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

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Abstract

The literature has extensively documented that monetary-policy announcements affect risk premia and risk perception in financial markets; however, little is known about how these effects shape real activity. Using daily aggregate risk shocks identified from equity-market returns and Treasury-yield changes, we provide causal evidence that an increase in risk perception stemming from FOMC announcement days curtails subsequent tangible capital investment by firms. In contrast to prior studies showing that financial constraints dampen investment responses to interest-rate shocks, we find that financial constraints instead magnify investment responses through the risk channel and propagate to financial variables. Consistent with a flight-to-quality mechanism that raises external financing costs for constrained firms, FOMC-day risk-perception changes cause these firms to: (1) reduce investment more sharply; (2) decelerate net borrowing; (3) accumulate larger cash buffers; and (4) experience the most severe investment reductions when their debt is short-term—that is, when rollover risk is highest. At the aggregate level, the investment response to risk-perception changes is state-dependent, strengthening with the share of high-rollover-risk firms; nevertheless, the unconditional aggregate effect remains muted because such firms hold relatively small tangible-capital stocks and therefore contribute little to the aggregate investment response.

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

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1. Introduction

In their seminal study, Bernanke and Kuttner [2005] demonstrate that monetary easing boosts equity prices not only by lowering the risk-free rate and raising expected dividends but, crucially, also by compressing the risk premium that investors require. Building on this insight, subsequent empirical work provides extensive evidence that both monetary policy actions and their announcements significantly influence risk premia and investors' risk perception[1]. Nevertheless, evidence remains scarce on how far these monetary policy-induced risk-perception shifts (hereafter MP risk-perception shifts) transmit to the real economy and shape corporate behaviour[2]. Whether MP risk-perception shifts deliver the sizeable macroeconomic consequences, as implied by macro-finance theories, remains an open and pressing question[3].

In this paper we present causal evidence that an increase in investors' aggregate risk perception—that is, investors perceive greater future market risk and uncertainty—stemming from monetary-policy announcement days depresses subsequent corporate investment in tangible capital. Crucially, financial constraints amplify this adverse effect and transmit it to financial variables; cross-firm heterogeneity in those constraints is the key determinant of the aggregate investment response to the risk-perception shift. We obtain these results by combining daily risk shocks extracted from financial-market prices with quarterly *Compustat* panel data, which provide rich variation across firms and over time in their financial positions.

To guide our empirical analysis, we begin by presenting the stylized model of Pflueger et al. [2020], which serves as our conceptual framework. The model highlights the core elements of risk-centric business-cycle theories, and we extend it with a simple feature: monetary policy can shift agents' perceptions of future aggregate risk[4]. Both household consumption uncertainty and firms' future cash-flow uncertainty are driven by aggregate risk. When monetary policy heightens perceived aggregate risk, the price of safe bonds rises because households—motivated by precautionary saving—place a higher value on safety. Confronted with the same risk, households simultaneously demand a larger premium to hold claims on risky corporate cash flows. The resulting increase in firms' cost of capital, via the Q-theory channel, dampens investment. This mechanism is strongest for firms

[1] The literature documents that monetary policy affects risk perception through various channels—for example, shifts in the macro outlook, changes in uncertainty, and improvements in borrower and lender balance sheets.

[2] Bauer et al. [2023] summarise recent financial market findings and emphasise the lack of real economy evidence: "...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 ...".

[3] See, for example, Drechsler et al. [2018]; Kekre and Lenel [2022].

[4] Intuitively, this captures both the change in risk induced by the interest rate itself and other channels operating through monetary policy announcements. In this simple model, we abstract by linking risk directly to the interest rate.

whose cash-flow uncertainty is especially sensitive to aggregate risk.

Empirically isolating the effect of monetary-policy–induced risk shifts on firm investment poses a substantial challenge. The analysis must disentangle the risk shifts effect from the conventional interest-rate channel and capture all risk changes generated by monetary-policy communication, not only components tied to the policy-rate move. To confront this challenge, we adopt the asset-pricing approach of Cieslak and Pang [2021] and extract daily aggregate cash-flow risk shocks from bond- and equity-market data using a structural VAR. These shocks reflect shifts in expected cash-flow uncertainty, are priced by investors, and raise safe-bond values because such bonds hedge the shock—properties consistent with the notion of aggregate risk in our conceptual framework. By construction, the cash-flow risk shock is orthogonal to both the interest-rate shock and the cash-flow growth shock. We focus on shocks that occur on FOMC announcement days (hereafter, *FOMC cash-flow risk shocks*) as proxies for monetary-policy-driven risk shifts. Our identification assumption is that, in an efficient market, publicly available information is priced in before the announcement; hence, within-day price changes represent genuinely unanticipated news. Because FOMC announcements are the dominant information events on those days, the resulting cash-flow risk shocks largely capture risk shifts triggered by the monetary-policy announcement[5].

