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

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Abstract

The literature extensively documents that monetary policy announcements convey information that affects risk premia and investors' risk perceptions, yet little is known about how these shifts influence real activity. Exploiting aggregate news shocks (decomposed into policy rate, growth, and risk components) identified from price changes across asset classes during the FOMC announcement window, I provide plausibly causal evidence that news that increases perceived cash flow risk reduces subsequent corporate investment in tangible capital, with effects amplified among firms with a high debt burden. The results hold after controlling for policy rate surprises, isolating non-policy announcement risk news. Consistent with a flight to quality mechanism in credit markets, announcement risk increasing news raises external finance costs for firms with a high debt burden. These firms curtail net borrowing and build precautionary cash buffers, and their investment cuts are sharper and concentrated when debt maturities are short—i.e., when rollover risk is high. At the aggregate level, the investment response to announcement risk news is state dependent: it is larger when the fraction of firms with high rollover risk is higher. Unconditionally, the effect is statistically insignificant because these firms account for a small share of the tangible capital stock and therefore, on average, contribute little to aggregate investment.

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

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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 new information released with monetary policy announcements materially moves risk premia and investors' risk perception (i.e., perceived risk and uncertainty about future cash flows).[1] Macro-finance theories assign a central role to time-varying risk perception in driving economic dynamics.[2] Yet evidence remains scarce on the extent to which risk-perception shifts triggered by new information from monetary policy announcements—referred to here as announcement risk news—transmit to the real economy and influence corporate behaviour.[3] Whether announcement risk news has sizeable macroeconomic consequences is therefore an open—and pressing—empirical question.

An equally pertinent question concerns the firm-level transmission of announcement risk news, namely which firms are most exposed and how financial frictions govern their differential exposure. This question is especially relevant for two reasons. First, during high-uncertainty episodes—such as the 2007–2008 financial crisis and the COVID-19 pandemic—financial frictions amplified the downturn: highly indebted firms and households 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 unexpected interest-rate changes. Assessing whether announcement risk news reinforces or counteracts this pattern has important implications for the design of monetary policy communication.

Corporate investment in tangible capital is the most volatile component of domestic output and accounts for a substantial share of it. In this paper, I provide plausibly causal evidence that when monetary policy announcements release information that raises investors' risk perception, subsequent corporate investment in tangible capital declines. Financial frictions transmit this news to 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 during the FOMC announcement window, with quarterly Compustat panel data, which provide rich

[1]Monetary policy announcements can alter risk perception by releasing news that changes views of the economic environment—for example, by signalling greater future uncertainty or by shifting intermediary balance-sheet strength. Section 6.1 reviews the literature on how monetary policy shapes risk perception.

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

[3]Bauer et al. [2023] summarises 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 ...".

time variation in firms' financial positions. The results also hold after controlling for policy rate surprises, isolating non-policy announcement risk news.

To guide the empirical analysis, I adopt the stylised model of Pflueger et al. [2020] as a conceptual framework and introduce a single modification that delivers testable predictions: unexpected monetary policy news affects not only the short-term interest rate but also aggregate risk perception, modelled as the expected volatility of aggregate growth.[4] In the model, aggregate risk perception governs households' consumption uncertainty and firms' future cash flow uncertainty. When monetary policy announcements release news that elevates perceived risk, 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 aggregate risk. A key empirical implication for identifying announcement news that drives risk perception is that such news 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 unexpected information from monetary policy announcements that shifts investors' risk perception poses substantial empirical challenges. In particular, because announcements can release both monetary (policy rate) and non-monetary information that alters risk perception,[5] it is easier to identify all risk related news jointly from announcements than to isolate each driving force separately. Following the news-shock literature, I extract risk related news from asset price movements in narrow windows around FOMC announcements (referred to here as FOMC risk news shocks). Under market efficiency, public information is fully priced in before the announcement, so price changes within the event window capture only unanticipated news.[6]

I construct the FOMC risk-news shock primarily with a structural method and complement it with two reduced-form approaches. The structural method follows the asset pricing framework of Cieslak and Pang [2021], extracting daily cash flow risk news shocks from equity and Treasury returns via a structural VAR. Using sign and monotonicity restrictions, the VAR decomposes FOMC-day asset price movements into orthogonal short rate news, growth news, and two risk news components; the cash flow risk news accords with

[4] This modification is intended to capture both the direct impact of policy rate news on risk perception and the additional non-monetary information conveyed in policy announcements, 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 for both types of risk news.

[5] See, for example, Cieslak and Schrimpf [2019], Bauer et al. [2023].

[6] 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 variance 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. The risk-news shocks constructed for the present analysis display the same properties.

the conceptual framework—positive news lowers equity prices, as investors demand a higher premium, while raising Treasury prices because safe bonds, which serve as hedges, become more valuable—reflecting a flight to safety. For robustness, I use two reduced-form methods: (i) the FOMC-day change in the option implied market risk premium of Martin [2017] and (ii) the principal component of risk sensitive financial indicators across multiple asset classes from Bauer et al. [2023]. All three FOMC risk-news shock measures are significantly and positively correlated.

I estimate firms' investment responses to FOMC risk news shocks using a panel local projections framework. The daily shocks are aggregated to the quarterly frequency and used 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 of Nakamura and Steinsson [2018a], extracted from interest rate futures and shown to capture unexpected policy rate changes and growth path information. 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 separate the effect of non-policy 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-policy announcement risk news on corporate investment.[7]

I find that a positive FOMC risk news shock, meaning that the announcement releases risk increasing news, is significantly associated with a lower subsequent tangible capital investment rate. A one unit shock, equivalent to a 66.5 basis point decline in the equity market index 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. This impact is economically modest. However, there is pronounced heterogeneity in the investment response related to financial frictions. The response increases with firms' debt burden, measured by the net debt to market ratio.[9] After a one unit FOMC risk news shock, highly indebted firms—the top 5 percent of the net debt to market distribution—cut tangible capital by nearly 1 percent over the subsequent year, roughly three times the 0.36 percent reduction observed for firms in the bottom 95 percent. This implies that announcement risk

[7] Bauer et al. [2023] show that high frequency policy rate surprises can move risk perception, which motivates including this control. In the main analysis and 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].

[8] This magnitude also corresponds to one standard deviation of the cash flow risk shock across all trading days.

[9] Net debt equals total debt plus preferred stock minus cash holdings. This measure accounts for liquidity holdings. 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 recent findings by 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. Therefore, it also reflects the ability to obtain new debt to roll over old debt.

news is transmitted mainly through these high debt burden firms.

Why are indebted firms more exposed to announcement risk news? I show that firms with a high net debt ratio have poorer credit quality ex ante: they carry lower long term and short term credit ratings. Given this, a plausible mechanism is that risk increasing announcement news triggers a flight to quality; investors become less willing to lend to risky, highly indebted firms, thereby raising the cost of external finance for new investment.[10] I cannot observe external financing costs directly, but indirect evidence comes from firms' liquidity management. Theoretical work, first noted by Keynes (1936) and later formalised by Riddick and Whited [2009] and Bolton et al. [2019], shows that when external finance becomes more expensive, firms reduce borrowing, rely more on internal funds and build precautionary cash buffers. Consistent with these predictions, I find that announcement risk news propagates to financial variables: after a positive FOMC risk news shock, firms with high debt burdens slow net debt issuance and accumulate cash much more aggressively than their low debt burden counterparts.

I provide further evidence that rollover risk is the key link between flight to quality in credit markets and investment cuts by indebted firms. I find that the investment response to a FOMC risk news shock is almost entirely concentrated in periods when highly indebted firms also face high rollover needs, measured by the share of debt maturing within one year. This pattern is consistent with the rollover risk literature (e.g., Acharya et al. [2011]). When funding conditions tighten, firms reliant on short term debt struggle to refinance and rollover risk rises; lenders respond by widening spreads, which further impedes refinancing. The resulting feedback loop drives external finance costs up dramatically and amplifies the effect of the shock on real investment. I also find that high rollover risk, proxied by having both a high debt to market ratio and high rollover needs, prolongs the investment contraction after positive FOMC risk news shocks and, at the industry level, triggers a reallocation of debt and capital from sectors with many high rollover risk firms toward those with fewer. Finally, a horse race regression that includes different FOMC day news shocks, 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 announcement news shocks, such as policy rate surprises, have no comparable effect.

I conduct a series of robustness checks to validate the firm level results. First, I reestimate the specifications with two alternative reduced form measures of 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

[10] Flight to quality episodes are often observed during periods of heightened uncertainty. A common theoretical explanation is that greater cash flow volatility increases default risk, especially for high debt burden firms. Because of agency problems and information frictions, uninformed investors demand a higher premium from such borrowers. Another mechanism is that value at risk constraints bind for lenders, forcing them to reallocate toward low risk borrowers.

[11] Extremely low debt burden firms (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 relation between credit score and debt burden.

only manufacturing firms, which are the largest users of tangible capital. Third, I replace the baseline net debt ratio with an alternative market based measure based solely on gross debt. Finally, I include additional high frequency monetary policy surprise variables that are widely used in the literature. Across all these exercises, the findings remain qualitatively unchanged.

The firm level results indicate that announcement risk increasing news 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, 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 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 barely 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 low debt firms—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 the literature. First, it extends the asset pricing literature that examines how monetary policy announcements shape risk perception and risk premia in financial markets.[12] Building on the seminal insight of Bernanke and Kuttner [2005], a growing body of high frequency evidence shows that information in monetary policy announcements has significant effects on risk measures and risky asset prices.[13] This paper extends that line of research by examining how announcement induced risk news affects the real economy. Several theoretical papers also explore broader macroeconomic effects of monetary policy related shifts in risk. Kekre and Lenel [2022] show that monetary policy driven wealth redistribution toward households with high

[12] An earlier strand of the literature focuses on asset price reactions—particularly stock price movements—around monetary policy announcements, with seminal contributions by Rigobon and Sack [2003, 2004].

[13] 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.

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 risk perception directly affects corporate investment.

Second, my paper contributes to the literature on the transmission of monetary policy to corporate investment.[14] This literature, dating back to 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 rich in characteristics such as 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 changes influence the market value of equity and, in turn, firms that rely on equity financing adjust investment and capital structure decisions in response to exogenous (policy rate induced) movements in their stock prices. My empirical strategy differs from this line of work—including Jeenas and Lagos [2024]—which primarily identifies monetary policy surprises via changes in short term interest rates within narrow event windows. Instead, I exploit complementary information in the same windows: I study how (cash flow) risk-related information embedded in FOMC announcements affects investment. Financial frictions also play a key role in my analysis, but through a different mechanism: risk increasing announcement news triggers a flight to quality in credit markets, raising external finance premia for lower quality, indebted firms. I further show that the combination of this flight to quality and firms' rollover needs generates a quantitatively large impact on the investment of indebted firms.

Third, my results also relate to the literature on uncertainty shocks and corporate investment, 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 shocks by inducing greater precautionary cash holdings and, consequently, lower capital expenditure. The announcement risk news I extract from asset prices likewise captures an uncertainty shock to future fundamentals, but one that is primarily driven by monetary policy announcements. Hence, my evidence carries policy implications, underscoring the importance of risk management in the communication of monetary policy. In addition, the mechanisms in Bloom [2009] and Alfaro et al. [2024] operate through an increase in the option value of delaying investment and borrowing in the presence of fixed adjustment costs. I document an additional, complementary channel: announcement risk news that increases perceived risk raises the cost of external finance, intensifying rollover pressure; firms with greater rollover needs therefore cut investment disproportionately. This mechanism is closely related to the argu-

[14] 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].

ment in Pflueger et al. [2020], who emphasize the role of the cost of capital when uncertainty is elevated.

