Real Effects of Bernanke–Kuttner: The Risk Channel of Monetary Policy Announcement on Corporate Investment

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Abstract

Monetary policy announcements convey information that shifts risk perceptions in financial markets, but little is known about the real effects of such "risk news." Using news shocks identified from asset price changes within the FOMC announcement window, I provide causal evidence that announcement news that raises financial market risk perceptions reduces subsequent corporate investment in tangible capital. At the firm level, this effect is heterogeneous and stronger among firms with higher debt burdens, which also face higher external financing costs after risk-raising announcement news, consistent with a flight-to-quality mechanism in credit markets. Investment cuts are concentrated when these highly indebted firms also have short debt maturities, indicating that rollover risk links heightened financing costs to real effects. At the aggregate level, the investment response to announcement risk news is insignificant unconditionally, but it is state-dependent: it becomes economically meaningful when the share of firms facing high rollover risk is larger.

Keywords: Monetary Policy, FOMC Announcements, Risk Perception, Investment, Financial Frictions, Firm Heterogeneity

JEL Classification: E22, E44, E52, E58, G12, G31

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"Monetary policy is 98 percent talk and only two percent action."

— Ben S. Bernanke

1. Introduction

In their seminal work, Bernanke and Kuttner [2005] show that unanticipated monetary easing raises equity prices not only by lowering the risk-free rate and increasing expected dividends, but also—crucially—by compressing the risk premium required by investors. Building on this insight, subsequent empirical work finds that news released with monetary policy announcements, both monetary and non-monetary, substantially moves market risk premia and risk perceptions in financial markets (i.e., investors' perceived level of risk and uncertainty in the future market).[1] Macro-finance theories suggest that time-varying risk perceptions in financial markets play a central role in driving economic dynamics, in part because they are linked to the cost of financing for firms.[2] Yet evidence remains scarce on the extent to which new information from announcements that drives market risk perceptions—referred to here as announcement risk news—transmits to the real economy and influences corporate behavior.[3] Whether announcement risk news has sizable real consequences is therefore an open empirical question.

An equally pertinent question concerns the transmission mechanism through which announcement risk news reaches firms: which firms are most exposed, and how financial frictions govern their differential exposure. This question is especially relevant for two reasons. First, during episodes when investors perceive extremely high risk—such as the 2007–2008 financial crisis and the COVID-19 pandemic—financial frictions amplified the downturn. Highly indebted firms and households faced greater difficulty accessing external financing and accounted for a disproportionately large share of the contraction in economic activity, suggesting that indebted firms may be a key conduit through which announcement risk news reaches the real economy. Second, prior evidence (e.g., Ottonello and Winberry [2020]) shows that a heavy debt burden attenuates firms' investment responses to policy rate surprises. Assessing whether announcement risk news reinforces or counteracts this pattern for policy rate transmission has important implications for the design of monetary policy communication.

[1] Previous empirical literature uses high-frequency event studies to establish that both news related to the policy rate and non-monetary news unrelated to the policy rate can move risky-asset prices; see, for example, Kroencke et al. [2021] and Cieslak and Schrimpf [2019]. A recent summary by Bauer et al. [2025] points out that nowadays central banks in developed countries are actively communicating risk and uncertainty to the public. In Section 6.1 I discuss several cases of non-monetary news related to risk that are released in monetary policy announcements.

[2] See, for example, Bloom [2009, 2014], Drechsler et al. [2018], Kekre and Lenel [2022].

[3] Bauer et al. [2023] summarizes recent financial market evidence and highlights the gap on real-economy effects: "...while there is extensive evidence that monetary policy affects risk premia in financial markets, significantly less is known about how large the consequences of these effects are for economic activity and inflation ...".

Corporate investment in tangible capital is the most volatile component of domestic output and accounts for a substantial share of it. It is also highly sensitive to aggregate shocks and is therefore a central focus of monetary policy transmission studies. In this paper, I provide plausibly causal evidence that when monetary policy announcements release information that raises financial market risk perceptions, subsequent corporate investment in tangible capital declines. Financial frictions transmit this risk news to firms' financing conditions and amplify the investment response. Cross-firm heterogeneity in financial positions therefore shapes the aggregate investment effect. I establish these results by combining aggregate news shocks (classified into policy rate, growth, and risk components), identified from cross-asset price changes within the FOMC announcement window, with quarterly Compustat panel data, which provide rich time variation in firms' financial positions. The results also hold after controlling for policy rate surprises, isolating the effect of non-monetary announcement risk news.

To guide the empirical analysis, I adopt the stylised risk-centric business cycle model of Pflueger et al. [2020] as a conceptual framework and introduce a single modification that yields testable predictions: unexpected monetary policy news affects not only the short-term interest rate but also risk perception, modelled as the time-varying expected volatility of aggregate growth.[4] In the model, risk aversion is constant, and risk perception governs households' future consumption uncertainty and firms' future cash flow uncertainty. When monetary policy announcements release news that elevates risk perception, the price of safe bonds rises (yields fall) because households, motivated by precautionary saving, place a higher value on safety while demanding a larger premium to hold claims on risky corporate cash flows. The ensuing increase in the cost of capital, transmitted through the standard Q-theory channel, curtails investment, with the strongest effects for firms whose cash flow uncertainty is more exposed to time-varying risk perception. From the model, a key empirical implication for identifying announcement risk news is that it shares properties with equity cash flow risk shocks: it raises production uncertainty and the equity risk premium, yet can be hedged with safe bonds, thereby pushing up safe bond prices.

Identifying the effect of announcement risk news poses substantial empirical challenges, particularly because announcements can release both monetary and non-monetary information that shift market risk perceptions. It is more empirically tractable to capture all of the news that drives market risk perceptions as a whole, rather than to isolate each driving force separately. Following the news shock literature, I extract risk news shocks from asset price movements in windows around FOMC announcements—referred to here as FOMC risk news shocks. Under market efficiency, financial markets are forward-looking and public information is fully priced in before the announcement, so price changes within

[4]This modification is intended to capture both the direct impact of policy rate news and non-monetary risk news on market risk perceptions, as often observed in practice. For tractability, the model links the shift in risk perception directly to the policy rate surprise. The empirical predictions nonetheless hold the same for both types of risk news.

the event window capture only unanticipated news about the future.[5]

I construct the FOMC risk news shock primarily using a structural method and complement it with two reduced-form approaches. The structural method follows the asset pricing framework of Cieslak and Pang [2021] and extracts daily cash flow risk news via a structural VAR. Exploiting stock-bond comovement, as implied by macro-finance theory, the structural VAR imposes sign and cross-maturity restrictions to decompose FOMC-day asset price movements into orthogonal short rate news, growth news, and two risk news shocks. The cash flow risk news shock accords with the conceptual framework: a positive shock lowers equity prices, as investors demand a higher premium, and raises Treasury prices, reflecting a flight to safety. For robustness, I use two reduced-form measures as alternative shock proxies: (i) the FOMC-day change in the option-implied market risk premium from Martin [2017], based on risk-neutral volatility; and (ii) the FOMC-day change in the first principal component of risk-sensitive financial indicators across multiple asset classes, following Bauer et al. [2023]. All three FOMC risk news shock measures are significantly and positively correlated. Moreover, none is predictable from macro and financial variables that commonly predict policy rate surprises, and none exhibits autocorrelation on FOMC days.

To study the real effect of announcement risk news, I estimate firms' investment responses to FOMC risk news shocks using a panel local projections framework. I aggregate the daily shocks to the quarterly frequency as the key explanatory variable. Local projections allow me to trace impulse responses while flexibly including controls. A crucial control is the high-frequency policy rate surprise from Nakamura and Steinsson [2018a], extracted from interest rate futures. This series is shown to capture unexpected policy rate changes and information about the growth path.[6] Including this surprise serves two purposes. First, it absorbs the conventional interest rate and growth outlook channels through which monetary policy affects investment, thereby controlling for competing transmission mechanisms. Second, it helps isolate the effect of non-monetary announcement risk news. Because any covariance between the two regressors is partialled out, adding the policy rate surprise leaves the coefficient on the risk news shock identified from variation orthogonal to policy rate surprises. With this specification, the impulse responses recover the impact of non-monetary announcement risk news on corporate investment.[7]

I find that a positive FOMC risk news shock—meaning that the announcement releases news that raise financial market risk perceptions—is associated with a significantly lower

[5]Previous studies show that FOMC announcements dominate the news flow on those days; equity prices, option-implied risk premia, and other risky asset prices exhibit markedly higher volatility than on other trading days. These patterns indicate that information in FOMC announcements is quantitatively important and that using a narrow event window mitigates background noise.

[6]Nakamura and Steinsson [2018a] also show that, in their study, this series is less related to risk premia.

[7]In contrast to Nakamura and Steinsson [2018a], Bauer et al. [2023] show that high-frequency policy rate surprises can move risk perceptions, which motivates including this control. In robustness checks, I also control for the other news shocks identified by the structural VAR and consider alternative high-frequency monetary policy surprises such as Gürkaynak et al. [2004] and Bauer and Swanson [2023].

subsequent tangible capital investment rate. A one-unit structural news shock, equivalent to a 66.5 basis-point decline in the equity market index return on FOMC days,[8] reduces the average investment rate by 0.496 percentage points over the next year, about 3 percent of the annual mean investment rate in the sample. This impact is economically modest. However, there is pronounced heterogeneity in the investment response related to financial frictions. The investment response increases with firms' debt burden, measured by net market leverage.[9] After a one-unit positive shock, firms in the top 5 percent of the net market leverage distribution reduce their tangible capital investment rate by nearly 1 percentage point over the subsequent year; this is approximately three times the 0.36 percentage point reduction among firms in the bottom 95 percent. This implies that announcement risk news is transmitted to real activity mainly through highly indebted firms.

Why are indebted firms more exposed to announcement risk news? I show that firms with higher net market leverage have weaker credit quality ex ante: they carry both lower long- and short-term credit ratings. Given this, a plausible mechanism is that announcement news that raises risk triggers a flight to quality: investors perceive higher risk and become less willing to lend to risky, highly indebted firms, thereby raising the cost of external finance for new investment.[10] I do not observe external financing costs directly, but I test this channel using indirect evidence from firms' liquidity management. Theoretical work, beginning with Keynes's *General Theory* and formalized by Riddick and Whited [2009] and Bolton et al. [2019], predicts that when external finance becomes more expensive, firms reduce borrowing, rely more on internal funds, and build precautionary cash buffers. In line with these theoretical predictions, I find that announcement risk news affects financial policies: after a positive FOMC risk news shock, firms with high debt burdens significantly reduce net debt issuance and accumulate cash, whereas firms with low debt burdens are little affected. Moreover, despite issuing less net debt, total interest expense rises for highly indebted firms. Taken together, these patterns indicate that announcement risk news disproportionately raises financing costs for highly indebted firms, consistent with a flight to quality mechanism.

[8] This magnitude also corresponds to one standard deviation of the structural cash flow risk shock across all trading days. On average, the quarterly structural shock has size 1.08 units, with the largest shock exceeding 4 units.

[9] Net market leverage is measured by the net-debt-to-market ratio. Net debt equals total debt plus preferred stock minus cash holdings, so the measure accounts for liquidity. The market-based denominator reflects expectations about the firm's future cash flows, profitability, and risk, and therefore speaks directly to its repayment capacity. In addition, the market-based ratio aligns with Lian and Ma [2021], who document that roughly 80 percent of U.S. public firms' debt is secured primarily by cash flows rather than by physical collateral. Hence it also reflects the ability to obtain new debt to roll over old debt.

[10] Flight to quality is often observed during periods of heightened risk and uncertainty. A common explanation is that when risk rises, financial intermediaries face tighter value-at-risk (VaR) constraints—due to regulation or withdrawal pressure—which reduces lending to riskier borrowers. I view flight to quality as a plausible channel for my results for two reasons: (i) the risk-news shock is identified with a flight-to-safety restriction, and (ii) firms sorted by net market leverage exhibit clear differences in ex ante credit risk.

I provide further evidence that rollover risk links a flight to quality in credit markets to investment cuts by indebted firms. The investment response to an FOMC risk news shock is concentrated in periods when highly indebted firms also face high refinancing intensity, measured by the share of debt maturing within one year. This pattern is in line with the rollover risk literature (e.g., the theoretical work by Acharya et al. [2011] and the empirical work by Almeida et al. [2009]): firms with a large volume of bonds maturing soon must repay or refinance in the short run; when funding conditions tighten, their rollover risk rises, which amplifies financing costs and leads to larger investment cuts. This finding further confirms that financing conditions are an important driver of the investment response. I also document that firms with both high leverage and high refinancing intensity, a combination that implies high rollover risk, experience a more persistent investment contraction after positive FOMC risk news shocks. At the industry level, such periods are associated with a reallocation of debt and capital from sectors that have many firms with high rollover risk toward those with fewer. Finally, a horse race regression that includes different FOMC day news shocks, each interacted with the rollover risk indicator, shows that only the risk news shock generates a significantly larger investment response among high rollover risk firms; other types of news shocks, such as policy rate surprises, have no comparable effect.

I conduct a series of robustness checks to assess the robustness of the firm-level results. First, I reestimate the specifications with two alternative reduced-form proxies for FOMC risk news shocks described earlier. Second, I use different subsamples: one that excludes firms with near-zero debt, which are largely unaffected by rollover considerations,[11] and another that includes only manufacturing firms, which are the largest users of tangible capital. Third, I replace the baseline net market leverage with an alternative market-based measure constructed solely from gross debt. Finally, I control for additional high-frequency monetary policy surprise variables that are widely used in the literature. Across all these exercises, the firm-level findings remain qualitatively unchanged.

The firm level results indicate that announcement news that raises market risk perception depresses investment, with effects concentrated among firms with high rollover risk. I exploit this heterogeneity to assess aggregate implications. I compute the aggregate investment rate by weighting each firm's investment rate by its capital stock,[12] and then estimate aggregate local projections. The estimates show that the economy wide share of high–rollover-risk firms governs the aggregate response: the impact of announcement risk news is state dependent, becoming stronger as that share rises. Because the market based debt burden measure makes the share of high–rollover-risk firms countercyclical (rising when equity values fall), a given shock generates a larger response in aggregate investment

[11] Firms with extremely low debt burdens (the lowest 5% by net debt-to-market) have credit scores that are unusually close to the median; excluding this group restores an approximately linear relationship between credit score and debt burden.

[12] Thus I focus on an in-sample aggregate, following Jeenas and Lagos [2024] and Chodorow-Reich [2014].

during recessions.

Although the conditional, state dependent effect is significant, the unconditional average impact of announcement risk news on aggregate investment is muted and statistically insignificant. A simple empirical counterfactual explains why. Firms with high rollover risk react more strongly but account for only a small share of the aggregate capital stock. By contrast, large firms in the low–rollover–risk group, which hold most of the economy's tangible capital, are little affected. As a result, the average aggregate investment response to announcement risk news is limited. Finally, because the firm-level regressions with time fixed effects capture only partial equilibrium responses, general equilibrium forces (for example, a reallocation of debt and demand toward firms with low debt) may further dampen the aggregate investment reaction to announcement risk news. Quantifying this effect would require a full general equilibrium model, which is beyond the scope of this paper.

Related Literature: This paper relates to several strands of literature. First, it extends the asset pricing literature that examines how monetary policy announcements shape risk perceptions and risk premia in financial markets.[13] Building on the seminal insight of Bernanke and Kuttner [2005], a growing body of high-frequency evidence shows that news in monetary policy announcements has significant effects on risk measures and risky asset prices, through both monetary and non-monetary information.[14] This paper extends that line of research by examining the real consequences of announcement news that shifts financial market risk perceptions. Several theoretical papers also explore broader macroeconomic effects of changes in risk related to monetary policy. Kekre and Lenel [2022] show that wealth redistribution driven by monetary policy toward households with high marginal propensities to bear risk lowers risk premia and stimulates activity, while Drechsler et al. [2018] demonstrate that easier policy reduces liquidity premia, encourages bank leverage, and ultimately raises asset prices and investment. Taking a different tack, this paper empirically investigates an information effect: information released at monetary policy announcements that alters financial market risk perceptions directly affects corporate investment, with a particular focus on non-monetary news rather than policy rate surprises.

Second, my paper contributes to the literature on the transmission of monetary policy to corporate policy, especially capital investment.[15] This literature, dating back to

[13] An earlier strand focuses on asset price reactions, particularly stock price movements around monetary policy announcements, without emphasizing the risk component, with seminal contributions by Rigobon and Sack [2003, 2004].

[14] Recent contributions include Hanson and Stein [2015], Campbell et al. [2014], Lucca and Moench [2015], Schmeling and Wagner [2016], Cieslak and Schrimpf [2019], Cieslak et al. [2019], Neuhierl and Weber [2019], Ozdagli and Velikov [2020], Ai and Bansal [2018], Ai et al. [2022], Cieslak and McMahon [2023], and Bauer et al. [2023]. A closely related study is Chaudhry [2020], which uses daily macro uncertainty shocks to analyze announcement effects on stock market returns.

[15] A parallel strand of research examines the transmission of monetary policy to households; see, for example, Wong et al. [2019] and van Binsbergen and Grotteria [2024].

Bernanke et al. [1994], emphasizes heterogeneous investment responses to interest rate movements across firms and the role of financial frictions in generating this heterogeneity. A recent revival combines high-frequency policy rate surprises with firm-level panel data to study how firm characteristics mediate monetary policy transmission, including distance to default Ottonello and Winberry [2020], credit spreads RT Ferreira et al. [2023], firm age Cloyne et al. [2023], cash holdings Jeenas [2023], and intangible capital Döttling and Ratnovski [2023]. Particularly relevant is Jeenas and Lagos [2024], which documents an asset pricing channel whereby policy rate surprises influence the market value of equity; firms that rely on equity financing then adjust investment and capital structure decisions in response to exogenous movements in their market value. My empirical strategy differs from this line of work, including Jeenas and Lagos [2024], which primarily identifies the effects of policy rate surprises in the monetary policy announcement window.[16] Instead, I exploit complementary information released in the same event windows: non-monetary information that drives financial market risk perceptions.

Third, this paper contributes to the literature on the real effects of uncertainty shocks, building on the seminal contribution of Bloom [2009]. Recent work, such as Alfaro et al. [2024], shows that financial frictions magnify the effects of uncertainty by inducing greater precautionary cash holdings and, consequently, lower capital expenditure. Under the assumption that risk aversion does not change within the high-frequency short window, the announcement risk news I study captures an uncertainty shock to future fundamentals perceived by financial markets and is primarily driven by monetary policy announcements. Hence, the evidence has policy implications: it underscores the importance of managing financial market risk perceptions in monetary policy communication. In Bloom [2009] and Alfaro et al. [2024], the mechanism operates through an increase in the option value of delaying investment and borrowing in the presence of fixed adjustment costs. I document a complementary channel in which announcement risk news raises the cost of external finance and intensifies rollover pressure for highly indebted firms. This mechanism is closely related to Pflueger et al. [2020], who emphasize the role of the cost of capital when market risk perceptions are elevated; their evidence is at the aggregate level, whereas mine focuses on the micro level.

The methodology also suggests a complementary approach to studying the causal effect of uncertainty. Identification is difficult because causality may run in both directions: uncertainty can depress economic activity, and weak activity can increase measured uncertainty (see Bloom [2009]; Baker et al. [2024]). The literature therefore often relies on natural experiments—such as natural disasters and terrorist attacks—as instruments (e.g., Baker et al. [2024]). I suggest high frequency identification as an additional approach:

[16] An exception is Hsu et al. [2025], who study the Fed's private information about economic prospects revealed at FOMC announcements. They construct a "Fed information shock" that captures news about future first-moment productivity or growth, in contrast to my focus on second-moment risk. They show that this information shock affects corporate investment by changing profitability.

by disentangling the high frequency information content of FOMC announcements, one can isolate risk related news shock while controlling for other economic information and thereby shed light on causality.

Finally, my empirical analysis is motivated by corporate finance theories of capital investment, liquidity management, and debt rollover (see Riddick and Whited [2009], Bolton et al. [2019], Hugonnier et al. [2015], Acharya et al. [2011]). Building on these theoretical foundations, I examine heterogeneous investment responses to announcement risk news across firms and then assess the aggregate implications of this cross-sectional evidence.

The rest of the paper proceeds as follows. Section 2 presents the conceptual framework and the theoretical predictions that guide the empirical analysis. Section 3 describes the empirical strategy and the data. Section 4 reports the main results, documenting the average investment response to announcement risk news and its heterogeneity by debt burden. Section 5 uncovers the transmission mechanism. Section 6 discusses the findings and provides additional robustness tests. Section 7 highlights the implications of the firm-level results for aggregate investment. Section 8 concludes with policy implications.

2. Conceptual Framework

In this section, I adopt the model of Pflueger et al. [2020], which provides the conceptual framework and the theoretical predictions that guide the empirical analysis. Although parsimonious, the model captures the core economic mechanisms emphasized by risk centered theories of the business cycle[17]. I extend the framework by incorporating a simple monetary policy rule to illustrate how shifts in aggregate risk perception, triggered by unanticipated policy news, affect firms' investment decisions.

2.1. Model

Risk and Monetary Policy

In Pflueger et al. [2020], the log growth rate of aggregate output, x_t, is modeled as a stochastic process given by $x_t = v_t$, where v_t represents an aggregate demand shock. The shock is mean zero, serially independent, and normally distributed with time varying variance, $v_t \sim N\left(0, \sigma^2_{v,t}\right)$. The variance $\sigma^2_{v,t}$ measures the risk associated with the aggregate demand shock.[18] The framework assumes that the economy operates in the neighborhood of its steady state, so the aggregate process captures deviations from that steady state level. This interpretation is analogous to the notion of the output gap, which tracks fluctuations around a long run trend.

[17]More general and quantitatively richer models in this literature include Gourio [2012], Fernández-Villaverde et al. [2015], and Caballero and Simsek [2020].

[18]Throughout the model section, the term "risk" refers to uncertainty about future outcomes and is represented mathematically by the variance.

I extend the framework by allowing the log growth rate process to be determined jointly by aggregate shocks and monetary policy. Specifically,

$$x_t \;=\; \theta\, i_t \;+\; v_t,$$

where i_t denotes the nominal interest rate. The parameter $\theta < 0$ captures the impact of the interest rate on consumption: a higher interest rate lowers current aggregate growth, consistent with IS curve intuition. Because the model abstracts from price dynamics, the monetary authority is assumed to follow a simple rule that reacts to current output growth:

$$i_t \;=\; \phi\, x_t \;+\; \epsilon_t,$$

where $\phi > 0$ measures the strength of the policy response. A positive ϕ therefore implies that monetary policy stabilizes aggregate demand fluctuations. The term ϵ_t is an additional i.i.d. shock with time invariant variance, $\epsilon_t \sim N(0, \sigma_\epsilon^2)$. It captures departures from the anticipated rule[19], and empirically corresponds to unanticipated news revealed at the monetary policy announcement.

By substituting the monetary policy rule into the aggregate growth process, x_t can be written as a function of the demand shock and the monetary-policy shock: $x_t \;=\; \omega\,\theta\,\epsilon_t \;+\; \omega\, v_t,$, where $\omega \equiv \frac{1}{1-\theta\phi}$ is a constant. Aggregate risk perception—captured by the variance of x_{t+1}—is therefore

$$\sigma^2_{x,t+1} \;=\; \omega^2\Big(\theta^2\sigma^2_\epsilon \;+\; \sigma^2_{v,t+1}\Big)\,.$$

A key feature in Pflueger et al. [2020] is that the perceived risk of the future demand shock evolves according to

$$\sigma^2_{v,t+1} \;=\; \exp\!\Big(a - b\, x_t\Big),$$

where a and b are constants with $b > 0$. This specification accords with evidence that risk premia are countercyclical and that perceived future uncertainty rises during economic downturns.[20]

[19] This is consistent with the concept discussed in Galí [2015]: "the stochastic component (. . .) in the policy rule (. . .) is referred to as a monetary policy shock. It should be interpreted as a random, transitory deviation from the usual conduct of monetary policy as anticipated by the public, due to a change in the policymaker's preferences, a response to an unusual unanticipated event, or simply an error in the implementation of monetary policy."

[20] See, for example, Bloom [2014], Martin [2017], and Nakamura et al. [2017].

Household Preferences and the Risk-Free Rate

A representative agent has constant relative risk aversion (CRRA) preferences, characterized by the risk aversion coefficient γ and the time discount factor β:

$$U \equiv E_t\left[\sum_{s=0}^{\infty} \beta^s \frac{C_{t+s}^{1-\gamma}}{1-\gamma}\right]. \tag{1}$$

The representative agent's consumption growth rate, Δc_{t+1}, follows the aggregate process $\Delta c_{t+1} = x_{t+1}$. The associated stochastic discount factor (SDF) is

$$M_{t+1} = \frac{\partial U/\partial C_{t+1}}{\partial U/\partial C_t} = \beta \frac{C_{t+1}^{-\gamma}}{C_t^{-\gamma}} = \beta \exp(-\gamma x_{t+1}). \tag{2}$$

Because x_{t+1} is normally distributed with mean zero, $\exp(-\gamma x_{t+1})$ is lognormal. Consequently, the time-t log real risk-free rate is $r_{f,t} = -\ln \beta - \frac{1}{2}\gamma^2\sigma_{x,t+1}^2$.[21]

Production

Firm production follows a standard Q-theory framework in which output is linear in capital:

$$Y_{it} = Z_{it}K_{it}.$$

Here, Y_{it} denotes the output of firm i at time t; K_{it} is the capital stock; and Z_{it} represents total factor productivity (TFP). The evolution of TFP follows the aggregate growth process

$$Z_{it+1} = \exp\left(s_i x_{t+1} - \frac{1}{2}s_i^2\sigma_{x,t+1}^2\right). \tag{3}$$

The firm specific parameter s_i governs exposure to the aggregate process. The adjustment term $-\frac{1}{2}s_i^2\sigma_{x,t+1}^2$ (from Jensen's inequality) normalizes the conditional mean so that $E_t[Z_{it+1}] = 1$ for all firms. Consequently, heterogeneity across firms stems solely from differences in cash flow uncertainty driven by exposure to aggregate risk.[22]

Capital accumulates according to $K_{it+1} = I_{it} + (1-\delta)K_{it}$, where I_{it} denotes investment and δ the depreciation rate. Investment incurs a capital adjustment cost $\Phi_{it} = \phi(I_{it}/K_{it})\,K_{it}$. To obtain a closed form for investment, the adjustment cost takes a standard quadratic form,

$$\phi\left(\frac{I_{it}}{K_{it}}\right) = \frac{I_{it}}{K_{it}} + \frac{1}{2}\left(\frac{I_{it}}{K_{it}}\right)^2. \tag{4}$$

Dividends equal output minus adjustment costs, $D_{it} = Y_{it} - \Phi_{it}$. For tractability, there are two additional assumptions. First, capital fully depreciates within each period ($\delta = 1$), so

[21] Detailed derivation is provided in Appendix C.

[22] Since x_{t+1} is normally distributed with mean zero, $\exp(s_i x_{t+1})$ is lognormal. I impose $s_i > \gamma/2$ for all firms to ensure that an increase in consumption volatility raises the firm's risk premium by more than the decline in the risk free rate. As a result, the cost of capital increases and aggregate investment declines.

the capital available for production in period $t+1$ equals investment in period t. Second, firms operate for a single period before exiting, with a new cohort entering each period. These assumptions reduce each firm's problem to a two period setup, as in investment based asset pricing (e.g., Lin and Zhang [2013]; Hou et al. [2015]). For the entering cohort at time t, $K_{it}=0$ implies $Y_{it}=0$, so

$$D_{it} = -\Phi_{it}, \quad D_{it+1} = Z_{it+1}K_{it+1}, \tag{5}$$

where, for entrants, the intensive rate I_{it}/K_{it} in Φ_{it} is interpreted relative to a notional scale of beginning of period capital (normalized to one) to keep (4) well defined. The firm maximizes the risk adjusted present value of dividends,

$$V_{it} = \max_{I_{it}} \left\{ D_{it} + E_t[M_{t+1}D_{it+1}] \right\}. \tag{6}$$

Risky Return and Real Investment

A central insight of Q-theory is that the market return on the marginal claim to the firm, R_{it+1}, equals the return on the firm's investment (see Lin and Zhang [2013]). The return on investment is defined as the marginal benefit of an additional unit of investment, equal to next period productivity divided by the marginal cost. Formally,

$$R_{it+1} = \frac{Z_{it+1}}{\phi'\left(\frac{I_{it}}{K_{it}}\right)} = \frac{\exp\left(s_i x_{t+1} - \frac{1}{2}s_i^2\sigma_{x,t+1}^2\right)}{\phi'\left(\frac{I_{it}}{K_{it}}\right)}. \tag{7}$$

Because $E_t[Z_{it+1}] = 1$ under the TFP normalization, the corresponding expected return is

$$E_t[R_{it+1}] = \frac{1}{\phi'\left(\frac{I_{it}}{K_{it}}\right)}. \tag{8}$$

For firm i, the Euler condition $1 = E_t[M_{t+1}R_{it+1}]$ holds. Combining this with the quadratic adjustment cost in Equation (4) yields

$$\ln\left(1 + \frac{I_{it}}{K_{it}}\right) = \ln(\beta) - \gamma\left(s_i - \frac{\gamma}{2}\right)\sigma_{x,t+1}^2, \tag{9}$$

where the left hand side is the log of one plus the investment–capital ratio. This expression implies that investment declines as aggregate risk $\sigma_{x,t+1}^2$ rises, provided the firm is sufficiently risky ($s_i > \frac{\gamma}{2}$), with a larger effect for firms with greater exposure s_i. The corresponding excess return is

$$\ln\Big(E_t[R_{it+1}]\Big) - r_{f,t} = \gamma s_i \sigma_{x,t+1}^2. \tag{10}$$

2.2. Equilibrium

In this simple model, perceived future aggregate risk is the sole channel through which unanticipated monetary policy news affects asset prices and capital investment. The key insights that guide my empirical analysis are summarized in the following propositions. I first characterize the model's equilibrium.

Proposition 1. *There exists a unique equilibrium such that the real risk-free rate satisfies the consumption Euler equation, the excess return on the firm's financial claims satisfies the asset pricing Euler equation, and investment satisfies Equation 9.*

Under the model's assumptions, perceived aggregate risk is endogenously linked to unanticipated monetary policy news:

Proposition 2. *When x_t is close to zero, an unanticipated monetary policy news that raises the policy rate increases perceived aggregate risk:*

$$\frac{d\,\sigma^2_{x,t+1}}{d\epsilon_t} = -\,b\,\omega^3\theta\,\exp(a) > 0.$$

The coefficient $-b\,\omega^3\theta\,\exp(a)$ summarizes the approximately linear response of perceived aggregate risk to an unanticipated policy news shock. Intuitively, a contractionary, rate-raising surprise lowers current growth, which heightens uncertainty about future conditions. It is worth noting that, for tractability, the model treats unanticipated monetary policy news solely as shocks to the policy rate. In practice, policy announcements may also convey information that directly changes the economic outlook and perceived risk. This abstraction does not alter the model's central empirical prediction, but it does shape the empirical specification and the interpretation of the results; I return to these issues in the next subsection. A first-order approximation of perceived aggregate risk around $x_t = 0$ yields:

Lemma 1. *Suppose aggregate growth x_t, the monetary policy news ϵ_t, and the demand shock v_t are small and close to zero. Perceived aggregate risk can then be approximated linearly as*

$$\sigma^2_{x,t+1} \;=\; \underbrace{\omega^2\theta^2\sigma^2_\epsilon + \omega^2\exp(a)}_{c} \;+\; \underbrace{-\,b\,\omega^3\exp(a)\,v_t}_{\kappa^v_{t+1}} \;+\; \underbrace{-\,b\,\omega^3\theta\,\exp(a)\,\epsilon_t}_{\kappa^\epsilon_{t+1}}.$$

Thus, perceived aggregate risk decomposes into three parts: a constant term c; a component driven by the current demand shock, κ^v_{t+1}; and a component driven by monetary policy news, κ^ϵ_{t+1}, which captures shifts in risk perceptions associated with information revealed at policy announcements. Taking the derivative of firm investment with respect to κ^ϵ_{t+1} yields:

Proposition 3. *Given Lemma 1 and $s_i > \gamma/2$, for any firm i, a positive realization of κ^{ϵ}_{t+1} reduces investment:*

$$\frac{d\ln\left(1+\frac{I_{it}}{K_{it}}\right)}{d\kappa^{\epsilon}_{t+1}} = -\gamma\left(s_i - \frac{\gamma}{2}\right) < 0.$$

The effect of policy induced shifts in risk perceptions on investment is stronger for firms with greater exposure s_i.