We quantify firms' investment responses to FOMC cash-flow risk shocks with a panel local-projection approach. This robust and flexible framework allow us to mitigate potential confounding from other monetary-policy transmission channels by controlling for additional economic shocks that arise on FOMC announcement days[6]. Our estimates show that an increase in aggregate risk on an FOMC announcement day is significantly associated with lower tangible-capital investment. A one-unit FOMC cash-flow risk shock—equivalent to a 66.5-basis-point decline in the equity-market index[7]—reduces average investment by 0.496% over the subsequent four quarters, roughly 3% of the average annual investment rate.

How do monetary-policy-induced risk shifts affect investment? The rich cross-sectional heterogeneity in firms' financial positions in our panel allows us to investigate whether financial constraints influence the responsiveness of investment to FOMC risk shocks. We explore this dimension for two reasons. First, during the high-risk period of 2007–2008, financial frictions played a central role in the dramatic fall in economic activity and capital investment. Second, the monetary-policy literature documents that financial frictions dampen the investment response to the classical interest-rate channel[8]. For policy design,

[5]Robustness checks using alternative proxies—daily changes in market risk premia—yield results consistent with our main findings.

[6]Specifically, we include the shocks recovered from our structural-VAR analysis and the high-frequency interest-rate surprises widely used in the literature.

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

[8]See, for example, Ottonello and Winberry [2020] and Döttling and Ratnovski [2023].

it is therefore important to establish whether the impact of risk shifts complements or contradicts this classical channel. Following prior accounting research Penman et al. [2007], we proxy for financial constraints with the net-debt-to-market-value ratio, which captures a firm's net market leverage[9]. This measure accords with the evidence in Lian and Ma [2021], who show that roughly 80% of U.S. public firms' debt is secured primarily by cash flows rather than by physical collateral. Our results reveal that financial constraints significantly amplify the impact of monetary-policy-induced risk shifts on investment: following a positive FOMC cash-flow risk shock, financially constrained firms—those in the top 5 percent of the net-debt-to-market ratio distribution—cut investment by roughly three times as much as their less-constrained counterparts in the bottom 95 percent.

Why are financially constrained firms more exposed to risk shifts on FOMC announcement days? We provide suggestive evidence that financially constrained firms—which generally have higher default risk and lower collateral value—face a larger increase in external financing costs than unconstrained firms after a positive risk shift, a phenomenon consistent with the well-documented investors flee to quality during high-risk periods. Although external financing costs are not directly observable, firms' balance-sheet variables offer indirect signals. Following a positive FOMC cash-flow risk shock, financially constrained firms—those that cut investment the most—also slow their debt issuance and accumulate cash more aggressively. This propagation to financial variables is consistent with the mechanism first noted by Keynes(1936) and formalised in Riddick and Whited [2009] and Bolton et al. [2019]: Firms finance investment with external funds or internal cash reserves. When current or expected external financing costs rise, externally funded investment become more expensive. Firms therefore cut back on external financing and accumulate precautionary cash to mitigate future funding costs, both moves can delay or curtail investment[10]. Our findings thus suggest that monetary-policy-induced risk shifts disproportionately raise the cost of external finance for financially constrained firms.

Additional evidence also supports the disproportionate increase in external financing costs. Elevated financing costs limit firms' debt capacity. According to theoretical work such as Acharya et al. [2011], firms facing debt constraints encounter greater difficulty in rolling over short-term debt when refinancing needs are high. As a result, their default risk increases, further reducing debt capacity and reinforcing a feedback loop that amplifies financing costs and depresses investment. We observe the same mechanism in our panel. We quantify firms' refinancing needs using *refinancing intensity*, defined as the ratio of debt maturing within one year to total debt. Our results show that the impact of FOMC cash flow risk shocks on future investment is particularly strong and concentrated among

[9] Net debt is defined as total debt plus preferred stock minus cash holdings.

[10] The effect is even stronger when non-convex (fixed or lumpy) adjustment costs are present in both capital installation and external financing. These kinks create a real option (delay investment) and a cash option (stock-pile liquidity to avoid costly issues). A higher financing cost raises the value of both options, so firms hoard cash, curb new borrowing, and postpone investment even more.

firms with high rollover risk—that is, firms with both high leverage and high refinancing intensity. This finding remains robust after (i) excluding firms with negligible debt, thereby focusing on indebted firms, and (ii) controlling for other monetary-policy shocks that could differentially affect high-rollover-risk firms.