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 assess the aggregate implications of this cross-sectional variation.

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.

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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[15]. 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, $v_t \sim N\big(0, \sigma^2_{v,t}\big)$. The variance $\sigma^2_{v,t}$ measures the risk associated with the aggregate demand shock.[16] 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.

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

[16] 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[17], 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.[18]

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:

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

[17] 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."

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

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 $r_{f,t} = -\ln \beta - \frac{1}{2}\gamma^2 \sigma^2_{x,t+1}$.[19]

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

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

The firm specific parameter s_i governs exposure to the aggregate process. The adjustment term $-\frac{1}{2} s_i^2 \sigma^2_{x,t+1}$ (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.[20]

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 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

[19] Detailed derivation is provided in Appendix C.

[20] 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.

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,

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

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

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

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,*

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

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

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

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.[21] 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.[22] 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 market efficiency, high frequency price movements reflect the arrival of new information.[23] 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

[21]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.

[22]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.

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

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.[24]

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 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.[25] 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[26]. 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,

[24]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.

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

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

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 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 $\omega^f_{t+1} = \left(w^c_{t+1},\ w^d_{t+1},\ w^{cr}_{t+1},\ w^{dr}_{t+1}\right)'$,[27] 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

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

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,[28] 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 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.[29]

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.[30] 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

[28]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.

[29]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.

[30]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.

FOMC announcements.[31] 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.[32] 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 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

[31] 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.

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

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.[33] 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.[34] 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 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.[35]

[Table 2 around here]

Table 2 reports correlations of FOMC day changes in the BBM risk index and $SVIX^2$ with the cash flow risk news shock. All series are constructed as the quarterly sum of daily measures, and I adjust the sign of BBM changes so that an increase indicates higher perceived risk. Both series are significantly correlated with the cash flow risk news shock. For completeness, the table also shows correlations with the discount rate risk news shock, which are smaller. For example, the BBM index has a correlation of 0.436 with the cash flow risk news shock (t statistic $= 5.224$) versus 0.179 with the discount rate risk news shock

[33] 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.

[34] 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.

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

(t statistic = 1.964). This supports the view that the alternative measures mainly capture cash flow risk news on FOMC announcement days.

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.

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.[36] 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.

[36] 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.

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 subgroup.[37] 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

[37] 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.

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. 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.[38] 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]

[38] 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.

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 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 slightly elevated credit risk similar to that of the middle groups. The appendix lists S&P credit ratings with the corresponding reverse credit scores and reports average reverse scores for each quantile of lagged *netML*; it also presents a robustness exercise that repeats the heterogeneity analysis 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.[39] 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,[40] 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

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

[40] 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.

(4) further indicates that this conditional effect intensifies after 2008, a period dominated by unconventional monetary policy.[41]

[Figure 5 around here]

Figure 6 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.

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 their ability to hold risky assets, amplifying the shift toward safe assets.[42]

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

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

[42] Value at risk constraints can stem from regulation or from funding based limits; see Brunnermeier and Sannikov [2014] for a model in which value at risk is tied to intermediaries' funding capacity.

in the structural VAR. 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.[43]

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 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

[43] 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.

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][44]—by showing a parallel reallocation in response to announcement risk news.

[Figure 6 around here]

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

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

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

After announcement risk increasing news, how do higher borrowing costs for indebted firms translate into pronounced investment cutbacks? Theory identifies rollover risk as a central driver. Acharya et al. [2011] show that firms financing long term assets with short term debt face heightened rollover risk when borrowing capacity contracts,[45] because refinancing maturing obligations becomes more difficult. As capacity tightens, expected default risk rises, credit limits become stricter, and borrowing capacity falls further, while maturing short term debt still must be repaid. The resulting liquidity shortfalls constrain capital 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.

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. [46] 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. 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.

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

[46] 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.

[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 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 %.[47] 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.2), confirming that the effects are not driven by firms with negligible debt.[48]

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

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

[48] AZL firms are largely uninvolved in debt rollovers. I follow Friewald et al. [2022] in defining AZL as leverage below 0.05; see Strebulaev and Yang [2013] for discussion of zero-leverage firms.

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**]

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.[49]

[49] Appendix B.4 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.

6. Further Discussion and Robustness

6.1. Discussion

How Monetary Policy Changes Cash Flow Uncertainty Empirical findings indicate that monetary-policy-driven cash flow uncertainty can have heterogeneous effects on firm investment. A key question is how monetary policy generates this uncertainty in practice. In my simplified model, the mechanism is abstracted as follows: when monetary policy constrains current consumption, agents perceive greater future uncertainty. In reality, however, the channels are more complex and have been extensively discussed in the asset pricing literature.

A relevant perspective is offered by Bauer et al. [2023], who argue that monetary policy announcements could reshape expectations about the economy and financial markets by releasing additional information, thereby altering overall uncertainty. Another important channel is the so-called "Fed Put" Cieslak and Vissing-Jorgensen [2021], Cieslak and McMahon [2023]. It implies that the Federal Reserve effectively provides insurance against recessions by easing policy—such as cutting interest rates—when adverse conditions arise. This perceived guarantee reduces downside risks, thereby mitigating cash flow uncertainty. Monetary policy can also influence the risk-taking behavior of financial institutions. As shown by Becker and Ivashina [2015], when interest rates are low, institutions seeking a certain return may "reach for yield" by assuming greater risk. This shift in risk appetite can alter lending practices, which, in turn, affects firms' external financing capacity and thus their cash flow uncertainty.

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. However, unlike my findings, they show that firms with higher default risk respond less to surprise reductions in short-term rates. Their argument is that relatively low risk firms face a flatter marginal financing cost curve, making them more sensitive to monetary policy shocks. Several methodological differences distinguish my paper from Ottonello and Winberry [2020]. First, they measure short-rate surprises based on current month federal funds futures within a short window around policy announcements, whereas I focus on cash-flow-risk shocks observed on FOMC days. Second, they measure risk using book leverage or default risk, while I employ market leverage and refinancing intensity (i.e., rollover risk). Third, their primary sample emphasizes the period of unconventional monetary policy prior to 2007, whereas my analysis spans the period since 1995 and highlights especially strong effects after 2008. In unreported results, I replicate Ottonello and Winberry [2020] by using their short-term rate surprises and book-leverage measures. Consistent with their findings, high-risk firms are less sensitive under those specifications. Interestingly, when I instead use more forward-looking interest rate shocks such as the path factor in Gürkaynak et al. [2022]

or the shocks in Nakamura and Steinsson [2018a], firms with higher default risk exhibit stronger responses to monetary policy announcements.

6.2. Additional Robustness Test

Alternative Measurements My main empirical analysis relies on the structural VAR from Cieslak and Pang [2021] to identify the cash-flow-risk shock on FOMC days as my primary proxy for monetary-policy-driven cash flow uncertainty. In Appendix B.5, I assess the robustness of my results by using alternative risk measures, also use risk changes on FOMC announcement days. As shown in AppendixB.5, changes in both of these alternative measures on FOMC days are significantly correlated with my identified cash-flow-risk shock. Substituting these measures into my main analysis alters some aspects of statistical significance but leaves the main results qualitatively intact. In particular, the heterogeneous responses based on firms' leverage remain robust under these alternative specifications.

Controlling for Other Interest Rate Shocks Appendix B.6 reports a robustness test that accounts for two additional monetary policy surprises from Gürkaynak et al. [2004]: the target factor and the path factor. These factors are constructed using interest rate futures surprises at different maturities. The target factor measures current federal funds rate target changes, while the path factor reflects expectations about future rate targets, making it akin to forward guidance. My results remain unchanged after including these two monetary policy surprises.

Subsample of Manufacturing Firms Tangible capital plays a particularly important role in these firms' production processes. In Appendix B.7, I show that my findings remain qualitatively robust when restricted to manufacturing firms (SIC codes 3000–3999).

Alternative Leverage Measure In Appendix B.8, I use the simple debt-to-market ratio instead of the net debt-to-market ratio as a proxy for financial risk. The results remain quantitatively unchanged.

7. Aggregate Implication

Firm level evidence is informative for the aggregate implications of FOMC risk news.[50] 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,

[50] 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.

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.

[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}. [51] 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 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]

[51] 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.

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[52]. 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 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

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

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 $\hat{i}^{\text{high}}_{t+8}$ and $\hat{i}^{\text{low}}_{t+8}$ are the cross sectional average investment growth rates within the two groups. The covariance component further decomposes as

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

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

Here $\hat{\text{cov}}^{g}_{t+8}$ 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:

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

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:

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

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 risk news that raises perceived aggregate risk has real effects by depressing subsequent corporate investment. Financial frictions are central to this transmission. Consistent with a flight to quality in credit markets, firms with a high debt burden face heightened external finance premia, accumulate more cash, and reduce net debt issuance. As a result, when rollover risk is high, these firms cut investment more and their tangible capital declines. At the aggregate level, the cross sectional share of firms with high rollover risk is a key determinant of how strongly announcement risk news passes through to aggregate investment.

My findings have clear policy implications. They highlight a novel channel through which monetary policy announcements affect the real economy beyond policy rate news: announcement risk news shifts perceived risk and, in turn, investment. This implies that policymakers should manage perceptions of risk about future economic conditions when communicating at announcements, because these perceptions influence real outcomes, with effects that are especially strong after 2008. The analysis also points to a design margin for policy communication: the timing of risk management around announcements should take into account the cross sectional distribution of firms' rollover risk.

My study is a first step toward examining the risk channel of monetary policy announcements using a reduced form approach. I use an asset pricing approach to infer changes in perceived risk around FOMC announcements and treat these changes as announcement risk news shocks. A natural direction for future work is to identify the sources of this news. In particular, it would be useful to separate 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 sources matter most for corporate decision making remains an open question. A second direction is to embed this channel in general equilibrium models in order to study its interaction with other monetary transmission mechanisms and to include additional agents such as financial institutions. This would clarify the general equilibrium effects of announcement risk news and provide a structural explanation for the heterogeneous corporate behavior documented in this paper.