Proposition 3 shows that contractionary policy news raises perceived aggregate risk, which increases the cost of capital through higher cash flow uncertainty. Consequently, average investment declines. In the cross section, firms with higher exposure s_i face a larger increase in cash flow uncertainty and respond with more pronounced investment cuts. Differentiating the risk-free rate with respect to κ^{ϵ}_{t+1} yields the following proposition:

Proposition 4. *Given Lemma 1, a positive realization of κ^{ϵ}_{t+1} lowers the risk-free rate:*

$$\frac{dr_{f,t}}{d\kappa^{\epsilon}_{t+1}} = -\frac{\gamma^2}{2} < 0.$$

Proposition 4 implies that a rise in perceived risk due to policy news leads households to increase precautionary saving. The resulting higher demand for safe assets depresses the risk-free rate and raises the prices of risk-free securities.

In addition, because κ^{ϵ}_{t+1} is (to first order) a linear function of the policy shock ϵ_t when x_t is near zero, the following corollary holds:

Corollary 1. *Given Lemma 1, the first derivatives of investment with respect to κ^{ϵ}_{t+1} and ϵ_t,*

$$\frac{d\ln\left(1+\frac{I_{it}}{K_{it}}\right)}{d\kappa^{\epsilon}_{t+1}} \quad \textit{and} \quad \frac{d\ln\left(1+\frac{I_{it}}{K_{it}}\right)}{d\epsilon_t},$$

share the same sign. Likewise, the first derivatives of the risk-free rate with respect to κ^{ϵ}_{t+1} and ϵ_t,

$$\frac{dr_{f,t}}{d\kappa^{\epsilon}_{t+1}} \quad \textit{and} \quad \frac{dr_{f,t}}{d\epsilon_t},$$

also have identical signs.

Corollary 1 implies that, in this simple model, because unanticipated policy news affects investment and the risk-free rate only through the induced change in perceived risk, the qualitative effect is the same whether expressed in terms of the risk perception change κ^{ϵ}_{t+1} or in terms of the policy news ϵ_t. This follows from the chain rule and the fact that $\frac{d\kappa^{\epsilon}_{t+1}}{d\epsilon_t} = -b\,\omega^3\theta\exp(a) > 0$.

2.3. Empirical Implications

The risk channel of monetary policy transmission Proposition 3 implies the following testable prediction:

Prediction 1: An increase in risk perception triggered by unanticipated policy news at a monetary policy announcement reduces firms' capital investment in the subsequent period.

I refer to this mechanism as the *risk channel* of monetary policy announcements for corporate investment. The empirical analysis therefore centers on testing the link between policy news that shifts risk perception and subsequent investment. Because the model transmits changes in risk perception to investment through the cost of capital, I also examine risk news and subsequent equity returns, which serve as an ex post measure of that cost.

Empirical strategy As noted above, the conceptual framework treats unanticipated monetary policy news purely as news about the short term policy rate. This simplification preserves the model's core mechanism: policy rate surprises shift risk perceptions and, in turn, future investment, because a short rate surprise directly affects current economic growth, which is linked to perceived future risk. In practice, however, monetary policy announcements convey a broader set of news that can move risk premia and risk perceptions (see, e.g., Cieslak and Schrimpf [2019], Kroencke et al. [2021]); in particular, announcements can contain information directly about future growth and cash flow uncertainty.[23] Although this reality does not overturn the model's empirical prediction, it implies that a suitable empirical strategy must also capture policy announcement news that directly shifts risk perceptions. Moreover, the risk channel is not the sole mechanism through which policy news influences investment; the traditional interest rate channel also operates in practice.[24] Consequently, the widely used high frequency short rate surprise cannot serve as a stand alone proxy or instrument for risk news. Put differently, Corollary 1 applies to the illustrative model but not to the data, because the model abstracts from the additional transmission channels present in the economy.

A practical and perhaps easier approach is therefore to capture all unanticipated news that drives risk perceptions during the announcement event window. This requires a forward looking indicator that is sensitive to news and captures shifts in risk perceptions. A natural candidate is the change in risk premia embedded in asset prices, because, under

[23]Prior studies document that policy announcements release information affecting risk perceptions, especially through non rate news. Evidence on the extent to which short rate surprises alone move perceived risk is mixed. Bauer et al. [2023] find that monetary policy shocks alter the common component of several risk measures, whereas Nakamura and Steinsson [2018a] and Pflueger et al. [2020] report little relation between short rate surprises and risk premia.

[24]Within the stylised model, the elasticity of investment with respect to a short rate surprise isolates the risk channel, as stated in Corollary 1, because no other channel is present. In reality, however, a short rate surprise can affect investment directly through the cost of funding, so both channels coexist.

market efficiency, high frequency price movements reflect the arrival of new information.[25] The standard short rate surprise nevertheless remains a valuable control variable. Previous studies show that high frequency surprises extracted from interest rate futures (e.g., Nakamura and Steinsson [2018a]) capture policy rate and growth information released at policy announcements. Including this control serves two purposes when regressing subsequent investment on announcement risk news: (i) it absorbs the traditional interest rate channel of investment, and (ii) because any covariance among the regressors is partialled out, the coefficient on the risk news measure is estimated using only variation orthogonal to policy rate and growth news. Put differently, the control removes the mechanism through which interest rate surprises shift risk perceptions and thereby indirectly influence capital investment, leaving the coefficient to reflect the effect of non policy risk news. Section 6.1 discusses how monetary policy communications influence risk perceptions and provides examples in which announcements speak directly to future cash flow risk.

Properties of risk news The Propositions imply empirical characteristics of the news that drives risk perceptions during the announcement window, which I use to identify and test the risk channel. This news is akin to a cash flow risk shock: it raises uncertainty about firms' future cash flows, is priced in equity markets, and increases expected excess returns. In practice, increases in this type of risk often trigger flight to safety: Treasury prices rise (yields fall) because Treasuries are safe assets with stable cash flows that hedge cash flow risk, so investors become more willing to hold them when cash flow risk increases.

These properties differ from those of news that increases discount rate uncertainty, which is not directly tied to the perceived risk of firms' future cash flows. Viewing equity as the sum of a long term bond and a claim on cash flow risk, news that heightens discount rate uncertainty also raises risk premia, but it simultaneously raises safe bond yields (lowers prices) because that uncertainty cannot be hedged. Although discount rate uncertainty is also priced in risk premia, it is distinct from the perceived risk about future cash flows that is the focus of this study.[26]

Debt burdens and the risk channel Proposition 3 states that the investment impact of the risk channel intensifies when a firm's cash flows are more exposed to aggregate risk, as captured by the parameter s_i. This provides an abstract representation of cross-sectional heterogeneity. Empirically, the rich variation in firms' balance sheet characteristics in the data allows to explore this heterogeneity once the relevant dimension is identified. I focus on debt burdens for two main reasons. First, extensive evidence from high-risk

[25] High frequency asset price changes are widely used in the news shock literature to identify aggregate news shocks; see, for example, Känzig [2021].

[26] Time varying uncertainty in the discount rate is common in consumption based models for explaining the equity premium and the bond term premium. Pflueger and Rinaldi [2022] employ a habit formation model with time varying discount rate uncertainty to account for the joint response of bond and equity markets to monetary policy surprises.

episodes—such as the Global Financial Crisis and the COVID-19 recession—shows that financial frictions were central to the sharp contractions in business investment and consumption, with households and firms carrying heavy debt burdens being most affected.[27] And these high indebted often seen face higher default risk increase when aggreagate economy become more uncertaint. Second, previous work, including Ottonello and Winberry [2020], finds that highly indebted firms are less responsive to the conventional interest rate channel; determining whether these firms react more or less to announcement risk news therefore has important implications for policy communication. In addition, (net) financial leverage is well known to shape the sensitivity of a firm's cost of capital to market risk[28]. Guided by these observations, I formulate the second empirical prediction, which is for the heterogenous investment response :

Prediction 2: Indebted firms react more strongly to risk increasing announcement news, reducing capital investment by more than their low-debt counterparts.

3. Empirical Strategy

My empirical strategy builds on a line of macroeconomic research that uses micro data to measure policy effects. As noted by Nakamura and Steinsson [2018b], dynamic causal inference proceeds in two steps: (1) identify plausibly exogenous policy shocks, and (2) estimate impulse responses with panel data once those shocks are in hand. This two-step approach is now standard, especially in recent studies of monetary policy transmission with micro data, including Ottonello and Winberry [2020], Wong et al. [2019], and Cloyne et al. [2023].

As discussed in Section 2.3, to investigate the risk channel of monetary policy announcements on corporate investment, the relevant policy shocks are news shocks, i.e., unanticipated information in the announcement that changes perceived future risk. Accordingly, my first step is to extract the risk news shock from asset price movements during the FOMC announcement window. After recovering the FOMC risk news shock, the second step estimates firms' investment responses using panel local projections, controlling for other types of announcement news, such as policy-rate surprises.

3.1. Identifying FOMC Risk News Shock

I primarily employ a structural approach to identify the FOMC risk news shock and use two related reduced form methods as robustness checks. The baseline structural method follows Cieslak and Pang [2021], which decomposes unexpected asset price movements into distinct economic news shocks within a structural VAR grounded in macro finance theory. Identification exploits high frequency comovements between equity returns and changes in

[27] See, for example, Mian et al. [2013] and Giroud and Mueller [2017].

[28] See, for example, Hamada [1972]; Penman et al. [2007].

Treasury yields across maturities. I summarize the key intuition of this procedure below; complete estimation details and results are provided in Appendix D.

The structural VAR builds on the idea that asset prices are driven by unanticipated information that perturbs the underlying state variables:

$$X_{t+1} = \mu + \Phi X_t + B\,\omega^f_{t+1},$$

where μ is a vector of constants, Φ is the matrix of autoregressive coefficients, and $X_t = \left(\Delta y^{(2)}_t,\ \Delta y^{(5)}_t,\ \Delta y^{(10)}_t,\ r^e_t\right)'$ stacks the daily changes in zero coupon Treasury yields at the 2, 5, and 10 year maturities together with the aggregate equity return. The vector of orthogonal news shocks is $\omega^f_{t+1} = \left(w^c_{t+1},\, w^d_{t+1},\, w^{cr}_{t+1},\, w^{dr}_{t+1}\right)'$,[29] and B is the contemporaneous impact matrix. Economic restrictions imposed on B govern how each shock affects the joint movement of yields and equity returns, enabling unexpected asset price changes to be decomposed into four orthogonal news shocks: cash flow growth news (w^c_{t+1}), short term discount rate news (w^d_{t+1}), cash flow risk news (w^{cr}_{t+1}), and discount rate risk news (w^{dr}_{t+1}).

The cash flow risk news shock is central to the empirical analysis because it captures revisions in the compensation investors demand for bearing aggregate cash flow uncertainty; Treasury prices typically rise when bad news arrives, as they hedge this risk. Discount rate risk, by contrast, is not diversifiable, so the associated news tends to move Treasury and equity prices in the same direction. This two factor structure in risk accords with the view that an equity claim can be regarded as the payoff of a long duration bond supplemented by exposure to cash flow risk.

Two sets of restrictions are imposed on the impact matrix B to identify the cash flow risk news shock. The first set consists of monotonicity restrictions across yield maturities, motivated by the affine term structure literature: short rate and growth news affect Treasury yields less as maturity increases,[30] whereas the two risk news shocks have larger effects at longer maturities because near term uncertainty is limited. These monotonicity restrictions therefore separate the two risk news shocks from the two short rate related shocks.

The second set of restrictions consists of sign restrictions that further distinguish the cash flow risk news shock from the discount rate risk news shock. These restrictions are grounded in the two factor risk structure discussed above. A positive cash flow risk news shock (w^{cr}_{t+1}) must lower equity prices by raising the risk premium investors demand for bearing greater cash flow uncertainty, while simultaneously raising Treasury prices (i.e., lowering yields) because government bonds hedge that uncertainty. This flight to safety is consistent with the risk perception properties in the conceptual framework, namely

[29] Each shock is standardized to zero mean and unit variance over the estimation sample, so $\mathrm{Var}(\omega^f_t) = I$.

[30] This pattern reflects the standard affine term structure assumption that the short rate and the growth rate are stationary and mean reverting; Cieslak and Pang [2021] summarizes supporting empirical evidence.

perceived uncertainty about future economic growth. In contrast, a positive discount rate risk news shock (w^{dr}_{t+1}) is required to reduce Treasury and equity prices, since discount rate uncertainty is not diversifiable.[31]

I estimate the structural VAR at the daily frequency using a sample that begins in 1983, matching the start date in Cieslak and Pang [2021] to keep my parameter estimates comparable to theirs.[32] I extend the sample through 2023. The VAR decomposes asset price movements each trading day, and my analysis focuses on results from scheduled FOMC meetings, defining the event window as the FOMC announcement day. I exclude unscheduled meetings because these events are noisy and often coincide with periods of heightened uncertainty, which makes it difficult to attribute changes in risk perceptions primarily to FOMC announcements.[33] The equity market index is obtained from Bloomberg, and daily Treasury yields are from Gürkaynak et al. [2007] which are continuously updated on the Federal Reserve's website.

[Figure 1 around here]

The estimation of the impact matrix uses data for all trading days from 1983 to 2023. Figure 1 shows cash flow risk news shocks on scheduled FOMC announcement days; positive values indicate news that increases cash flow risk. By construction, these daily news shocks have a mean of zero and unit variance over the estimation sample. Therefore, one unit in Figure 1 corresponds to one standard deviation of the cash flow risk news shock across all trading days (values are expressed in standard deviation units). In Appendix D, I show quantitatively that a one unit positive shock is associated with a contemporaneous decline of 66.5 basis points (0.665%) in the equity market index.[34] Moreover, the responses of both equity returns and Treasury bond yields are highly persistent, remaining close in magnitude to the initial impact for up to one year.

Figure 1 starts in 1994, when the Federal Reserve began communicating announcements to markets via press releases. It shows that cash flow risk news shocks tend to be negative on FOMC announcement days, suggesting that these announcements typically resolve uncertainty about future cash flows and thus reduce risk perceptions. Several notable events

[31] For the remaining two shocks, the sign restrictions are as follows. A positive cash flow growth shock (w^{c}_{t+1}) is restricted to increase equity prices and decrease Treasury bond prices, because stronger fundamentals raise expected cash flows directly while also pushing up the discount rate; in equities the direct cash flow effect dominates, whereas for Treasury bonds only the discount rate channel is operative. A positive short term discount rate shock (w^{d}_{t+1}) is restricted to lower Treasury bond prices by increasing yields and to reduce equity prices because future cash flows are discounted more heavily.

[32] Cieslak and Pang [2021] justify this start date by noting that the Federal Reserve's shift to an explicit interest rate targeting regime in the early 1980s improves the identification of short term discount rate shocks.

[33] Some unscheduled FOMC meetings, such as the one on March 15, 2020, occurred on a Sunday, complicating the real time capture of stock market reactions.

[34] A one unit positive shock is also associated with a contemporaneous decline of 3.7 basis points in the 10 year Treasury bond yield.

are associated with large shock magnitudes. For instance, the announcement of QE2 led to a substantial decline in risk perception, whereas the Operation Twist program resulted in a sharp increase. Additionally, the July 26, 2023, FOMC announcement produced the largest reduction in risk perception, despite coinciding with a widely anticipated rate hike that pushed interest rates to their highest level in more than 22 years. A likely factor behind this effect was Federal Reserve Chair Powell's statement that "Fed staff is no longer forecasting a recession," which significantly lowered perceived future risk.

[Table 1 around here]

Table 1 reports summary statistics for daily cash flow risk news shocks computed for all trading days and, separately, for scheduled FOMC days across samples. Three key findings emerge. First, news shocks on FOMC days are, on average, more negative and have larger absolute values. Second, the dispersion of these shocks, measured by both the interquartile range and the variance, is substantially higher on FOMC days. Third, in the post 2008 subsample, both the absolute values and the dispersion of shocks are higher; specifically, in the sample starting in 1994 the variance on FOMC days is roughly twice that for average trading days, and this ratio rises to approximately three when considering only the post 2008 period. These findings suggest that FOMC announcements convey more new information regarding future cash flow risk, especially post 2008.

Following standard practice in the literature (e.g., Wong et al. [2019], Ottonello and Winberry [2020], and Jeenas and Lagos [2024]), I aggregate daily cash flow risk news shocks observed on scheduled FOMC announcement days into a quarterly series to match the firm level balance sheet data.[35] The resulting quarterly series, denoted ϵ_t^{cr}, serves as the main independent variable, referred to as the *FOMC risk news shock*, in the investment regressions.

The structural VAR offers the advantage of decomposing asset price changes on FOMC announcement days into distinct news types, covering nearly all channels through which announcements can affect asset prices. The structural estimation provides clear economic intuition behind the estimated news shocks.[36] However, one potential concern is misspecification of the structural model. To address this, I complement my analysis with two additional reduced form measures derived from asset prices as robustness checks. First, I use FOMC day changes in the risk perception index from Bauer et al. [2023] (the "BBM

[35]This aggregation assumes that the shocks are orthogonal to economic variables within each quarter. This assumption is plausible here, since markets have access to contemporaneous information and the shocks are extracted solely from asset price changes, so they reflect unanticipated information beyond the current economic environment.

[36]The literature documents that monetary policy announcements affect asset prices through multiple channels, including policy rate decisions, growth outlooks, uncertainty regarding monetary policy, and uncertainty about future economic conditions. These correspond to the four distinct news shocks identified by the structural VAR.

Index"), constructed from the first principal component of 14 risk sensitive financial indicators. This measure aligns with the idea that changes in aggregate risk perceptions should be reflected broadly across risky assets. Second, I consider FOMC day changes in $SVIX^2$, an option implied lower bound on the market risk premium from Martin [2017], based on the risk neutral variance of excess returns.[37]

[Table 2 around here]

Table 2 reports correlations between FOMC-day changes in the BBM risk index and $SVIX^2$ and the structural cash flow risk news shock. Each series is constructed as the quarterly sum of its FOMC-day values, and the sign of BBM changes is inverted so that increases reflect higher perceived risk. Both proxies are statistically significantly correlated with the cash flow risk news shock. For reference, the table also reports correlations with the structural discount rate risk news shock, which are smaller. For illustration, the BBM index correlates 0.436 with the cash flow risk news shock (t-statistic = 5.224), compared with 0.179 with the discount rate risk news shock (t-statistic = 1.964). This pattern supports the interpretation that these alternative proxies primarily capture cash flow risk news on FOMC announcement days. Appendix B.2 further reports the daily correlations on FOMC announcement days, showing that the two reduced-form proxies are even more strongly correlated with the cash flow risk news and only weakly correlated with the discount rate risk. In addition, Appendix B.2 also shows these measures co-move strongly with standard volatility proxies VIX, reinforcing the view that they track financial market risk perceptions.

3.2. Investment Response to FOMC Risk News Shocks

I employ a Jordà [2005] style panel local projection method to investigate the corporate investment response to FOMC risk news shocks.

Average response: I first estimate the average response of investment using

$$\log k_{j,t+h} - \log k_{j,t} = \alpha_j + \alpha_y + \beta^h \, \epsilon_t^{cr} + \Gamma_Z' Z_{j,t-1} + \Gamma_A' A_{t-1} + e_{j,t,h}, \tag{11}$$

where $k_{j,t}$ is the book value of tangible capital for firm j in quarter t, and $h = 0, 1, \ldots, H$ indexes the projection horizon. The term α_j denotes firm fixed effects, and α_y denotes year fixed effects. The vector $Z_{j,t-1}$ contains lagged firm level controls (financial position, total assets, sales growth, liquid assets, asset returns, and operating leverage) measured before the shock.

[37] I utilize the version constructed using six month options.

Quarter fixed effects cannot be included because they would absorb all variation generated by aggregate quarterly shocks; instead, I use year fixed effects α_y.[38] The vector A_{t-1} collects lagged macroeconomic controls (real GDP growth, the unemployment rate, and four quarter inflation) to account for quarterly macro fluctuations. To control for alternative monetary policy transmission channels and isolate the impact of risk news (that is, the component not driven by other news; see Section 2.3), the macroeconomic controls also include the concurrent FOMC news shocks from the structural VAR and the high frequency interest rate surprises of Nakamura and Steinsson [2018a]. My coefficient of interest, β^h, captures the cumulative response of investment from t to $t+h$ to the FOMC risk news shock ϵ_t^{cr}; it represents the semi elasticity of investment with respect to this shock.

Differential response. To analyze heterogeneity in investment responses arising from cross sectional variation in debt burden, I estimate a panel local projection with a linear interaction term:

$$\log k_{j,t+h} - \log k_{j,t} = \alpha_j + \alpha_t + \gamma^h X_{j,t-1} + \beta^h X_{j,t-1}\, \epsilon_t^{cr} + \Gamma'_Z Z_{j,t-1} + e_{j,t,h}, \tag{12}$$

where the key regressor is the interaction between the firm's lagged debt burden measure, $X_{j,t-1}$, and the FOMC risk news shock, ϵ_t^{cr}. This term captures how a firm's cumulative investment response varies with its degree of debt burden. Quarterly time fixed effects, α_t, are included, subsuming the year fixed effects and the macroeconomic controls. I also estimate specifications that interact debt burden with the other FOMC news shocks or with the interest rate surprise; these serve to control for alternative transmission channels and help isolate the pure effect of risk news.

The specification in (12) imposes a linear interaction, and the coefficient β^h captures cross sectional differences in responses. To check robustness, I follow Cloyne et al. [2023] and Anderson and Cesa-Bianchi [2024] and estimate a dummy variable model:

$$\log k_{j,t+h} - \log k_{j,t} = \alpha_j + \sum_{g=1}^{G} \beta_g^h\, I\Big[X_{j,t-1} \in g\Big]\, \epsilon_t^{cr} + \sum_{g=1}^{G} \gamma_g^h\, I\Big[X_{j,t-1} \in g\Big] + \Gamma'_Z Z_{j,t-1} + \Gamma'_A A_{t-1} + e_{j,t,h}, \tag{13}$$

where the indicator $I\Big[X_{j,t-1} \in g\Big]$ equals one if the firm's debt burden falls in group g. Groups can be multidimensional (for example, firms that are both small and highly indebted). Equation (13) provides a semiparametric estimate: each coefficient β_g^h captures the average response within subgroup g. Compared with (12), this dummy variable approach relaxes the linearity assumption and yields more flexible estimates for each sub-

[38] I also estimate specifications with sector year or sector time fixed effects (α_{sy} and α_{st}), which capture time varying investment opportunities at the sector level.

group.[39] Equation (13) includes the same set of control variables as equation (11).

3.3. Discussion on Identification

The two step causal inference I standard in the literature, but the application of this procedure still faces identification threats, especially when isolating the unanticipated information in FOMC announcements that drives risk perceptions. In the following, I examine the main empirical concern and justify my identification choices.

Window length: The asset pricing based approach is well suited to obtain announcement risk news because financial markets are sensitive to risk related news and incorporate publicly available information almost instantaneously. Asset prices recorded before an announcement already embed any expected policy response. However, high frequency identification requires specifying an event window in which price movements primarily reflect unanticipated information and can be attributed to the FOMC announcement. In principle, the methodology of Cieslak and Pang [2021] could be applied with 30 or 60 minute intraday windows, as in Cieslak and Schrimpf [2019]. Window length involves a balance: a longer window is more likely to capture the full market reaction but admits more background noise, whereas a shorter window reduces noise yet risks truncating the response. Following Känzig [2021], I adopt a one day window for two main reasons. (i) Unlike policy rate surprises, news that changes risk perceptions may take longer for investors to absorb. Empirical evidence in Schmeling and Wagner [2016] shows that risk premium adjustments after central bank announcements can persist into the next trading day. (ii) Very short windows yield extremely small shocks. This weak signal problem reduces statistical power and hinders precise estimation of standard errors for the real effect impulse responses.

Background noise: Using a daily window raises the concern that it may also capture other news not tied to the announcement. To gauge this background noise, Table 1 compares the variance of the cash flow risk news shock on all trading days with its variance on FOMC announcement days. Over the full sample, the announcement day variance is roughly twice as large as that on all trading days, and after 2008 it is almost three times as large. These ratios indicate that FOMC communications convey substantially more information about future cash flow risk. Some residual noise remains, however, so the shock should be viewed as an imperfect yet informative measure. For my key results on heterogeneous investment responses, I report estimates for both the full sample and the post 2008 subsample, with the latter less exposed to background noise.

Shock exogeneity: The event window approach ensures that the FOMC risk news shock is unanticipated. In Appendix B.3, I provide additional diagnostic evidence showing that the shock identified via the structural VAR and two alternative reduced form measures

[39] A linear interaction may be distorted by extreme values of the conditioning variable, yet those tail observations (such as firms with exceptionally high debt burdens) are central to my analysis. The dummy variable specification captures their average behavior without discarding them.

are not predictable using standard predictors of interest rate surprises, and that there is no evidence of autocorrelation. A remaining concern is that the shock could also reflect other types of news released simultaneously, thereby confounding channels. Two features mitigate this concern. First, the structural VAR isolates the cash flow risk news shock by requiring it to be orthogonal to the other news shocks. Second, the local projection framework allows the inclusion of controls; I add the high frequency interest rate surprise, which accounts for any covariance between the FOMC risk news shock and policy rate or growth information. This allows me to verify whether the main results change after adding controls and to interpret the shock coefficient as the effect of non policy announcement risk news.

Power problem. In the second step, I estimate the impulse response of firm investment to the FOMC risk news shock using a linear panel local projection approach. A standard concern with this method is limited statistical power, because high frequency shocks may be small or transitory. Appendix D shows that this concern is not relevant here: a one unit daily cash flow risk news shock lowers equity prices by 66.5 basis points, and the effect persists for several quarters. The quarterly FOMC risk news shock often reaches several units, so the shocks are both economically sizable and statistically informative. My analysis also emphasizes heterogeneity in investment. Identification comes from interacting the shock with firm level characteristics that vary across firms and over time. This cross sectional variation improves the precision of the estimated heterogeneous responses; causal inference ultimately relies on differences in firms' reactions to large shocks.

One could instead use the FOMC risk news shock as an instrument for quarterly risk perception measures. However, these measures are themselves constructed from asset prices that react strongly to the shock, so the instrumental variable specification would be close to a re scaled version of the direct local projections and would yield very similar results. I accordingly adopt the direct local projection method in my empirical analysis.

3.4. Data

I construct a quarterly panel of firm balance sheet data from Compustat. Following Ottonello and Winberry [2020] and Jeenas [2023], the investment rate $\log k_{j,t+h} - \log k_{j,t}$ is the h-quarter log change in the book value of firm j's tangible capital stock measured at the end of period t. All investment rates are winsorized at the 1% level in both tails. I exclude financial firms (SIC 6000–6999) and public utilities (SIC 4900–4999), as well as firms with missing or negative assets or sales. To ensure reliable estimation of firm fixed effects, I retain only firms with at least 40 quarters of data. Appendix A describes variable construction and sample selection, and Appendix B.1 reports summary statistics for the main variables.

The panel spans 1995Q1–2023Q4 and contains 321,268 firm quarter observations. I start the sample in 1995Q1 because the regressions control for the high frequency interest rate surprise of Nakamura and Steinsson [2018a], which is available only from 1995Q1.[40] This window covers almost the entire period, beginning in 1994, during which the Federal Reserve has communicated each announcement to markets via press releases. In addition to the Compustat data and the variables used in the structural VAR, I also draw on CRSP for equity returns and on Standard & Poor's for long and short term corporate bond ratings.

4. The Risk Channel

This section tests two main empirical predictions. First, I show that, on average, announcement risk increasing news reduces corporate investment in tangible capital. Second, I document heterogeneity in this response: firms with higher debt burdens react more strongly.

4.1. Average Investment Response

Table 3 reports the estimated average firm level response of tangible capital investment over the subsequent four quarters, based on specification (11). All firm level panel regressions report Driscoll–Kraay standard errors [Driscoll and Kraay, 1998], which are robust to heteroskedasticity, serial correlation, and cross sectional dependence. In column (1), the coefficient on the FOMC risk news shock, ϵ_t^{cr}, is statistically significant at the 5% level. Because the regression includes firm and year fixed effects, the estimate implies that a positive ϵ_t^{cr} is associated with a decline in the firm's investment rate over the next four quarters, after controlling for time invariant firm heterogeneity and aggregate annual trends. This finding supports Proposition 3 of the conceptual framework: when a monetary policy announcement releases new information that raises risk perceptions, firms, on average, cut back investment. Quantitatively, a one unit positive ϵ_t^{cr} (corresponding to a fall of 66.5 basis points in the equity market index) reduces the one year investment rate by 0.496%. Given the sample mean of 17.52%, this is about 3% of a typical annual investment rate, a magnitude that is economically modest.

[Table 3 around here]

Columns (2)–(4) of Table 3 progressively add fixed effects and controls. Column (2) replaces year fixed effects with year by sector fixed effects to capture time varying sector level trends. Column (3) adds firm level balance sheet controls: size, debt leverage, operational leverage, profitability, sales growth, and liquidity. Column (4) further includes the high frequency interest rate surprise of Nakamura and Steinsson [2018a], which, as shown

[40] The series is constructed from tick by tick data on federal funds futures and Eurodollar futures of various maturities, data that are not available prior to 1995.

in previous studies, captures news about the policy rate and the growth outlook around the announcement. These variables account for alternative monetary policy transmission channels and for mechanisms through which interest rate surprises change risk perceptions. The regression partials out their covariance with the risk news shock. With these additional controls, the baseline results from Column (1) are robust across specifications: the coefficient remains statistically significant and declines only slightly in magnitude. In Column (4), where the coefficient measures the investment effect of announcement risk news orthogonal to other news, the estimate is smaller at -0.363 but remains significant at the 5% level. Column (4) confirms that non policy risk news released at FOMC announcements also has significant real effects on firms.

[Figure 2 around here]

The local projection specification in Equation (11) allows me to trace the dynamic path of tangible capital after a shock. Figure 2 plots the impulse response coefficients (estimated with the same controls as Column (2) of Table 3) and their confidence intervals for horizons up to eight quarters. The estimates show that a positive FOMC risk news shock, on average, reduces tangible capital from the second quarter after the shock onward, with the contraction peaking around the fourth quarter. Although the effect remains negative thereafter, it gradually declines in magnitude and becomes statistically insignificant at longer horizons. This response serves as a benchmark for the heterogeneity analysis that follows, assessing whether financial frictions amplify and prolong the investment response.

[Table 4 around here]

The motivating framework posits that the cost of capital is the key mechanism linking announcement risk news to corporate investment; therefore, the FOMC risk news shock should be reflected in the cost of capital. I test this prediction using Equation (11), replacing the dependent variable with subsequent realized equity returns—an ex post proxy for the cost of capital [Pflueger et al., 2020]. Table 4 reports the estimates: the coefficient on ϵ_t^{cr} is positive, statistically significant, and similar across specifications. Figure 3 plots the impulse response of the cost of capital over the next eight quarters. The cumulative effect, significant from the first period, peaks around the fourth quarter and remains near that level thereafter, indicating that the cost of capital response persists for an extended period. Taken together, these results support the prediction that monetary policy announcements can dampen corporate investment by releasing news that increases risk perceptions; non policy risk news also plays an important role in this channel.

[Figure 3 around here]

4.2. Financial Friction and Heterogeneous Investment Responses

I next examine whether financial frictions, in the form of heterogeneous debt burdens, shape the risk channel from monetary policy announcements to corporate investment. Following the accounting literature [Penman et al., 2007], I measure heterogeneity in financial position with *net market leverage*, defined as the ratio of net debt to the market value of equity, *netML*. This measure reflects a firm's debt burden and repayment capacity for three reasons. First, because it is market based, it captures investors' expectations of future cash flows and profitability, and thus perceived repayment risk. Second, it nets debt against cash holdings, combining leverage and liquidity to gauge the true debt burden. Third, it is consistent with Lian and Ma [2021], who show that roughly 80% of U.S. nonfinancial corporate debt is collateralized by cash flows rather than physical assets; market value therefore directly captures this cash flow potential, so *netML* also indicates a firm's ability to roll over existing debt with new borrowing. Formally,

$$netML = \frac{\text{Total Debt} + \text{Preferred Stock} - \text{Cash}}{\text{Market Equity}},$$

where *Total Debt* equals long term debt (`DLTTQ`) plus debt in current liabilities (`DLCQ`), *Preferred Stock* is `PSTKQ`, and *Cash* denotes cash and short term investments (`CHEQ`). *Market Equity* is the number of common shares outstanding multiplied by the share price (CRSP). Net debt can be negative when a firm holds excess cash.