The investment effects of monetary-policy-induced risk shifts are highly concentrated among firms with high rollover risk. This concentration is pivotal because it identifies the dimension of heterogeneity—the distribution of rollover risk across firms—that governs the aggregate impact of the shock. We document several aggregate findings along this dimension. First, because only high-rollover-risk firms cut investment sharply, the conditional aggregate response to an FOMC cash-flow risk shock significantly depends on the economy-wide share of such firms. Our market-based leverage metric makes this share countercyclical: it rises when equity values fall, so identical shocks produce larger contractions in aggregate investment during recessions. Second, the same concentration mechanism drives sectoral reallocation. Industries with a greater proportion of high-rollover-risk firms experience larger declines in both investment and borrowing after a positive FOMC cash-flow risk shock. This industry-level effect is most pronounced in the post-2008 period and is weaker when monetary policy operates through conventional interest-rate channels.

However, the unconditional average transmission of monetary-policy-driven risk shifts to aggregate investment is weaker and delayed. Following the literature, we compute aggregate investment by weighting each firm's investment by its capital size. Using aggregate local projections, we find that aggregate investment is significantly less sensitive to FOMC cash-flow risk shocks over a one-year horizon than firm-level estimates suggest, although its responsiveness strengthens over a two-year horizon. To clarify this pattern, we conduct a counterfactual analysis following Crouzet and Mehrotra [2020]. While high-rollover-risk firms are more sensitive to the shock at the firm level, their contribution to aggregate investment is limited by their relatively small capital stock. Moreover, within the low-risk group—which holds a larger share of total capital—smaller firms are disproportionately more affected by the shock than their larger counterparts. These findings account for the weaker responsiveness of aggregate investment.

Related Literature: Our paper connects to three strands of literature. First, our study naturally follows the theoretical and empirical asset pricing literature that examines how monetary policy and monetary policy announcements shape risk premia in financial markets[11]. Several studies also explore the broader economic effects this risk premium change. Kekre and Lenel [2022] show that monetary policy redistributes wealth toward households with high marginal propensities to take risk, reducing risk premia and stimu-

[11]Recent work includes: 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], Bauer et al. [2023]. One paper that shares a similar intuition with our empirical strategy is Chaudhry [2020], which identifies daily macro uncertainty to study announcement effects on stock market returns.

lating the economy. Drechsler et al. [2018] demonstrate that monetary policy influences the liquidity premium, thereby lowering the cost of leverage, encouraging banks to increase leverage, and ultimately reducing risk premia while boosting asset prices and investment. In this paper, we empirically document a risk channel of monetary policy on firm investment. Specifically, we focus on a key component that influences risk premia—aggregate cash flow uncertainty. We show that monetary-policy-driven aggregate cash flow uncertainty strongly predicts future capital investment, particularly for firms with high financial and rollover risk.

Our paper contributes to the recent literature on monetary policy transmission to firm investment[12]. This literature focuses particularly on the heterogeneous investment responses of firms to monetary policy shocks based on firm 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]. A particularly interesting and relevant study is Jeenas and Lagos [2024], which proposes an asset pricing channel where monetary policy affects the market price of a firm's stock. In turn, investment and capital-structure decisions of firms that rely on equity financing respond to exogenous (policy-induced) variations in their stock prices. However, our empirical approach differs substantially from prior studies, including Jeenas and Lagos [2024], which primarily identify monetary policy shocks using short-term interest rate changes in narrow event windows. Instead, we take a different approach by using aggregate cash flow uncertainty shocks around monetary policy announcements. This allows us to capture uncertainty changes driven by monetary policy and demonstrate their direct effect on investment, independent of short term discount rates and future cash flow.

Our paper also contributes to the literature on uncertainty shocks and firm investment, notably building on the seminal work of Bloom [2009]. More recent studies, such as Alfaro et al. [2024], highlight how financial frictions amplify the effects of uncertainty shocks by strengthening firms' precautionary cash holdings, thereby reducing capital investment. We extend this literature by focusing on aggregate cash flow uncertainty shocks driven by monetary policy. Our findings suggest that uncertainty management in monetary policy communication—through clear economic outlooks and credible forward guidance—could play a role in mitigating the adverse effects of uncertainty on firm investment.