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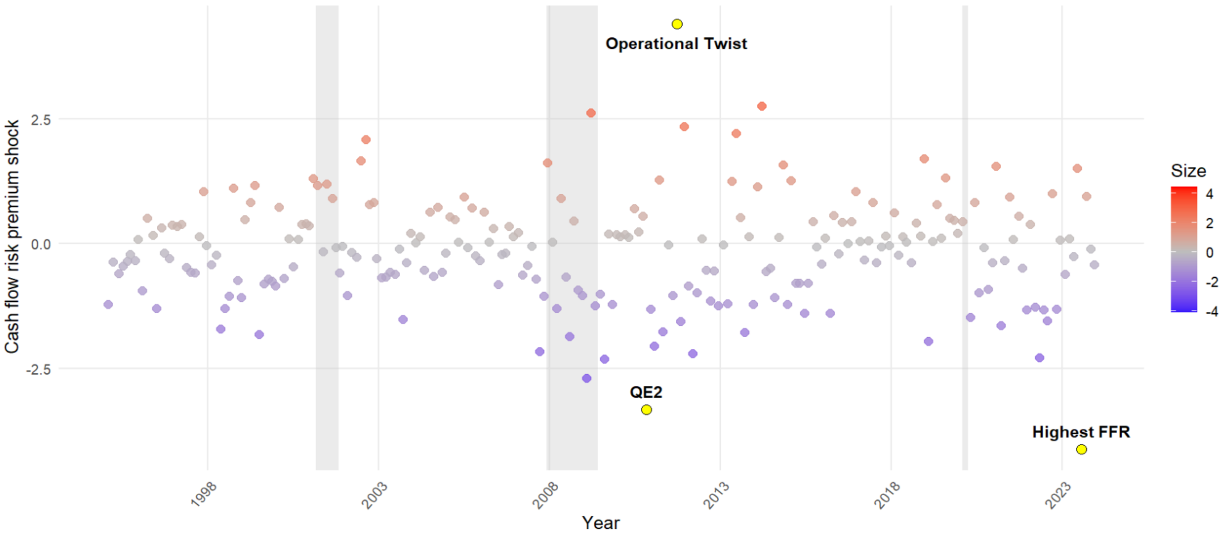
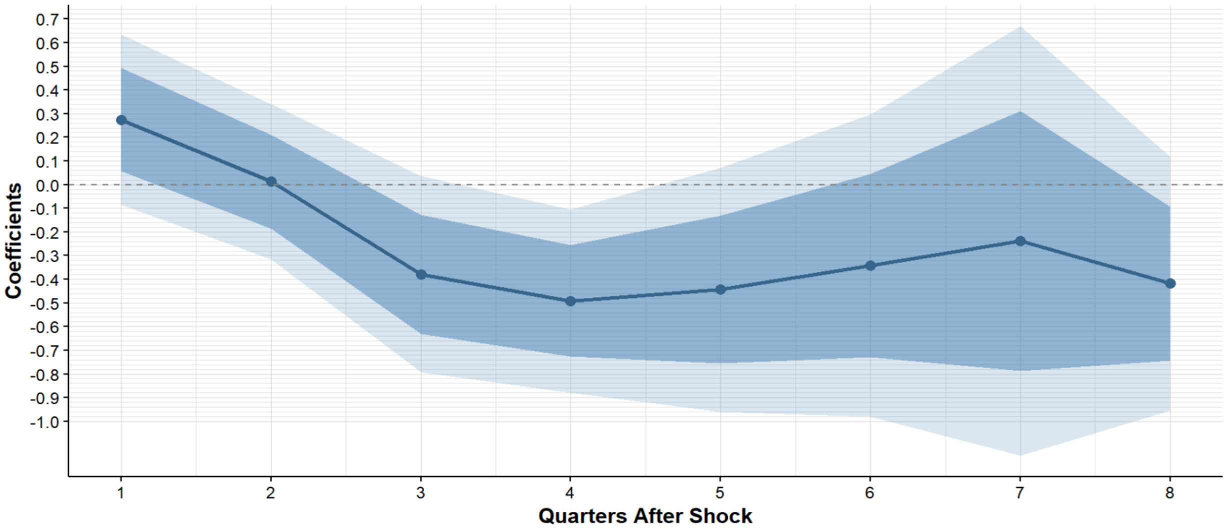
Figure 1: Cash Flow Risk News Shocks on Scheduled FOMC Announcement Days



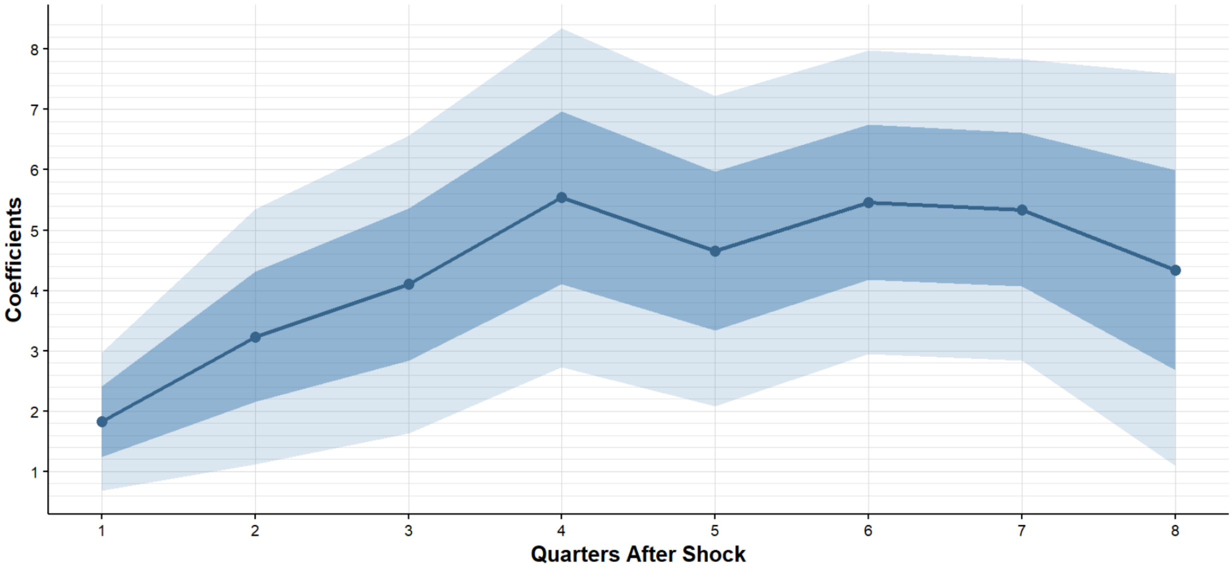
This figure plots the identified cash flow risk news shocks on all scheduled FOMC announcement days from 1995 to 2023. Shocks are obtained from a structural VAR estimated with bond and equity data for all trading days in 1983–2023. The shocks are normalized to have mean zero and unit standard deviation 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 × year fixed effects. The inner and outer shaded areas denote 68% and 90% confidence intervals, respectively, based on Driscoll–Kraay standard errors.

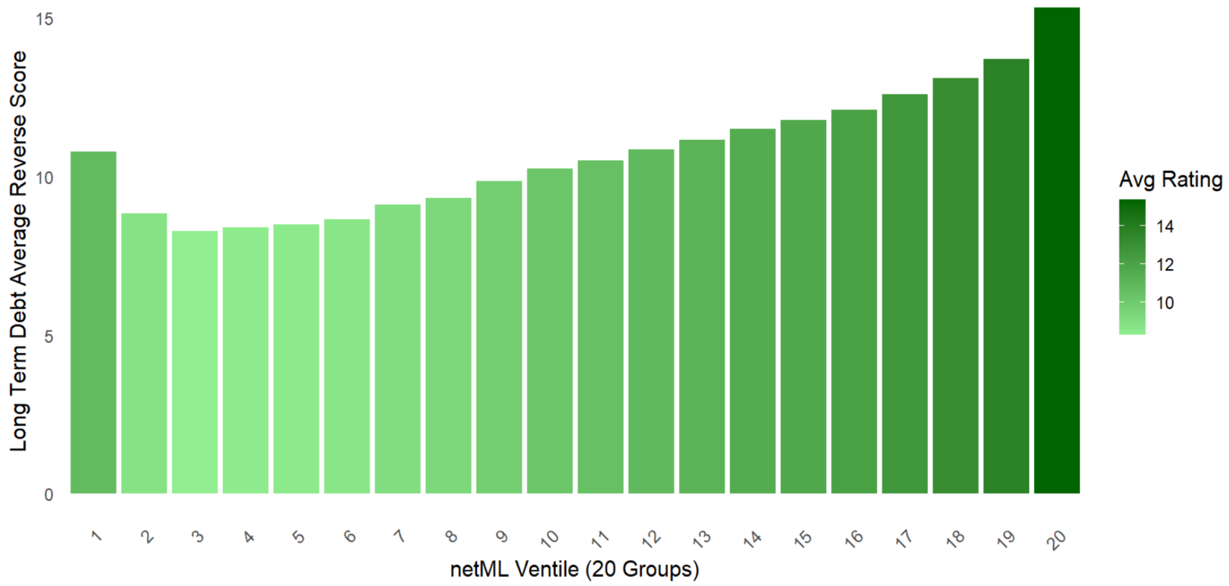
Figure 3: Risk Channel: Dynamics of the Ex Post Cost of Capital Response



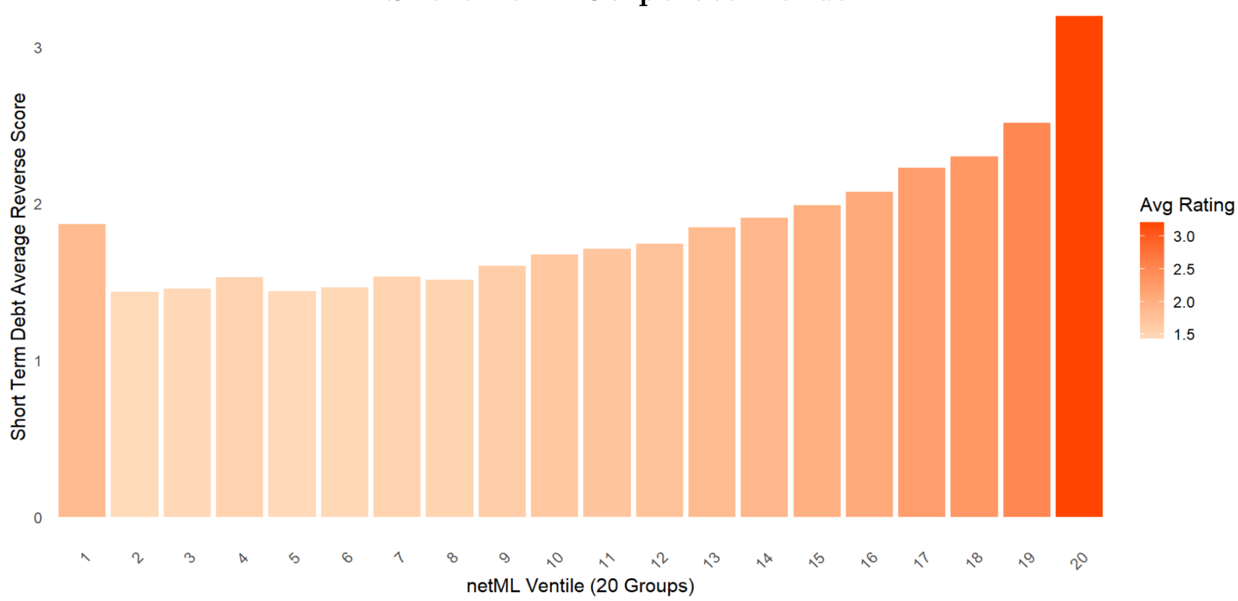
This figure shows the dynamic response of the cost of capital to FOMC risk news shocks. The regression follows Equation (11); the dependent variable is the change in the log equity price over the next one to eight quarters. The sample is a quarterly panel of Compustat firms from 1995 to 2023. The regressions 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