[Figure 4 around here]

Net market leverage captures firm credit risk. To demonstrate this, I merge the Compustat sample with S&P corporate credit ratings (1995–2017) for both long term and short term debt. Long term ratings span 22 categories (AAA+ to SD); short term ratings span 9 categories (A-1 to D). I convert each rating scale into a *reverse credit score*, where a higher number indicates higher default risk (e.g., SD = 22 and AAA+ = 1 for long term debt; D = 9 and A-1 = 1 for short term debt). Figure 4 plots the average reverse credit score for 20 portfolios sorted by lagged *netML*. Two patterns emerge. First, firms in the highest leverage group also exhibit the highest credit risk, for both long and short term debt. Second, the relationship between lagged *netML* and credit risk is close to linear: groups with higher net market leverage exhibit progressively higher reverse scores. The only departure from this pattern occurs in the first group, which consists of firms with virtually no debt and shows a elevated credit risk similar to that of the middle groups. Appendix B.4 lists

S&P credit ratings and their corresponding reverse credit scores, and reports the average reverse score for each decile of lagged *netML*; Appendix B.8 reports a robustness check that repeats all heterogeneity analyses and mechanism tests after excluding firms with extremely low debt.

[Table 5 around here]

Table 5 shows that debt burden significantly amplifies the investment response to announcement risk news. I estimate Equation (12) via a local projection in which the key interaction term is the product of lagged net market leverage, $netML_{t-1}$, and the FOMC risk news shock, ϵ_t^{cr}. Column (1) reproduces the baseline specification from Table 3, including firm fixed effects, year by industry fixed effects, and the full set of macroeconomic controls. Column (2) replaces the year by industry effects with time by industry fixed effects, thereby allowing the inclusion of a time fixed effect that absorbs aggregate shocks. Column (3) adds firm level balance sheet covariates (each interacted with ϵ_t^{cr}) and further interacts $netML_{t-1}$ with business cycle proxies to permit differential cyclical sensitivities across debt levels; it also includes the high frequency interest rate surprise of Nakamura and Steinsson [2018a], interacted with net market leverage, to control for confounding channels. Across all specifications, the coefficient on $\epsilon_t^{cr} \times netML_{t-1}$ is negative and significant at the 1% level, although its magnitude declines as additional controls are introduced. Thus, firms with higher debt burdens, and hence higher ex ante credit risk, cut investment more sharply after monetary policy announcements that increase risk perceptions, indicating that financial frictions are central to the transmission of announcement risk news.

The heterogeneous effect is quantitatively meaningful. Because lagged *netML* is standardized, the interaction coefficient in Column (3) (the most saturated specification) is -0.68. Hence, when two firms differ by one standard deviation in *netML*, the more leveraged firm cuts its one year investment by an additional 0.68% after a one unit increase in the FOMC risk news shock.[41] The effect is larger for firms with extreme indebtedness: those in the top 0.5 percent of the *netML* distribution (99.5th percentile) are 2.62 standard deviations above the median,[42] implying that they reduce one year investment by about 1.78% more than the median firm when the shock rises by one unit. A comparison of Columns (3) and (4) further indicates that this conditional effect intensifies after 2008, a period dominated by unconventional monetary policy.[43]

[41] This equals $0.68/17.52 \approx 3.9\%$ of the sample mean annual investment rate of 17.52%.

[42] Extreme right tail observations are retained because, following Ottonello and Winberry [2020], their behavior is informative for studying financial frictions in monetary policy transmission. To guard against bias if the relationship is nonlinear, I also estimate subgroup specific averages using a semiparametric dummy regression.

[43] The post 2008 subsample is also less affected by the background noise concern discussed above.

[Figure 5 around here]

Figure 5 presents complementary evidence using the semiparametric dummy interaction specification in Equation (13), which recovers average effects for subsamples. In each regression, I split the sample into "higher" and "lower" groups based on whether a firm's lagged net market leverage (netML) exceeds the 50th, 75th, 90th, or 95th percentile, while controlling for the high frequency interest rate surprise. Panel A reports full sample results that closely match those from the linear specification: as the percentile cutoff rises, firms in the "higher" group show progressively larger negative investment responses to a positive FOMC risk news shock. In every case, high debt burden firms cut investment more than their low debt counterparts, and the gap widens at higher thresholds. Consistent with the linear interaction results, Panel B shows that after 2008 firms in the high debt burden subsamples display even stronger negative responses, further widening the divergence between low and high debt groups. These semiparametric estimates confirm that highly indebted firms are particularly sensitive to announcement risk news and are the primary transmitters of it.

In Appendix B.5, I show that the greater sensitivity among high debt firms also appears in other outcomes and behaviors. Relative to low-debt firms, high-debt firms exhibit lower growth in total assets and lower levels of sales and cost of sales (COGS, including materials, labor, and production overhead).These patterns indicate that risk rasing announcement news not only slows the buildup of production capital but also reduces operating scale and balance sheet size. However, I do not observe statistically significant differential responses in inventories or innovation outcomes (intangible asset growth and R&D expenditure).[44]

5. Mechanism Behind Heterogeneous Investment Responses: Flight to Quality

The previous section shows that debt burden amplifies the investment response to FOMC risk news. This section examines why financial frictions transmit this channel. A natural mechanism is *flight to quality*: when perceived aggregate risk rises, investors rebalance toward safe assets and away from risky assets, widening the premium between them. Such episodes are well documented during high uncertainty periods (e.g., the Global Financial Crisis and the COVID-19 shock), both across asset classes (for example, favoring bonds over equities) and within a class (as when the credit spread between AAA and BBB rated bonds widens countercyclically). A key driver of this mechanism is that financial intermediaries face value at risk constraints; as aggregate risk rises, these constraints tighten and limit

[44] Intangible asset growth and R&D expenditure have substantial missing observations, so the estimates should be interpreted with caution.

their ability to hold risky assets, amplifying the shift toward safe assets.[45]

This mechanism maps naturally into the heterogeneous responses in the data. Figure 4 shows that firms with high market leverage also exhibit higher *ex ante* credit risk. The FOMC risk news shock is identified with flight to quality characteristics via sign restrictions in the structural VAR.[46] When a monetary policy announcement releases news that raises perceived cash flow uncertainty, investors expect highly indebted firms to face higher default risk and are therefore less willing to lend to them, increasing financing costs and tightening access to external finance.[47]

This section tests the flight to quality mechanism by investigating whether FOMC risk news shocks raise external finance costs disproportionately for highly indebted firms; it then traces how the resulting increase in financing costs depresses investment through rollover pressure. Because external finance costs are not directly observable, I infer them from firms' debt and cash management behavior. In addition, conventional policy rate tightening and business cycle conditions can affect funding costs for indebted firms, so all specifications explicitly control for aggregate conditions and for the interest rate surprise.

5.1. Flight to Quality and Borrowing Costs

As originally proposed in Keynes's *General Theory*, limited access to external finance heightens the importance of balance sheet liquidity, which safeguards future investment plans. Recent theories such as Riddick and Whited [2009] and Bolton et al. [2019] formalize this idea and show that when external financing becomes costly, firms reduce new borrowing and rely more on internal cash flows to build liquidity for future projects. I therefore infer cross sectional differences in financing costs from the responses of firms' borrowing and liquidity holdings to announcement risk news.

Debt Reallocation

I first examine borrowing behavior by response of debt growth to announcement risk news. Table 6 reports estimates from the interaction regression in Equation (12), with the dependent variable defined as the total debt growth rate over the next four quarters. Across all specifications, firms with higher net leverage reduce borrowing significantly more than their lower leverage counterparts in response to a positive FOMC risk news shock; the

[45] Value at Risk (VaR) constraints can arise directly from regulatory requirements. They can also stem from funding-side pressures: higher portfolio VaR increases withdrawal risk and the cost of funding, reducing risk appetite, as in intermediary models such as Brunnermeier and Sannikov [2014], Vayanos [2004], and He and Krishnamurthy [2013].

[46] Appendix B.6 shows that a positive FOMC risk news shock is associated with a wider Moody's BBB–AAA credit spread, controlling for interest rate surprises and aggregate conditions.

[47] Earlier work documents flight to quality episodes in credit markets and their real effects: Lang and Nakamura [1995] show that the share of new loans priced below *prime* + 1% (a proxy for "safe" lending) is countercyclical, and Bernanke et al. [1994] find that constraints on lower quality borrowers tighten in recessions, with quantitatively significant macroeconomic consequences.

interaction coefficient is negative and statistically significant at the 1% level. This finding is consistent with a flight to quality mechanism in credit markets, whereby financing costs rise more for ex ante riskier firms.

[Table 6 around here]

Figure 6 plots the estimated coefficients for average debt responses across leverage subgroups and reveals a debt reallocation effect that is not fully captured in Table 6. Following a one unit FOMC risk news shock (equivalent to a 66.5 basis point decline in the equity market index), firms in the upper half of the net market leverage distribution increase their debt by 5.11%, whereas firms in the lower half reduce theirs by 1.82%. The contrast intensifies at higher leverage levels: firms in the top 5% cut debt by 3.43% over the subsequent year, while the remaining 95% show a marginal increase of about 1%. This pattern suggests that, after risk increasing announcement news, credit flows away from highly leveraged firms toward low leverage firms. Perceived as safer borrowers, low leverage firms face unchanged (or even looser) borrowing constraints because lenders are more willing to extend credit to them, whereas highly leveraged firms encounter higher financing costs and tighter credit limits. This result complements evidence that credit markets exhibit flight to quality in the business cycle—see Lang and Nakamura [1995] and Halling et al. [2025][48]—by showing a parallel reallocation in response to announcement risk news.

[Figure 6 around here]

Interest expense. In Appendix B.7, I show that high debt firms experience a larger rise in interest expense than low debt firms after risk rasing announcement news. The effect starts immediately after news coming. Interest expense is not informative on its own, because it can increase either when financing becomes more expensive or when firms expand borrowing. However, given the result in Figure 6 that high debt firms reduce debt growth on average after risk rasing announcement news, the higher interest expense is more consistent with higher financing costs rather than larger borrowing. This pattern supports the view that a flight to quality in external finance limits high debt firms' access to funding.

[48] Halling et al. [2025] show that a large share of listed firms increase leverage during recessions, primarily those with low credit risk.

Precautionary Cash Holding

[**Table 7 around here**]

I provide further evidence for the flight to quality mechanism by examining the response of cash holdings to announcement risk news. When external finance costs rise, theory predicts that firms borrow less and accumulate more cash to fund future investment. I therefore reestimate the interaction regression with the growth rate of cash holdings over the next four quarters as the dependent variable. Table 7 reports the results. Column (1) shows that both the coefficient on the FOMC risk news shock and its interaction with net market leverage (netML) are positive and statistically significant at the 5 % level. Hence, after risk increasing announcement news, all firms increase precautionary cash holdings, and the effect is especially pronounced for highly indebted firms. Quantitatively, a one standard deviation rise in net market leverage amplifies the cash accumulation response by roughly 3 % for a one unit FOMC risk news shock. Columns (2) and (3), which add quarter by industry fixed effects and the full set of firm level and aggregate controls, yield similar results. Column (4) shows that the heterogeneous cash response is even stronger in the post 2008 period, mirroring the pattern observed for investment.

Figure 7 plots average cash holdings responses for leverage subgroups, estimated using the dummy regression specification in Equation (13). The figure corroborates the linear interaction results: all subgroups exhibit a positive semi elasticity of cash holdings with respect to the FOMC risk news shock, and the response is much stronger for firms with higher market leverage. The effect is particularly pronounced for the top 5% of firms, whose precautionary cash holdings are especially sensitive to the FOMC risk news shock. Taken together with the debt growth results, these findings indicate that highly indebted firms face higher external finance costs after announcement risk increasing news.

[**Figure 7 around here**]

5.2. Linking Financing Costs to Investment: Rollover Pressure

Following risk-increasing announcement news, how do higher borrowing costs for indebted firms translate into sharp investment cutbacks? Theory identifies *rollover risk* as a central driver. For example, Acharya et al. [2011] show that firms financing long-term assets with short-term debt face heightened rollover risk when borrowing capacity contracts.[49] Refinancing maturing obligations becomes more difficult; expected default risk rises; credit

[49] See also He and Xiong [2012] and Jungherr et al. [2024], as well as the empirical evidence in Kalemli-Özcan et al. [2022].

limits tighten even as short-term debt continues to come due. The resulting liquidity shortfalls constrain investment (and production). Consequently, even a modest increase in external finance costs can produce a disproportionately large decline in investment for the most leveraged firms. This theoretical channel also has strong empirical support: as a case in point, Almeida et al. [2009] study U.S. public firms during the 2007 to 2008 crisis and show that, holding exposure to the credit supply shock constant, firms with a larger share of long term debt maturing soon after August 2007 reduced investment more.

To investigate the role of rollover risk, I measure firms' rollover need with the refinancing intensity ratio (RI) from Friewald et al. [2022]:

$$RI = \frac{dlcq}{dlcq + dlttq},$$

where $dlcq$ is debt maturing within one year and $dlttq$ is long term debt. A higher RI indicates greater reliance on short term borrowing and therefore higher rollover need. Throughout, I use "rollover risk" to denote the joint condition of high leverage and high rollover need (high RI); firms meeting both conditions face greater exposure to rollover risk. [50] I estimate an extended version of specification (12) that includes a triple interaction among the FOMC risk news shock, RI, and $netML$ to test whether high rollover need amplifies the effect of debt burden on investment responses. This test is also informative about whether credit supply dynamics are an important driver of the investment response and therefore provides further evidence of flight to quality in credit markets. For ease of interpretation, I define the indicator $\mathbf{1}\{RI_{t-1}^{\text{high}}\}$, which equals one for firms whose RI exceeds the sample median.

[Table 8 around here]

Table 8 reports the triple interaction regression estimates and shows that rollover need is the key channel linking higher borrowing costs to sharp investment cuts among highly indebted firms. In column (1), comparing the triple interaction with the double interaction shows that the increase in the investment response with debt burden exists only among firms with high rollover need; no such leverage effect appears for firms with low rollover need. Column (2) shows that the triple interaction coefficient is larger in the sample after 2008, suggesting that the effect of rollover risk strengthened during the era of unconventional monetary policy.

Columns (3) and (4) replace the $netML$ variable with an indicator, $\mathbf{1}\{netML_{t-1}^{\text{high}}\}$, set to one for firms whose $netML$ exceeds the 75th percentile in the sample. In this

[50] Friewald et al. [2022] show that firms with a high RI earn higher returns because they bear more systemic risk. Their measure uses debt maturing within three years relative to total debt. I focus on one year maturities to align with the intuition in Acharya et al. [2011] that rollover risk intensifies as average debt maturity shortens.

specification, the triple interaction coefficient captures the effect of the risk news shock on investment when rollover risk is high—defined as high leverage together with high rollover need—while holding constant the separate effects of each factor. The estimates imply a sizeable effect: for a one-unit positive FOMC risk news shock, firms with both high leverage and high rollover need reduce the one-year investment rate by an additional 1.403 %.[51] Notably, once the triple interaction is included, the double interaction between the risk news shock and the high leverage indicator is no longer negative, indicating that the adverse investment response to announcement risk news arises primarily when high leverage coincides with substantial rollover need. The results are unchanged when I exclude almost zero leverage (AZL) firms (Appendix B.8), confirming that the effects are not driven by firms with negligible debt.

Figure 8 shows that rollover risk extends the investment response to FOMC risk news. The figure plots the coefficients on the triple interaction term, using the same specification as columns (3) and (4) of Table 8. Firms that are both highly leveraged and have high rollover need (high rollover risk) continue to cut investment over the subsequent eight quarters after a one-unit positive FOMC risk news shock. The effect is substantial and cumulative, with the contraction deepening as the horizon lengthens. Compared with Figure 2, which shows that the average investment response peaks in quarter 4 and then declines, Figure 8 highlights the persistence of the response under high rollover risk.

[Figure 8 around here]

Figure 9 plots the one year ahead average investment responses for four groups of firms, classified by whether their $netML$ and RI exceed specified thresholds. In Panel A, the high leverage threshold is the 75th percentile of $netML$, and the high rollover need threshold is the sample median of RI. The investment response to a one unit FOMC risk news shock is concentrated among firms facing high rollover risk (high leverage and high rollover need): firms with both low market leverage and low rollover need reduce investment by only -0.412%, and those with either high leverage or high rollover need show little to no response. By contrast, firms that are both highly leveraged and have high rollover need cut investment by -0.950%. These results underscore that rollover risk is the key link transmitting FOMC risk news to investment, especially for indebted firms. Panel C raises the leverage cutoff to the 90th percentile of $netML$; the average investment response for the high rollover risk group becomes more negative, reinforcing this conclusion. Panels B and D show the same pattern in the sample after 2008.

[Figure 9 around here]

[51] This reduction corresponds to roughly 10 % of the average annual investment rate.

A potential concern is that other information released on FOMC announcement days—such as growth outlook or policy rate news—might disproportionately affect firms with high rollover risk and thus drive the results. To address this, Table 9 reestimates the triple interaction specification from columns (3) and (4) of Table 8 and augments it with the three additional FOMC news shocks from the structural VAR and the high frequency interest rate surprise of Nakamura and Steinsson [2018a]. Each shock is triple interacted with the indicators for high net market leverage and high refinancing intensity, providing a "horse race" across channels. The coefficient on the triple interaction with the FOMC risk news shock remains negative and statistically significant, with a similar magnitude, whereas the corresponding coefficients for the other news shocks are not statistically significant. This evidence confirms that risk news, rather than policy related news from FOMC announcements, drives the investment response among firms with high rollover risk.

[Table 9 around here]

Building on the finding that the investment response is concentrated in firms with high rollover risk, I show that the same mechanism also drives industry dynamics. Specifically, capital is expected to reallocate from industries with a higher share of firms with high rollover risk toward those with a lower share following a risk increasing announcement news, and this effect should be particularly strong after 2008. I modify specification (12) by interacting the FOMC risk news shock with the industry share of firms with high rollover risk, computed at the two digit SIC level. Panel A of Table 10 uses the quarterly, time varying share. After 2008, the decline in investment following a positive FOMC risk news shock is larger as the industry share rises, consistent with reallocation across industries; debt reallocation follows the same pattern. Panel B repeats the exercise with a time invariant share, treating rollover risk as an inherent industry characteristic, and finds even stronger effects. In the full sample, the estimates are not statistically significant but have the same sign.

[Table 10 around here]

5.3. Reconciling Empirical Heterogeneity with the Motivating Model

In the motivating model, firm heterogeneity is summarized by s_i, which measures how strongly a firm's cash flow uncertainty and required return respond to perceived aggregate risk. A larger s_i implies that, following announcement risk increasing news, cash flow volatility and the cost of capital rise by more, reducing investment. In empirical analysis, I focus on differences in debt burden, a proxy for firms' ex ante credit risk and, by implication, as a proxy for s_i. When perceived risk increases, a flight to quality in credit markets widens external finance premia disproportionately for highly indebted firms. These firms then rely more on internal cash flows, which are volatile, further heightening uncertainty about near-term funding and investment.

Although the model abstracts from explicit debt financing, the core implication—that greater exposure to announcement risk news raises financing costs and depresses investment—holds in both the theory and the evidence. Consistent with this channel, indebted firms facing high rollover risk (short maturities) exhibit larger investment contractions, providing a concrete link between higher financing costs and investment responses.

Even from a stricter cost of equity perspective, the empirical findings align with the model's implications. Under the pecking order view, equity holders, as residual claimants, receive what remains after servicing debt obligations. When risk increases raise financing costs, access to new debt tightens and debt capacity shrinks, removing a buffer against adverse shocks (such as cash flow shortfalls or macroeconomic downturns). As a result, residual payouts to equity become more sensitive to shocks, increasing the volatility of equity cash flows. Investors therefore require a higher expected return, which raises the cost of equity. This effect is strongest for firms with both high leverage and high near-term refinancing needs. Rollover pressure makes equity more directly exposed to heightened default risk, so investors demand greater compensation in the form of a higher expected return.[52]

6. Further Discussion and Robustness

6.1. Discussion

Selected announcement risk news cases: How do monetary policy announcements release news that alters aggregate risk perception? One perspective, following Bauer et al. [2023], is that announcements can contain surprises about the policy rate that change the economic outlook and thereby indirectly move perceived risk, since perceived uncertainty is generally lower when economic growth is strong. In my analysis, this indirect channel is controlled for by adding the monetary policy surprise.

Another view is that monetary policy announcements can convey nonmonetary information that directly affects risk perception, as documented by Cieslak and Schrimpf [2019], Kroencke et al. [2021], Gardner et al. [2022]. Below, I present illustrative examples of risk-related nonmonetary news in policy announcements. The most direct type of risk-related nonmonetary news is when policymakers explicitly flag the degree of uncertainty or risk.

[52] Appendix B.9 examines the ex post cost-of-capital response to the FOMC risk news shock across four groups defined by leverage and refinancing intensity. All groups exhibit higher equity returns, with the largest increase for firms with both high leverage and high rollover need, mirroring the investment responses.

In the FOMC statement on May 7, 2025, the Committee kept the rate unchanged but noted that "uncertainty about the economic outlook has increased further," and, in the press conference, Chair Powell stated that "uncertainty about the path of the economy is extremely elevated and that the downside risks have increased," while repeatedly emphasizing substantial uncertainty about the impact of tariff policy on the economy. A similar episode occurred at the ECB on February 7, 2008: the Governing Council left the rate unchanged, and President Trichet stated in the press conference that "uncertainty about the prospects for economic growth is unusually high and the risks surrounding the outlook for economic activity have been confirmed to lie on the downside."

Another type is when announcements implicitly convey information that signals a change in risk. On July 26, 2023, the Federal Reserve raised the policy rate to its highest level in about two decades, as widely expected, yet equity prices rose sharply; in the press conference, Chair Powell noted that the Fed staff no longer forecast a recession, reversing the earlier staff view, which market participants interpreted as a reduction in perceived downside risk.

Another type is when announcements implicitly convey information that reduces perceived risk. For example, on July 26, 2023, the Federal Reserve raised the policy rate to its highest level in about two decades, as widely expected, yet equity prices rose sharply; in the press conference, Chair Powell stated that the Fed staff's view on the likelihood of a recession had changed—they "no longer forecast a recession," which differed from the earlier staff view—and markets interpreted this as a reduction in perceived downside risk. Policy commitments also operate as implicit risk-reduction signals which try to temper downside uncertainty: during the COVID period, FOMC statements repeatedly opened with the assurance that "The Federal Reserve is committed to using its full range of tools to support the U.S. economy in this challenging time," and, in Europe during the sovereign-debt crisis, President Draghi's July 26, 2012 pledge to do "whatever it takes" to preserve the euro was widely viewed as lowering risk premia on sovereign bonds in the euro-area periphery. Such signals reduce risk premia and yields, raise sovereign bond prices, and lessen perceived default and macroeconomic risks.

In addition to explicitly or implicitly communicating about risk and uncertainty,[53] other announcement content can also change risk perceptions. A particularly salient and representative situation, documented by Kroencke et al. [2021], arises when announced policy deviates from market expectations: perceived risk tends to increase when the announced policy departs from expectations and to decrease when it is consistent with them, independent of the policy rate change itself. A canonical example is the 2013 "taper tantrum": Surprised by the announcement, analysts concluded that "investors always freak out at what looks like a sea change in policy." Large deviations from expectations heighten per-

[53] In the discussion paper Bauer et al. [2025], the authors present evidence and note that narrative risk assessments, including policy statements, monetary policy reports, and official speeches, are common approaches for communicating uncertainty and risks at central banks in advanced economies.

ceived uncertainty about the future economic environment.

Relation to Ottonello and Winberry [2020] Ottonello and Winberry [2020] is among the most influential studies on how financial frictions shape the transmission of monetary policy. Unlike my findings, they show that firms with higher debt burdens (and thus higher default risk) respond less to surprise reductions in short-term rates. Their explanation is that relatively low default risk firms face a flatter marginal external financing cost schedule, making them more sensitive to monetary policy shocks. Several methodological differences help explain why I find that firms with higher debt burdens and default risk are more responsive. (i) They measure surprises in the short-term policy rate from policy announcements using current-month federal funds futures, whereas I focus on news that changes risk perception identified from risky assets. (ii) They proxy financial heterogeneity with book leverage or distance to default, while I employ market leverage, which is more consistent with U.S. borrowing practice. (iii) Their sample emphasizes the period before 2008, whereas my analysis spans 1995 onward and highlights especially strong effects after 2008. (iv) I also consider debt maturity as an additional dimension. In unreported results, I replicate Ottonello and Winberry [2020] using their short-term rate surprises and book-leverage measures; consistent with their findings, firms with higher debt burdens are less sensitive under those specifications. Interestingly, when I instead use more forward-looking interest rate surprises—such as the path factor in Gürkaynak et al. [2022] or the shocks in Nakamura and Steinsson [2018a]—firms with higher debt burdens exhibit stronger responses to monetary policy surprises.

6.2. Additional Robustness Tests

The main text reports several robustness checks; In the appendix there are additional checks.

Alternative Measurements My main empirical analysis relies on the structural VAR in Cieslak and Pang [2021] to identify the FOMC risk news shock. As noted in Section 3, I also use two alternative FOMC risk news measures—the FOMC-day change in the BBM risk index of Bauer et al. [2023] and $SVIX^2$ from Martin [2017]—to assess robustness. As shown in Appendix B.10, these alternatives change some aspects of statistical significance but leave the main results qualitatively intact. In particular, the heterogeneity analysis (i.e., the transmission channel that is the focus of the paper) remains robust and statistically significant under these alternative measures.

Controlling for Other Interest Rate Shocks Appendix B.11 reports a robustness test that includes two commonly used monetary policy surprises from Gürkaynak et al. [2004]: the *target* factor and the *path* factor. These factors are constructed from interest rate futures surprises at different maturities; the target factor captures current federal funds rate target changes, while the path factor reflects expectations about future targets (forward guidance). The results are unchanged after controlling for these two surprises.

Subsample of Manufacturing Firms Tangible capital plays a particularly important role in manufacturing. In Appendix B.12, I show that the findings remain qualitatively robust when restricting the sample to manufacturing firms (SIC codes 3000–3999).

Alternative Leverage Measure In Appendix B.13, I replace the net debt-to-market ratio with the simple debt-to-market ratio as the proxy for debt burden, thereby excluding cash holdings and preferred stock. The results remain quantitatively similar.

Controlling for Growth Expectations A potential concern is that monetary policy announcements may also shift long run growth expectations. The baseline specification includes the high frequency policy rate surprise of Nakamura and Steinsson [2018a], which captures short run growth news in the announcement window but does not necessarily reflect longer horizon revisions. In addition, the structural VAR assumes mean reversion in growth news; although Cieslak and Pang [2021] provide supporting evidence, this assumption remains contestable. To address these concerns, I augment the regressions with contemporaneous revisions in survey based growth expectations from the Survey of Professional Forecasters (Philadelphia Fed). Although these series are lower frequency, they should absorb policy induced movements in growth beliefs. Specifically, I include (i) the annual change in the 10 year expected real GDP growth rate and its interactions with net market leverage and refinancing intensity, and (ii) the quarterly change in the 1 year expected real GDP growth rate and its corresponding interactions to capture short run expectation revisions. As shown in Appendix B.14, the main results are unchanged after adding these controls, whether the FOMC risk news shock is measured using the structural approach or constructed from the BBM risk index.

The Role of Book to Market A further concern is that our market leverage measure is mechanically related to book to market (B/M) because both load on market equity. If the results merely reflect differences in growth opportunities versus assets in place, a risk or uncertainty shock could induce stronger investment delays among low B/M (high growth) firms, as highlighted by the real options view. However, this view seems less plausible than the financial friction mechanism. In Appendix B.15, I re-estimate the regressions to allow for B/M based heterogeneity; the B/M×shock interaction is economically insignificant.

7. Aggregate Implication

Firm level evidence is informative for the aggregate implications of FOMC risk news.[54] Building on the key finding that investment responses are concentrated among firms with high rollover risk (both high market leverage and high rollover need), I examine the aggregate implications along this dimension. Assuming that only partial equilibrium channels operate, with no general equilibrium feedback, the aggregate impact equals to the sum of the firm specific responses estimated in the panel regressions with time fixed effect. Under this assumption, the aggregate investment response is state dependent and varies with the share of firms with high rollover risk in the economy.

[Figure 10 around here]

Figure 10 shows the quarterly share of firms classified as having high rollover risk. A firm is defined as high rollover risk if its net market leverage $netML$ is above the 75th percentile and its rollover need RI is above the sample mean, with both thresholds computed over all firms and quarters. The share is strongly countercyclical: when market valuations fall in downturns, net market leverage rises, so firms with high rollover risk are more concentrated in recessions.

[Table 11 around here]

Table 11 shows that the average investment response is state dependent and varies with the contemporaneous share of firms with high rollover risk. To show this, I augment the baseline specification by interacting the FOMC risk news shock with the contemporaneous share of firms with high rollover risk. The interaction coefficient is negative and statistically significant, indicating that the effect of a positive shock becomes more contractionary as the share increases. In Column (1), the coefficient on the standalone shock is 1.10, whereas the coefficient on the interaction term is -0.178. When about 6% of firms face rollover risk, a level typical in expansions, the shock has essentially no effect on the one-year average investment rate. By contrast, in recessions, when the share peaks around 15%, a one-unit positive shock lowers average investment by 1.57%, an economically large effect. This pattern is robust to the inclusion of additional controls and when the sample is restricted to the period after the introduction of unconventional monetary policy.

[54] I examine the in sample aggregate effect, similar to Jeenas and Lagos [2024]. Although this is not a population estimate, it is informative about aggregate outcomes because the Compustat sample accounts for a large share of corporate capital; firms covered by Compustat are listed and are, on average, much larger than nonlisted private firms.

[Figure 11 around here]

The average investment response is state dependent but does not equal the aggregate response, because the aggregate investment rate is a capital weighted average of firm level rates. To measure aggregate investment, I follow Crouzet and Mehrotra [2020] and Lagos and Zhang [2020] and compute total tangible capital in the Compustat sample at time t and $t+4$ as

$$K_t = \sum_{i \in I_t} k_{i,t}, \qquad K_{t+4} = \sum_{i \in I_t} k_{i,t+4},$$

where I_t denotes all firms in the sample at time t. The aggregate growth rate over the next four quarters is

$$G_{t+4} = \frac{K_{t+4} - K_t}{K_t}.$$

To assess the role of rollover risk, I also construct separate aggregate investment rates at time t for firms with high rollover risk, G^{high}_{t+4}, and for the remaining firms (low rollover risk), G^{low}_{t+4}. [55] Aggregate investment rates for other horizons are constructed analogously. Figure 11 plots the resulting time series of G^{high}_{t+4} and G^{low}_{t+4}. Aggregate investment growth is consistently lower among firms with high rollover risk, with the gap especially pronounced during recessions. Although the two series move closely together, G^{high}_{t+4} is noticeably more volatile, suggesting that rollover risk amplifies fluctuations in aggregate investment.

[Table 12 around here]

I estimate the following time series local projection to study the aggregate investment response to the FOMC risk news shock:

$$G_{t+n} = \alpha + \beta\, \epsilon^{cr}_t \cdot p_t + X_{t-1} + e_t \tag{14}$$

where G_{t+n} denotes the n-period aggregate investment rate, p_t is the share of firms with high rollover risk at time t, and X_{t-1} is the set of lagged aggregate controls; I also control for the contemporaneous interest rate surprise. Table 12 reports the effect at horizon n conditional on the share of high rollover risk firms. The interaction term is negative and statistically significant across horizons, confirming that the aggregate investment response is stronger when the share of high rollover risk firms is larger. In recessions, when the share peaks at about 15%, a one unit positive shock reduces the aggregate investment

[55] Consistent with Figure 9, the sample is restricted to firms with nonmissing net market leverage and rollover need at time t. At each t, I retain only firms with capital observations available for the subsequent four quarters (or eight quarters when computing eight quarter growth) to avoid complications due to entry and exit. A firm is classified as high rollover risk at time t if its net market leverage exceeds the 75th percentile and its rollover need is above the panel median.

rate by 0.87%, an effect that is economically nonnegligible, although smaller than the firm level average estimate in Table 11. It is worth noting that time fixed effects cannot be included, which allows general equilibrium feedback to operate in the estimates. Even so, state dependence remains statistically significant. In addition, Figure 12 shows that the interaction effect strengthens with the horizon, consistent with the firm level evidence in Figure 8 that rollover risk prolongs and amplifies the response to announcement risk news.

