once I have set up the grids, I use value function iteration to find a solution. For each realization of the signal, I pre-compute an posterio transition matrix for the aggregate states using the algorithm proposed by Farmer and Toda (2017). I then solve the model given firms' posterior beliefs.

For each case, I use the following algorithm to find a solution:

1. Initialize a default policy function d^0.
2. Iterate until convergence of the default policy:
   i) Given the default policy d^n, calculate the bond price schedule $Q(A, R, z, k', b')$ consistent with expected default at each state point.
   ii) Solve the firm's problem via value function iteration:
      a. Guess an initial value function $V^0(A, R, z, k, b)$.
      b. At each state point, compute the value of default and continuation, and determine the optimal policy for k', b', and default.
      c. Update the value function until convergence: stop when $\max |V^{k+1} - V^k| \leq \epsilon$.
   iii) Use the converged value function to update the default decision rule d^{n+1}.
   iv) Update d^0 until: $\max |d^{n+1} - d^n| < \epsilon$. Otherwise, return to step i).

3. Compute the stationary distribution of firms using the non-stochastic simulation method of Young (2010), given the optimal policy functions.

4. Simulate the model given the policy functions and ergodic distribution.

The outcome of this procedure is the set of equilibrium policy functions for k', b', default decisions, the bond price function, and the value function defined over the grid (A, R, z, k, b) for each signal realization. Steps 1-3 are executed for each signal before simulation.

C.2 Impulse Response Function Computation

To quantify the dynamic effects of uncertainty and forward guidance shocks, I compute generalized impulse response functions (IRFs) following the approach of Koop et al. (1996). This method accounts for non-linearities by computing the average difference in outcomes across simulated paths, rather than relying on derivatives or local approximations.

The algorithm proceeds in the following steps:

1. **Simulation Setup.** I simulate N_{irf} independent economies of 3000 firms for T_{irf} periods, with and without the shock.

2. **Shock Design.** In the baseline (no-shock) path, the economy receives no TFP shock and no signal from the central bank. In the shock scenario, a realization of a TFP shock occurs with probability p_{irf} in period T_{shock}, pushing productivity to a high value. To isolate the effect of central bank communication, I simulate two additional counterfactuals:

    - *Signal + Shock*: The central bank sends a signal (news shock) in $T_{\text{shock}} - 1$, followed by an actual TFP shock.
    - *Signal + No Shock*: The central bank sends the same signal, but the TFP shock does not materialize. This counterfactual captures the effects of a communication error.

3. **Simulation.** For each of the N_{irf} simulation draws:

    - I simulate the exogenous TFP path using a discrete Markov chain.
    - Given the path and signal, I solve the model forward to obtain time paths of aggregate variables: capital, output, and total debt.

4. **IRF Computation.** At each horizon $t = 1, ..., T_{\text{irf}}$, I compute the average percentage deviation from the no-shock path:

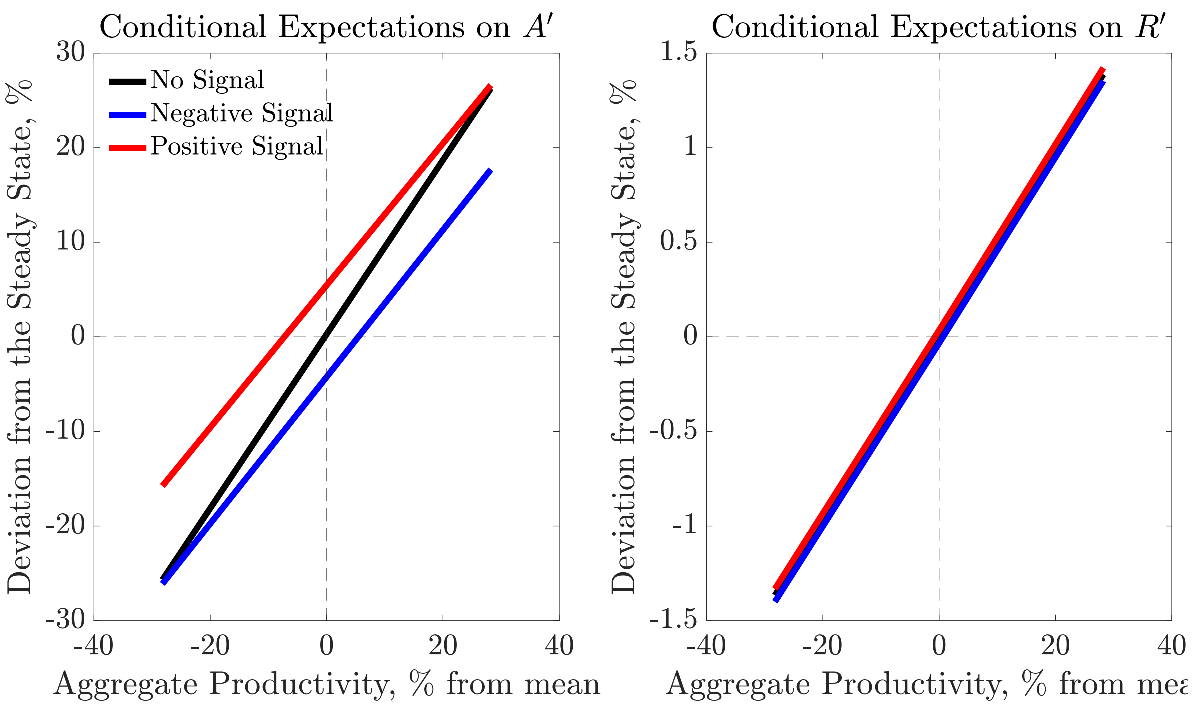
$$\text{IRF}_K(t) = \frac{1}{N_{\text{irf}}} \sum_{n=1}^{N_{\text{irf}}} \frac{K_{t,n}^{\text{shock}} - K_{t,n}^{\text{noshock}}}{K_{t,n}^{\text{noshock}}}$$

   This allows me to separately quantify the effects of pure shocks, anticipated shocks (signals), and mistaken expectations (signal without shock).

The result is a set of time series for the IRFs under different scenarios (shock only, signal + shock, signal + no shock), for both normal and high-leverage economies. For the high leverage economy, I repeat the entire IRF computation starting from a high-leverage initial condition to assess how responses vary with financial fragility. These paths highlight how forward guidance interacts with firm balance sheet conditions to amplify or mitigate the effects of shocks.

C.3 Impact of Fed signal on firms' expectations

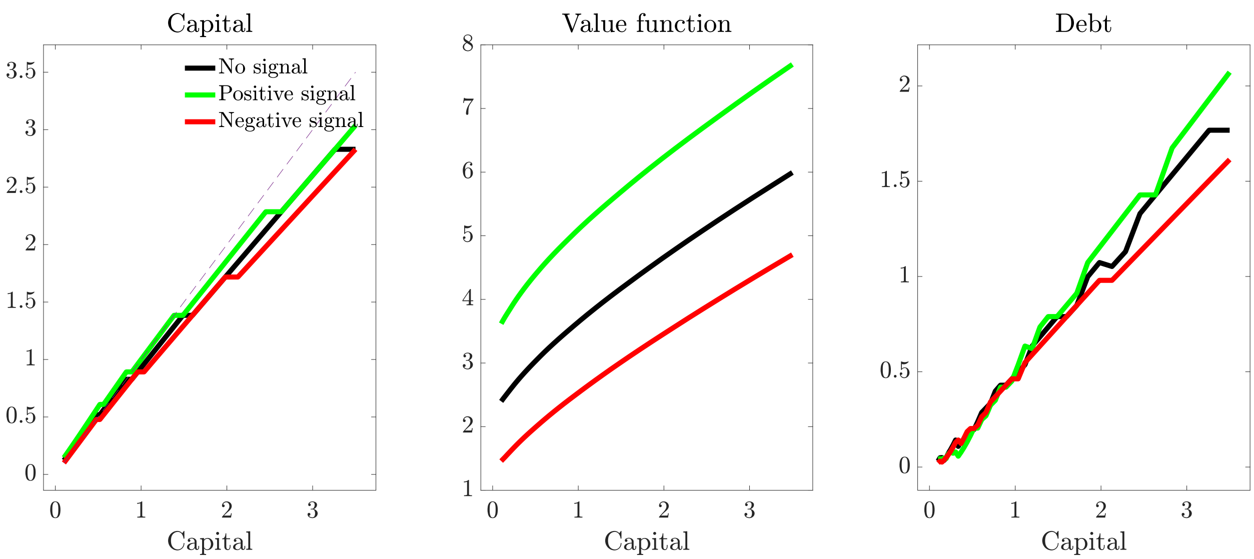
Figure 14: Effect of Fed signals on conditional expectations of future states



Notes: The figure shows conditional expectations of next-period aggregate productivity (A', left panel) and the interest rate (R', right panel) across current aggregate productivity states. Expectations are reported as percentage deviations from their steady-state values. The black line corresponds to the case with no signal, the blue line to a negative signal, and the red line to a positive signal.