Long Term Corporate Bonds

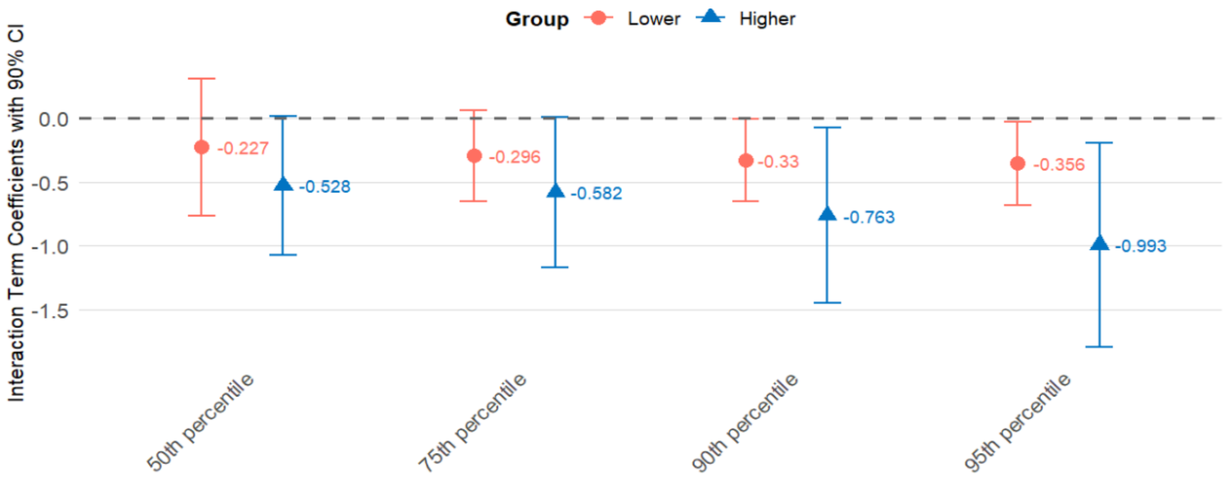


Short Term Corporate Bonds

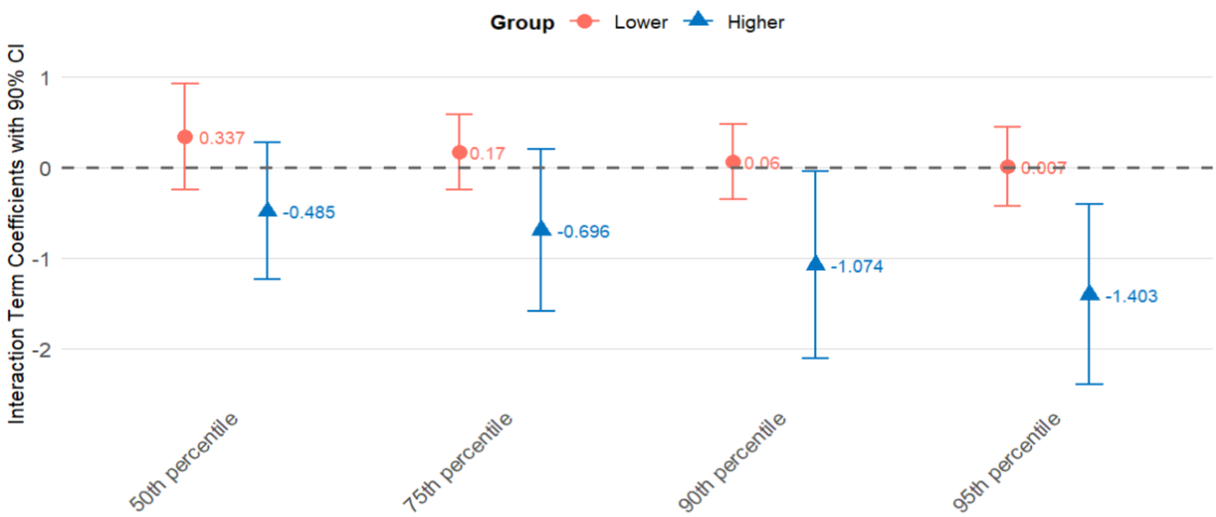


This figure shows the relationship between net market leverage (netML) and reverse credit scores for long term and short term corporate bonds. Firms are sorted into 20 portfolios by lagged netML from low to high. Credit ratings are converted to reverse credit scores, so higher scores indicate higher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

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



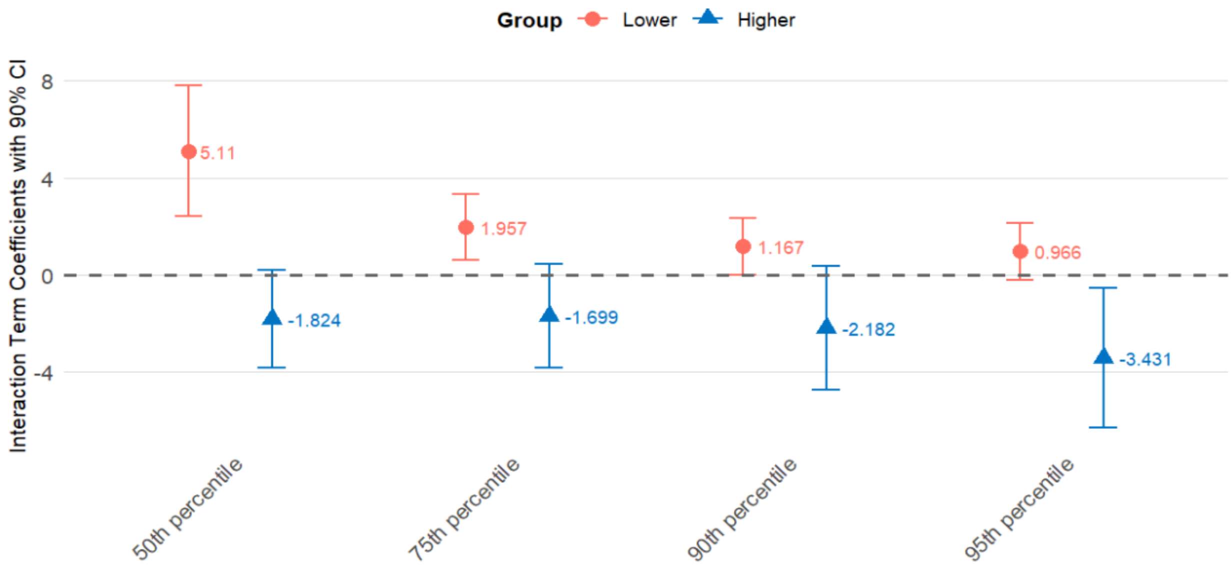
Panel A: Full Sample



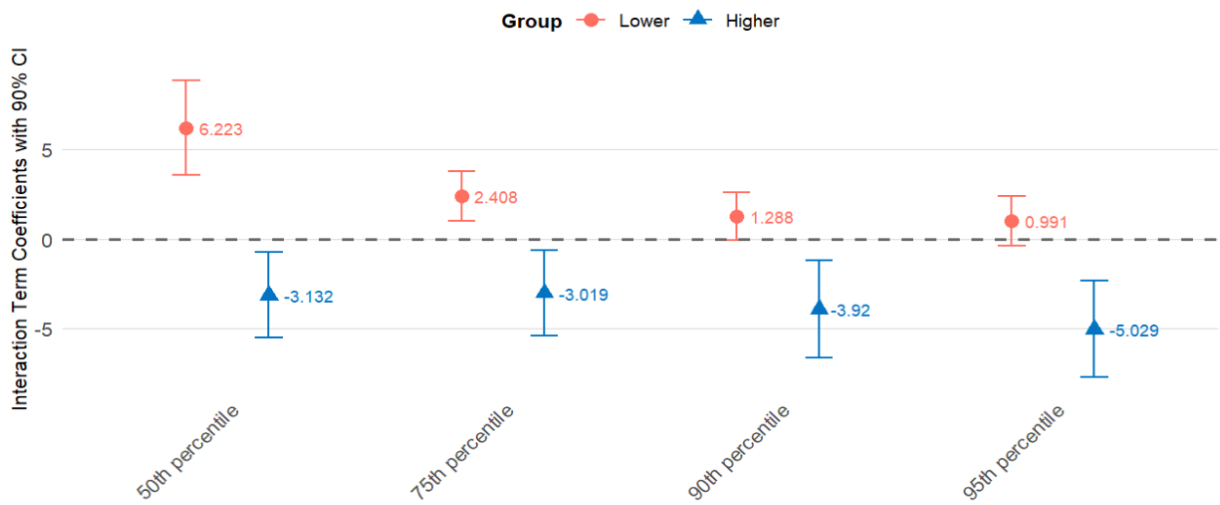
Panel B: Post-2008 Sample

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



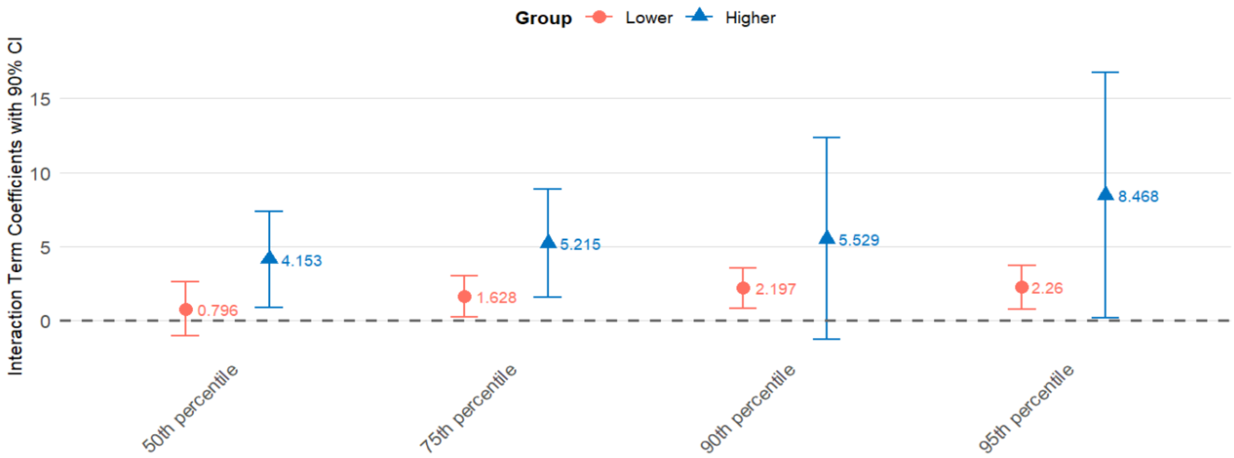
Panel A: Full Sample



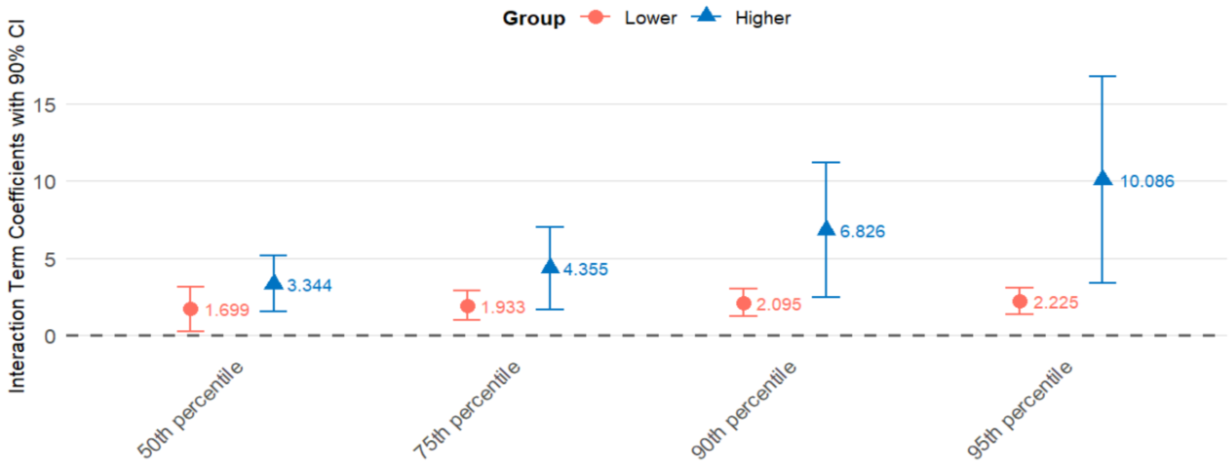
Panel B: Post-2008 Sample

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 $\times$ 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 7: Mechanism: Subgroup Average Cash Holdings Response by Net Market Leverage