[**Figure 12 around here**]

The previous results confirm a state dependent conditional effect of announcement risk news on aggregate investment. However, the unconditional aggregate response is not statistically significant. Table 13 presents aggregate local projection estimates without the interaction term. Panel A reports results for aggregate investment with all firms: after a one unit positive FOMC risk news shock, the four quarter response is near zero; at the eight quarter horizon it is −0.33% and remains insignificant[56]. Panels B and C report responses of aggregate investment for high rollover risk firms and, respectively, for the remaining low risk firms. Only the high rollover risk group exhibits a significant negative response to a positive FOMC risk news shock, with the effect strengthening at longer horizons (for example, a coefficient of −0.837, significant at the 5% level, at the eight quarter horizon). The low risk group's coefficients are consistently small and insignificant. Taken together, these estimates imply that, on average, announcement risk news has a limited impact on aggregate investment. Only the portion attributable to high rollover risk firms shows strong response. Why, then, is the unconditional aggregate response insignificant even though the shock transmits strongly to high rollover risk firms? To answer this, I quantify the contribution of high rollover risk firms to the aggregate response using a simple empirical counterfactual analysis.

[**Table 13 around here**]

A Simple Counterfactual Analysis I quantify the components of the aggregate response using a decomposition that follows Crouzet and Mehrotra [2020]. The aggregate investment response over eight quarters is written as the sum of (i) the contribution from the within group average firm level investment growth for high and low rollover risk firms and (ii) a covariance term that captures the interaction between initial firm size and subsequent growth. I focus on the horizon of eight quarters because the aggregate response is

[56] This is similar to the firm level result in Figure 2.

strongest, both for all firms and for the high rollover risk group, and because high rollover risk prolongs and amplifies the investment response.

Specifically, the aggregate eight quarter investment growth satisfies

$$G_{t+8} \;=\; \hat{\imath}^{\text{low}}_{t+8} \;+\; s_t\Big(\hat{\imath}^{\text{high}}_{t+8} - \hat{\imath}^{\text{low}}_{t+8}\Big) \;+\; \widehat{\text{cov}}_{t+8}, \tag{15}$$

where $s_t \equiv K^{\text{high}}_t / K_t$ is the initial share of the capital stock held by high rollover risk firms, and $\hat{\imath}^{\text{high}}_{t+8}$ and $\hat{\imath}^{\text{low}}_{t+8}$ are the cross sectional average investment growth rates within the two groups. The covariance component further decomposes as

$$\widehat{\text{cov}}_{t+8} \;=\; \widehat{\text{cov}}^{\text{low}}_{t+8} \;+\; s_t\Big(\widehat{\text{cov}}^{\text{high}}_{t+8} - \widehat{\text{cov}}^{\text{low}}_{t+8}\Big)\,. \tag{16}$$

Here $\widehat{\text{cov}}^{g}_{t+8}$ is the within group cross sectional covariance between firms' initial tangible capital and their subsequent capital growth for group $g \in \{\text{low}, \text{high}\}$. This covariance term reflects that the aggregate series is the initial capital weighted average of firm level growth. When smaller firms grow faster, the covariance between size and growth is negative, which reduces aggregate investment growth relative to the simple unweighted cross sectional average.

I use the decomposition to construct counterfactual aggregate investment growth at horizon $t + 8$ and study their responses to the FOMC risk news shock. The first two counterfactual series replace the between group difference in average firm level investment growth while leaving the covariance between initial size and subsequent growth unchanged:

$$\begin{aligned} G^{(1)} &= G_{t+8} - s_t\left(\hat{\imath}^{\text{high}}_{t+8} - \hat{\imath}^{\text{low}}_{t+8}\right), \\ G^{(2)} &= G_{t+8} + (1 - s_t)\left(\hat{\imath}^{\text{high}}_{t+8} - \hat{\imath}^{\text{low}}_{t+8}\right). \end{aligned}$$

Here $G^{(1)}$ imposes the low rollover risk group's average investment growth on all firms, and $G^{(2)}$ imposes the high rollover risk group's average growth, with the size and investment covariance held at its data value in both cases. Next, I also remove the between group difference in the covariance component so that both the average growth and the covariance match a single group:

$$\begin{aligned} G^{(3)} &= G_{t+8} - s_t\left(\hat{\imath}^{\text{high}}_{t+8} - \hat{\imath}^{\text{low}}_{t+8}\right) - s_t\left(\widehat{\text{cov}}^{\text{high}}_{t+8} - \widehat{\text{cov}}^{\text{low}}_{t+8}\right), \\ G^{(4)} &= G_{t+8} + (1 - s_t)\left(\hat{\imath}^{\text{high}}_{t+8} - \hat{\imath}^{\text{low}}_{t+8}\right) + (1 - s_t)\left(\widehat{\text{cov}}^{\text{high}}_{t+8} - \widehat{\text{cov}}^{\text{low}}_{t+8}\right). \end{aligned}$$

By construction, $G^{(3)}$ matches the low rollover risk group in both the average investment growth and the covariance between size and growth, while $G^{(4)}$ matches the high rollover risk group on both margins.

[**Table 14 around here**]

Table 14 reports linear local projection regressions without interaction terms. Column (1) presents the baseline that uses the eight quarter aggregate investment rate. The remaining columns replace the dependent variable with the counterfactual aggregate investment rates defined above. Comparing Columns (1) and (2), removing the contribution of the high rollover risk group's average investment rate has little effect on the aggregate response to the FOMC risk news shock: the coefficient moves slightly from -0.330 to -0.315, indicating a limited contribution from these firms. Comparing Columns (1) and (3), imposing the high rollover risk group's average investment rate on all firms yields a more negative response of -0.434, which remains statistically insignificant. These results indicate that high rollover risk firms react more strongly to the shock but exert only a modest influence on the aggregate response, consistent with their small share of tangible capital—roughly 10 percent of the total in the Compustat public firm sample on average.

Columns (4) and (5) report results based on counterfactual series that also align the covariance between initial capital size and subsequent investment across groups. Column (4) uses $G^{(3)}$ and Column (5) uses $G^{(4)}$. Relative to Column (3), which imposes the high rollover risk group's average investment rate on all firms while leaving the covariance at its data value, Column (5) further imposes the covariance observed in the high rollover risk group. The point estimate then falls from -0.434 in Column (3) to -0.824 in Column (5) and becomes statistically significant. These results highlight the central role of the covariance component. Within the high rollover risk group, the covariance between firm size and subsequent investment becomes more negative after a positive FOMC risk news shock, indicating that larger firms cut investment more than smaller firms. By contrast, large firms in the low rollover risk group, which hold most tangible capital, are relatively less affected; as a result, the average aggregate investment response to the announcement risk news is limited.

8. Conclusion

This paper provides new evidence on the risk channel of monetary policy announcements. I show that announcement news that raises financial market risk perceptions has real effects by depressing subsequent corporate investment in tangible capital. The effect is stronger for firms with high debt burdens and low credit quality, thereby suggesting that financial frictions are central to this transmission. I further document the transmission mechanism: risk-raising announcement news induces a flight to quality in credit markets; firms with a high debt burden face higher external financing costs, which triggers high rollover pressure when these firms also have large amounts of debt maturing soon, forcing them to cut back investment. At the aggregate level, the cross-sectional share of firms with high rollover pressure is a key determinant of how strongly announcement risk news passes through to aggregate investment.

My findings carry clear policy implications. They highlight a novel channel through which monetary policy announcements affect the real economy beyond policy rate news. Policymakers should consider the consequences for financial market risk perceptions when communicating with the public at announcements. From a more constructive perspective, the analysis also suggests that intervention in market risk perceptions through communication may serve as a tool for influencing targeted firms and aggregate investment dynamics; however, its timing should take into account the cross-sectional distribution of firms' financial positions.

My study is a first step toward examining the risk channel of monetary policy announcements. I rely on price changes around FOMC announcements across asset classes to identify announcement news that drives financial market risk perceptions. A natural direction for future work is to identify the sources of this news. In particular, it would be useful to disentangle whether it arises from the tone of the announcement or from specific textual features, such as descriptions, topics, or words, as in Schmeling and Wagner [2016], Cieslak and McMahon [2023], and Gnan et al. [2022]. Determining which dimensions of communication matter most for corporate decision making remains an open question. A second direction is to embed this channel into policy counterfactuals to study its interaction with other monetary transmission mechanisms and to evaluate which forces primarily drive the effect of monetary policy announcements on aggregate investment. Such analysis would be informative for future policy design.

References

Viral V Acharya, Douglas Gale, and Tanju Yorulmazer. Rollover risk and market freezes. *The Journal of Finance*, 66(4):1177–1209, 2011.

Hengjie Ai and Ravi Bansal. Risk preferences and the macroeconomic announcement premium. *Econometrica*, 86(4):1383–1430, 2018.

Hengjie Ai, Leyla Jianyu Han, Xuhui Nick Pan, and Lai Xu. The cross section of the monetary policy announcement premium. *Journal of Financial Economics*, 143(1):247–276, 2022.

Ivan Alfaro, Nicholas Bloom, and Xiaoji Lin. The finance uncertainty multiplier. *Journal of Political Economy*, 132(2):577–615, 2024.

Heitor Almeida, Murillo Campello, Bruno Laranjeira, and Scott Weisbenner. Corporate debt maturity and the real effects of the 2007 credit crisis. Technical report, National Bureau of Economic Research, 2009.

Gareth Anderson and Ambrogio Cesa-Bianchi. Crossing the credit channel: credit spreads and firm heterogeneity. *American Economic Journal: Macroeconomics*, 16(3):417–446, 2024.

Scott R Baker, Nicholas Bloom, and Stephen J Terry. Using disasters to estimate the impact of uncertainty. *Review of Economic Studies*, 91(2):720–747, 2024.

Michael Bauer, Travis Berge, Giuseppe Fiori, Francesca Loria, and Molin Zhong. Accounting for uncertainty and risks in monetary policy. 2025.

Michael D. Bauer and Eric T. Swanson. A reassessment of monetary policy surprises and high-frequency identification. *NBER Macroeconomics Annual*, 37(1):87–155, 2023.

Michael D Bauer, Ben S Bernanke, and Eric Milstein. Risk appetite and the risk-taking channel of monetary policy. *Journal of Economic Perspectives*, 37(1):77–100, 2023.

Ben S Bernanke and Kenneth N Kuttner. What explains the stock market's reaction to federal reserve policy? *The Journal of finance*, 60(3):1221–1257, 2005.

Ben S Bernanke, Mark Gertler, and Simon Gilchrist. The financial accelerator and the flight to quality, 1994.

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

Nicholas Bloom. Fluctuations in uncertainty. *Journal of economic Perspectives*, 28(2): 153–176, 2014.

Patrick Bolton, Neng Wang, and Jinqiang Yang. Investment under uncertainty with financial constraints. *Journal of Economic Theory*, 184:104912, 2019.

Markus K Brunnermeier and Yuliy Sannikov. A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421, 2014.

Ricardo J Caballero and Alp Simsek. A risk-centric model of demand recessions and speculation. *The Quarterly Journal of Economics*, 135(3):1493–1566, 2020.

John Y Campbell, Carolin Pflueger, and Luis Manuel Viceira. Monetary policy drivers of bond and equity risks. 2014.

Aditya Chaudhry. The causal impact of macroeconomic uncertainty on expected returns. *Available at SSRN 3711584*, 2020.

Gabriel Chodorow-Reich. The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *The Quarterly Journal of Economics*, 129(1): 1–59, 2014.

Anna Cieslak and Michael McMahon. Tough talk: The fed and the risk premium. *Available at SSRN*, 2023.

Anna Cieslak and Hao Pang. Common shocks in stocks and bonds. *Journal of Financial Economics*, 142(2):880–904, 2021.

Anna Cieslak and Andreas Schrimpf. Non-monetary news in central bank communication. *Journal of International Economics*, 118:293–315, 2019.

Anna Cieslak, Adair Morse, and Annette Vissing-Jorgensen. Stock returns over the fomc cycle. *The Journal of Finance*, 74(5):2201–2248, 2019.

James Cloyne, Clodomiro Ferreira, Maren Froemel, and Paolo Surico. Monetary policy, corporate finance, and investment. *Journal of the European Economic Association*, 21 (6):2586–2634, 2023.

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

Robin Döttling and Lev Ratnovski. Monetary policy and intangible investment. *Journal of Monetary Economics*, 134:53–72, 2023.

Itamar Drechsler, Alexi Savov, and Philipp Schnabl. A model of monetary policy and risk premia. *The Journal of Finance*, 73(1):317–373, 2018.

John C Driscoll and Aart C Kraay. Consistent covariance matrix estimation with spatially dependent panel data. *Review of economics and statistics*, 80(4):549–560, 1998.

Jesús Fernández-Villaverde, Pablo Guerrón-Quintana, Keith Kuester, and Juan Rubio-Ramírez. Fiscal volatility shocks and economic activity. *American Economic Review*, 105(11):3352–3384, 2015.

Nils Friewald, Florian Nagler, and Christian Wagner. Debt refinancing and equity returns. *The Journal of Finance*, 77(4):2287–2329, 2022.

Jordi Galí. *Monetary policy, inflation, and the business cycle: an introduction to the new Keynesian framework and its applications*. Princeton University Press, 2015.

Ben Gardner, Chiara Scotti, and Clara Vega. Words speak as loudly as actions: Central bank communication and the response of equity prices to macroeconomic announcements. *Journal of Econometrics*, 231(2):387–409, 2022.

Xavier Giroud and Holger M Mueller. Firm leverage, consumer demand, and employment losses during the great recession. *The Quarterly Journal of Economics*, 132(1):271–316, 2017.

Phillipp Gnan, Maximilian Schleritzko, Maik Schmeling, and Christian Wagner. *Deciphering monetary policy shocks*. Centre for Economic Policy Research, 2022.

Francois Gourio. Disaster risk and business cycles. *American Economic Review*, 102(6): 2734–2766, 2012.

Refet Gürkaynak, Hatice Gökçe Karasoy-Can, and Sang Seok Lee. Stock market's assessment of monetary policy transmission: The cash flow effect. *The Journal of Finance*, 77 (4):2375–2421, 2022.

Refet S Gürkaynak, Brian P Sack, and Eric T Swanson. Do actions speak louder than words? the response of asset prices to monetary policy actions and statements. *The Response of Asset Prices to Monetary Policy Actions and Statements (November 2004)*, 2004.

Refet S Gürkaynak, Brian Sack, and Jonathan H Wright. The us treasury yield curve: 1961 to the present. *Journal of monetary Economics*, 54(8):2291–2304, 2007.

Michael Halling, Jin Yu, and Josef Zechner. The dynamics of corporate debt structure. *Swedish House of Finance Research Paper*, (20-3), 2025.

Robert S Hamada. The effect of the firm's capital structure on the systematic risk of common stocks. *The journal of finance*, 27(2):435–452, 1972.

Samuel G Hanson and Jeremy C Stein. Monetary policy and long-term real rates. *Journal of Financial Economics*, 115(3):429–448, 2015.

Zhiguo He and Arvind Krishnamurthy. Intermediary asset pricing. *American Economic Review*, 103(2):732–770, 2013.

Zhiguo He and Wei Xiong. Rollover risk and credit risk. *The Journal of Finance*, 67(2): 391–430, 2012.

Kewei Hou, Chen Xue, and Lu Zhang. Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3):650–705, 2015.

Alex Hsu, Indrajit Mitra, Yu Xu, and Linghang Zeng. The fed information effect and the profitability channel of monetary policy: Evidence and theory. *Georgia Tech Scheller College of Business Research Paper*, (4451789), 2025.

Julien Hugonnier, Semyon Malamud, and Erwan Morellec. Capital supply uncertainty, cash holdings, and investment. *The Review of Financial Studies*, 28(2):391–445, 2015.

Priit Jeenas. *Firm balance sheet liquidity, monetary policy shocks, and investment dynamics.* Universitat Pompeu Fabra, Department of Economics and Business, 2023.

Priit Jeenas and Ricardo Lagos. Q-monetary transmission. *Journal of Political Economy*, 132(3):971–1012, 2024.

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

Joachim Jungherr, Matthias Meier, Timo Reinelt, and Immo Schott. Corporate debt maturity matters for monetary policy. *International Finance Discussion Paper*, (1402), 2024.

Şebnem Kalemli-Özcan, Luc Laeven, and David Moreno. Debt overhang, rollover risk, and corporate investment: Evidence from the european crisis. *Journal of the European Economic Association*, 20(6):2353–2395, 2022.

Diego R Känzig. The macroeconomic effects of oil supply news: Evidence from opec announcements. *American Economic Review*, 111(4):1092–1125, 2021.

Rohan Kekre and Moritz Lenel. Monetary policy, redistribution, and risk premia. *Econometrica*, 90(5):2249–2282, 2022.

Tim A Kroencke, Maik Schmeling, and Andreas Schrimpf. The fomc risk shift. *Journal of Monetary Economics*, 120:21–39, 2021.

Ricardo Lagos and Shengxing Zhang. Turnover liquidity and the transmission of monetary policy. *American Economic Review*, 110(6):1635–1672, 2020.

William W Lang and Leonard I Nakamura. ‘flight to quality’in banking and economic activity. *Journal of Monetary Economics*, 36(1):145–164, 1995.

Chen Lian and Yueran Ma. Anatomy of corporate borrowing constraints. *The Quarterly Journal of Economics*, 136(1):229–291, 2021.

Xiaoji Lin and Lu Zhang. The investment manifesto. *Journal of Monetary Economics*, 60 (3):351–366, 2013.

David O Lucca and Emanuel Moench. The pre-fomc announcement drift. *The Journal of finance*, 70(1):329–371, 2015.

Ian Martin. What is the expected return on the market? *The Quarterly Journal of Economics*, 132(1):367–433, 2017.

Atif Mian, Kamalesh Rao, and Amir Sufi. Household balance sheets, consumption, and the economic slump. *The Quarterly Journal of Economics*, 128(4):1687–1726, 2013.

Emi Nakamura and Jón Steinsson. High-frequency identification of monetary non-neutrality: the information effect. *The Quarterly Journal of Economics*, 133(3):1283–1330, 2018a.

Emi Nakamura and Jón Steinsson. Identification in macroeconomics. *Journal of Economic Perspectives*, 32(3):59–86, 2018b.

Emi Nakamura, Dmitriy Sergeyev, and Jon Steinsson. Growth-rate and uncertainty shocks in consumption: Cross-country evidence. *American Economic Journal: Macroeconomics*, 9(1):1–39, 2017.

Andreas Neuhierl and Michael Weber. Monetary policy communication, policy slope, and the stock market. *Journal of Monetary Economics*, 108:140–155, 2019.

Whitney K Newey and Kenneth D West. A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. 1986.

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

Ali Ozdagli and Mihail Velikov. Show me the money: The monetary policy risk premium. *Journal of Financial Economics*, 135(2):320–339, 2020.

Stephen H Penman, Scott A Richardson, and Irem Tuna. The book-to-price effect in stock returns: accounting for leverage. *Journal of accounting research*, 45(2):427–467, 2007.

Carolin Pflueger and Gianluca Rinaldi. Why does the fed move markets so much? a model of monetary policy and time-varying risk aversion. *Journal of Financial Economics*, 146 (1):71–89, 2022.

Carolin Pflueger, Emil Siriwardane, and Adi Sunderam. Financial market risk perceptions and the macroeconomy. *The Quarterly Journal of Economics*, 135(3):1443–1491, 2020.

Leigh A Riddick and Toni M Whited. The corporate propensity to save. *The Journal of Finance*, 64(4):1729–1766, 2009.

Roberto Rigobon and Brian Sack. Measuring the reaction of monetary policy to the stock market. *The quarterly journal of Economics*, 118(2):639–669, 2003.

Roberto Rigobon and Brian Sack. The impact of monetary policy on asset prices. *Journal of monetary economics*, 51(8):1553–1575, 2004.

Thiago RT Ferreira, Daniel Ostry, and John H Rogers. Firm financial conditions and the transmission of monetary policy. *FEDS Working Paper*, 2023.

Maik Schmeling and Christian Wagner. Does central bank tone move asset prices? *Journal of Financial and Quantitative Analysis*, pages 1–48, 2016.

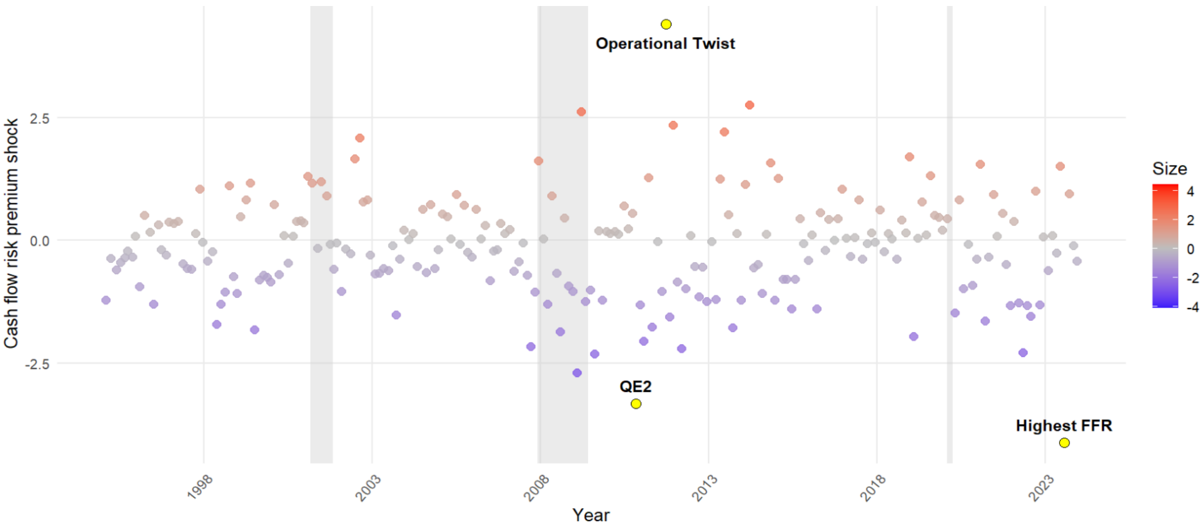
Ilya A Strebulaev and Baozhong Yang. The mystery of zero-leverage firms. *Journal of financial Economics*, 109(1):1–23, 2013.

Jules H van Binsbergen and Marco Grotteria. Monetary policy wedges and the long-term liabilities of households and firms. Technical report, National Bureau of Economic Research, 2024.

Dimitri Vayanos. Flight to quality, flight to liquidity, and the pricing of risk, 2004.

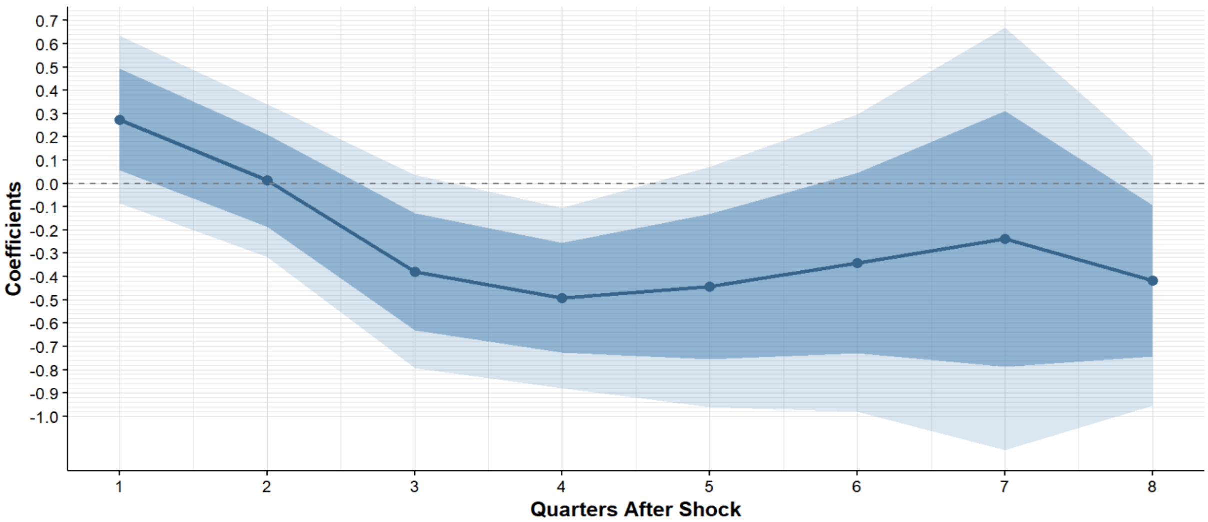
Arlene Wong et al. Refinancing and the transmission of monetary policy to consumption. *Unpublished manuscript*, 20(4), 2019.

Figure 1: Cash Flow Risk News Shocks on Scheduled FOMC Announcement Days



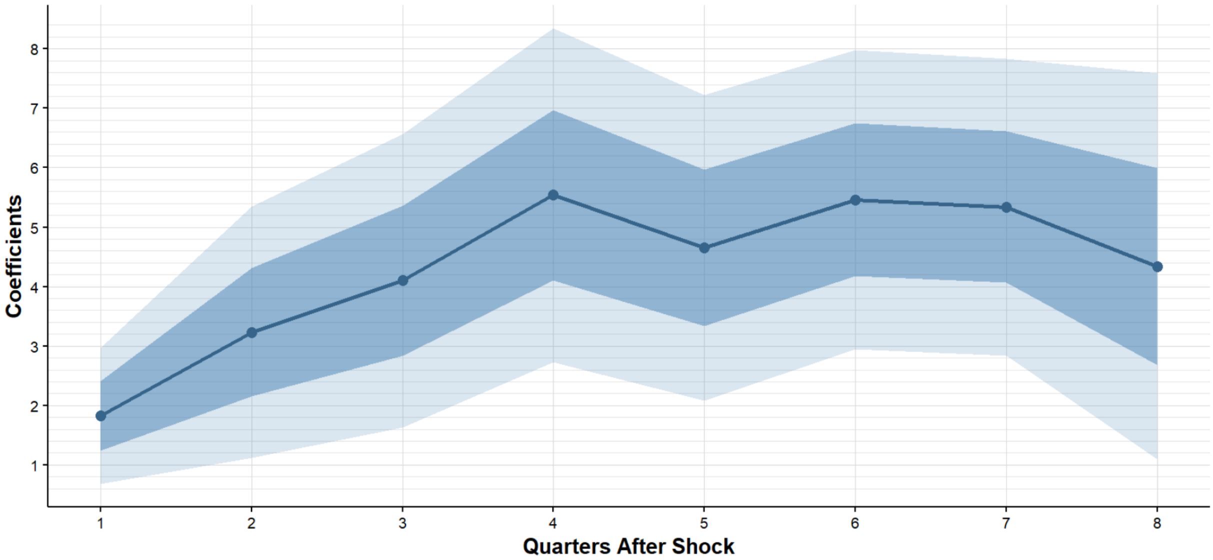
This figure plots the identified cash flow risk news shocks on all scheduled FOMC announcement days from 1995 to 2023. Shocks are obtained from a structural VAR estimated with bond and equity data for all trading days in 1983–2023. The shocks are normalized to have mean zero and unit standard deviation over the estimation sample; the values on the y axis are expressed in standard deviation units across all trading days.

Figure 2: Risk Channel: Dynamics of the Firm Level Average Investment Response



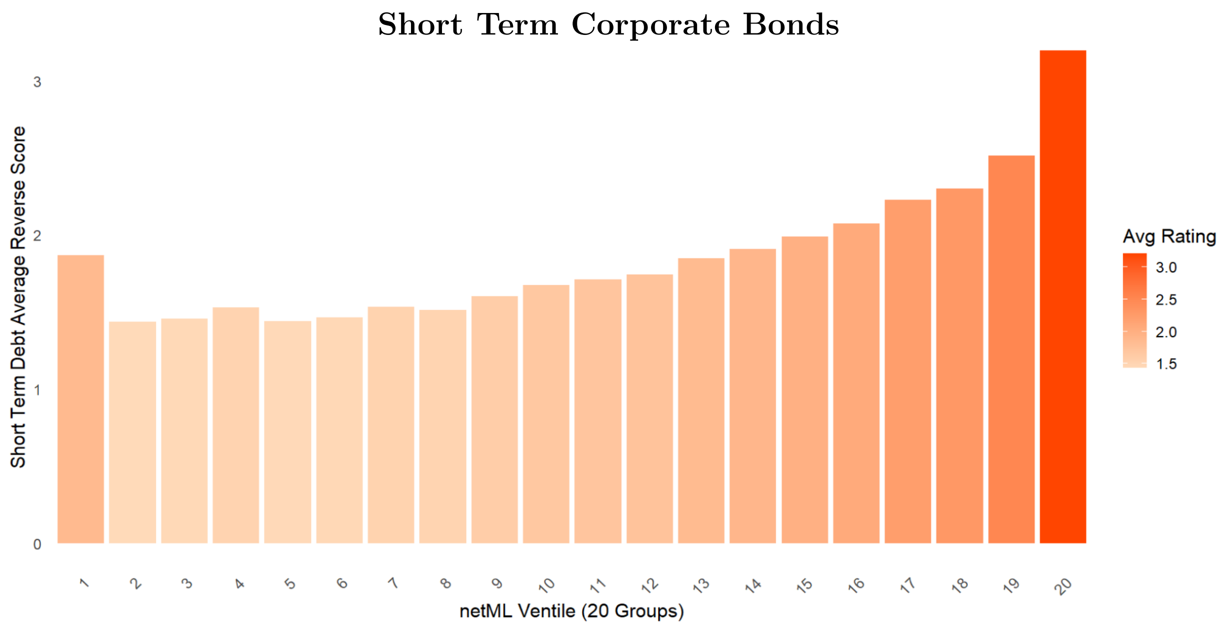
This figure shows the dynamic response of investment to FOMC risk news shocks. The regression follows Equation (11); the dependent variable is the change in the log book value of tangible capital over the next one to eight quarters. The sample is a quarterly panel of Compustat firms from 1995 to 2023. The regressions include macro controls (lags 1 to 4 of inflation, GDP growth, and unemployment) and firm and industry $\times$ year fixed effects. The inner and outer shaded areas denote 68% and 90% confidence intervals, respectively, based on Driscoll–Kraay standard errors.

Figure 3: Risk Channel: Dynamics of the Ex Post Cost of Capital Response



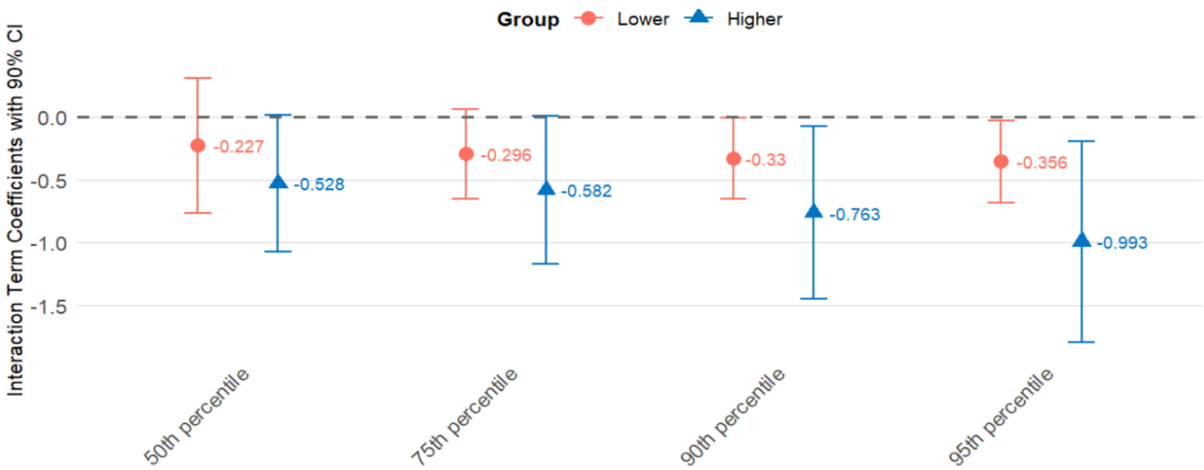
This figure shows the dynamic response of the cost of capital to FOMC risk news shocks. The regression follows Equation (11); the dependent variable is the change in the log equity price over the next one to eight quarters. The sample is a quarterly panel of Compustat firms from 1995 to 2023. The regressions include macroeconomic controls (lags 1 to 4 of inflation, GDP growth, and unemployment) and firm and industry × year fixed effects. The inner and outer shaded areas denote 68% and 90% confidence intervals, respectively, based on Driscoll–Kraay standard errors.