C.4 Policy function in the stationary equilibrium

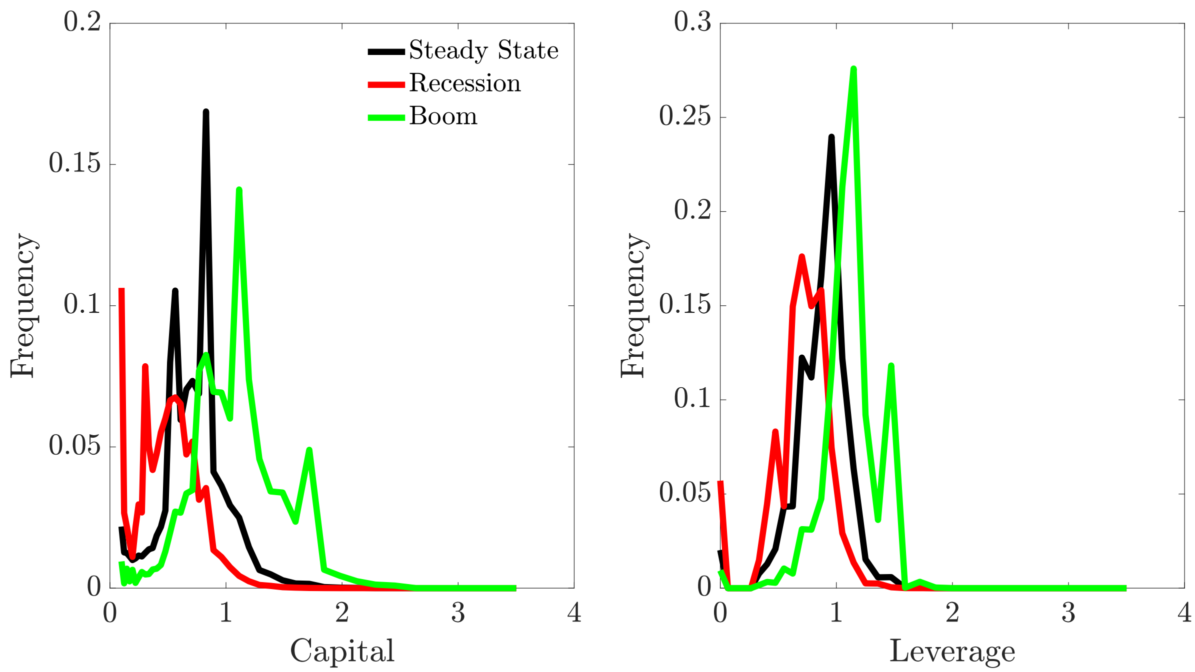
Figure 15: Policy functions over capital



Notes: The figure plots firms' policy functions for capital, debt, and the value function in the stationary equilibrium as a function of the capital stock and no debt. Idiosyncratic productivity and aggregate states are fixed at their steady-state values. The black line reports the policy function when no signal is sent. The red line shows the policy functions when the Fed sends a negative signal about future TFP (one standard deviation below steady state), while the green line shows the case of a positive signal (one standard deviation above steady state). All policy functions are computed using the model parameterization reported in Tables 2 and 3.

C.5 Ergodic distribution along capital and debt

Figure 16: Marginal distribution of the firms



Notes: The figure shows the marginal density of firms in the stationary equilibrium over capital stock and leverage. I fix idiosyncratic productivity at its steady-state value and vary the aggregate state for TFP while keeping real interest rate at 4%. The black line shows the marginal density when TFP is at its steady-state level. The red line shows the density when TFP is one standard deviation below the steady state ("Recession"), and the green line shows the density when TFP is one standard deviation above ("Boom"). In all scenarios, no signal is sent by the Fed. The ergodic distribution is approximated following the method of Young (2010).