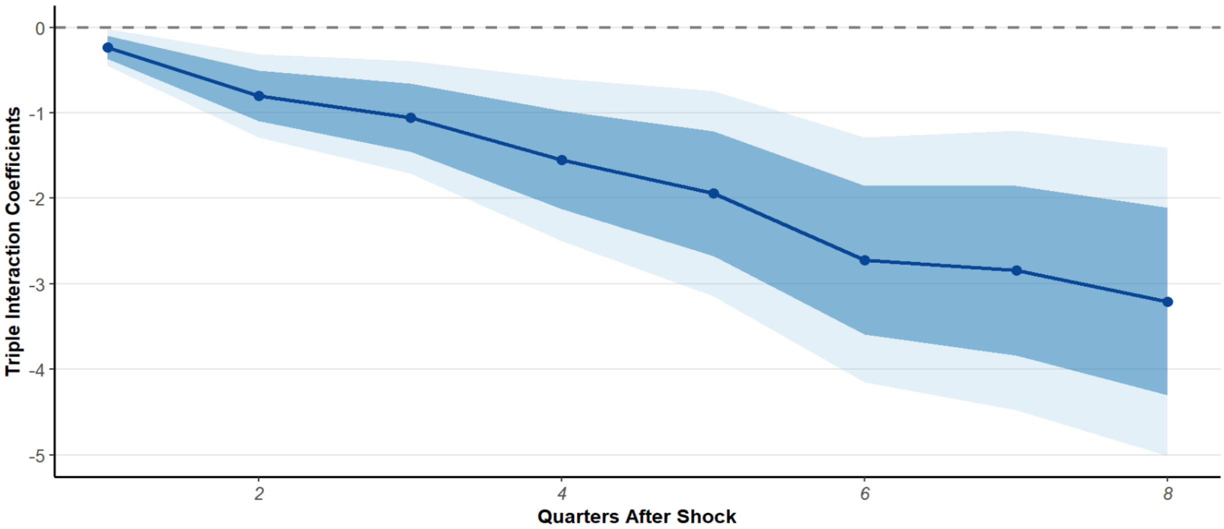
Panel A: Full Sample



Panel B: Post-2008 Sample

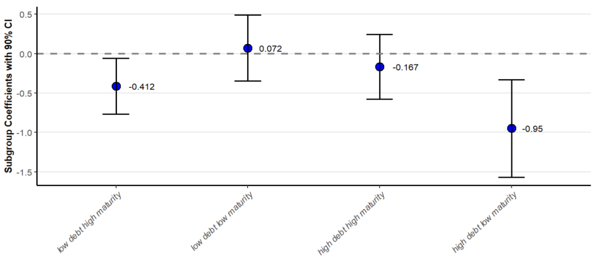
This figure reports regression results based on Equation (13). The dependent variable is the change over the next four quarters in the log of cash holdings. The main independent variable is the FOMC risk news shock interacted with binary indicators for high or low firm level lagged net market leverage (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

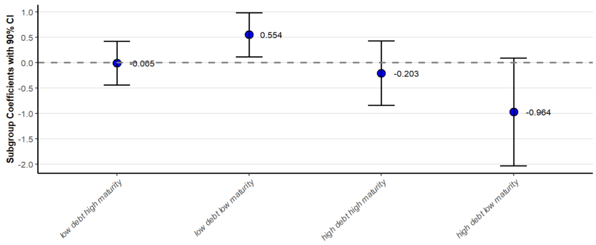


This figure shows the dynamic effect of rollover risk on the investment response to the FOMC risk news shock. Estimates are from Equation 12, with the dependent variable defined as the change in the log book value of tangible capital stock at horizons one through eight quarters ahead. The key regressor 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.

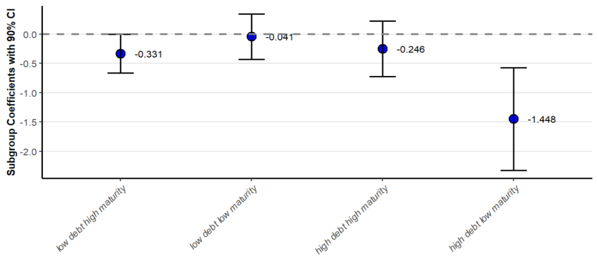
Figure 9: Mechanism: Subgroup Average Investment Responses by Rollover Risk



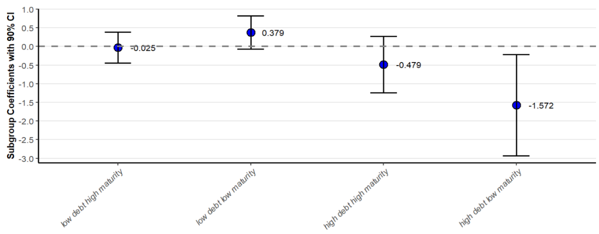
Panel A: Full sample with 75th percentile of netML



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



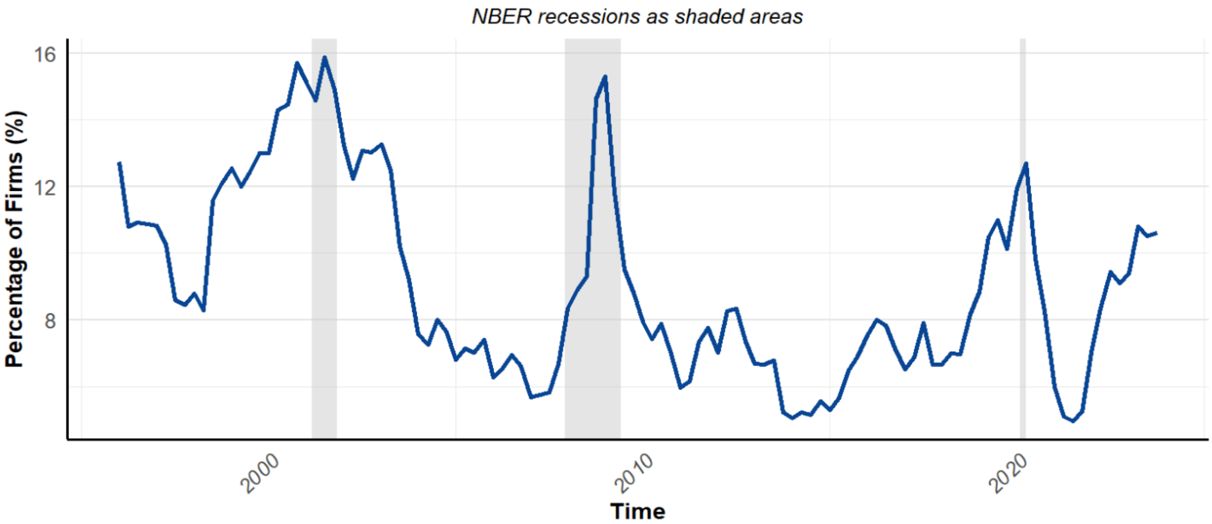
Panel C: Full sample with 90th percentile of netML



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

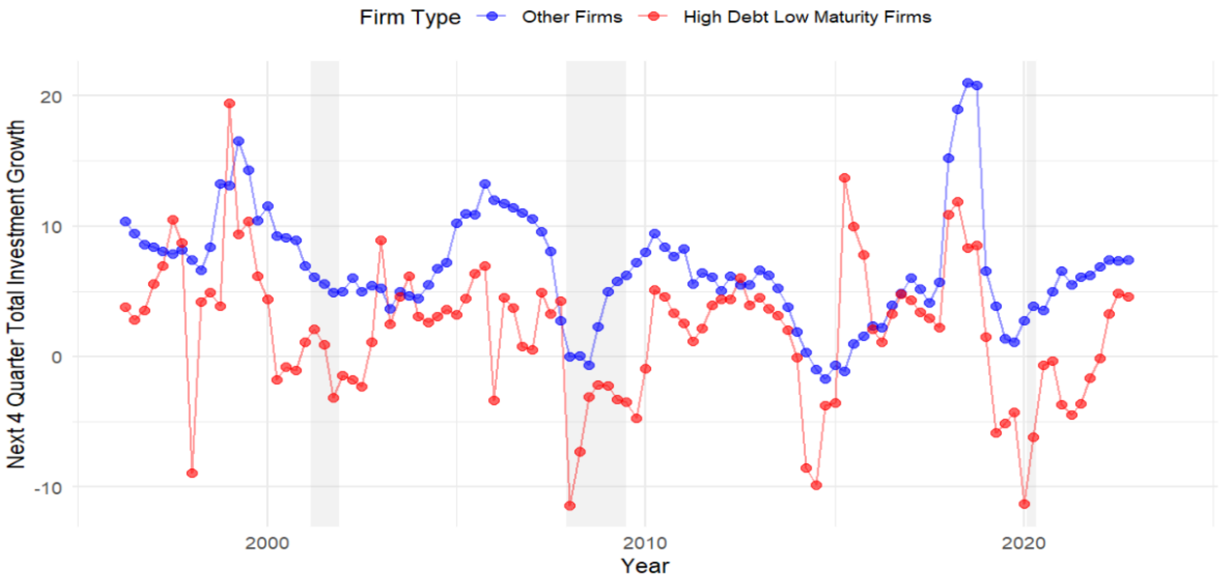
This figure reports estimates from Equation 13. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The key regressor is a triple interaction of the FOMC risk news shock, an indicator for high net market leverage (netML), $\mathbf{1}\{netML_{t-1}^{high}\}$, 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