Figure 4: Average Reverse Credit Score by Net Market Leverage

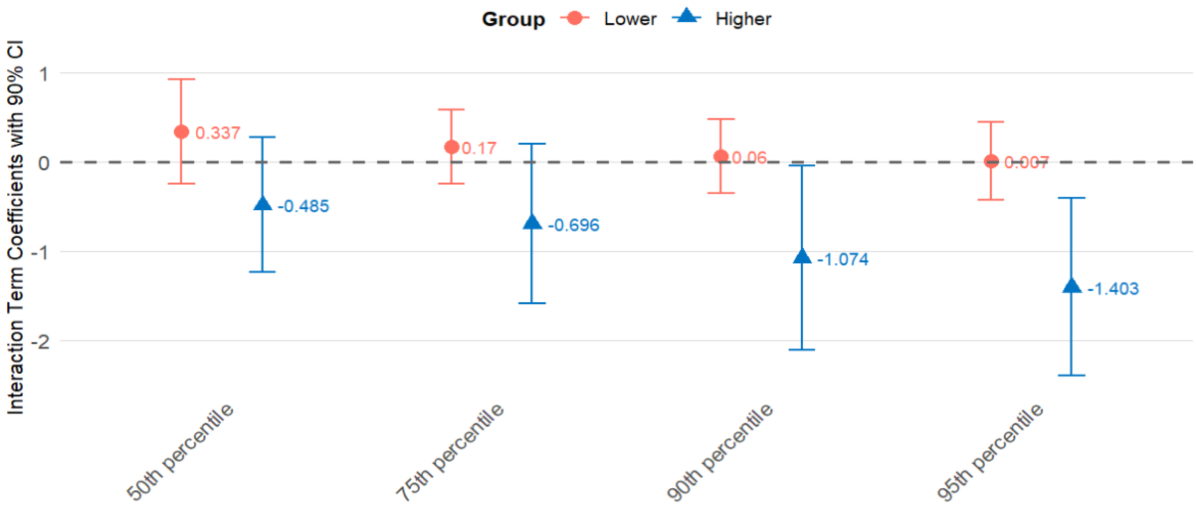


This figure shows the relationship between net market leverage (netML) and reverse credit scores for long term and short term corporate bonds. Firms are sorted into 20 portfolios by lagged netML from low to high. Credit ratings are converted to reverse credit scores, so higher scores indicate higher credit risk.

Figure 5: Risk Channel: Subgroup Average Investment Response by Net Market Leverage



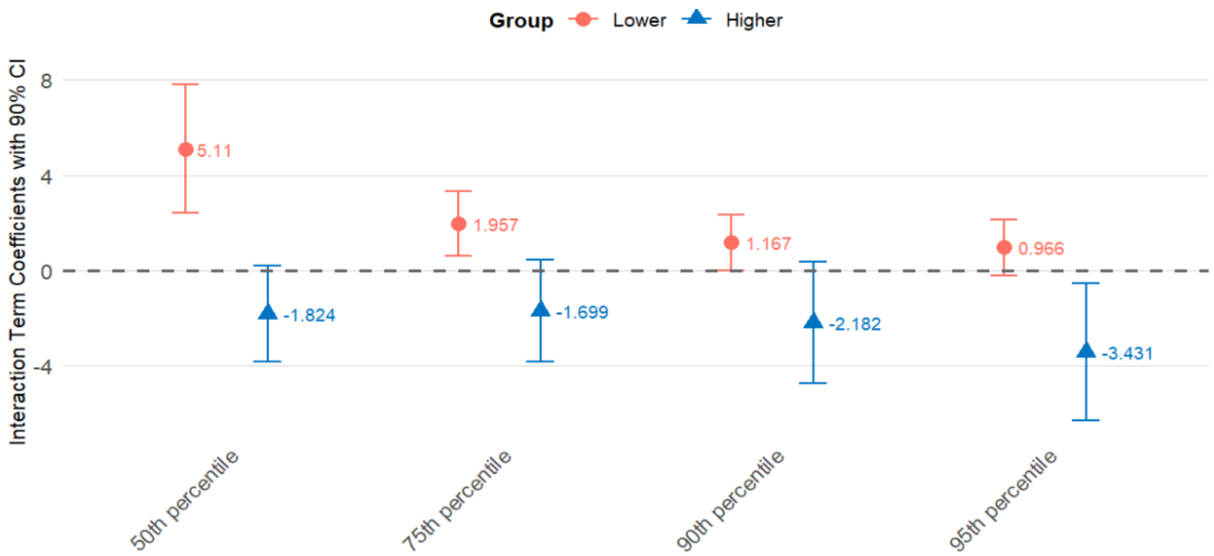
Panel A: Full Sample



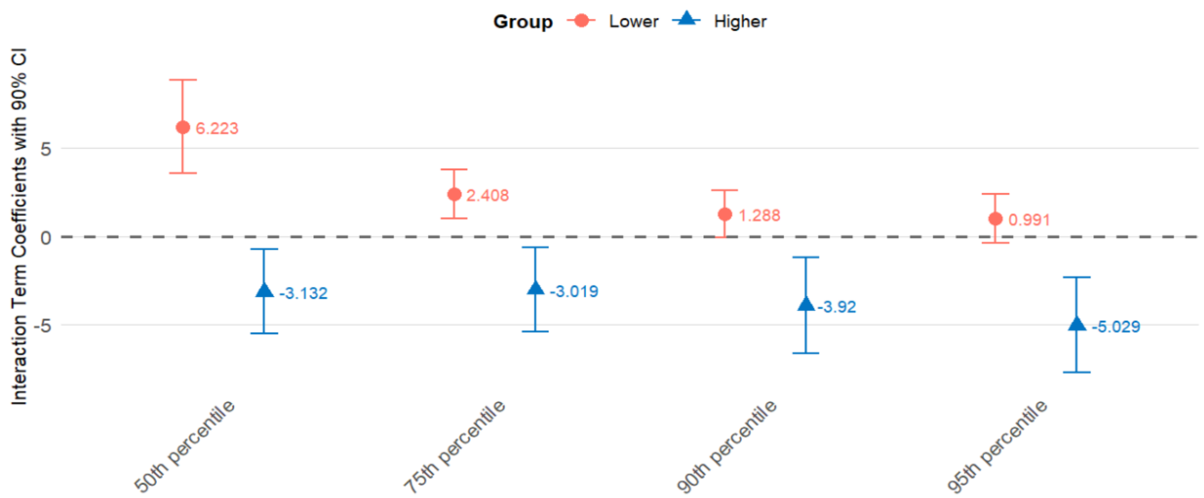
Panel B: Post-2008 Sample

This figure reports regression results based on Equation (13). The dependent variable is the change over the next four quarters in the log book value of tangible capital. The main independent variable is the FOMC risk news shock interacted with binary indicators for high or low firm level lagged net market leverage (netML). Firms in the high group have lagged netML above a given percentile cutoff. The sample is a quarterly panel of Compustat firms from 1995 to 2023 in Panel A and from 2008 to 2023 in Panel B. The regressions include macroeconomic controls, firm fixed effects, year × industry fixed effects, and high frequency monetary policy surprise series from Nakamura and Steinsson [2018a]. Macroeconomic controls are lags 1 to 4 of inflation, GDP growth, and unemployment. The figure also shows 90% pointwise confidence intervals based on Driscoll–Kraay standard errors.

Figure 6: Mechanism: Subsample Average Debt Response by Net Market Leverage



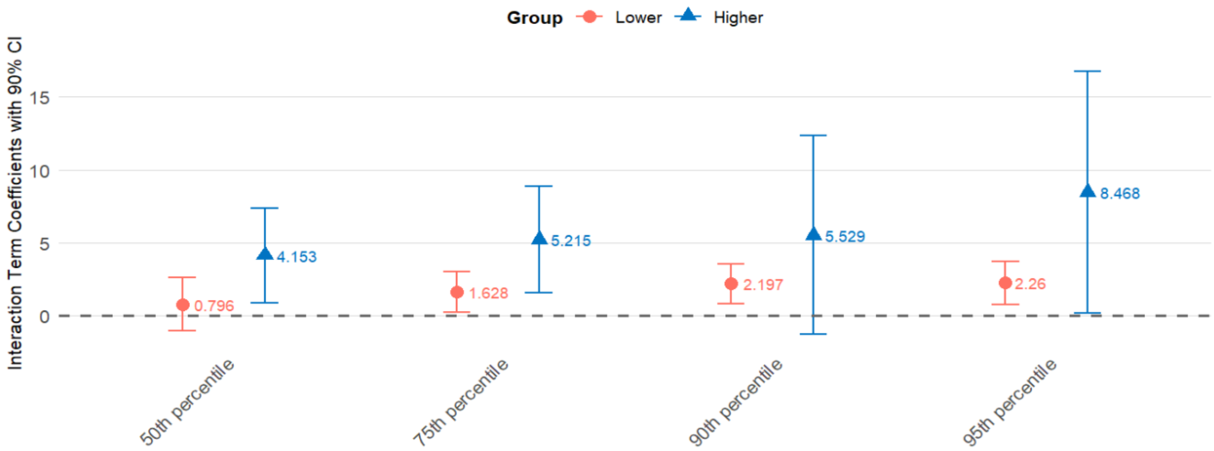
Panel A: Full Sample



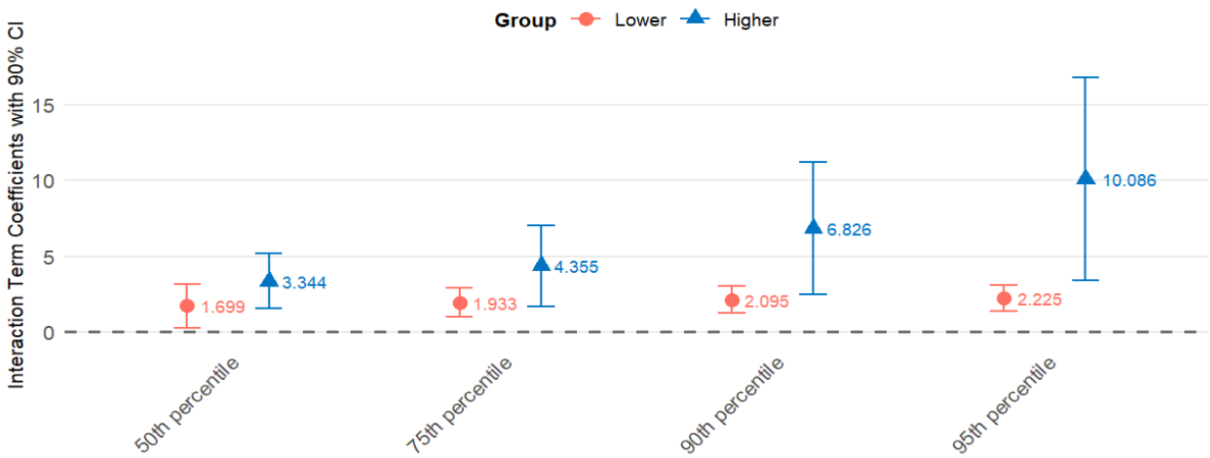
Panel B: Post-2008 Sample

This figure reports regression results based on Equation (13). The dependent variable is the change over the next four quarters in log total debt. The main independent variable is the FOMC risk news shock interacted with binary indicators for high or low firm level lagged net market leverage (netML). Firms in the high group have lagged netML above a given percentile cutoff defined relative to the full sample distribution. The sample is a quarterly panel of Compustat firms from 1995 to 2023 in Panel A and from 2008 to 2023 in Panel B. The regressions include macroeconomic controls, firm fixed effects, year × industry fixed effects, and the high frequency monetary policy surprise series from Nakamura and Steinsson [2018a]. Macroeconomic controls are lags 1 to 4 of inflation, GDP growth, and unemployment. The figure also shows 90% pointwise confidence intervals based on Driscoll–Kraay standard errors.

Figure 7: Mechanism: Subgroup Average Cash Holdings Response by Net Market Leverage



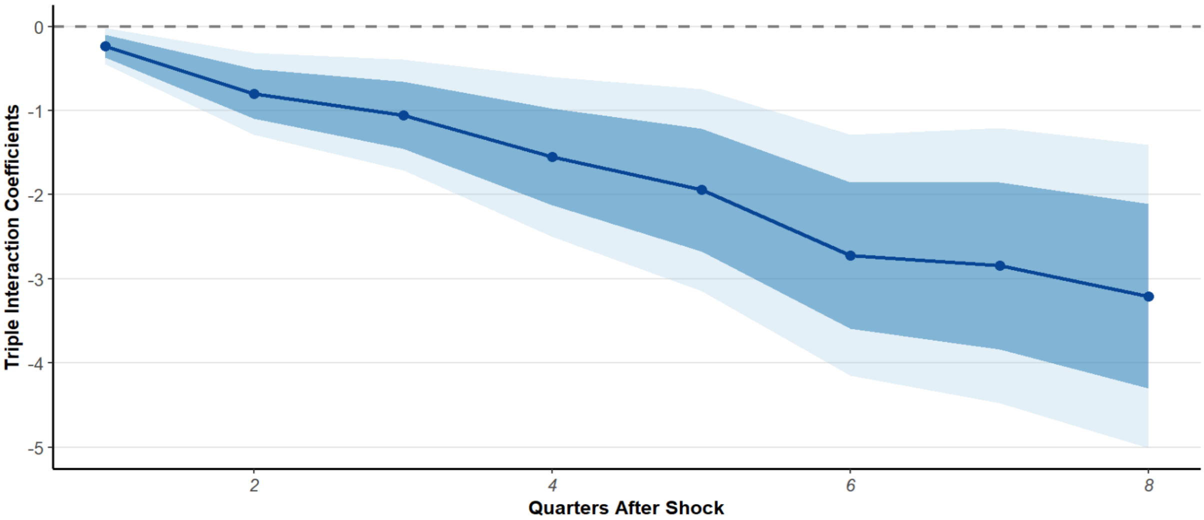
Panel A: Full Sample



Panel B: Post-2008 Sample

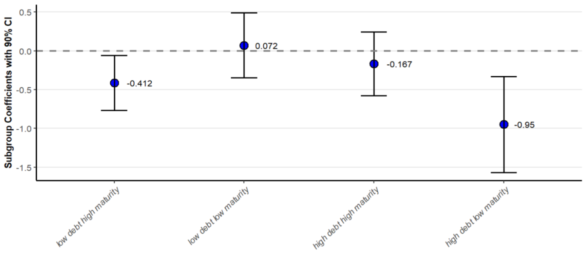
This figure reports regression results based on Equation (13). The dependent variable is the change over the next four quarters in the log of cash holdings. The main independent variable is the FOMC risk news shock interacted with binary indicators for high or low firm level lagged net market leverage (netML). Firms in the high group have lagged netML above a given percentile cutoff defined relative to the full sample distribution. The sample is a quarterly panel of Compustat firms from 1995 to 2023 in Panel A and from 2008 to 2023 in Panel B. The regressions include macroeconomic controls, firm fixed effects, year $\times$ industry fixed effects, and the high frequency monetary policy surprise series from Nakamura and Steinsson [2018a]. Macroeconomic controls are lags 1 to 4 of inflation, GDP growth, and unemployment. The figure also shows 90% pointwise confidence intervals based on Driscoll–Kraay standard errors.

Figure 8: Mechanism: Dynamics of the Rollover Risk Effect on Investment

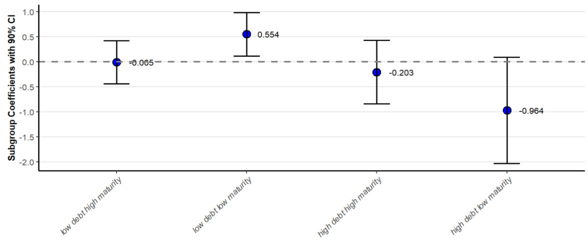


This figure shows the dynamic effect of rollover risk on the investment response to the FOMC risk news shock. Estimates are from Equation 12, with the dependent variable defined as the change in the log book value of tangible capital stock at horizons one through eight quarters ahead. The key regressor is a triple interaction of the FOMC risk news shock, an indicator for high net market leverage, $\mathbf{1}\{netML_{t-1}^{high}\}$, and an indicator for high rollover need, $\mathbf{1}\{RI_{t-1}^{high}\}$. The indicator $\mathbf{1}\{RI_{t-1}^{high}\}$ equals one for firms whose rollover need (debt maturing within one year relative to total debt) is above the sample median; $\mathbf{1}\{netML_{t-1}^{high}\}$ equals one for firms with netML above the 75th percentile of the sample. The sample is a quarterly panel of Compustat firms from 1995 to 2023. The regressions include firm fixed effects and industry $\times$ quarter fixed effects. The inner and outer shaded areas denote the 68% and 90% confidence intervals, respectively, based on standard errors computed using the Driscoll and Kraay method.

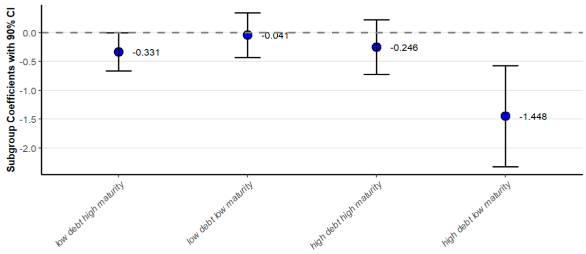
Figure 9: Mechanism: Subgroup Average Investment Responses by Rollover Risk



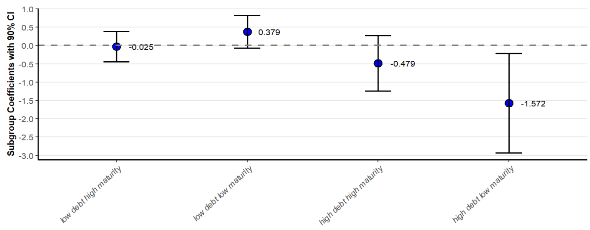
Panel A: Full sample with 75th percentile of netML



Panel B: Post-2008 with 75th percentile of netML



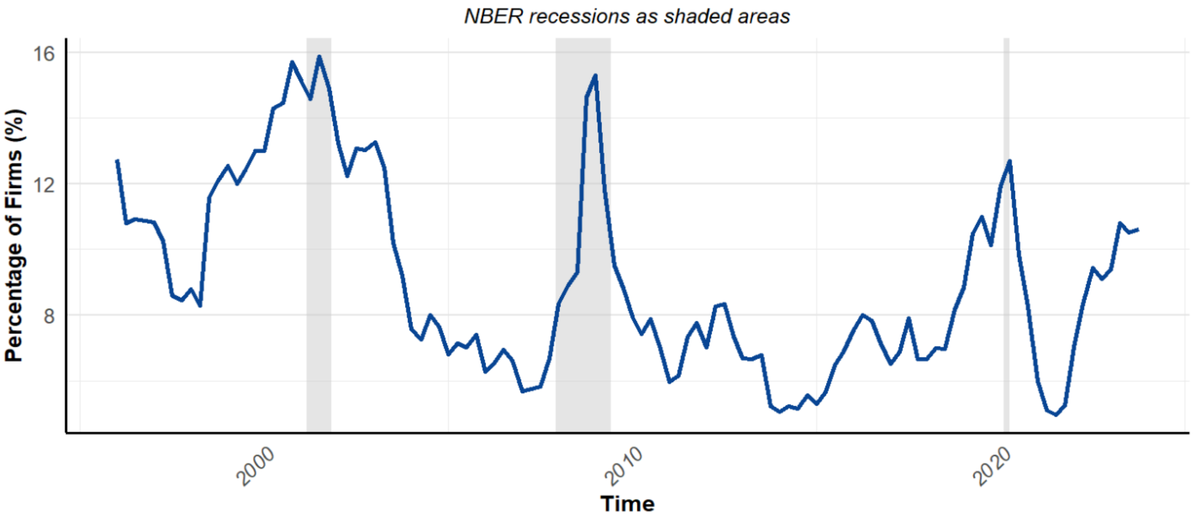
Panel C: Full sample with 90th percentile of netML



Panel D: Post-2008 with 90th percentile of netML

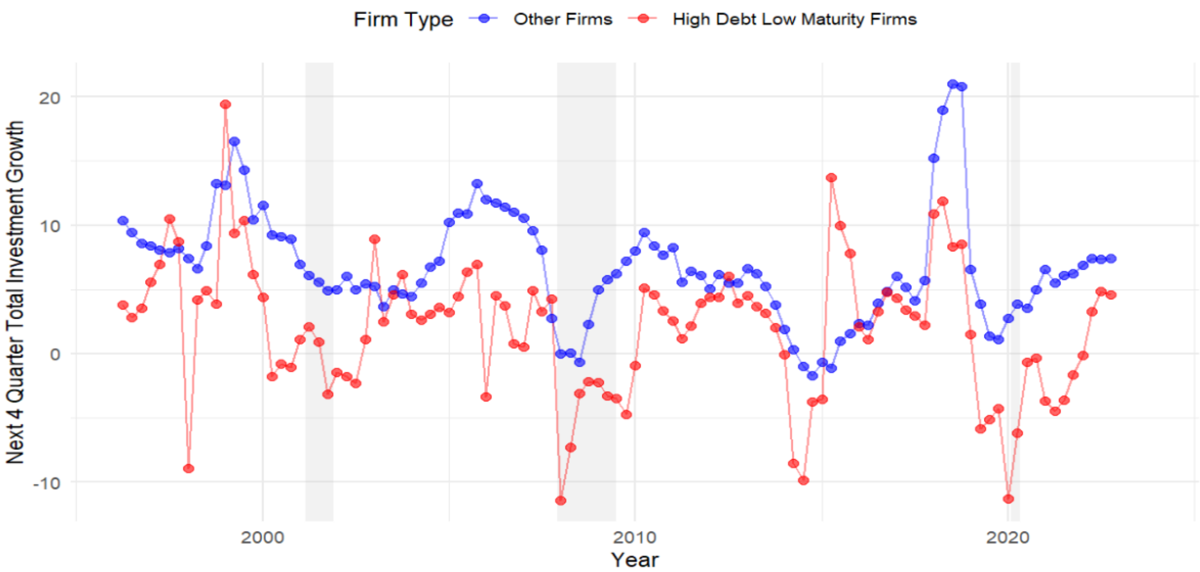
This figure reports estimates from Equation 13. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The key regressor is a triple interaction of the FOMC risk news shock, an indicator for high net market leverage (netML), $\mathbf{1}\{netML_{t-1}^{high}\}$, and an indicator for high rollover need (low maturity), $\mathbf{1}\{RI_{t-1}^{high}\}$. The indicator $\mathbf{1}\{RI_{t-1}^{high}\}$ equals one for firms whose rollover need (debt maturing within one year relative to total debt) is above the sample median. The indicator $\mathbf{1}\{netML_{t-1}^{high}\}$ equals one for firms with netML above the 75th percentile (Panels A and B) or the 90th percentile (Panels C and D). The sample is a quarterly panel of Compustat firms from 1995 to 2023. The regressions include macroeconomic controls, firm fixed effects, and year $\times$ industry fixed effects; macroeconomic controls are the one- to four-quarter lags of inflation, GDP growth, unemployment, and the high-frequency monetary policy surprise series from Nakamura and Steinsson [2018a]. The interaction of the two indicators, $\mathbf{1}\{RI_{t-1}^{high}\} \times \mathbf{1}\{netML_{t-1}^{high}\}$, is included in the specification. The figure shows 90% pointwise confidence intervals based on standard errors computed using the Driscoll and Kraay method.

Figure 10: Aggregate: Share of Firms with High Rollover Risk



This figure shows the quarterly share of firms with high rollover risk. A firm is classified as high rollover risk if its net market leverage $netML$ is above the 75th percentile and its rollover need RI is above the median; both thresholds are evaluated in the full sample. The series is constructed from a quarterly panel of Compustat firms from 1995 to 2023. Shaded areas denote NBER designated recessions.

Figure 11: Aggregate: Capital Growth for High and Low Rollover Risk Groups



This figure shows the quarterly growth in aggregate capital for firms with high rollover risk and for firms with low rollover risk. A firm is classified as high rollover risk in quarter t if its net market leverage $netML$ is above the 75th percentile and its rollover need RI is above the panel median. Capital growth (investment) is measured over the next four quarters. The series are constructed from a quarterly panel of Compustat firms from 1995 to 2023. Shaded areas denote NBER designated recessions.

Figure 12: Aggregate: Dynamic Investment Response Conditional on the Share of Firms with High Rollover Risk

This figure plots the impulse response of aggregate investment to the FOMC risk news shock (ϵ_t^{cr}) conditional on the share of firms with high rollover risk ($\mathbf{p}_t$). The solid line shows the estimated coefficient on the interaction $\epsilon_t^{cr} \times \mathbf{p}_t$ at each horizon; the dark and light shaded areas are 68% and 90% Newey and West confidence bands (eight lags; Newey and West [1986]). Responses are shown for the subsequent eight quarters. A firm is classified as high rollover risk if its net market leverage $netML$ exceeds the 75th percentile and its rollover need RI is below the median, with both thresholds computed over all firms and quarters. At each date, $\mathbf{p}_t$ is the fraction of firms meeting these criteria. All regressions include the one to four quarter lags of inflation, real GDP growth, and the unemployment rate, along with the contemporaneous Nakamura and Steinsson interest rate surprise.

Table 1: Summary Statistics of Daily Cash Flow Risk Shocks

	Statistics						
Sample	**MAV**	**P5**	**P25**	**Median**	**P75**	**P95**	**Variance**
FOMC Days (From 1994)	0.842	-1.999	-0.752	-0.180	0.443	1.239	1.667
All Trading Days (From 1994)	0.668	-1.373	-0.518	-0.028	0.478	1.504	0.855
FOMC Days (From 2008)	1.007	-2.184	-0.853	-0.242	0.386	1.350	2.480
All Trading Days (From 2008)	0.673	-1.408	-0.521	-0.051	0.473	1.527	0.881

This table reports summary statistics for daily cash flow risk shocks by subperiod. "FOMC Days" refers to scheduled FOMC announcement days. The shocks are estimated using a structural VAR with bond and equity data for all trading days from 1983 to 2023. The series is normalized to have mean zero and unit standard deviation over the estimation sample, so the values are expressed in standard deviation units computed over all trading days in 1983–2023. "MAV" denotes the mean of the absolute values of the shocks. "P5," "P25," "Median," "P75," and "P95" denote the 5th, 25th, 50th, 75th, and 95th percentiles, respectively.

Table 2: Correlations Among FOMC Risk News Shocks Across Methods

	ϵ_t^{risk}			ϵ_t^{svix}	
	ϵ_t^{cr}	ϵ_t^{dr}		ϵ_t^{cr}	ϵ_t^{dr}
Correlation	0.436	0.179	Correlation	0.396	0.275
95% interval	[0.278, 0.572]	[-0.001, 0.349]	95% interval	[0.232, 0.538]	[0.099, 0.434]
t stat	5.224	1.964	t stat	4.647	3.082

This table reports correlations among four series: changes in the risk index of Bauer et al. [2023] (BBM), changes in SVIX of Martin [2017], and the cash flow risk news shock and the discount rate risk news shock from the structural VAR. All four measures are constructed as the quarterly sum of daily changes or shocks occurring on scheduled FOMC announcement days.