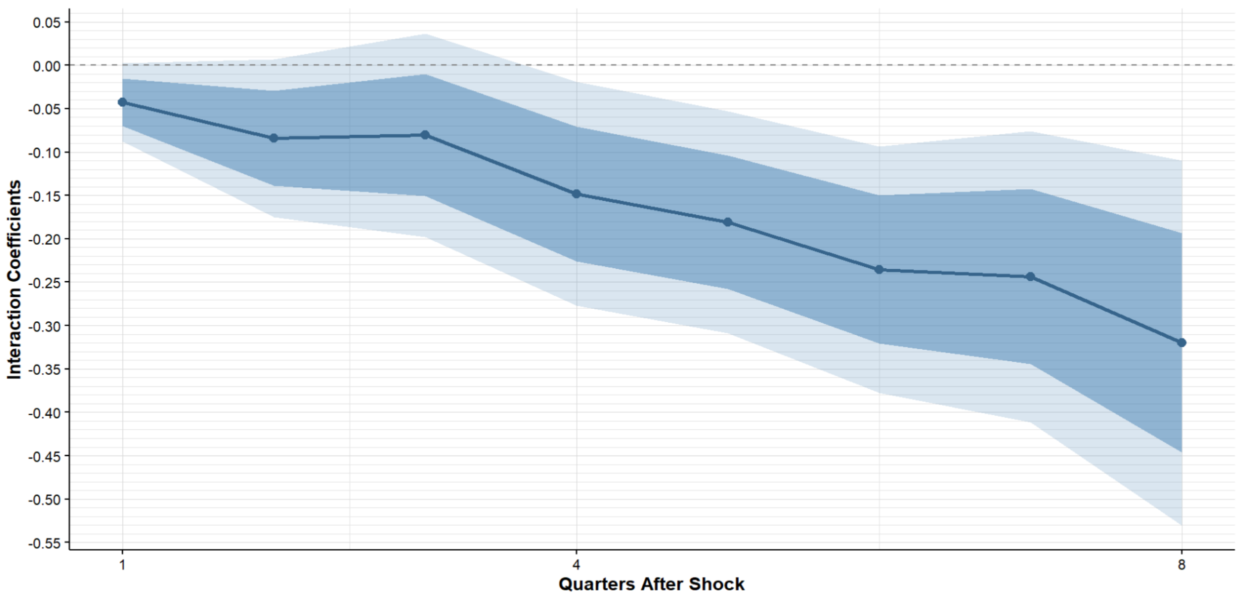
This figure shows the quarterly share of firms with high rollover risk. A firm is classified as high rollover risk if its net market leverage $netML$ is above the 75th percentile and its rollover need RI is above the median; both thresholds are evaluated in the full sample. The series is constructed 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 × 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	247,250	247,250	238,394	103,146
Adjusted R^2	0.109	0.119	0.146	0.171
Sample	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	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	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 $\times$ Industry FE	✓	✓	✓	✓
ϵ_t^{cr} $\times$ Firm Controls	✓	✓	✓	✓
$\Delta GDP_{t-1} \times netML_{t-1}$	✓	✓	✓	✓
Observations	199,062	87,733	199,062	103,112
Adjusted R^2	0.165	0.207	0.168	0.208
Sample	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 × Industry FE	✓	✓
ϵ_t^{cr} × Firm Controls	✓	✓
$\Delta GDP_{t-1} \times netML_{t-1}$	✓	✓
Observations	199,062	199,062
Adjusted R^2	0.168	0.168
Sample	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	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 $\times$ Industry FE	✓	✓	✓	✓
Macro Controls	✓	✓	✓	✓
Firm Controls		✓		✓
Interest rate Surprise $\times$ $\boldsymbol{p}_t$		✓		✓
Observations	295,470	238,411	126,572	86,295
Adjusted R^2	0.100	0.145	0.142	0.178
Sample	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	113	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: Conuterfactual Aggregate Investment Analysis

	(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 regression results for the aggregate counterfactual investment response to FOMC cash flow risk shocks. The dependent variable is the counterfactual aggregate investment rate. All regressions include macroeconomic controls, which consist of one- to four-quarter lags of inflation, GDP growth, unemployment, and the Nakamura-Steinson shocks. Standard errors, shown in parentheses, are calculated using Newey-West Newey and West [1986] with 8 lags. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Online Appendix

A. Sample Selection and 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%.

Variable Construction:

- **Investment:** Defined as $\Delta \log(k_{j,t+n})$, this variable represents the logarithmic change in the tangible capital stock of firm j from period t to $t+n$. Tangible capital stock is calculated based on changes in net plant, property, and equipment (*ppentq*). If a firm has a missing *ppentq* observation between two periods with non-missing values, the observation is excluded from the regression rather than applying linear interpolation, following the approach of Ottonello and Winberry [2020]. Investment is winsorized at the 1% level on both tails of the distribution.
- **Net Market Leverage:** Measured as the net debt-to-market ratio (net market leverage), this variable is defined as the sum of total debt (short-term debt (*dlcq*) and long-term debt (*dlttq*)) plus preferred stock (*pstkq*), minus cash holdings (*cheq*), all 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), 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. Triple Interaction Excluding Almost Zero Debt Firms

[Table 17 around here]

I examine the relationship between rollover risk and investment response by employing the same triple interaction term regression as in my main analysis. To ensure the robustness of my results, I further exclude firms with negligible leverage (AZL, or "Almost Zero Leverage"). This exclusion ensures that my findings are not driven by low-leverage firms but rather by firms with higher rollover risk. Following the methodology of Strebulaev and Yang [2013], I first exclude all firms with a book leverage ratio below 0.05. I then define high financial risk firms as those with a net debt-to-market ratio above the 75th percentile across firms and time within the non-AZL sample. Similarly, high refinancing intensity firms are identified as those with a short-term debt maturity ratio above the median within the non-AZL sample. As shown in Table 17, this adjustment does not alter my main findings: firms with high net market leverage and high refinancing intensity exhibit significantly lower investment following an FOMC cash flow risk shock.

B.3. Triple interaction control for other monetary policy shock

Table 9 tests the robustness of the triple interaction term regression by controlling for other FOMC-related shocks. A primary concern is that firms with high rollover risk may be disproportionately affected by other monetary policy transmission channels, such as changes in the short-term discount rate or the release of additional economic information. To address this, I include triple interaction terms for the other three FOMC shocks, as well as the interest rate shock from Nakamura and Steinsson [2018a], all interacted with dummy variables for high net market leverage and high refinancing intensity as controls. I also include all relevant double interaction and non-interaction terms. Column (1) presents the results with the interest rate shock triple interaction term, while Column (2) adds the interest rate shock and the triple interaction terms for the other three FOMC shocks. The main results from my primary channel remain unchanged, with no significant difference in significance or magnitude.

B.4. Triple interaction of cost of capital

[Figure 13 around here]

In this section, I present the results of the ex-post cost of capital, proxied by the heterogeneous response of equity returns to FOMC cash flow risk shocks, based on rollover risk. As shown, FOMC cash flow shocks predict an increase in equity returns over a four-quarter period. Firms exhibit stronger reactions to these shocks when they have higher net market leverage and higher refinancing intensity. These results remain consistent when I define high net market leverage as firms with a net debt-to-market ratio above the 90th percentile across firms and time. These findings suggest that firms with higher rollover risk face a higher cost of capital.

B.5. Alternative Risk Index

To assess the robustness of my main results, particularly whether they are driven by my identification of aggregate cash flow risk shocks on FOMC announcement days, I consider two alternative measures of aggregate cash flow uncertainty.

[Table 18 around here]

[Figure 14 around here]

Table 18 replicates the main firm-level investment results using the BBM risk index from Bauer et al. [2023]. Several key findings emerge. First, all documented results remain qualitatively consistent: higher risk predicts lower investment, particularly for firms with high financial frictions and high rollover risk. Additionally, firms with high net market leverage reduce debt growth and accumulate more cash. Second, while the significance of the heterogeneous firm response remains intact, the statistical significance of the average firm investment response declines. One possible explanation is that the risk shock does not purely reflect cash flow uncertainty. However, given that cash flow uncertainty constitutes a major component of the BBM risk index, the main findings regarding heterogeneous investment, debt reduction, and cash accumulation remain robust.

Figure 14 examines the robustness of the subgroup average response to changes in the FOMC BBM risk index using the dummy interaction approach from equation 13. The results remain consistent when using the FOMC cash flow risk shock, showing that firms with high net market leverage reduce investment more significantly. Additionally, changes in the FOMC BBM risk index predict a debt reallocation effect between high- and low-financial-risk firms. High-risk firms also increase their cash holdings in response to rising risk. Furthermore, the decline in investment is primarily concentrated among firms with high rollover risk. These findings confirm the robustness of the subgroup response across alternative risk measures.

[Table 19 around here]

Table 19 replicates the main firm-level results using an SVIX2 from Martin [2017] as an alternative aggregate cash flow uncertainty proxy. The findings are similar to those obtained with the BBM risk index. Although the average effect is less significant, the heterogeneous effects on investment, debt, and cash holdings remain statistically significant. These results are qualitatively consistent with my main findings.

B.6. Control other monetary policy shocks

In this section, I further control for monetary policy shocks from Gürkaynak et al. [2004] (GSS). GSS shocks are among the most widely used measures of monetary policy shocks. They are constructed using principal components derived from changes in interest rate futures within a short-term window around FOMC announcements. The first component, the target factor, captures changes in the short-term interest rate target. The second component, the path factor, reflects expectations about future interest rates and is closely related to forward guidance. I aggregate both factors to the quarterly level and include them as control variables in my analysis. Table 20 presents the results. In column (1), I include both the target and path factors as controls. In columns (2) to (4), I interact these factors with the net debt-to-market ratio. In columns (5) and (6), I introduce a triple interaction term that includes the FOMC cash flow risk shock, the GSS factors, and the net debt-to-market ratio. This approach allows me to examine whether the effects of these monetary policy shocks vary disproportionately across firms with different levels of net market leverage and rollover risk, and explain my main findings. As shown in the table, my main results remain robust both qualitatively and quantitatively.

[Table 20 around here]

B.7. Sample Restricted to Manufacturing Firms

In this section, I test the robustness of my main firm-level results by replicating the analysis using a subsample of manufacturing firms (SIC codes 3000-3999). Tangible capital investment is particularly important for these firms, as their production heavily relies on plants and fixed equipment. Manufacturing firms account for nearly half of the observations in the full sample. Table 21 presents the results for the manufacturing subsample. I find that the results are similar to those of my main analysis, with the only difference being that the heterogeneous investment response based on net market leverage is marginally insignificant. All other findings remain consistent with my previous results.

[Table 21 around here]

B.8. Using Debt-to-Market Ratio

Table 22 replaces the financial risk measure of net debt-to-market ratio (net market leverage) with the debt-to-market ratio (market leverage). Unlike the net debt-to-market ratio, which adjusts for preferred stock and cash holdings, the debt-to-market ratio is calculated as total debt divided by market equity. Despite this change in measurement, all heterogeneous firm response results remain robust. This indicates that the findings are consistent regardless of whether net debt-to-market ratio or debt-to-market ratio is used to capture financial risk.

[Table 22 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^f_{t+1} following a VAR process:

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

where X_t is the vector of daily asset price changes:

$$X_t = (\Delta y^{(2)}_t,\ \Delta y^{(5)}_t,\ \Delta y^{(10)}_t,\ r^e_t),$$

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:

$$\omega^f_{t+1} = (w^c_t,\ w^d_t,\ w^{cr}_t,\ w^{dr}_t),$$

The four shocks have unit variance, i.e., $\mathrm{Var}(\omega^f_t) = I$. 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^f_{t+1} 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^c_{t+1}: captures investors' expectations about future cash flow growth.

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

3. **Discount rate risk premium shock** w^{dr}_t: 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^{cr}_t: 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.[53] 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 $\text{Var}(\omega_t^*) = I$. 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 reduced-form shocks becomes:

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

[53] 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.

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 15 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 15 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 23 around here**]

Table 23 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 16 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 16 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:

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

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

where S^{high}_t 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:

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

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:

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

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

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

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

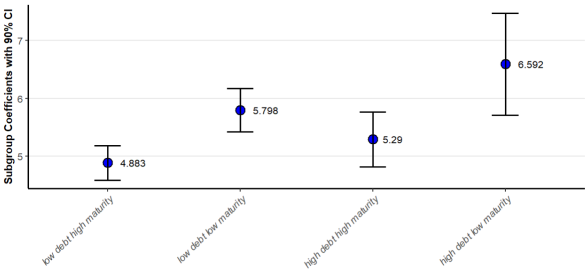
This table reports firm-level summary statistics for firms with non-missing values for both net debt-to-market ratio and refinancing intensity. All variables are quarterly data from Compustat, covering the period from 1995 to 2023.

Table 17: Firm-Level Investment Response to Rollover Risk, Excluding Almost Zero-Debt Firms

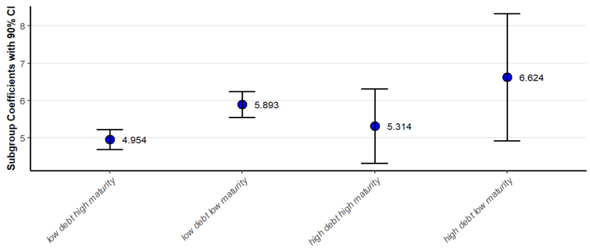
	$\log(k_{t+4}) - \log(k_t)$	
	(1)	**(2)**
$\epsilon_t^{cr} \times \mathbf{1}\{netDMR_{t-1}^{high}\}$	0.288	-0.02
	(0.201)	(0.493)
$\epsilon_t^{cr} \times \mathbf{1}\{netDMR_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$	-1.198***	-1.55***
	(0.409)	(0.555)
Firm FE	✓	✓
Quarter $\times$ Industry FE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

This table reports regression results based on Equation 12. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The key independent variable is a triple interaction term comprising the FOMC cash flow risk shock, an indicator for high net debt-to-market ratio (netDMR), $\mathbf{1}\{netDMR_{t-1}^{high}\}$, and an indicator for short debt maturity, $\mathbf{1}\{RI_{t-1}^{high}\}$. The indicator $\mathbf{1}\{RI_{t-1}^{high}\}$ identifies firms with a refinancing intensity (debt maturing within one year relative to total debt) above the sample median. Similarly, $\mathbf{1}\{netDMR_{t-1}^{high}\}$ captures firms with a netDMR above the 75th percentile of the sample. The sample comprises a quarterly panel of Compustat firms from 1995 to 2023, excluding firms with almost zero debt. Firm-level controls include one-quarter lagged values of size, net debt-to-market ratio, sales growth, asset returns, operational leverage, and the short-term asset ratio. The last two columns additionally incorporate the lagged GDP growth rate interacted with the lagged net debt-to-market ratio to account for differences in cyclical sensitivities across firms. For brevity, non-interacted coefficients and other double interaction terms are omitted. Standard errors, reported in parentheses, are calculated using the Driscoll–Kraay method, which addresses clustering by both firm and time. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 13: Subsample Cost of Capital Response Based on Rollover Risk



Panel A: Full sample with 75th Percentile of netDMR



Panel B: Full sample with 90th Percentile of netDMR

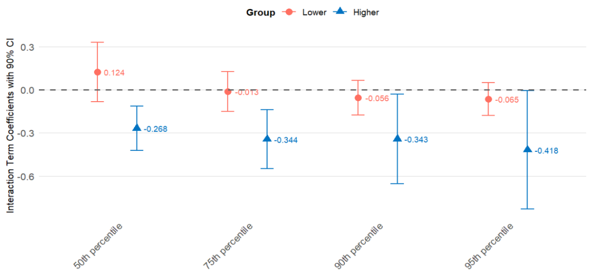
This plot reports regression results based on equation 13. The dependent variable is the four-quarter change in the log equity price. The main independent variable is a triple interaction term consisting of the FOMC cash flow risk shock, an indicator variable for high netDMR, $\mathbf{1}\{netDMR_{t-1}^{high}\}$, and an indicator variable for high refinancing intensity, $\mathbf{1}\{RI_{t-1}^{high}\}$. The indicator $\mathbf{1}\{RI_{t-1}^{high}\}$ represents firms with a short maturity ratio (debt maturing in less than one year to total debt) above the sample median. Similarly, $\mathbf{1}\{netDMR_{t-1}^{high}\}$ identifies firms with a netDMR above the 75th or 90th percentile of the sample. The sample includes a quarterly panel of Compustat firms from 1995 to 2023. The regressions include macroeconomic controls, firm fixed effects, year $\times$ industry fixed effects, and the indicator variable $\mathbf{1}\{RI_{t-1}^{high}\} \times \mathbf{1}\{netDMR_{t-1}^{high}\}$. Macroeconomic controls include lagged values (one to four quarters) of inflation, GDP growth, and unemployment. The table also presents 90% pointwise confidence intervals based on standard errors computed using the Driscoll–Kraay method, accounting for clustering by firm and time.

Table 18: Robustness: Main Results Using the Risk Index from Bauer et al. [2023]

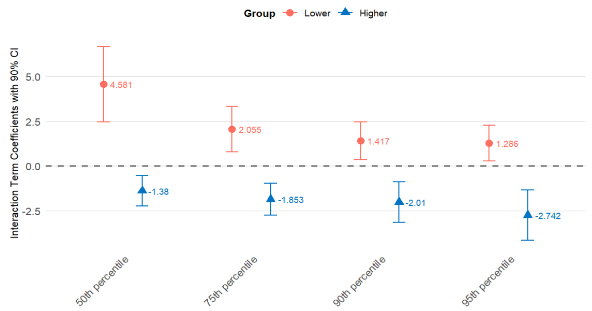
4 quarters growth rate	Capital	Capital	Debt	Cash	Capital	Capital
	(1)	(2)	(3)	(4)	(5)	(6)
ϵ_t^{risk}	-0.235					
	(0.250)					
$\epsilon_t^{risk} \times netDMR_{t-1}$		-0.881***	-3.47***	1.104*		
		(0.195)	(0.821)	(0.633)		
$\epsilon_t^{risk} \times netDMR_{t-1} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-0.315	
					(0.348)	
$\epsilon_t^{risk} \times \mathbf{1}\{netDMR_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$						-0.909**
						(0.411)
Firm FE	✓	✓	✓	✓	✓	✓
Year $\times$ Industry FE	✓					
Macro Controls	✓					
Quarter $\times$ Industry FE		✓	✓	✓	✓	✓
$\epsilon_t^{risk} \times$ Firm Controls		✓	✓	✓	✓	✓
Observations	298,082	238,418	196,105	237,584	199,086	199,086
Adjusted R^2	0.099	0.147	0.069	0.080	0.166	0.169
Sample	Full	Full	Full	Full	Full	Full

This table reports a robustness test of the main firm-level investment results using an alternative proxy for cash flow risk, the risk index from Bauer et al. [2023]. The independent variable is the quarterly sum of daily changes in the risk index on scheduled FOMC announcement days. The dependent variable is the four-quarter-ahead change in tangible capital investment, cash growth, or debt growth. The sample consists of a quarterly panel of Compustat firms spanning 1995 to 2023. Macro controls include lagged values (one to four quarters) of inflation, GDP growth, and unemployment. Firm-level controls include lagged (one quarter) size, net debt-to-market ratio, sales growth, asset return, operational leverage, and short-term asset ratio. Standard errors, reported in parentheses, are computed using the Driscoll–Kraay method, clustering by firm and time. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

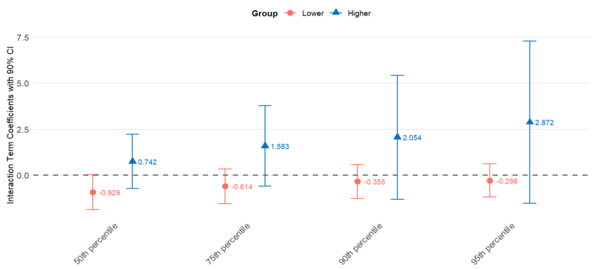
Figure 14: Subsample Firm-Level Investment Response Using the Risk Index from Bauer et al. [2023]



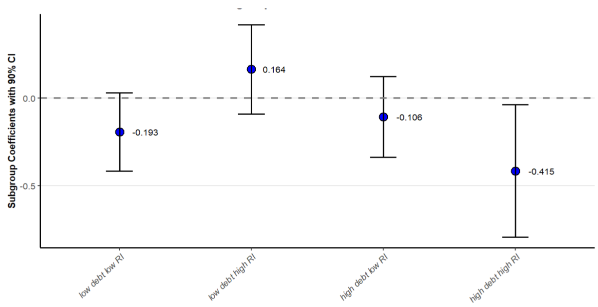
Panel A: Tangible Capital Investment Based on Net Market Leverage



Panel B: Debt Growth Based on Net Market Leverage



Panel C: Cash Growth based on Net Market Leverage



Panel D: Tangible Capital Investment Based on Rollover Risk

This table presents regression results based on equation 13. The key independent variable is the interaction term between the FOMC BBM risk change and an indicator variable for high netDMR, $\mathbf{1}\{netDMR^{low}_{t-1}\}$, or a triple interaction that includes an additional indicator for high refinancing intensity, $\mathbf{1}\{RI^{high}_{t-1}\}$. The indicator $\mathbf{1}\{RI^{high}_{t-1}\}$ identifies firms with refinancing intensity—measured as the ratio of debt maturing within one year to total debt—above the sample median. Similarly, $\mathbf{1}\{netDMR^{high}_{t-1}\}$ represents firms with a netDMR above the 75th percentile of the sample. The sample consists of a quarterly panel of Compustat firms from 1995 to 2023. The regressions control for macroeconomic variables, firm fixed effects, year $\times$ industry fixed effects, and the interaction term $\mathbf{1}\{RI^{high}_{t-1}\} \times \mathbf{1}\{netDMR^{low}_{t-1}\}$. Macroeconomic controls include the lagged values (one to four quarters) of inflation, GDP growth, and unemployment. The table also reports 90% pointwise confidence intervals, computed using standard errors clustered at the firm level.