Table 3: Risk Channel: Firm Level Average Investment Response

	$log(k_{t+4}) - log(k_t)$			
	(1)	(2)	(3)	(4)
ϵ_t^{cr}	-0.496**	-0.489**	-0.411**	-0.363**
	(0.236)	(0.235)	(0.184)	(0.183)
Firm FE	✓	✓	✓	✓
Year FE	✓			
Year × Industry FE		✓	✓	✓
Macro Controls	✓	✓	✓	✓
Firm Controls			✓	✓
Interest Rate Surprise				✓
Observations	297,988	297,988	239,904	239,904
Adjusted R^2	0.092	0.099	0.144	0.146

This table reports regression results based on Equation (11). The dependent variable is the change over the next four quarters in the log book value of tangible capital. The main independent variable is the FOMC risk news shock. The sample is a quarterly panel of Compustat firms from 1995 to 2023. Macro controls include lags 1 to 4 of inflation, GDP growth, and unemployment. Firm level controls include lag 1 of size, net debt to market ratio, sales growth, asset return, operational leverage, and the short term asset ratio. The interest rate surprise is the high frequency surprise series from Nakamura and Steinsson [2018a]. Standard errors, reported in parentheses, are Driscoll–Kraay. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Risk Channel: Firm Level Average Ex Post Cost of Capital Response

	$log(p_{t+4}) - log(p_t)$			
	(1)	(2)	(3)	(4)
ϵ_t^{cr}	5.536***	5.538***	5.477***	5.913***
	(1.437)	(1.438)	(1.453)	(1.524)
Firm FE	✓	✓	✓	✓
Year FE	✓			
Year × Industry FE		✓	✓	✓
Macro Controls	✓	✓	✓	✓
Firm Controls			✓	✓
Interest Rate Surprise				✓
Observations	256,529	256,529	234,388	234,388
Adjusted R^2	0.111	0.120	0.153	0.156

This table reports regression results based on Equation (11). The dependent variable is the change over the next four quarters in the log equity price. The main independent variable is the FOMC risk news shock. The sample is a quarterly panel of Compustat firms from 1995 to 2023. Macro controls include lags 1 to 4 of inflation, GDP growth, and unemployment. Firm level controls include lag 1 of size, net debt to market ratio, sales growth, asset return, operational leverage, and the short term asset ratio. The interest rate surprise is the high frequency monetary policy surprise series from Nakamura and Steinsson [2018a]. Standard errors, reported in parentheses, are Driscoll–Kraay. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Risk Channel: Heterogeneous Investment Response by Net Market Leverage

	$log(k_{t+4}) - log(k_t)$			
	(1)	(2)	(3)	(4)
ϵ_t^{cr}	-0.432**			
	(0.193)			
$\epsilon_t^{cr} \times netML_{t-1}$	-1.496***	-1.403***	-0.68***	-1.046***
	(0.320)	(0.301)	(0.236)	(0.379)
Firm FE	✓	✓	✓	✓
Year $\times$ Industry FE	✓			
Macro Controls	✓			
Quarter $\times$ Industry FE		✓	✓	✓
ϵ_t^{cr} $\times$ Firm Controls			✓	✓
$\Delta GDP_{t-1} \times netML_{t-1}$			✓	✓
Interest Rate Surprise $\times$ $netML_{t-1}$			✓	✓
Observations	247,250	247,250	238,394	103,146
Adjusted R^2	0.109	0.119	0.146	0.171
Sample Period	Full	Full	Full	Post-2008

This table presents regression results based on Equation (12). The dependent variable is the change over the next four quarters in the log book value of tangible capital. The main independent variable is the FOMC risk news shock interacted with the firm level lagged net market leverage (netML). The sample is a quarterly panel of Compustat firms from 1995 to 2023. Firm level controls include lag 1 of size, net market leverage, sales growth, asset return, operational leverage, and the short term asset ratio. The last two columns also include lagged GDP growth interacted with lagged net market leverage to allow for differences in cyclical sensitivities across firms. Non interacted coefficients are omitted for brevity. The interest rate surprise is the high frequency monetary policy surprise series from Nakamura and Steinsson [2018a]. Standard errors, shown in parentheses, are Driscoll–Kraay. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Mechanism: Heterogeneous Debt Response by Net Market Leverage

	$log(Debt_{t+4}) - log(Debt_t)$			
	(1)	(2)	(3)	(4)
ϵ_t^{cr}	0.750			
	(0.698)			
$\epsilon_t^{cr} \times netML_{t-1}$	-5.757***	-5.36***	-2.636***	-5.085***
	(1.107)	(1.074)	(0.914)	(1.395)
Firm FE	✓	✓	✓	✓
Year × Industry FE	✓			
Macro Controls	✓			
Quarter × Industry FE		✓	✓	✓
ϵ_t^{cr} × Firm Controls			✓	✓
$\Delta GDP_{t-1} \times netML_{t-1}$			✓	✓
Interest Rate Surprise × $netML_{t-1}$			✓	✓
Observations	201,683	201,683	196,076	86,295
Adjusted R^2	0.058	0.059	0.069	0.090
Sample Period	Full	Full	Full	Post-2008

This table presents regression results based on Equation (12). The dependent variable is the change over the next four quarters in log total debt. The main independent variable is the FOMC risk news shock interacted with firm level lagged net market leverage (netML). The sample is a quarterly panel of Compustat firms from 1995 to 2023. Firm level controls include lag 1 of size, net debt to market ratio, sales growth, asset return, operational leverage, and the short term asset ratio. The last two columns also include lagged GDP growth interacted with lagged net debt to market ratio to allow for differences in cyclical leverage sensitivities across firms. Non interacted coefficients are omitted for brevity. The interest rate surprise is the high frequency monetary policy surprise series from Nakamura and Steinsson [2018a]. Standard errors, shown in parentheses, are Driscoll–Kraay. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Mechanism: Heterogeneous Cash Holdings Response by Net Market Leverage

	$log(Cash_{t+4}) - log(Cash_t)$			
	(1)	(2)	(3)	(4)
ϵ_t^{cr}	2.446**			
	(0.976)			
$\epsilon_t^{cr} \times netML_{t-1}$	2.923**	2.43**	1.566*	4.579**
	(1.141)	(1.067)	(0.896)	(1.768)
Firm FE	✓	✓	✓	✓
Year × Industry FE	✓			
Macro Controls	✓			
Quarter × Industry FE		✓	✓	✓
ϵ_t^{cr} × Firm Controls			✓	✓
$\Delta GDP_{t-1} \times netML_{t-1}$			✓	✓
Interest Rate Surprise × $netML_{t-1}$			✓	✓
Observations	246,823	246,823	237,555	103,112
Adjusted R^2	0.061	0.065	0.080	0.106
Sample Period	Full	Full	Full	Post-2008

This table presents regression results based on Equation (12). The dependent variable is the change over the next four quarters in the log of cash holdings. The main independent variable is the FOMC risk news shock interacted with firm level lagged net market leverage (netML). The sample is a quarterly panel of Compustat firms from 1995 to 2023. Firm level controls include lag 1 of size, net market leverage, sales growth, asset return, operational leverage, and the short term asset ratio. The last two columns also include lagged GDP growth interacted with lagged net market leverage to allow for differences in cyclical leverage sensitivities across firms. Non interacted coefficients are omitted for brevity. The interest rate surprise is the high frequency monetary policy surprise series from Nakamura and Steinsson [2018a]. Standard errors, shown in parentheses, are Driscoll–Kraay. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Mechanism: Heterogeneous Investment Responses by Rollover Risk

	$\log(k_{t+4}) - \log(k_t)$			
	(1)	**(2)**	**(3)**	**(4)**
$\epsilon_t^{cr} \times netML_{t-1}$	0.504**	0.158		
	(0.249)	(0.505)		
$\epsilon_t^{cr} \times netML_{t-1} \times \mathbf{1}\{RI_{t-1}^{high}\}$	-1.478***	-1.764***		
	(0.391)	(0.581)		
$\epsilon_t^{cr} \times \mathbf{1}\{netML_{t-1}^{high}\}$			0.678***	0.306
			(0.190)	(0.247)
$\epsilon_t^{cr} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$			-1.403***	-1.499***
			(0.418)	(0.548)
Firm FE	✓	✓	✓	✓
Quarter × Industry FE	✓	✓	✓	✓
ϵ_t^{cr} × Firm Controls	✓	✓	✓	✓
$\Delta GDP_{t-1} \times netML_{t-1}$	✓	✓	✓	✓
Observations	199,062	103,112	199,062	103,112
Adjusted R^2	0.165	0.207	0.168	0.208
Sample Period	Full	Post-2008	Full	Post-2008

This table reports estimates from Equation 12. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The key regressor is a triple interaction of the FOMC risk news shock, lagged net market leverage (netML), and an indicator for high rollover need, $\mathbf{1}\{RI_{t-1}^{high}\}$. Columns (3) and (4) replace the continuous netML with an indicator for high netML, $\mathbf{1}\{netML_{t-1}^{high}\}$. The indicator $\mathbf{1}\{RI_{t-1}^{high}\}$ equals one for firms whose rollover need (debt maturing in less than one year divided by total debt) is above the sample median; $\mathbf{1}\{netML_{t-1}^{high}\}$ equals one for firms with netML above the 75th percentile of the sample. The sample is a quarterly panel of Compustat firms from 1995 to 2023. Firm-level controls (lagged one quarter) include size, net debt-to-market ratio, sales growth, asset return, operating leverage, and the short-term asset ratio. The last two columns additionally include lagged GDP growth interacted with lagged net debt-to-market ratio to control for differences in cyclical leverage sensitivities across firms. Coefficients on non-interacted controls and other double interactions are omitted for brevity. Standard errors, shown in parentheses, are computed using the Driscoll–Kraay method. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Mechanism: Heterogeneity by Rollover Risk, Controlling for Other News

	$\log(k_{t+4}) - \log(k_t)$	
	(1)	**(2)**
$\epsilon_t^{cr} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$	-1.522***	-1.388**
	(0.552)	(0.549)
$\epsilon_t^{ns} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$	-3.071	8.871
	(12.482)	(14.173)
$\epsilon_t^{c} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$		-0.615
		(0.376)
$\epsilon_t^{dr} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$		0.023
		(0.291)
$\epsilon_t^{d} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$		-0.344
		(0.367)
Firm FE	✓	✓
Quarter $\times$ Industry FE	✓	✓
ϵ_t^{cr} $\times$ Firm Controls	✓	✓
$\Delta GDP_{t-1} \times netML_{t-1}$	✓	✓
Observations	199,062	199,062
Adjusted R^2	0.168	0.168
Sample Period	Full	Full

This table reports estimates from Equation 12. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The key regressors are triple interactions between the quarterly sum of each FOMC news shock on scheduled FOMC days, an indicator for high net market leverage, $\mathbf{1}\{netML_{t-1}^{high}\}$, and an indicator for high rollover need, $\mathbf{1}\{RI_{t-1}^{high}\}$. The indicator $\mathbf{1}\{RI_{t-1}^{high}\}$ equals one for firms whose rollover need (debt maturing within one year relative to total debt) is above the sample median; $\mathbf{1}\{netML_{t-1}^{high}\}$ equals one for firms with netML above the 75th percentile of the sample. ϵ_t^{ns} denotes the policy rate surprise from Nakamura and Steinsson [2018a]. The sample is a quarterly panel of Compustat firms from 1995 to 2023. Firm-level controls (lagged one quarter) include size, net market leverage, sales growth, asset return, operating leverage, the short-term asset ratio, and lagged GDP growth interacted with lagged net market leverage to absorb differences in cyclical leverage sensitivities across firms. Coefficients on non-interacted controls and on double interactions are not reported for brevity. Standard errors, shown in parentheses, are computed using the Driscoll and Kraay method. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Mechanism: Industry Level Capital and Debt Reallocation

	$log(k_{t+4}) - log(k_t)$		$log(Debt_{t+4}) - log(Debt_t)$	
Panel A: Time varying industry level percentage				
	(1)	(2)	(3)	(4)
$\epsilon_t^{cr} \times \boldsymbol{p}_t^{Ind}$	-0.002	-0.037*	0.009	-0.126*
	(0.013)	(0.021)	(0.072)	(0.069)
Adjusted R^2	0.110	0.149	0.069	0.093
Panel B: Fixed industry level percentage				
	$log(k_{t+4}) - log(k_t)$		$log(Debt_{t+4}) - log(Debt_t)$	
	(1)	(2)	(3)	(4)
$\epsilon_t^{cr} \times \boldsymbol{p}^{Ind}$	-0.029	-0.054**	-0.108	-0.175**
	(0.019)	(0.027)	(0.095)	(0.071)
Adjusted R^2	0.109	0.148	0.069	0.093
Specifications:				
Firm FE	✓	✓	✓	✓
Quarter	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Interest Rate Surprise $\times$ $\boldsymbol{p}_t$	✓	✓	✓	✓
Observations	238,411	86,295	196,089	86,772
Sample Period	Full	Post-2008	Full	Post-2008

This table reports estimates from Equation 11. The dependent variables are the four-quarter change in the log book value of tangible capital stock and in the log value of total debt. The key regressor is the FOMC risk news shock interacted with the industry share of firms classified as having high rollover risk (computed at the two digit SIC level). Firms with high rollover risk are defined as those with net market leverage above the 75th percentile and rollover need above the median. **Panel A** uses a time varying industry share, recalculated each quarter. **Panel B** uses a time invariant share, equal to the average over the full sample. The sample is a quarterly panel of Compustat firms from 1995 to 2023. Firm level controls (lagged one quarter) include size, net market leverage, sales growth, asset return, operating leverage, and the short term asset ratio. The interest rate surprise is the high frequency monetary policy surprise series from Nakamura and Steinsson [2018a]. Standard errors, shown in parentheses, are computed using the Driscoll and Kraay method. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Average Investment Response Conditional on the Aggregate Share of High Rollover Risk

	$log(k_{t+4}) - log(k_t)$			
	(1)	(2)	(3)	(4)
ϵ_t^{cr}	1.1*	1.05*	4.023***	5.107*
	(0.645)	(0.534)	(1.411)	(2.737)
$\epsilon_t^{cr} \times \boldsymbol{p}_t$	-0.178**	-0.16**	-0.54***	-0.75*
	(0.078)	(0.065)	(0.2)	(0.39)
Firm FE	✓	✓	✓	✓
Year × Industry FE	✓	✓	✓	✓
Macro Controls	✓	✓	✓	✓
Firm Controls		✓		✓
Interest rate Surprise × $\boldsymbol{p}_t$		✓		✓
Observations	295,470	238,411	126,572	86,295
Adjusted R^2	0.100	0.145	0.142	0.178
Sample Period	Full	Full	Post-2008	Post-2008

This table reports estimates from Equation 11. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The key regressor is the FOMC risk news shock interacted with the contemporaneous share of firms classified as having high rollover risk. Firms with high rollover risk are defined as those with net market leverage above the 75th percentile and rollover need above the median. The sample is a quarterly panel of Compustat firms from 1995 to 2023. Macro controls include the one- to four-quarter lags of inflation, GDP growth, and unemployment. Firm level controls (lagged one quarter) include size, net debt to market ratio, sales growth, asset return, operating leverage, and the short term asset ratio. The interest rate surprise is the high frequency monetary policy surprise series from Nakamura and Steinsson [2018a]. Standard errors, reported in parentheses, are computed using the Driscoll and Kraay method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Aggregate: Investment Response Conditional on the Share of Firms with High Rollover Risk

	Aggregate investment $G_{t+h} = \log K_{t+h} - \log K_t$		
	(1)	(2)	(3)
	h=1	h=4	h=8
ϵ_t^{cr}	0.507*	1.354*	2.553*
	(0.280)	(0.730)	(1.446)
$\boldsymbol{p}_t$	−0.032	−0.159	−0.380
	(0.063)	(0.367)	(0.810)
$\epsilon_t^{cr} \times \mathbf{p}_t$	−0.043*	−0.148**	−0.320***
	(0.025)	(0.072)	(0.116)
Observations	114	110	106
Macro controls	✓	✓	✓
Interest rate surprise	✓	✓	✓
R^2	0.162	0.188	0.262

This table reports regression estimates of the aggregate investment response to the FOMC risk news shock (ϵ_t^{cr}) conditional on the share of firms with high rollover risk ($\mathbf{p}_t$). A firm is classified as high rollover risk if its net market leverage $netML$ is above the 75th percentile and its rollover need RI is above the median; both thresholds are computed in the full sample. Each quarter, $\mathbf{p}_t$ equals the fraction of firms meeting these criteria. All regressions include macro controls—the one to four quarter lags of inflation, real GDP growth, and the unemployment rate—as well as the contemporaneous Nakamura and Steinsson interest rate surprise. The dependent variable is the aggregate investment to capital ratio over the subsequent 1, 4, or 8 quarters. Newey and West standard errors with eight lags Newey and West [1986] are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Aggregate: Unconditional Investment Responses

	(1)	(2)
Panel A	G_{t+4}	G_{t+8}
ϵ_t^{cr}	-0.008	-0.330
	(0.205)	(0.409)
R^2	0.180	0.226
Panel B	G_{t+4}^{low}	G_{t+8}^{low}
ϵ_t^{cr}	0.053	-0.227
	(0.221)	(0.415)
R^2	0.187	0.230
Panel C	G_{t+4}^{high}	G_{t+8}^{high}
ϵ_t^{cr}	-0.495*	-0.837**
	(0.281)	(0.398)
R^2	0.186	0.321
Observations	110	106
Macro controls	✓	✓
Interest rate surprise	✓	✓

This table reports estimates of the aggregate investment response to the FOMC risk news shock. All regressions include macro controls: the one to four quarter lags of inflation, GDP growth, and unemployment, as well as the Nakamura and Steinsson interest rate surprise. Standard errors, shown in parentheses, are computed using Newey and West Newey and West [1986] with the number of lags set to the forecast horizon. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14: Aggregate: Counterfactual Investment Response

	(1)	(2)	(3)	(4)	(5)
	G_{t+8}	$G^{(1)}$	$G^{(2)}$	$G^{(3)}$	$G^{(4)}$
ϵ_t^{cr}	-0.330	-0.315	-0.434	-0.271	-0.824**
	(0.409)	(0.405)	(0.571)	(0.405)	(0.373)
Observations	106	106	106	106	106
Macro controls	✓	✓	✓	✓	✓
Interest rate surprise	✓	✓	✓	✓	✓

This table reports estimates of the counterfactual aggregate investment response to the FOMC risk news shock. The dependent variable is the counterfactual aggregate investment rate over subsequent quarters. All regressions include macroeconomic controls: the one to four quarter lags of inflation, GDP growth, and unemployment, as well as the Nakamura and Steinsson shocks. Standard errors, shown in parentheses, are computed using Newey and West Newey and West [1986] with eight lags. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Online Appendix

A. Sample Selection and Main Firm level Variable Construction

Sample Selection: My sample selection follows the procedure outlined in Ottonello and Winberry [2020], with minor adjustments. Firms are excluded sequentially based on the following criteria:

- Firms not incorporated in the United States (*fic* = USA) or those reporting in a currency other than the U.S. dollar (*curncdq* = USD).
- Firms operating in the finance, insurance, and real estate sectors (SIC $\in$ [6000, 6799]) or utilities (SIC $\in$ [4900, 4999]).
- Firms with fewer than 40 periods of investment observations.
- Firms with negative total assets or more than one missing observation in total assets.
- Firm observations with negative sales or quarterly acquisitions exceeding 5%.

Main Variable Construction:

- **Investment:** Defined as $\Delta \log(k_{j,t+n})$, this variable is the logarithmic change in the tangible capital stock of firm j from period t to $t+n$. Following Ottonello and Winberry [2020] and Jeenas [2023], tangible capital stock is calculated using a perpetual-inventory method. For each firm, I set the first value of capital to the level of gross property, plant, and equipment (*ppegtq*). From that period onward, I compute the evolution of capital based on changes in net property, plant, and equipment (*ppentq*). If *ppentq* is missing at any intermediate date, the corresponding observation is excluded from the regression (following Jeenas [2023]), rather than linearly interpolated as in Ottonello and Winberry [2020]. Investment is winsorized at the 1% level on both tails of the distribution.
- **Net Market Leverage (*netML*):** Measured as the net debt-to-market ratio, defined as total debt (short-term debt (*dlcq*) plus long-term debt (*dlttq*)) plus preferred stock (*pstkq*), minus cash holdings (*cheq*), divided by market equity. Market equity is calculated as the number of common shares outstanding multiplied by the share price from CRSP. In robustness tests, I also use the debt-to-market ratio (market leverage, ML), defined as total debt divided by market equity.
- **Debt Growth:** Defined as $\Delta \log(d_{j,t+n})$, this variable represents the logarithmic change in the total debt stock of firm j from period t to $t+n$. Debt Growth is winsorized at the 1% level on both tails.

- **Cash Growth:** Defined as $\Delta \log(c_{j,t+n})$, this variable represents the logarithmic change in the cash holdings of firm j from period t to $t+n$. Cash Growth is winsorized at the 1% level on both tails.

- **Refinance Intensity:** This variable is measured as the ratio of short-term debt ($dlcq$) to total debt.

- **Size:** Measured as the natural logarithm of total assets (atq).

- **Short-Term Asset Ratio:** This variable is calculated as the ratio of current assets ($actq$) to total assets.

- **Operating Leverage:** Following prior literature, this variable is measured as the sum of the cost of goods sold ($cogs$) and selling, general, and administrative expenses ($xsgaq$), divided by total assets.

- **Return on Assets (ROA):** Measured as income before extraordinary items (ibq) divided by total assets.

- **Sales Growth:** Measured as the logarithmic difference in sales ($saleq$).

- **Sectoral Dummies:** Following Ottonello and Winberry [2020], I classify firms into the following sectors based on their SIC codes: (i) agriculture, forestry, and fishing: SIC $\in$ [0, 999]; (ii) mining: SIC $\in$ [1000, 1499]; (iii) construction: SIC $\in$ [1500, 1799]; (iv) manufacturing: SIC $\in$ [2000, 3999]; (v) transportation, communications, electric, gas, and sanitary services: SIC $\in$ [4000, 4999]; (vi) wholesale trade: SIC $\in$ [5000, 5199]; (vii) retail trade: SIC $\in$ [5200, 5999]; (viii) services: SIC $\in$ [7000, 8999].

B. Additional Tables

B.1. Summary Statistics

[Table 15 around here]

[Table 16 around here]

Table 15 presents the summary statistics for the full sample used in my analysis from 1995 to 2023. Table 16 presents the summary statistics for firms with the rollover risk measure, which have non-missing values for both the net debt-to-market ratio and refinancing intensity. These firms constitute my main analysis sample for the rollover risk channel and its aggregate implications.

B.2. Daily Correlations of Risk and Volatility Proxies on FOMC Announcement Days

Figure 14 reports pairwise sample correlations among the risk and volatility proxies on FOMC announcement days. Panel (a) summarizes the correlations between the three risk-news measures—the structural cash flow risk news shock, the change in the BBM risk index (sign-inverted so that increases reflect higher perceived risk), and the change in $SVIX^2$—and the change in VIX. All three series co-move strongly with VIX. Panel (b) shows that the two reduced-form proxies (BBM change and $SVIX^2$) are strongly correlated with the structural cash flow risk news shock. Panel (c) shows that these proxies are only weakly correlated with the structural discount rate risk news shock. Taken together, Panels (b) and (c) indicate that the reduced-form proxies mainly capture perceived cash flow risk news on FOMC announcement days, consistent with the financial market risk perception I aim to capture.

[Figure 14 around here]

B.3. Additional Shock diagnostic

[Table 17 around here]

To assess exogeneity, I test whether the FOMC risk news shock proxies are predictable in a specification following Bauer and Swanson [2023]. The predictors are six macroeconomic and financial variables measured immediately before each FOMC announcement: the most recent nonfarm payrolls surprise; one-year employment growth; the three-month log change in the S&P 500 index; the three-month change in the yield-curve slope; the three-month change in the Bloomberg Commodity Spot Price Index; and the average one-month Treasury skewness. The dependent variables are the three announcement-day FOMC risk news measures: the structural VAR shock, the change in the BBM risk index, and the change in SVIX^2. As shown in Table 17, while these predictors have strong explanatory power for interest rate surprises on FOMC days, they exhibit essentially no predictive power for the three risk news measures. Only the S&P 500 variable shows modest predictive power for SVIX^2. The structural VAR shock and the BBM index change are effectively unpredictable, with R^2 of 0.013 and 0.024, respectively; even for SVIX^2, the R^2 is 0.044, far below the 0.15–0.20 range reported for interest rate surprises in Bauer and Swanson [2023]. Figure 13 further shows no evidence of autocorrelation for these announcement-day measures.

[Figure 13 around here]

B.4. Credit rating and Reverse Credit Score

[Table 18 around here]

I use S&P credit ratings from Compustat Legacy (North America) over 1995–2017. Ratings are monthly; I keep the last observation in each quarter and merge them to Compustat quarterly balance sheets. I retain firm–quarter observations only when both the rating and lagged *netML* are non-missing. The final sample contains 58,878 firm–quarters with long-term bond ratings and 14,112 with short-term bond ratings. Long-term ratings span 22 categories (AAA to SD); short-term ratings span 9 categories (A-1 to D). I convert ratings to a reverse credit score in which higher values indicate higher default risk: long-term scores run from 1 (AAA) to 22 (SD), and short-term scores from 1 (A-1) to 9 (D). Table 18 lists the ratings and their corresponding reverse scores.

[Table 19 around here]

Table 19 reports the average reverse scores for long-term and short-term bond S&P ratings by deciles of lagged *netML*. As net market leverage increases, ex ante default risk rises. The pattern is monotonic except for Decile 1, which shows an abnormally high score comparable to Decile 5. The highest decile (Decile 10) exhibits extremely high scores and default risk.

B.5. Other Firm Outcomes: Heterogeneous Responses Based on Debt Burden

Table 20 investigates heterogeneous responses of other firm outcomes to announcement risk news. Columns (1)–(3) use as dependent variables the cumulative change over the next four quarters in inventories, total assets, and intangible assets, constructed analogously to the four-quarter change in tangible capital (investment). Columns (4)–(6) use the log level in quarter $t+4$ of sales, cost of sales (COGS), and R&D expenditure; coefficients in these columns are interpreted as elasticities with respect to the shock. Cost of sales is measured by COGS, including raw materials, labor, and other production related expenses. The specifications include a linear interaction between the FOMC risk news shock and net market leverage, which identifies the differential response between high debt and low debt firms.

[Table 20 around here]

The estimates show that, after a risk rasing announcement news, high debt firms reduce total assets, sales, and cost of sales by more than low debt firms. This pattern is consistent with the main finding that high debt firms cut tangible capital more, indicating a scaling down of production and a reduction in balance sheet size. Differences are not statistically significant for inventories, intangible assets, or R&D expenditure. For intangible assets and R&D expenditure there are substantial missing observations, so these results should be interpreted with caution.

B.6. FOMC Risk News Shock and Credit Spread

[Figure 15 around here]

Figure 15 shows the relationship between the FOMC risk news shock and the subsequent Moody's BBB–AAA credit spread. I regress the spread on the FOMC risk news shock, controlling for the concurrent interest-rate surprise and lagged macroeconomic conditions. The estimates indicate that a positive risk news shock is associated with a wider BBB–AAA spread, implying higher funding costs for lower-rated borrowers and consistent with flight-to-quality behavior.

B.7. Interest Expense Responses by Debt Burden

In this section I examine heterogeneous responses of interest expense by debt burden. The dependent variable is log interest expense (Compustat `xintq`) at horizons $t+1$, $t+4$, and $t+8$. Coefficients are interpreted as elasticities with respect to the FOMC risk news shock. Table 21 reports the results. Columns (1), (3), and (5) include year $\times$ industry fixed effects, so both the main shock coefficient and the interaction with net market leverage are identified. Columns (2), (4), and (6) include quarter $\times$ industry fixed effects, which absorb common time variation; in these specifications only the interaction term is identified.

[Table 21 around here]

Three patterns emerge from Table 21. First, the main shock coefficient is positive but not statistically significant, indicating a modest baseline increase in interest expense. Second, all interaction terms are positive, showing that high debt firms increase interest expense by more than low debt firms after risk rasing announcement news. Third, the differential response is strongest on impact, attenuates by $t+4$, and is not significant by $t+8$. This attenuation is also evident in Figure 16, which plots the interaction coefficients and confidence bands over the next eight quarters.

[Figure 16 around here]

Interest expense on its own is not informative, since it can rise because financing becomes more expensive or because firms borrow more. Combined with the separate result that high debt firms reduce debt growth after risk rasing announcement news, the increase in interest expense points toward higher financing costs, consistent with a flight to quality that limits high debt firms' access to funding.

B.8. Robustness to Low-Leverage Exclusions: Bottom Decile and AZL

[Table 22 around here]

Figure 4 shows that firms in the bottom 5% of lagged *netML* exhibit abnormally high credit risk. Excluding these firms, the relationship between *netML* and credit ratings is monotonic: higher *netML* corresponds to higher credit risk. The flight to quality pattern should therefore persist after removing these extremely low leverage firms. To test robustness, I reestimate the main results on a sample that drops the bottom decile of lagged *netML*. The results indicate that the pattern is driven by high leverage firms rather than by extremely low leverage firms, consistent with flight to quality.

[Table 23 around here]

Friewald et al. [2022] argue that firms with almost zero leverage are irrelevant for rollover dynamics and therefore exclude them. To ensure that my finding—that the investment response is concentrated among firms with high rollover risk—is not driven by zero leverage firms, I exclude firms with almost zero leverage (AZL) and reestimate the triple interaction regression. Specifically, I drop all observations with net market leverage below 0.05.[57] In the remaining All-but-AZL sample, I define high leverage firms as those with net market leverage above the 75th percentile pooled across firms and time. High rollover need firms are those with a short term debt maturity ratio above the median in the same sample. As shown in Table 23, this adjustment leaves the main results unchanged: firms with high net market leverage and high rollover need reduce investment significantly after an FOMC cash flow risk shock. This supports the view that rollover risk links external financing costs to investment.

B.9. Response of the Cost of Capital by Rollover Risk

[Figure 17 around here]

In this section, I examine how rollover risk shapes the heterogeneous response of the cost of capital to the FOMC risk news shock. The cost of capital is proxied by an ex post measure, the realized equity return. Figure 17 shows average responses for four groups formed by the 2×2 split using net market leverage (high if above the 75th percentile) and rollover need (high if above the median). FOMC risk news shocks are followed by an increase in the cost of capital over the subsequent four quarters. The increase is strongest for firms with both high leverage and high rollover need (i.e., shorter debt maturity), indicating elevated rollover risk. The pattern is robust to an alternative leverage cutoff that defines high as a net market leverage value above the 90th percentile across firms and time. Overall, these results suggest that firms facing greater rollover risk experience a larger cost of capital response to the FOMC risk news shock.

[57] The cutoff choice follows Strebulaev and Yang [2013], who use book leverage; here I use net market leverage.

B.10. Alternative Risk Index

The main results in this paper rely on the risk news shock identified from the structural VAR in Cieslak and Pang [2021]. This structural approach provides clear economic interpretation for the identified shock but may be sensitive to misspecification. To assess robustness—especially for the response heterogeneity results—I consider two alternative reduced form proxies for the FOMC risk news shock. First, I use the BBM risk index of Bauer et al. [2023], defined as the first principal component of fourteen risk sensitive financial indicators spanning multiple asset classes. The idea is that aggregate risk perception in financial markets should be reflected in prices across asset classes. Second, I use the option implied lower bound on the equity risk premium, SVIX^2, from Martin [2017], which is constructed from risk neutral volatility. Neither proxy separates cash flow risk from other sources of risk. However, Table 2 shows that both are highly correlated with the cash flow (fundamental) risk component extracted from the structural VAR, suggesting that perceived cash flow risk is an important component of these alternative measures. For the regressions, I construct quarterly proxies by summing the FOMC announcement day changes in each measure within the quarter, aligning the series with the firm level panel.

[Table 24 around here]

Table 24 replicates the main firm level investment results using the BBM risk index as a proxy for the FOMC risk news shock. Two findings emerge. First, the main heterogeneity results are qualitatively unchanged: risk increasing news predicts lower investment, with the effect stronger among firms with high debt burden and high rollover risk. Consistent with the flight to quality in credit market, high debt burden firms also reduce debt growth and accumulate more cash. Second, while the heterogeneous responses remain statistically significant, the average firm investment response is less significant. A plausible explanation is that the BBM proxy does not isolate perceived cash flow risk from other risks. This does not alter the paper's central mechanism: the heterogeneous response and the implied transmission channel remain robust. Note that the baseline already implies an economically modest average response; the BBM risk index delivers a result that is economically consistent with the baseline evidence.

[Figure 18 around here]

Figure 18 examines the robustness of the subgroup average responses by using the BBM risk index as a proxy for the FOMC risk news shock and applying the dummy interaction specification in Equation 13. The patterns are consistent with the baseline. In particular, the debt reallocation between high debt burden and low debt burden firms persists, and the investment response remains concentrated among firms with high rollover risk, as in the baseline subgroup average analysis.

[Table 25 around here]

Table 25 replicates the main firm level results using changes in SVIX^2 as an alternative proxy for the FOMC risk news shock. The findings are similar to those based on the BBM risk index. While the average effect is less significant, the heterogeneous effects on investment, debt, and cash holdings remain statistically significant. These results support the robustness of the main findings.

B.11. Controlling for Other Policy Rate Surprises

As a robustness check, I replace the baseline policy rate surprise controls (the one from Nakamura and Steinsson [2018a]) with the Gürkaynak, Sack, and Swanson (GSS) factors [Gürkaynak et al., 2004]. The GSS shocks, widely used in the literature, are obtained as principal components of changes in interest-rate futures within a short window around FOMC announcements: the first ("target") factor captures the change in the short-term policy target, and the second ("path") factor reflects expectations about the future path of policy (forward guidance). I aggregate both factors to the quarterly frequency and include them as controls. Table 26 reports the results. Column (1) includes the target and path factors as controls. Columns (2)–(5) interact these factors with the net debt-to-market ratio to test whether the effects of GSS policy rate surprises vary with firms' debt burdens. The findings closely match the baseline: the signs and magnitudes of the heterogeneous responses are robust, and the main conclusions are unchanged. In unreported tests, I also control for the interest-rate surprise orthogonal to lagged macroeconomic conditions from Bauer and Swanson [2023]; the results remain robust.

[Table 26 around here]

B.12. Manufacturing Subsample

I replicate the main analysis using a subsample of manufacturing firms (SIC 3000–3999). Tangible capital investment is especially salient for these firms, whose production relies heavily on plants and fixed equipment. Manufacturing observations account for nearly half of the full sample. Because these firms operate within the same broad sector, their investment opportunities are more comparable than in the full cross-section. Table 27 reports the results. The findings closely mirror the baseline: all main effects are consistent in sign and magnitude, with one exception—the heterogeneous investment response by net market leverage is not statistically significant. Overall, these results indicate that the baseline patterns are not primarily driven by sectoral differences.

[Table 27 around here]

B.13. Using Market Leverage

Table 28 re-estimates the baseline specifications replacing the debt-burden measure, net market leverage (net debt-to-market ratio), with market leverage (debt-to-market ratio). The latter does not adjust for preferred stock or cash holdings and is defined as total debt divided by market equity. Despite this change in measurement, the heterogeneous firm responses remain almost unchanged relative to the baseline.

[Table 28 around here]

B.14. Control for growth expectation

I construct contemporaneous growth expectation revisions using the Survey of Professional Forecasters (Philadelphia Fed). For the long run expectation, I use the mean 10 year expected real GDP growth. This item is collected once at the beginning of each year, so I take the year over year change and assign that revision to all quarters of the same year to capture policy related shifts in long run beliefs.

For the short run expectation, which is available quarterly, I proxy the short run growth expectation by the average of the current quarter and the next four quarters of expected real GDP growth. Because the survey is fielded in the second month of each quarter and may occur before or after the FOMC announcement, I define the quarterly short run revision as the change from one quarter ahead to one quarter behind (lead one minus lag one). This ensures that the monetary policy announcement in that quarter lies within the expectation revision window.

Table 29 reports results after controlling for both revisions. Panel (a) uses the FOMC risk news shock based on the structural cash flow risk news shock, and Panel (b) uses the BBM risk index. Column (1) includes the two revisions. Columns (2) to (4) include their interactions with net market leverage. Column (5) adds the interaction for the high leverage and high refinancing intensity indicator. Across specifications, the results remain qualitatively consistent with the main findings.