Table 19: Robustness: Main Results Using the Market SVIX2 from Martin [2017]

4 quarters growth rate	Capital	Capital	Debt	Cash	Capital	Capital
	(1)	(2)	(3)	(4)	(5)	(6)
ϵ_t^{risk}	-0.042					
	(0.042)					
$\epsilon_t^{risk} \times netDMR_{t-1}$		-0.202**	-0.869***	0.295*		
		(0.084)	(0.310)	(0.160)		
$\epsilon_t^{risk} \times netDMR_{t-1} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-0.132	
					(0.122)	
$\epsilon_t^{risk} \times \mathbf{1}\{netDMR_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$						-0.195**
						(0.089)
Firm FE	✓	✓	✓	✓	✓	✓
Year $\times$ Industry FE	✓					
Macro Controls	✓					
Quarter $\times$ Industry FE		✓	✓	✓	✓	✓
$\epsilon_t^{risk} \times$ Firm Controls		✓	✓	✓	✓	✓
Observations	298,082	238,418	196,105	237,584	199,086	199,086
Adjusted R^2	0.099	0.147	0.069	0.080	0.166	0.169
Sample	Full	Full	Full	Full	Full	Full

This table reports a robustness test of the main firm-level investment results using an alternative proxy for cash flow risk, the SVIX2 from Martin [2017]. The independent variable is the quarterly sum of daily changes in the SVIX2 on scheduled FOMC announcement days. The dependent variable is the four-quarter-ahead change in tangible capital investment, cash growth, or debt growth. The sample consists of a quarterly panel of Compustat firms spanning 1995 to 2023. Standard errors, reported in parentheses, are computed using the Driscoll–Kraay method, clustering by firm and time. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 20: Robustness: Main Results Controlling for Monetary Policy Shocks from Gürkaynak et al. [2004]

4 quarters growth rate	Capital	Capital	Debt	Cash	Capital	Capital
	(1)	(2)	(3)	(4)	(5)	(6)
ϵ_t^{cr}	-0.464**					
	(0.227)					
$\epsilon_t^{cr} \times netDMR_{t-1}$		-0.976***	-4.636***	2.352*		
		(0.230)	(0.858)	(1.212)		
$\epsilon_t^{cr} \times netDMR_{t-1} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-1.609***	
					(0.418)	
$\epsilon_t^{cr} \times \mathbf{1}\{netDMR_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$						-1.375***
						(0.399)
Firm FE	✓	✓	✓	✓	✓	✓
Year $\times$ Industry FE	✓					
Macro Controls	✓					
Quarter $\times$ Industry FE		✓	✓	✓	✓	✓
$\epsilon_t^{risk} \times$ Firm Controls		✓	✓	✓	✓	✓
GSS Shock Controls	✓	✓	✓	✓	✓	✓
Observations	298,082	238,418	196,105	237,584	199,086	199,086
Adjusted R^2	0.099	0.144	0.070	0.080	0.165	0.168
Sample	Full	Full	Full	Full	Full	Full

This table presents robustness tests of the main firm-level results, incorporating control variables for path and target factors from Gürkaynak et al. [2004], as well as interaction terms with net market leverage and rollover risk measures. The independent variable is the FOMC cash flow risk shock, and the dependent variables are the four-quarter-ahead changes in tangible capital investment, cash growth, and debt growth. The sample comprises a quarterly panel spanning the period from 1995 to 2023. Standard errors, reported in parentheses, are calculated using the Driscoll–Kraay method, with clustering by firm and time. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 21: Robustness: Main Results Using Only Manufacturing Firms

4 quarters growth rate	Capital	Capital	Debt	Cash	Capital	Capital
	(1)	(2)	(3)	(4)	(5)	(6)
ϵ_t^{cr}	-0.428**					
	(0.198)					
$\epsilon_t^{cr} \times netDMR_{t-1}$		-0.608	-5.268***	3.512*		
		(0.497)	(2.363)	(1.936)		
$\epsilon_t^{cr} \times netDMR_{t-1} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-1.188	
					(0.838)	
$\epsilon_t^{cr} \times \mathbf{1}\{netDMR_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$						-2.194***
						(0.628)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓					
Macro Controls	✓					
Quarter FE		✓	✓	✓	✓	✓
$\epsilon_t^{risk} \times$ Firm Controls		✓	✓	✓	✓	✓
Observations	153,303	125,629	102,598	125,232	104,119	199,086
Adjusted R^2	0.092	0.127	0.067	0.080	0.144	0.147
Sample	Full	Full	Full	Full	Full	Full

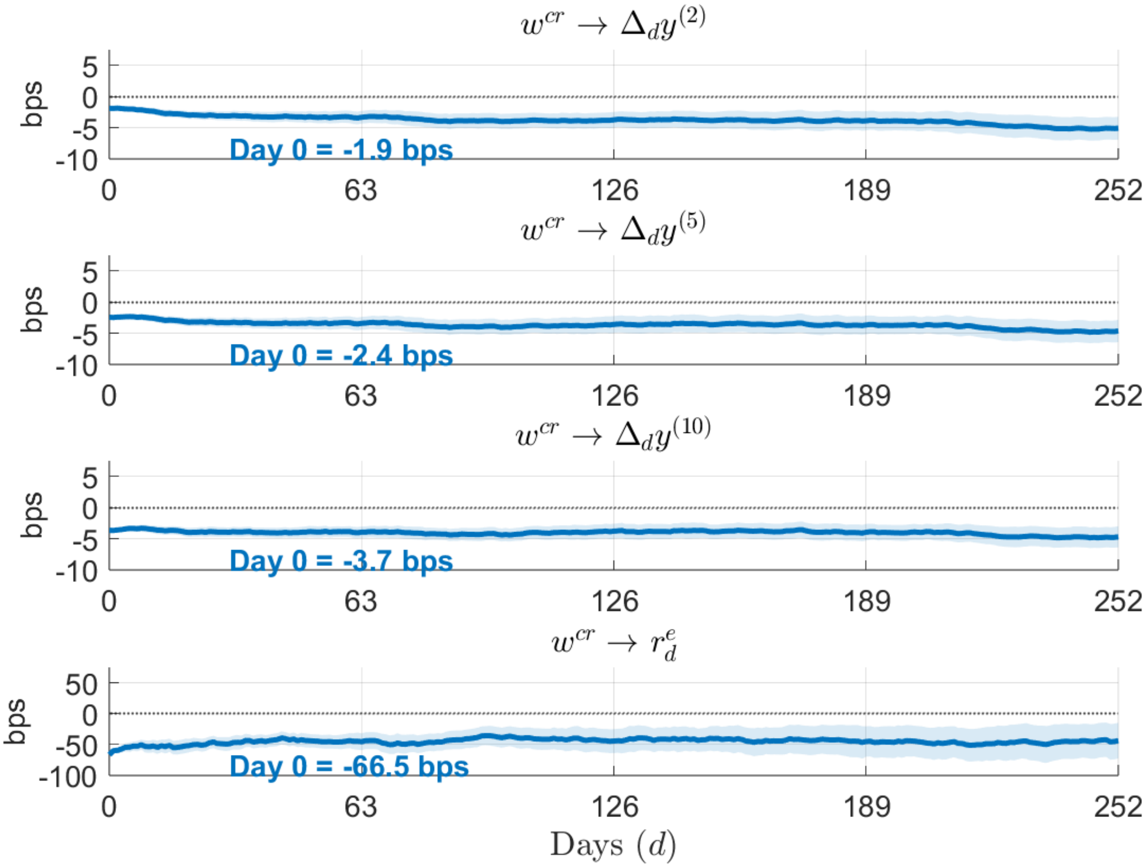
This table presents a robustness test of the main firm-level investment results using a sample restricted to manufacturing firms. The independent variable is the FOMC cash flow risk shock, while the dependent variable is the four-quarter-ahead change in tangible capital investment, cash growth, or debt growth. The sample consists of a quarterly panel covering the period from 1995 to 2023. Standard errors, reported in parentheses, are computed using the Driscoll–Kraay method, clustering by firm and time. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 22: Robustness: Main Results Using Debt-to-Market Ratio as a Financial Risk Measure

4 quarters growth rate	Capital	Capital	Debt	Cash	Capital	Capital
	(1)	(2)	(3)	(4)	(5)	(6)
ϵ_t^{cr}	-0.491**					
	(0.235)					
$\epsilon_t^{cr} \times DMR_{t-1}$		-1.101***	-4.752***	1.440		
		(0.251)	(0.843)	(1.162)		
$\epsilon_t^{cr} \times DMR_{t-1} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-1.919***	
					(0.412)	
$\epsilon_t^{cr} \times \mathbf{1}\{DMR_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$						-1.141***
						(0.426)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓					
Macro Controls	✓					
Quarter FE		✓	✓	✓	✓	✓
$\epsilon_t^{risk} \times$ Firm Controls		✓	✓	✓	✓	✓
Observations	298,082	238,418	196,105	237,584	199,086	199,086
Adjusted R^2	0.099	0.147	0.069	0.080	0.167	0.170
Sample	Full	Full	Full	Full	Full	Full

This table presents a robustness test of the main firm-level investment results using the net debt-to-market ratio as a measure of financial risk. The independent variable is the FOMC cash flow risk shock, while the dependent variable is the four-quarter-ahead change in tangible capital investment, cash growth, or debt growth. The sample consists of a quarterly panel covering the period from 1995 to 2023. Standard errors, reported in parentheses, are computed using the Driscoll–Kraay method, clustering by firm and time. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Figure 15: Impulse Response Function



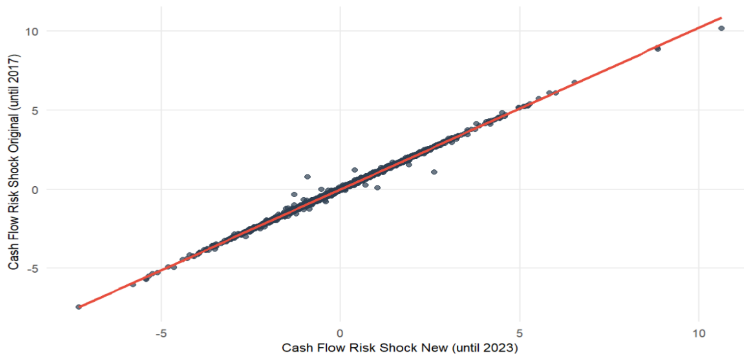
This figure presents the impulse responses of cumulative yield changes and stock returns to the cash flow risk shock. The magnitudes are expressed in basis points. The response horizon is one year, and the plot highlights the response at day 0. The shock is identified using a structural VAR, as described 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 23: Correlation Between Original and Updated Shock Series

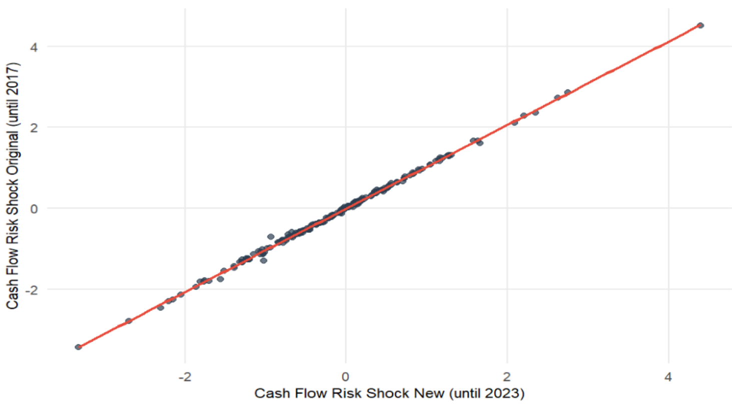
All Trading Days	ϵ_t^c	ϵ_t^d	ϵ_t^{cr}	ϵ_t^{dr}
Correlation	0.9959	0.9897	0.9988	0.9983
95% interval	[0.9957, 0.9960]	[0.9892, 0.9901]	[0.9987, 0.9988]	[0.9982, 0.9983]
FOMC Days	ϵ_t^c	ϵ_t^d	ϵ_t^{cr}	ϵ_t^{dr}
Correlation	0.9997	0.9994	0.9992	0.9997
95% interval	[0.9996, 0.9998]	[0.9992, 0.9996]	[0.9989, 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 16: 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.