[Table 29 around here]

B.15. Role of book to market ratio

I examine whether the response to the announcement risk news varies with the lagged book to market (B/M) ratio. Columns (1)–(3) of Table 30 show no statistically significant B/M×shock interaction for investment, debt, or cash. Column (4) shows that adding the B/M interaction does not change the stronger response of high rollover risk firms. Taken together, the evidence points to financial frictions and financing costs as the main transmission of announcement risk news, rather than investment delays implied by the real options view.

[Table 30 around here]

C. Model Derivation

C.1. Derivation

Substitute the policy rule into the consumption growth equation:

$$x_t = \theta(\phi x_t + \epsilon_t) + v_t,$$

and solve for x_t:

$$x_t = \frac{\theta}{1-\theta\phi}\epsilon_t + \frac{1}{1-\theta\phi}v_t.$$

Define $\omega = \frac{1}{1-\theta\phi}$, then:

$$x_t = \omega\theta\epsilon_t + \omega v_t.$$

Comparative Static of $\sigma^2_{v,t+1}$ with Respect to ϵ_t

Future variance of v_t is influenced by x_t:

$$\sigma^2_{v,t+1} = \exp(a - bx_t),$$

The sensitivity of $\sigma^2_{v,t+1}$ with respect to ϵ_t is:

$$\frac{d\sigma^2_{v,t+1}}{d\epsilon_t} = \exp(a - bx_t) \cdot (-b)\frac{dx_t}{d\epsilon_t}.$$

Since $\frac{dx_t}{d\epsilon_t} = \omega\theta$, evaluating at $x_t = 0$:

$$\left.\frac{d\sigma^2_{v,t+1}}{d\epsilon_t}\right|_{x_t=0} = -b\omega\theta\exp(a).$$

Comparative Static of $\sigma^2_{x,t+1}$ with Respect to ϵ_t

The variance of the next period's consumption growth is:

$$\sigma^2_{x,t+1} = \omega^2(\theta^2\sigma^2_\epsilon + \exp(a - bx_t)),$$

The sensitivity with respect to ϵ_t is:

$$\frac{d\sigma^2_{x,t+1}}{d\epsilon_t} = \omega^2 \cdot \frac{d}{d\epsilon_t}\exp(a - bx_t).$$

Applying the chain rule:

$$= \omega^2\exp(a - bx_t) \cdot (-b)\frac{dx_t}{d\epsilon_t}.$$

Substitute $\frac{dx_t}{d\epsilon_t} = \omega\theta$, evaluating at $x_t = 0$:

$$\left.\frac{d\sigma^2_{x,t+1}}{d\epsilon_t}\right|_{x_t=0} = -b\omega^3\theta\exp(a).$$

C.2. Risk-Free Rate and Risky Return

The stochastic discount factor (SDF) is:

$$M_{t+1} = \beta\exp(-\gamma x_{t+1}),$$

From the Euler equation, the time-t log real risk-free rate is:

$$1 = E_t\left[\exp(r_{ft})M_{t+1}\right] = \exp(r_{ft})\beta\exp\left(\frac{1}{2}\gamma^2\sigma^2_{x,t+1}\right),$$

which leads to:

$$r_{ft} = -\ln(\beta) - \frac{1}{2}\gamma^2\sigma^2_{x,t+1}.$$

The marginal return on capital for firm i is:

$$R_{it+1} = \frac{\frac{dY_{it+1}}{dK_{it+1}}}{\frac{d\Phi_{it}}{dI_{it}}} = \frac{\exp\left(s_i x_{t+1} - \frac{1}{2}s_i^2\sigma^2_{x,t+1}\right)}{\phi'\left(\frac{I_{it}}{K_{it}}\right)}.$$

Taking the conditional expectation based on information available at time t:

$$E_t[R_{it+1}] = \frac{1}{\phi'\left(\frac{I_{it}}{K_{it}}\right)}.$$

Substituting R_{it+1} into the Euler equation:

$$1 = \frac{E_t\left[M_{t+1}\exp\left(s_i x_{t+1} - \frac{1}{2}s_i^2\sigma^2_{x,t+1}\right)\right]}{\phi'\left(\frac{I_{it}}{K_{it}}\right)} = \frac{\beta\exp\left(\frac{1}{2}\left((\gamma - s_i)^2 - s_i^2\right)\sigma^2_{x,t+1}\right)}{\phi'\left(\frac{I_{it}}{K_{it}}\right)}.$$

Thus, the logarithm of the expected return on capital must satisfy:

$$\ln\left(E_t[R_{it+1}]\right) = -\ln\beta - \frac{1}{2}\left((\gamma - s_i)^2 - s_i^2\right)\sigma^2_{x,t+1}.$$

Finally, combining this with the expression for the real risk-free rate, I obtain the equation for the excess return:

$$\ln\left(E_t[R_{it+1}]\right) - r_{ft} = \gamma s_i\sigma^2_{x,t+1}.$$

D. Detail of the Structural VAR

The empirical structural VAR model with sign and magnitude restrictions proposed in Cieslak and Pang [2021] aims to recover economic shocks from asset prices. This model is based on the intuition that asset prices can be decomposed as an affine function of state variables. Macro-finance models typically embed exogenous shocks to the endowment process, risk premia, and short-term interest rates to drive asset pricing dynamics. The restrictions are also motivated by the structure of macro-finance theory regarding how shocks influence asset prices.

The detail of the VAR is as follows: assume asset prices X_{t+1} are driven by shocks to the state variables ω_{t+1}^{f} following a VAR process:

$$X_{t+1} = \mu + \Phi X_t + B\omega_{t+1}^{f},$$

where X_t is the vector of daily asset price changes:

$$X_t = (\Delta y_t^{(2)},\ \Delta y_t^{(5)},\ \Delta y_t^{(10)},\ r_t^{e}),$$

representing the changes in zero-coupon Treasury yields for 2, 5, and 10 years, as well as the market return. Here, μ is a constant, and Φ is the matrix of dynamic coefficients. The vector of shocks to the state variables is:

$$\omega_{t+1}^{f} = (w_t^{c},\ w_t^{d},\ w_t^{cr},\ w_t^{dr}),$$

The four shocks have unit variance, i.e., $\mathrm{Var}(\omega_t^{f}) = I$. B is the impact matrix that governs the contemporaneous structural relationships between the shocks and asset prices. By imposing restrictions on the impact matrix B (described later) according to the structural relation between shocks and asset pricing in macro-finance models, the identified shocks in ω_{t+1}^{f} can acquire distinct economic interpretations related to the typical state variables in macro-finance, including cash flow, discount rate, and risk premium. The four economic shocks this structural VAR aims to obtain are:

1. **Cash flow growth shock** ω_{t+1}^{c}: captures investors' expectations about future cash flow growth.

2. **Discount rate shock** ω_{t+1}^{d}: affects the risk-free component of the discount rate.

3. **Discount rate risk premium shock** w_t^{dr}: reflects the compensation investors demand for exposure to discount rate uncertainty, driving both bond and stock prices in the same direction.

4. **Cash flow risk premium shock** w_t^{cr}: captures the compensation investors require

for equity cash flow risk, with bonds acting as a hedge and thus moving in the opposite direction to equities.

These two risk premium shocks build on the view that an equity claim can be thought of as a combination of a long-term bond that is only exposed to discount rate uncertainty and a risky cash flow claim that is exposed to both discount rate and cash flow uncertainty.

To identify the four economic shocks, two main sets of restrictions motivated by macro-finance theory are imposed on the impact matrix B:

$$B = \begin{pmatrix} b_c^{(2)} & b_d^{(2)} & b_{cr}^{(2)} & b_{dr}^{(2)} \\ b_c^{(5)} & b_d^{(5)} & b_{cr}^{(5)} & b_{dr}^{(5)} \\ b_c^{(10)} & b_d^{(10)} & b_{cr}^{(10)} & b_{dr}^{(10)} \\ b_c^{e} & b_d^{e} & b_{cr}^{e} & b_{dr}^{e} \end{pmatrix}$$

The first set of restrictions applies cross-maturity constraints. These restrictions are motivated by the intuition from affine term structure models and empirical evidence: the effects of short-term rate-related shocks—namely, the cash flow growth shock and the discount rate shock—decline with maturity, as these shocks are typically mean-reverting and thus have diminishing influence in the long run. In contrast, long-term bonds are more exposed to uncertainty about the future and therefore more sensitive to risk premium shocks. Formally, this set of restrictions imposes a monotonic relationship on the magnitude of each shock's impact on bond yields across maturities: the impact of short-term rate-related shocks decreases with maturity, while the impact of risk premium shocks increases with maturity. These cross-maturity restrictions help separate the two **risk premium shocks** from the two short-term rate-related shocks. Specifically, the imposed restrictions are as follows:

Cash Flow Growth: $|b_c^{(2)}| > |b_c^{(10)}|$ and $|b_c^{(5)}| > |b_c^{(10)}|$, **Discount Rate:** $|b_d^{(2)}| > |b_d^{(5)}| > |b_d^{(10)}|$,

Cash Flow Risk: $|b_{cr}^{(2)}| < |b_{cr}^{(5)}| < |b_{cr}^{(10)}|$, **Discount Rate Risk:** $|b_{dr}^{(2)}| < |b_{dr}^{(5)}| < |b_{dr}^{(10)}|$.

After applying the cross-maturity restrictions, the second set consists of sign restrictions, which aim to further distinguish the two cash flow risk premium shocks—specifically, to separate the cash flow risk shock from the discount rate risk shock. These sign restrictions are summarized by the following matrix:

$$\begin{pmatrix} + & + & - & + \\ + & + & - & + \\ + & + & - & + \\ + & - & - & - \end{pmatrix}$$

The intuition behind these sign restrictions is as follows: A positive cash flow growth shock, denoted by ω_{t+1}^{c}, increases both bond yields and equity returns, reflecting improved economic fundamentals.[58] In contrast, a positive discount rate shock, ω_{t+1}^{d}, raises bond yields and reduces equity returns, as it leads to heavier discounting of future cash flows.A positive cash flow risk premium shock, w_t^{cr}, increases the compensation required by investors for bearing equity cash flow risk, thereby lowering equity prices. However, since bonds are not exposed to this risk and act as a hedge, their yields tend to decline(bond price increase). In contrast, a positive discount rate risk premium shock, w_t^{dr}, raises the expected returns on both bonds and equities, but depresses their current prices as investors demand compensation for an unhedgeable source of risk that affects both asset classes. The two-factor structure of the risk premium is based on the idea that an equity claim can be viewed as a combination of a long-term bond and a risky cash flow component. These opposing co-movements between bond yields and equity returns are essential for distinguishing the cash flow risk shock from the discount rate risk shock and ensuring that the identified cash flow risk shock is consistent with the conceptual framework.

In addition to the two main sets of restrictions, Cieslak and Pang [2021] introduces a third set of within-asset restrictions. These restrictions govern the relative contribution of different shocks to the conditional volatility of Treasury yields across maturities. Specifically, they reflect the idea that the volatility of short-term Treasury yields (e.g., 2-year) is primarily driven by cash flow and discount rate shocks, while the volatility of long-term Treasury yields (e.g., 10-year) is mainly influenced by risk premium shocks:

$$\left(b_c^{(2)}\right)^2 + \left(b_d^{(2)}\right)^2 > \left(b_{cr}^{(2)}\right)^2 + \left(b_{dr}^{(2)}\right)^2$$
$$\left(b_c^{(10)}\right)^2 + \left(b_d^{(10)}\right)^2 < \left(b_{cr}^{(10)}\right)^2 + \left(b_{dr}^{(10)}\right)^2$$

The estimation process follows the standard procedure for sign-restricted VARs, beginning with the Cholesky decomposition of the variance-covariance matrix of the reduced-form shocks u_t:

$$\Omega_u = PP',$$

where P is a lower triangular matrix. The reduced-form shocks can then be written as $u_t = P\omega_t^*$, where ω_t^* represents orthonormal shocks with $\mathrm{Var}(\omega_t^*) = I$. These shocks correspond to a recursive identification, and their economic interpretation depends on the variable ordering—a feature that is generally not aligned with my intended interpretation. To address this limitation, we can apply an *orthonormal rotation matrix* Q_i to generate alternative sets of uncorrelated shocks:

$$\omega_t(Q_i) = Q_i\omega_t^*,$$

which preserves orthogonality, since $Q_iQ_i' = I$. The corresponding representation of the

[58] Periods of strong economic growth are typically associated with higher discount rates and bond yields due to the 'Ramsey' component in the stochastic discount factor.

reduced-form shocks becomes:

$$u_t = PQ_i'\omega_t(Q_i),$$

where $B = PQ_i'$ serves as the impact matrix of interest. The rotation matrices Q_i are generated using *QR decomposition*, and only those for which $B = PQ_i'$ satisfies the previously discussed sign and magnitude restrictions are retained. This procedure is repeated until 1,000 admissible shock sets $\omega_t(Q_i)$ are obtained. From these, the final structural shocks ω_t are selected using the *median target (MT)* approach, in which the asset price responses associated with the chosen shock set are closest to the median responses across all 1,000 admissible sets.

In my empirical implementation, using data from 1983 to 2023, we obtain the impact matrix B selected via the median target (MT) approach as follows:

$$B = \begin{pmatrix} 0.0340 & 0.0363 & -0.0190 & 0.0157 \\ 0.0370 & 0.0246 & -0.0243 & 0.0364 \\ 0.0195 & 0.0180 & -0.0365 & 0.0417 \\ 0.5770 & -0.4803 & -0.6653 & -0.5414 \end{pmatrix}$$

As shown, the coefficients for the equity market return are considerably larger than those for bond yields. This reflects the much higher volatility of equity returns compared to Treasury yields.

I follow the same procedure as in Cieslak and Pang [2021], applying the identified shocks in a local projection framework to estimate the impulse responses of asset prices over a one-year horizon. Figure 19 presents the daily impulse response of asset prices to a one-standard-deviation cash flow risk shock. The results show that the shock has highly persistent effects on both Treasury yields and equity returns. Importantly, the response is statistically significant and remains economically meaningful throughout the one-year period following the initial impact.

[Figure 19 around here]

Moreover, my estimated cash flow risk shock—based on a longer sample (1983–2023)—produces a larger immediate effect on equity prices, with a decline of 66.5 basis points, compared to 63 basis points reported in the original study using data through 2017. It is important to note that the shocks are constructed to have zero mean and unit standard deviation. Thus, the impulse responses quantify the effect of a one-standard-deviation cash flow risk shock across all trading days. In my case, this corresponds to a 66.5 basis point drop in the equity index and a 3.7 basis point decline in the 10-year Treasury yield, providing a concrete benchmark for interpreting the magnitude of the estimated shock.

[Table 31 around here]

Table 31 reports the correlations between the original shock series identified by Cieslak and Pang [2021], using data from 1983 to 2017, and my updated shock series constructed using data from 1983 to 2023. Since the estimation period differs, the resulting impact matrices—and consequently, the identified shocks—may also differ. However, as shown in the table, the two sets of estimated shocks are highly correlated over their overlapping sample period. This is particularly true on FOMC announcement days, where the correlation coefficients for all four shocks exceed 0.999. In addition, Figure 20 plots my updated cash flow risk shock on the x-axis against the original series on the y-axis. The figure demonstrates that, for both all trading days and FOMC announcement days, the observations lie nearly along the 45-degree line, indicating an extremely strong correlation between the two series. Together, the table and figure confirm the consistency of my updated shock estimates relative to the original series.

[Figure 20 around here]

E. Decomposition of Aggregate Investment

I follow the decomposition method outlined in Crouzet and Mehrotra [2020]. The construction of the variables is as follows: consider a group of firms with high rollover risk. Let:

$$\hat{i}_{t+8}^{\text{high}} = \frac{1}{\#S_t^{\text{high}}} \sum_{i \in S_t^{\text{high}}} i_{i,t+8}$$

$$\hat{\text{cov}}_{t+8}^{\text{high}} = \sum_{i \in S_t^{\text{high}}} \left(w_{i,t} - \frac{1}{\#S_t^{\text{high}}} \right) \left(i_{i,t+8} - \hat{i}_{t+8}^{\text{high}} \right)$$

where S_t^{high} is the set of firms with high rollover risk at time t, and $w_{i,t} = \frac{k_{i,t}}{K_t}$ represents the share of each firm in the group. The covariance term captures the relationship between each firm's initial size and its subsequent investment. Since aggregate investment can be viewed as the size-weighted sum of firm-level investment, I can express it as:

$$G_{t+8}^{\text{high}} = \hat{i}_{t+8}^{\text{high}} + \hat{\text{cov}}_{t+8}^{\text{high}}$$

Next, consider two groups of firms: those with high rollover risk and those with low rollover risk. Aggregate investment growth can then be decomposed as:

$$G_{t+8} = s_t G_{t+8}^{\text{high}} + (1 - s_t) G_{t+8}^{\text{low}}$$

where s_t is the capital share of high-rollover-risk firms, defined as $s_t = \frac{K_t^{\text{high}}}{K_t}$. Thus, total investment growth can be further decomposed as:

$$G_{t+8} = s_t \hat{i}_{t+8}^{\text{high}} + s_t \hat{\text{cov}}_{t+8}^{\text{high}} + (1 - s_t) \hat{i}_{t+8}^{\text{low}} + (1 - s_t) \hat{\text{cov}}_{t+8}^{\text{low}}$$

Table 15: Summary Statistics: Full Sample

Variable	**P10**	**Median**	**P90**	**Mean**	**Std Dev**	**Observations**
Investment Rate	-0.081	0.000	0.124	0.018	0.118	312,661
Cash Growth	-0.450	-0.005	0.882	0.209	0.936	315,560
Debt Growth	-0.222	-0.004	0.264	0.031	0.377	253,008
net Debt to Market Ratio	-0.287	0.055	1.041	0.276	0.768	266,633
log Total Asset	2.278	5.591	8.716	5.512	2.422	323,162
Short term asset ratio	0.169	0.518	0.870	0.520	0.251	316,942
Return of Asset	-0.120	0.007	0.036	-0.025	0.101	323,868
Sale Growth	-0.201	0.019	0.288	0.042	0.255	308,262
Operation Leverage	0.065	0.222	0.562	0.277	0.215	324,677
Reifinancing Intensity	0.000	0.128	0.977	0.289	0.339	260,904

This table presents firm-level summary statistics for the full sample used in analysis. All variables are quarterly data from Compustat, covering the period from 1995 to 2023.

Table 16: Summary Statistics: Firms with Rollover Risk Measure

Variable	**P10**	**Median**	**P90**	**Mean**	**Std Dev**	**Observations**
Investment Rate	-0.063	0.002	0.101	0.015	0.090	215,217
Cash Growth	-0.437	0.000	0.848	0.182	0.809	214,311
Debt Growth	-0.202	-0.004	0.242	0.029	0.331	209,613
Net Debt to Market Ratio	-0.184	0.130	1.233	0.398	0.857	215,513
Log Total Asset	3.294	6.283	9.062	6.231	2.124	219,166
Short-Term Asset Ratio	0.158	0.465	0.799	0.474	0.230	215,790
Return on Assets	-0.066	0.009	0.033	-0.007	0.055	218,770
Sales Growth	-0.182	0.019	0.250	0.034	0.208	215,404
Operating Leverage	0.069	0.217	0.512	0.259	0.181	219,038
Refinancing Intensity	0.000	0.107	0.851	0.251	0.312	213,788

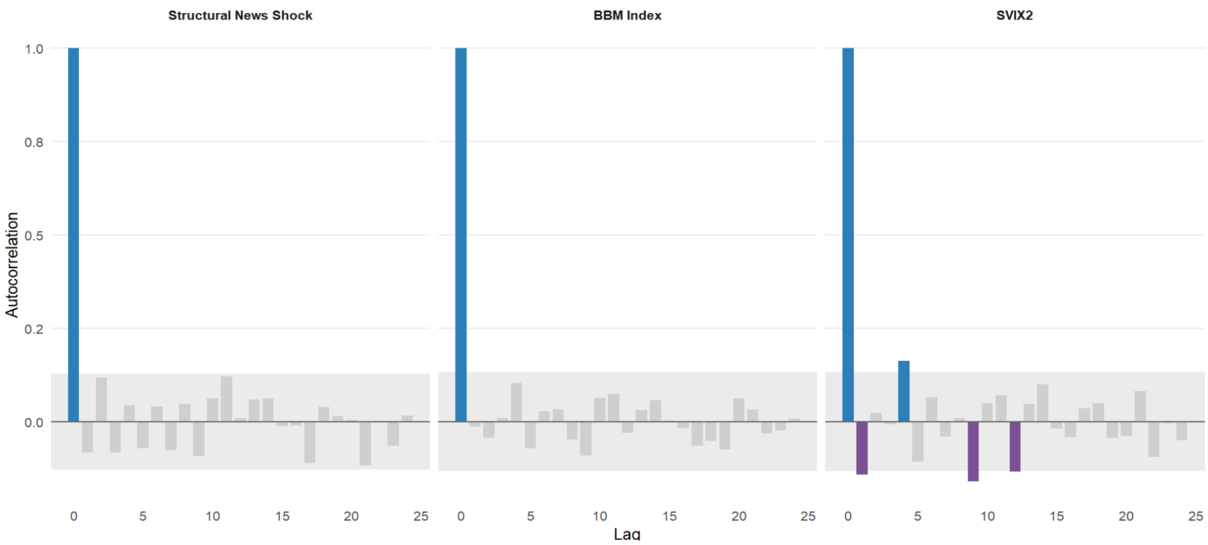
This table reports firm-level summary statistics for firms with non-missing values for both net debt-to-market ratio and refinancing intensity. All variables are quarterly data from Compustat, covering the period from 1995 to 2023.

Table 17: Appendix:Predicting FOMC Risk News Shocks with Macroeconomic and Financial Data

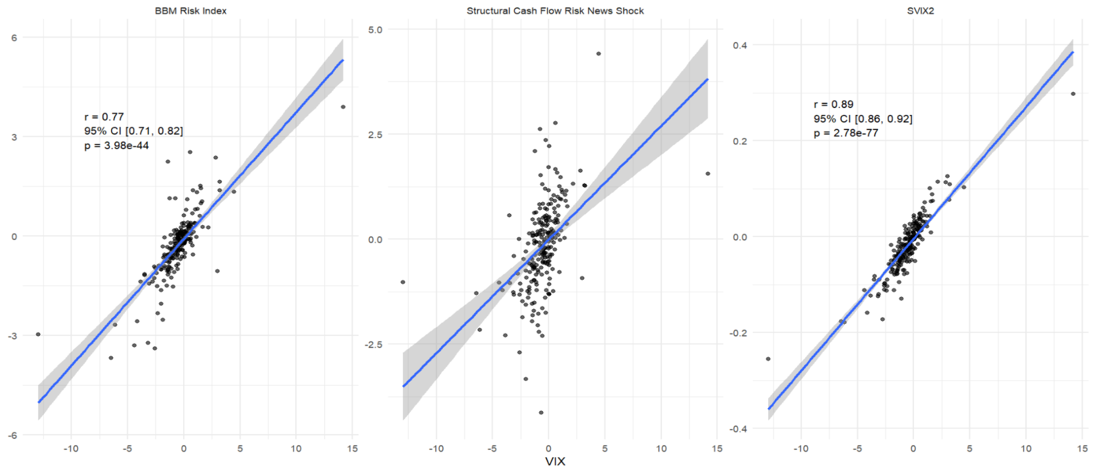
	Structural Shock	BBM Index	SVIX2
Nonfarm payrolls	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Empl. growth (12m)	-0.002	0.021	-0.003
	(0.035)	(0.044)	(0.002)
Δ log S&P 500 (3m)	-0.139	-1.519	0.154**
	(1.343)	(1.859)	(0.070)
Δ Slope (3m)	-0.161	0.034	0.001
	(0.155)	(0.113)	(0.007)
Δ log Comm. price (3m)	-0.091	-0.310	-0.045
	(1.057)	(1.144)	(0.054)
Treasury skewness	-0.235	0.117	-0.002
	(0.191)	(0.167)	(0.012)
Observations	220	220	220
R^2	0.013	0.024	0.044

This table reports predictive regressions for three FOMC risk news shock measures using macroeconomic and financial variables. Shock measures are constructed from FOMC announcement-day observations at the daily frequency and aggregated to the quarterly level. The sample spans 1995–2023. Standard errors are Newey–West with 8 lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

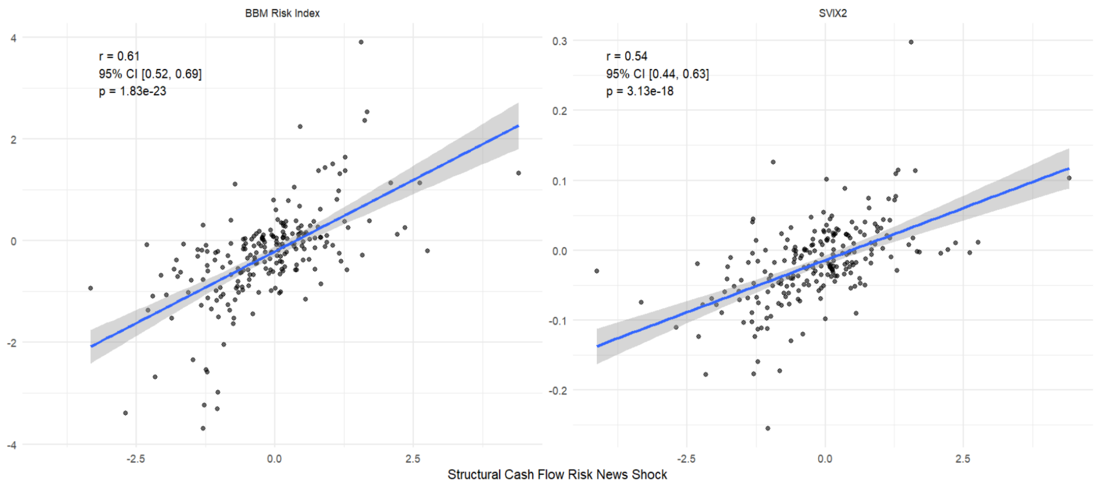
Figure 13: Appendix: Autocorrelation of FOMC Risk News Shocks



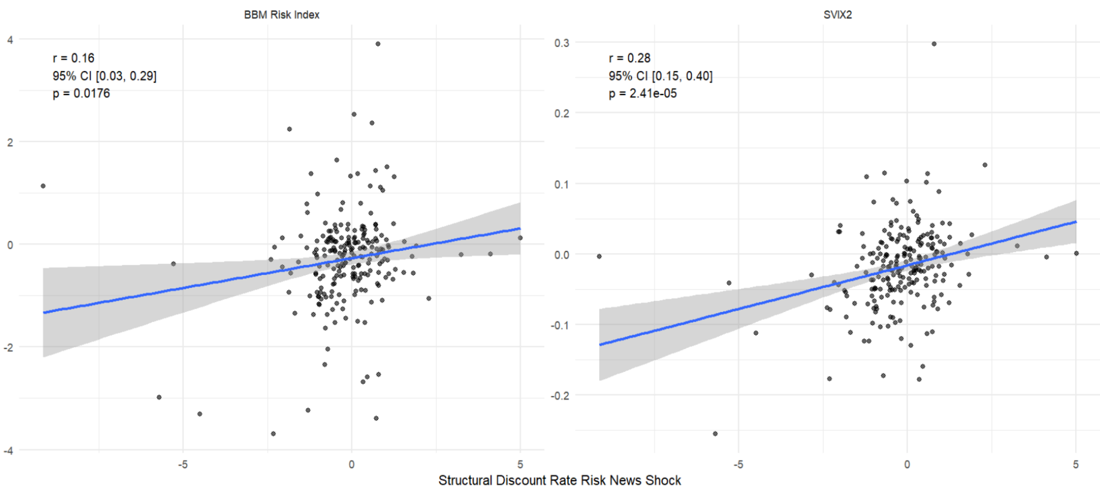
This figure plots the sample autocorrelation functions for three FOMC risk news shock measures over lags 0–25. The shaded bands represent 95% confidence intervals.



(a) Three risk news measures and VIX



(b) Reduced form measures vs. structural cash flow risk news shock



(c) Reduced form measures vs. structural discount rate risk news shock

Figure 14: Daily correlations between risk news and volatility measures on FOMC announcement days

Table 18: Appendix: S&P Credit Ratings and Reverse Credit Scores

Panel A: Long Term Bond

Rating	Reverse score
AAA	1
AA+	2
AA	3
AA-	4
A+	5
A	6
A-	7
BBB+	8
BBB	9
BBB-	10
BB+	11
BB	12
BB-	13
B+	14
B	15
B-	16
CCC+	17
CCC	18
CCC-	19
CC	20
C	21
SD	22

Panel B: Short Term Bond

Rating	Reverse score
A-1	1
A-2	2
A-3	3
B	4
B-1	5
B-2	6
B-3	7
C	8
D	9

This table lists S&P long- and short-term credit ratings and their corresponding reverse credit scores (higher values indicate higher default risk).

Table 19: Appendix: Average Reverse Credit Score by Decile of Net Market Leverage

Panel A: Long term bond rating										
Net Market Leverage	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
	1–10%	11–20%	21–30%	31–40%	41–50%	51–60%	61–70%	71–80%	81–90%	91–100%
Average Reverse Score	9.81	8.34	8.57	9.23	10.05	10.68	11.33	11.94	12.86	14.51
Observations	5888	5888	5888	5888	5888	5888	5888	5888	5887	5887
Panel B: Short term bond rating										
Net Market Leverage	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
	1–10%	11–20%	21–30%	31–40%	41–50%	51–60%	61–70%	71–80%	81–90%	91–100%
Average Reverse Score	1.65	1.49	1.45	1.52	1.64	1.73	1.88	2.03	2.26	2.85
Observations	1412	1412	1411	1411	1411	1411	1411	1411	1411	1411

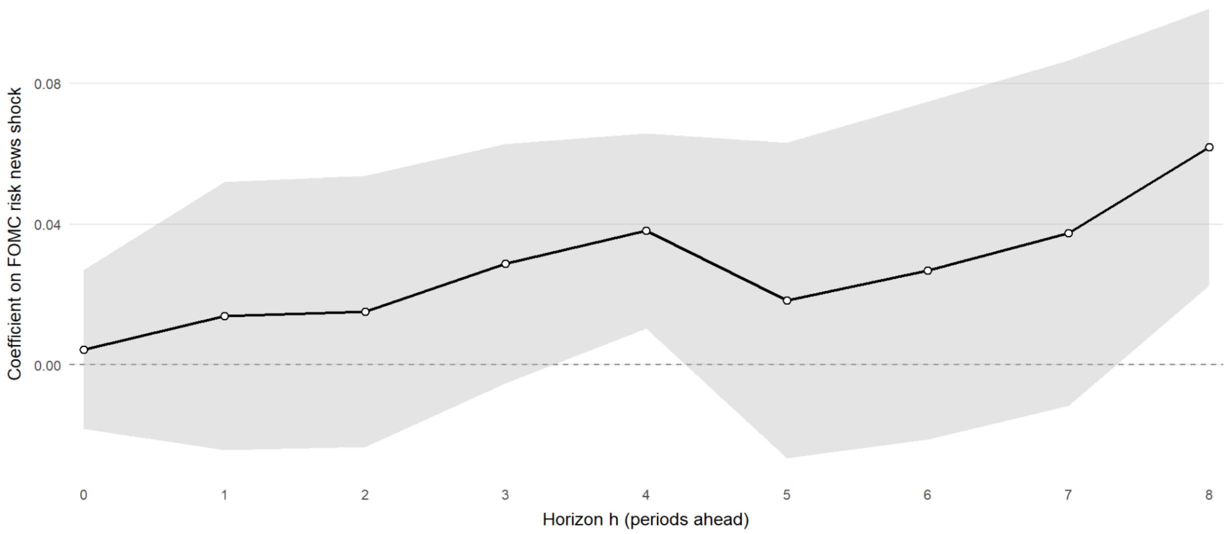
This table shows the average reverse credit score by decile of lagged net market leverage (*netML*). Reverse scores are based on S&P credit ratings from 1995–2017. Observations require non-missing values for both lagged *netML* and the rating.

Table 20: Appendix: Heterogeneous Responses of Other Firm Outcomes by Debt Burden

	(1) Inventory	(2) Total Asset	(3) Intangible	(4) Sale	(5) COGS	(6) R&D
$\epsilon_t^{cr} \times netML_{t-1}$	-0.200	-0.898***	-6.521	-0.470***	-0.456***	1.434
	(0.265)	(0.168)	(18.419)	(0.145)	(0.120)	(1.109
Firm FE	✓	✓	✓	✓	✓	✓
Quarter $\times$ Industry FE	✓	✓	✓	✓	✓	✓
$\epsilon_t^{cr} \times$ Firm Controls	✓	✓	✓	✓	✓	✓
IR Surprise $\times netML_{t-1}$	✓	✓	✓	✓	✓	✓
Observations	189,405	238,724	146,294	236,895	236,630	103,55
Adjusted R^2	0.130	0.178	0.481	0.949	0.954	0.934
Sample Period	Full	Full	Full	Full	Full	Full

This table reports estimates from Equation 12 for heterogeneous responses of other firm outcomes by debt burden. Columns (1)–(3) use as dependent variables the cumulative change over the next four quarters in inventories, total assets, and intangible assets. Columns (4)–(6) use the log level in quarter t+4 of sales, cost of sales (COGS), and R&D expenditure. The key regressor is the interaction between the FOMC risk news shock and net market leverage. The sample is a quarterly Compustat panel from 1995–2023. Firm level controls (lagged one quarter) include size, net market leverage, sales growth, asset return, operating leverage, and the short term asset ratio. The interest rate surprise control follows Nakamura and Steinsson [2018a]. Standard errors (in parentheses) are computed using the Driscoll–Kraay method. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 15: Appendix: FOMC Risk News Shock and Moody's BBB–AAA Credit Spread



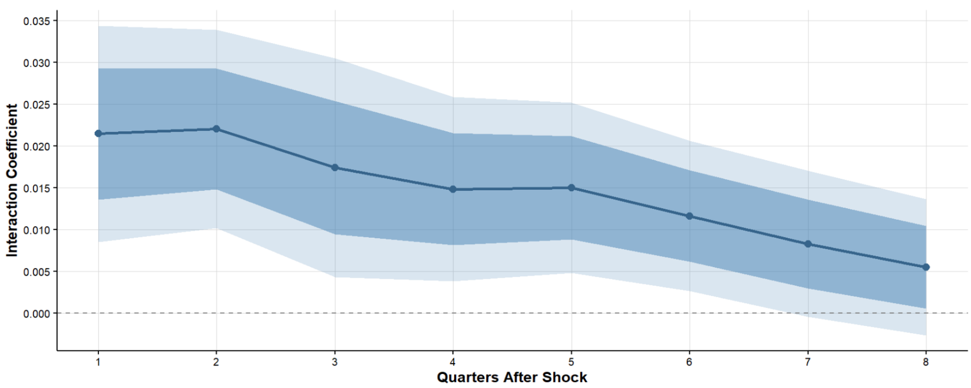
This figure shows the relationship between the FOMC risk news shock and Moody's BBB–AAA credit spread. Each point reports the coefficient from regressions of the future h-quarter change in the spread ($h = 0, \ldots, 8$) on the shock, controlling for the concurrent interest-rate surprise and two lags of GDP growth, the unemployment rate, and inflation. The shaded area denotes 90% confidence intervals based on Newey–West standard errors with 8 lags.

Table 21: Appendix: Interest expense elasticities with respect to FOMC risk news shocks

	log(XINT$_{t+n}$)					
	(1)	(2)	(3)	(4)	(5)	(6)
	n=1	n=1	n=4	n=4	n=8	n=8
ϵ_t^{cr}	1.304		1.579		2.160	
	(1.110)		(1.226)		(1.448)	
$\epsilon_t^{cr} \times netML_{t-1}$	2.167***	2.146***	1.450**	1.484**	0.570	0.550
	(0.776)	(0.786)	(0.653)	(0.669)	(0.491)	(0.494)
Firm FE	✓	✓	✓	✓	✓	✓
Year × Industry FE	✓		✓		✓	
Macro Controls	✓		✓		✓	
Quarter × Industry FE		✓		✓		✓
$\epsilon_t^{cr}\times$ Firm Controls	✓	✓	✓	✓	✓	✓
IR Surprise $\times netML_{t-1}$	✓	✓	✓	✓	✓	✓
Observations	189,668	189,668	182,273	182,273	172,094	172,094
Adjusted R^2	0.868	0.868	0.863	0.863	0.857	0.857
Sample Period	Full	Full	Full	Full	Full	Full

This table reports estimates specification Equation 12 for the response of interest expense to FOMC risk news shocks. The dependent variables are log interest expense (Compustat `xintq`) at quarters t+1, t+4, and t+8. The key regressor is the interaction between the FOMC risk news shock and net market leverage. The sample is a quarterly Compustat panel from 1995–2023. Firm level controls (lagged one quarter) include size, net market leverage, sales growth, asset return, operating leverage, and the short term asset ratio. The interest rate surprise control follows Nakamura and Steinsson [2018a]. Standard errors (in parentheses) are computed using the Driscoll–Kraay method. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 16: Appendix: Dynamic Response of Interest Expense



This figure plots the interaction-term coefficients from Table 21, column (2), where the dependent variable is log interest expense over the next eight quarters (t+1 to t+8). The series traces the dynamic elasticity of interest expense with respect to the FOMC risk news shock. Shaded bands denote 90% (outer) and 68% (inner) confidence intervals based on Driscoll–Kraay standard errors.

Table 22: Appendix: Robustness of Heterogeneous Responses Excluding the Bottom Decile of Net Market Leverage

	Capital	Debt	Cash	Capital	Capital
	(1)	(2)	(3)	(4)	(5)
$\epsilon_t^{cr} \times netML_{t-1}$	-1.018***	-4.218***	1.578*		
	(0.208)	(0.710)	(0.949)		
$\epsilon_t^{cr} \times netML_{t-1} \times \mathbf{1}\{RI_{t-1}^{high}\}$				-1.779***	
				(0.338)	
$\epsilon_t^{cr} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-1.352***
					(0.414)
Firm FE	✓	✓	✓	✓	✓
Quarter × Industry FE	✓	✓	✓	✓	✓
$\epsilon_t^{cr}\times$ Firm Controls	✓	✓	✓	✓	✓
Interest Rate Surprise × $netML_{t-1}$	✓	✓	✓	✓	✓
Observations	216,019	185,751	215,023	188,450	188,450
Adjusted R^2	0.163	0.070	0.082	0.173	0.177
Drop bottom 10% $netML_{t-1}$	✓	✓	✓	✓	✓
Sample Period	Full	Full	Full	Full	Full

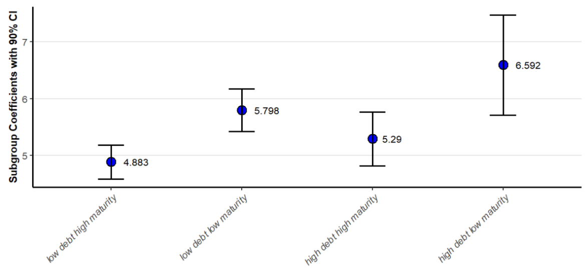
This table reports estimates from Equation 12 to assess the robustness of the main heterogeneous response after excluding firms whose lagged net market leverage lies in the bottom 10%. The dependent variables are the four quarter change in the log book value of tangible capital stock, log total debt, and log cash holdings. The key regressors are the FOMC risk news shock interacted with net market leverageThe key regressor is the interaction between the FOMC risk news shock and net market leverage. The sample is a quarterly Compustat panel from 1995–2023. Firm level controls (lagged one quarter) include size, net market leverage, sales growth, asset return, operating leverage, and the short term asset ratio. The interest rate surprise control follows Nakamura and Steinsson [2018a]. Standard errors (in parentheses) are computed using the Driscoll–Kraay method. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 23: Appendix: Robustness of the Rollover Risk Effect Excluding Almost Zero Leverage Firms

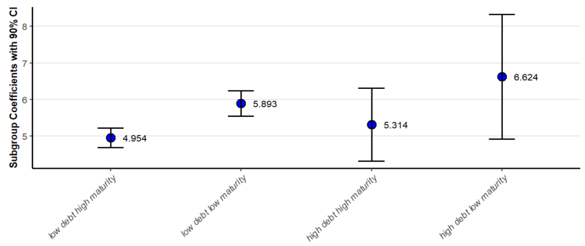
	$\log(k_{t+4}) - \log(k_t)$	
	(1)	**(2)**
$\epsilon_t^{cr} \times \mathbf{1}\{netML_{t-1}^{high}\}$	0.288	-0.02
	(0.201)	(0.493)
$\epsilon_t^{cr} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$	-1.198***	-1.55***
	(0.409)	(0.555)
Firm FE	✓	✓
Quarter × Industry FE	✓	✓
ϵ_t^{cr} × Firm Controls	✓	✓
$\Delta GDP_{t-1} \times netML_{t-1}$	✓	✓
Observations	133,225	71,280
Adjusted R^2	0.207	0.226
Drop AZL firms	✓	✓
Sample Period	Full	Post-2008

This table reports estimates from Equation 12. The dependent variable is the four quarter change in the log book value of tangible capital stock. The key regressor is a triple interaction of the FOMC risk news shock, an indicator for high net market leverage, $\mathbf{1}\{netML_{t-1}^{high}\}$, and an indicator for high rollover need, $\mathbf{1}\{RI_{t-1}^{high}\}$. The indicator $\mathbf{1}\{RI_{t-1}^{high}\}$ equals one for firms whose refinancing intensity (debt maturing within one year relative to total debt) is above the sample median; $\mathbf{1}\{netML_{t-1}^{high}\}$ equals one for firms with netML above the 75th percentile of the sample. The sample is a quarterly panel of Compustat firms from 1995 to 2023 and excludes firms with almost zero leverage, defined as netML below 0.05. Firm level controls (lagged one quarter) include size, net market leverage, sales growth, asset return, operating leverage, and the short term asset ratio. For brevity, coefficients on non interacted controls and on other double interactions are not reported. Standard errors, shown in parentheses, are computed using the Driscoll and Kraay method. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 17: Appendix: Subgroup Average Cost of Capital Responses by Rollover Risk



Panel A: Full sample with 75th percentile of netML



Panel B: Full sample with 90th percentile of netML

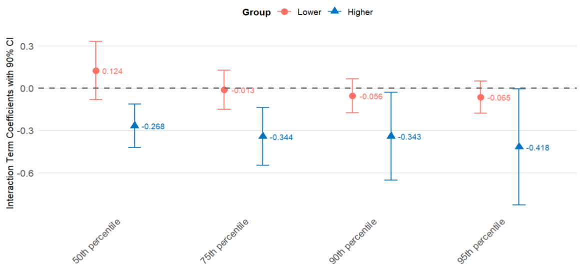
This figure reports estimates from Equation 13. The dependent variable is the four-quarter change in the log equity price. The key regressor is a triple interaction of the FOMC risk news shock, an indicator for high net market leverage (netML), $\mathbf{1}\{netML_{t-1}^{high}\}$, and an indicator for high rollover need (low maturity), $\mathbf{1}\{RI_{t-1}^{high}\}$. The indicator $\mathbf{1}\{RI_{t-1}^{high}\}$ equals one for firms whose rollover need (debt maturing within one year relative to total debt) is above the sample median. The indicator $\mathbf{1}\{netML_{t-1}^{high}\}$ equals one for firms with netML above the 75th percentile (Panels A) or the 90th percentile (Panels B). The sample is a quarterly panel of Compustat firms from 1995 to 2023. The regressions include macroeconomic controls, firm fixed effects, and year $\times$ industry fixed effects; macroeconomic controls are the one- to four-quarter lags of inflation, GDP growth, unemployment, and the high-frequency monetary policy surprise series from Nakamura and Steinsson [2018a]. The interaction of the two indicators, $\mathbf{1}\{RI_{t-1}^{high}\} \times \mathbf{1}\{netML_{t-1}^{high}\}$, is included in the specification. The figure shows 90% pointwise confidence intervals based on standard errors computed using the Driscoll and Kraay method.

Table 24: Appendix: Main Analysis Using the BBM Risk Index as an Alternative Proxy for FOMC Risk News

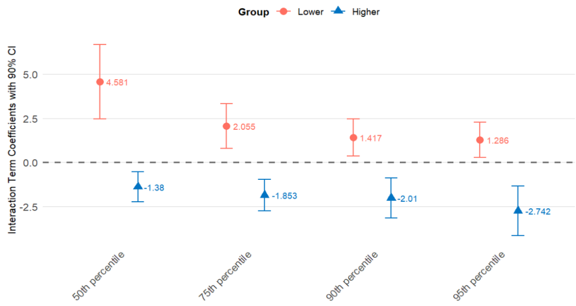
4 quarters growth rate	Capital	Capital	Debt	Cash	Capital
	(1)	(2)	(3)	(4)	(5)
ϵ_t^{BBM}	-0.235				
	(0.250)				
$\epsilon_t^{BBM} \times netML_{t-1}$		-0.881***	-3.72***	1.367**	
		(0.195)	(0.917)	(0.688)	
$\epsilon_t^{BBM} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-0.931**
					(0.411)
Firm FE	✓	✓	✓	✓	✓
Year $\times$ Industry FE	✓				
Macro Controls	✓				
Quarter $\times$ Industry FE		✓	✓	✓	✓
$\epsilon_t^{BBM} \times$ Firm Controls		✓	✓	✓	✓
Interest Rate Surprise $\times$ $netML_{t-1}$		✓	✓	✓	✓
Observations	298,082	238,418	196,105	237,584	199,086
Adjusted R^2	0.099	0.147	0.069	0.080	0.169
Sample	Full	Full	Full	Full	Full

This table reports robustness results for the firm-level investment regressions using an alternative proxy for FOMC risk news shocks: the FOMC-day change in the risk index of Bauer et al. [2023](BBM Index). The index is the first principal component of 14 risk-sensitive indicators across asset classes. The key regressor ϵ^{BBM} is the quarterly sum of the index's daily changes on scheduled FOMC announcement days. The dependent variables are four quarter ahead growth in tangible capital investment, cash, and debt. The sample is a quarterly Compustat panel from 1995–2023. Heterogeneity specifications include the high-frequency monetary policy surprises of Nakamura and Steinsson [2018a] interacted with net market leverage to account for the other channels and isolate non-policy risk news. Firm-level controls (lagged one quarter) include size, net market leverage, sales growth, asset return, operating leverage, and the short term assets ratio. Standard errors, shown in parentheses, are computed using the Driscoll and Kraay method. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

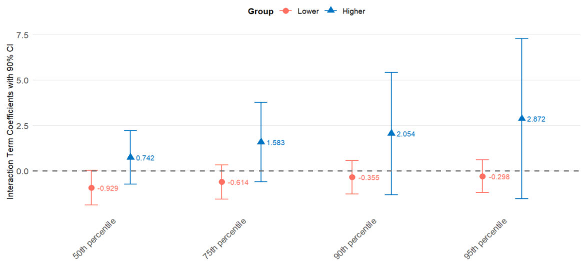
Figure 18: Appendix: Subgroup Average Responses Using the BBM Risk Index as an Alternative Proxy for FOMC Risk-News



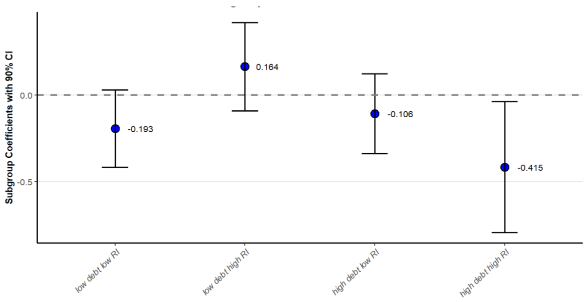
Panel A: Investment response by netML



Panel B: Debt response by netML



Panel C: Cash response by netML



Panel D: Investment response by netML and RI

This figure plots coefficients from regressions based on equation 13 that examine subgroup-average firm responses to FOMC risk news, using an alternative measure defined as the FOMC-day change in the risk index of Bauer et al. [2023](BBM Index). Panels A–C show the interaction between the risk-news shock and an indicator for high net market leverage, $\mathbf{1}\{netML_{t-1}^{high}\}$; results are displayed separately for the high- and low-netML groups. Panel D shows the triple interaction that additionally includes an indicator for high refinancing intensity, $\mathbf{1}\{RI_{t-1}^{high}\}$, yielding four groups by (netML high/low) $\times$ (RI high/low). The indicator $\mathbf{1}\{RI_{t-1}^{high}\}$ identifies firms with refinancing intensity—debt maturing within one year divided by total debt—above the sample median. The indicator $\mathbf{1}\{netML_{t-1}^{high}\}$ flags firms with net market leverage above the 75th percentile. The sample is a quarterly Compustat panel from 1995 to 2023. Regressions include firm fixed effects; year $\times$ industry fixed effects; macroeconomic controls (lags 1–4 of inflation, GDP growth, and unemployment); contemporaneous high-frequency interest rate surprises from Nakamura and Steinsson [2018a] in the FOMC window; and the interaction $\mathbf{1}\{RI_{t-1}^{high}\} \times \mathbf{1}\{netML_{t-1}^{low}\}$. Shaded bands show 90% pointwise confidence intervals based on standard errors clustered at the firm level.

Table 25: Appendix: Main Analysis Using SVIX^2 as an Alternative Proxy for FOMC Risk News

4 quarters growth rate	Capital	Capital	Debt	Cash	Capital
	(1)	(2)	(3)	(4)	(5)
ϵ_t^{svix}	-0.042				
	(0.042)				
$\epsilon_t^{svix} \times netML_{t-1}$		-0.202**	-0.869***	0.295*	
		(0.084)	(0.310)	(0.160)	
$\epsilon_t^{svix} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-0.202**
					(0.090)
Firm FE	✓	✓	✓	✓	✓
Year × Industry FE	✓				
Macro Controls	✓				
Quarter × Industry FE		✓	✓	✓	✓
$\epsilon_t^{svix}\times$ Firm Controls		✓	✓	✓	✓
Interest Rate Surprise × $netML_{t-1}$		✓	✓	✓	✓
Observations	298,082	238,418	196,105	237,584	199,086
Adjusted R^2	0.099	0.147	0.069	0.080	0.169
Sample	Full	Full	Full	Full	Full

This table reports robustness checks for the firm-level regressions that replace the baseline risk-news measure with an alternative proxy: the change in SVIX^2 on scheduled FOMC announcement days, following Martin [2017]. The key regressor, ϵ^{svix}, is the quarterly sum of those SVIX^2 changes. The dependent variables are four-quarter-ahead growth in tangible capital investment, cash, and debt. Specifications mirror those in Table 24 and the main text. The sample is a quarterly Compustat panel from 1995–2023. Standard errors (in parentheses) are computed using the Driscoll–Kraay method. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 26: Appendix: Main Analysis Controlling for GSS Policy Rate Surprises

4 quarters growth rate	Capital	Capital	Debt	Cash	Capital
	(1)	(2)	(3)	(4)	(5)
ϵ_t^{cr}	-0.464**				
	(0.227)				
$\epsilon_t^{cr} \times netML_{t-1}$		-0.976***	-4.636***	2.352*	
		(0.230)	(0.858)	(1.212)	
$\epsilon_t^{cr} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-1.375***
					(0.399)
Firm FE	✓	✓	✓	✓	✓
Year × Industry FE	✓				
Macro Controls	✓				
Quarter × Industry FE		✓	✓	✓	✓
$\epsilon_t^{cr}\times$ Firm Controls		✓	✓	✓	✓
GSS Shock Controls	✓	✓	✓	✓	✓
Observations	298,082	238,418	196,105	237,584	199,086
Adjusted R^2	0.099	0.144	0.070	0.080	0.168
Sample	Full	Full	Full	Full	Full

This table reports robustness checks that add the Gürkaynak–Sack–Swanson (GSS; Gürkaynak et al. 2004) policy-rate factors as controls. Column (1) includes the target and path factors. Columns (2)–(5) interact these factors with net market leverage to test for heterogeneous effects. The main regressor is the FOMC risk-news shock. Dependent variables are four-quarter-ahead growth in tangible capital investment, cash, and debt. The sample is a quarterly Compustat panel from 1995–2023. Standard errors (in parentheses) are Driscoll–Kraay. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 27: Appendix: Main Analysis for the Manufacturing Subsample

4 quarters growth rate	Capital	Capital	Debt	Cash	Capital
	(1)	(2)	(3)	(4)	(5)
ϵ_t^{cr}	-0.428**				
	(0.198)				
$\epsilon_t^{cr} \times netML_{t-1}$		-0.608	-5.268***	3.512*	
		(0.497)	(2.363)	(1.936)	
$\epsilon_t^{cr} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-2.194***
					(0.628)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓				
Macro Controls	✓				
Quarter FE		✓	✓	✓	✓
$\epsilon_t^{cr} \times$ Firm Controls		✓	✓	✓	✓
Interest Rate Surprise $\times$ $netML_{t-1}$		✓	✓	✓	✓
Observations	153,303	125,629	102,598	125,232	104,119
Adjusted R^2	0.092	0.127	0.067	0.080	0.147
Sample	Full	Full	Full	Full	Full

This table reports robustness checks that restrict the sample to manufacturing firms (SIC 3000–3999). The main regressor is the FOMC risk news shock. Dependent variables are four-quarter-ahead growth in tangible capital investment, cash, and debt. The sample is a quarterly Compustat panel covering 1995–2023. Standard errors (in parentheses) are Driscoll–Kraay, robust to heteroskedasticity, serial correlation, and cross-sectional dependence. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 28: Appendix: Main Analysis Using Market Leverage as the Debt-Burden Measure

4 quarters growth rate	Capital	Capital	Debt	Cash	Capital
	(1)	(2)	(3)	(4)	(5)
ϵ_t^{cr}	-0.491**				
	(0.235)				
$\epsilon_t^{cr} \times ML_{t-1}$		-1.101***	-4.752***	1.440	
		(0.251)	(0.843)	(1.162)	
$\epsilon_t^{cr} \times \mathbf{1}\{ML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-1.141***
					(0.426)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓				
Macro Controls	✓				
Quarter FE		✓	✓	✓	✓
$\epsilon_t^{cr} \times$ Firm Controls		✓	✓	✓	✓
Interest Rate Surprise $\times$ ML_{t-1}		✓	✓	✓	✓
Observations	298,082	238,418	196,105	237,584	199,086
Adjusted R^2	0.099	0.147	0.069	0.080	0.170
Sample	Full	Full	Full	Full	Full

This table reports robustness checks of the main firm-level results using market leverage (debt-to-market ratio) as the measure of debt burden, defined as total debt divided by market equity. The main regressor is the FOMC risk news shock. Dependent variables are four-quarter-ahead growth in tangible capital investment, cash, and debt. The sample is a quarterly panel covering 1995–2023. Standard errors (in parentheses) are computed using the Driscoll–Kraay method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 29: Appendix: Main Analysis Controlling for Contemporaneous Growth Expectation Revisions

	Dependent variable: 4-quarter growth rate				
	Capital (1)	**Capital** (2)	**Debt** (3)	**Cash** (4)	**Capital** (5)
Panel A: FOMC risk news shock using structural shock $\boldsymbol{\epsilon_t^{cr}}$					
ϵ_t^{cr}	-0.487**				
	(0.231)				
$\epsilon_t^{cr} \times netML_{t-1}$		-0.790***	-3.827***	1.764*	
		(0.213)	(0.836)	(0.993)	
$\epsilon_t^{cr} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-1.390***
					(0.628)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓				
Macro Controls	✓				
Quarter FE		✓	✓	✓	✓
$\epsilon_t^{cr} \times$ Firm Controls		✓	✓	✓	✓
Interest Rate Surprise $\times netML_{t-1}$		✓	✓	✓	✓
Growth expectation controls	✓	✓	✓	✓	✓
Observations	297,801	238,189	195,924	237,355	198,898
Adjusted R^2	0.092	0.146	0.069	0.080	0.147
Sample	Full	Full	Full	Full	Full
Panel B: FOMC risk news shock using BBM Index $\boldsymbol{\epsilon_t^{BBM}}$					
ϵ_t^{BBM}	-0.216				
	(0.248)				
$\epsilon_t^{BBM} \times netML_{t-1}$		-0.776***	-3.384***	1.180*	
		(0.218)	(0.877)	(0.636)	
$\epsilon_t^{BBM} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-0.963**
					(0.404)
Firm FE	✓	✓	✓	✓	✓
Year $\times$ Industry FE	✓				
Macro Controls	✓				
Quarter $\times$ Industry FE		✓	✓	✓	✓
$\epsilon_t^{BBM} \times$ Firm Controls		✓	✓	✓	✓
Interest Rate Surprise $\times netML_{t-1}$		✓	✓	✓	✓
Growth expectation controls	✓	✓	✓	✓	✓
Observations	297,801	238,189	195,924	237,355	198,898
Adjusted R^2	0.092	0.147	0.069	0.080	0.169
Sample	Full	Full	Full	Full	Full

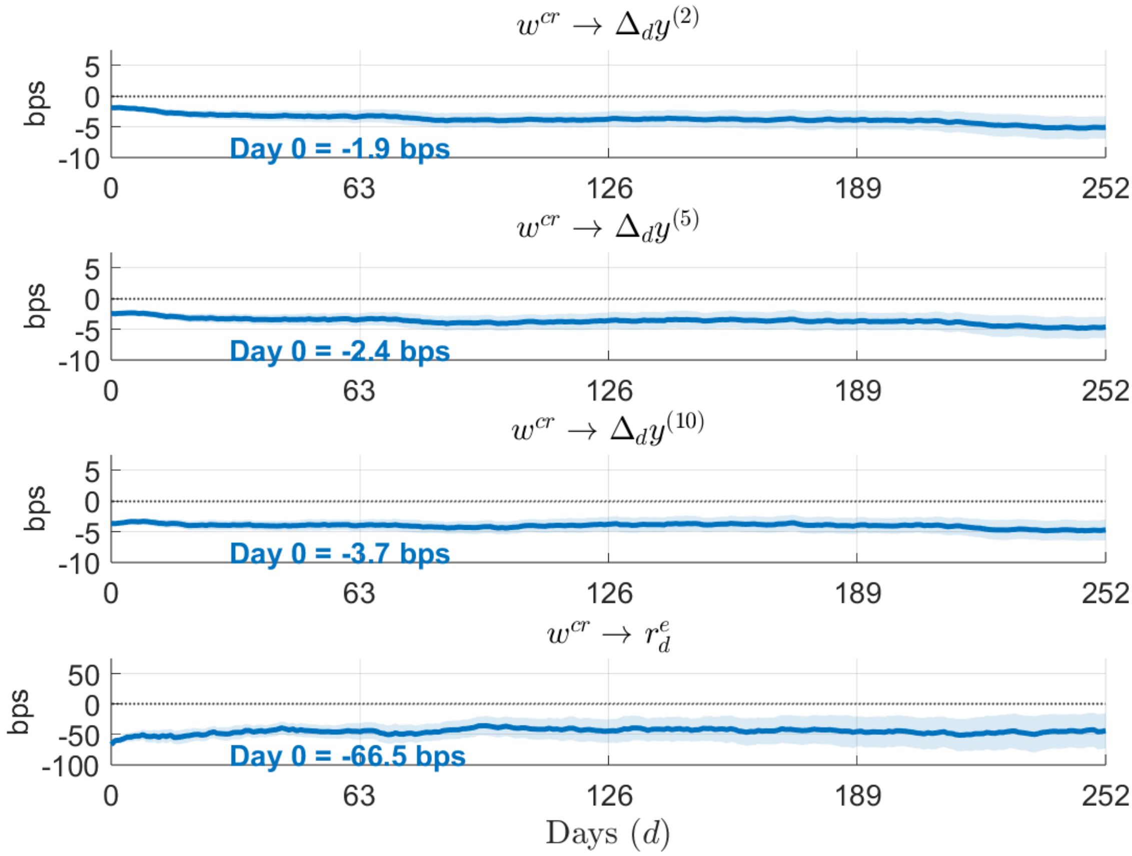
This table reports robustness checks of the main firm level results that control for contemporaneous short run and long run growth expectation revisions, using data from the Survey of Professional Forecasters. The main regressor is the FOMC risk news shock constructed using either the BBM risk index or the structural cash flow risk shock. Dependent variables are four quarter ahead growth in tangible capital investment, cash, and debt. The sample is a quarterly panel covering 1995–2023. Standard errors (in parentheses) are computed using the Driscoll–Kraay method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 30: Appendix: Heterogeneity by Book to Market Ratio

4 quarters growth rate	Capital	Debt	Cash	Capital
	(1)	(2)	(3)	(4)
$\epsilon_t^{cr} \times BM_{t-1}$	-0.239	-0.882	0.370	-0.198
	(0.274)	(0.642)	(0.827)	(0.187)
$\epsilon_t^{cr} \times \mathbf{1}\{netML_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$				-1.367***
				(0.364)
Firm FE	✓	✓	✓	✓
Year FE				
Macro Controls				
Quarter FE	✓	✓	✓	✓
$\epsilon_t^{cr} \times$ Firm Controls	✓	✓	✓	✓
Interest Rate Surprise $\times$ ML_{t-1}	✓	✓	✓	✓
Observations	228,508	186,721	227,700	189,599
Adjusted R^2	0.156	0.073	0.079	0.179
Sample	Full	Full	Full	Full

This table reports heterogeneity results based on the lagged book to market ratio. The main regressor is the FOMC risk news shock interacted with the lagged book to market ratio. Dependent variables are four quarter ahead growth in tangible capital investment, cash, and debt. The last column also includes the shock interacted with the high leverage and high refinancing intensity dummy to compare the financing cost channel. The sample is a quarterly panel covering 1995–2023. Standard errors (in parentheses) are computed using the Driscoll–Kraay method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Figure 19: Impulse Response Function



This figure presents the impulse responses of cumulative yield changes and stock returns to the cash flow risk shock. The magnitudes are expressed in basis points. The response horizon is one year, and the plot highlights the response at day 0. The shock is identified using a structural VAR, as described in the paper, with the impact matrix selected via the median target method. The impulse responses are estimated using local projections. Both the VAR and projection steps use data from 1983 to 2023. The light blue shaded area represents the 95% confidence interval, constructed using Newey-West standard errors with lag length $d + 1$.

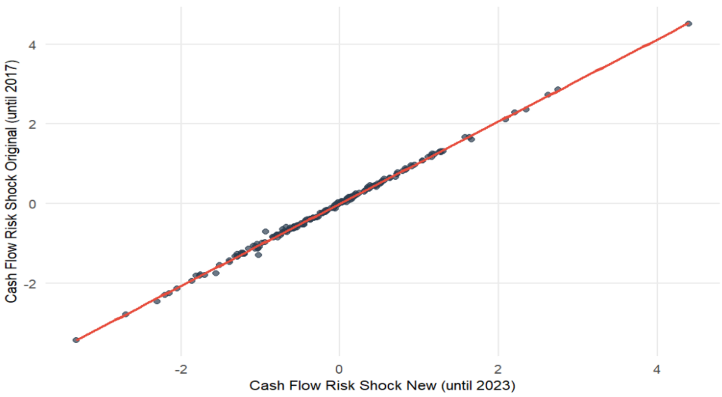
Table 31: Correlation Between Original and Updated Shock Series

All Trading Days	ϵ_t^c	ϵ_t^d	ϵ_t^{cr}	ϵ_t^{dr}
Correlation	0.9959	0.9897	0.9988	0.9983
95% interval	[0.9957, 0.9960]	[0.9892, 0.9901]	[0.9987, 0.9988]	[0.9982, 0.9983]
FOMC Days	ϵ_t^c	ϵ_t^d	ϵ_t^{cr}	ϵ_t^{dr}
Correlation	0.9997	0.9994	0.9992	0.9997
95% interval	[0.9996, 0.9998]	[0.9992, 0.9996]	[0.9989, 0.9994]	[0.9996, 0.9998]

This table reports the correlation between the original shock series identified by Cieslak and Pang [2021], using data from 1983 to 2017, and the updated shock series calculated by the authors using data from 1983 to 2023. Due to the difference in sample periods, the two approaches yield different VAR coefficients and impact matrices, resulting in discrepancies between the identified shock series, even within the overlapping sample. The first column compares the series on all trading days within the overlapping period, while the second column focuses on FOMC announcement days only.

Figure 20: Comparison of Original and Updated Cash Flow Risk Shocks

(a) All trading days



(b) FOMC announcement days only

These plots display the relationship between the original cash flow risk shocks identified by Cieslak and Pang [2021] (1983–2017, vertical axis) and the updated series constructed by the authors using data from 1983 to 2023 (horizontal axis). The top panel compares the series across all trading days in the overlapping period, while the bottom panel focuses exclusively on FOMC announcement days.