The rest of the paper proceeds as follows. Section 2 presents the conceptual framework guiding the empirical analysis. Section 3 explains the empirical strategy, and Section 4 discusses the data and measurement choices. Section 5 presents the main empirical results, focusing on the average and heterogeneous investment responses to FOMC cash flow risk shocks. Section 6 examines the mechanisms behind the heterogeneous investment response. Section 7 discusses our findings and provides additional robustness tests. Sec-

[12] A parallel strand of research examines monetary policy transmission to households, such as Wong et al. [2019] and van Binsbergen and Grotteria [2024].

tion 8 highlights the implications of our findings for the aggregate firm distribution and aggregate investment. Section 9 concludes the paper.

2. Conceptual Framework

In this section, we present the model developed by Pflueger et al. [2020], which serves as a conceptual framework for our empirical analysis. Despite its simplicity, the model captures the key economic mechanisms emphasized in risk-centric theories of the business cycle.[13] We extend their framework by introducing a basic monetary policy rule to illustrate how aggregate risk shifts induced by monetary policy influence firms' investment decisions.

2.1. Model

Risk and Monetary Policy

Following Pflueger et al. [2020], we model log aggregate consumption growth as a stochastic process defined by $x_t = v_t$, where v_t denotes an aggregate demand shock. The shock follows a mean-zero, independently and identically distributed (i.i.d.) normal distribution with time-varying heteroskedasticity, $v_t \sim N(0, \sigma^2_{v,t})$. The term $\sigma^2_{v,t}$ captures the risk associated with the aggregate demand shock[14]. This framework assumes the economy operates around a steady state, with the consumption process reflecting deviations from that steady-state level[15].

We further assume that log aggregate consumption growth is influenced by both aggregate shocks and monetary policy. Specifically, the log aggregate growth is given by:

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

where i_t denotes the nominal interest rate. The parameter $\theta < 0$ governs the effect of the nominal interest rate on consumption, implying that an increase in the interest rate reduces current aggregate growth. This aligns with the intuition of an IS curve. The monetary authority follows a simple policy rule:

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

where $\phi > 0$ represents the policy response to aggregate shocks. A positive ϕ indicates that monetary policy acts as a stabilizing mechanism to counteract aggregate demand shocks. The term ϵ_t is an independent policy shock, assumed to be normally distributed with

[13] Earlier contributions in this literature include Gourio [2012], Fernández-Villaverde et al. [2015], and Caballero and Simsek [2020].

[14] Throughout the model section, the term "risk" is equivalent to uncertainty about future outcome and is represented mathematically by the variance.

[15] This interpretation is analogous to the concept of the output gap, which captures fluctuations around a long-run trend.

time-invariant variance: $\epsilon_t \sim N(0, \sigma_\epsilon^2)$. These unanticipated deviations reflect the idea that monetary policy does not perfectly adhere to the rule in offsetting demand shocks[16]. These deviations capture unexpected policy errors or temporary shifts in the policymaker's preferences[17].

By substituting the monetary policy rule into the consumption growth process, we express x_t as a function of the aggregate demand shock and the monetary policy shock:

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

where ω is a constant defined as $\omega = \frac{1}{1-\theta\phi}$. The perceived aggregate risk for the next period, represented by the variance of x_{t+1}, is then given by:

$$\sigma_{x,t+1}^2 = \omega^2(\theta^2\sigma_\epsilon^2 + \sigma_{v,t+1}^2).$$

We further assume that the heteroskedastic conditional variance $\sigma_{v,t+1}^2$, which reflects the perceived risk of future demand shocks, evolves according to:

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

where a and b are constants, with $b > 0$. This specification aligns with existing literature documenting the countercyclical nature of risk premia and the tendency for perceived future uncertainty to increase during economic downturns.[18]

Household Preferences and the Risk-Free Rate

A representative agent has a constant relative risk aversion (CRRA) utility function characterized by a risk aversion coefficient γ and a time discount factor β:

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

The log consumption growth Δc_{t+1} follows the aggregate process $\Delta c_{t+1} = x_{t+1}$. The corresponding stochastic discount factor (SDF) is given by:

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

[16]This is consistent with the concept discussed in Galí [2015], where "[t]he 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."

[17]See Cieslak and McMahon [2023].

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

Given that x_{t+1} follows a normal distribution with mean zero, the term $\exp(-\gamma x_{t+1})$ is log-normally distributed. As a result, the time-t log real risk-free rate is given by $r_{ft} = -\ln\beta - \frac{1}{2}\gamma^2\sigma^2_{x,t+1}$[19].

Production

Firm production is modeled using a standard Q-theory framework, where output is determined by a linear production function in capital:

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

Here, Y_{it} denotes the output of firm i at time t, K_{it} is the firm's capital stock, and Z_{it} represents total factor productivity (TFP). The evolution of TFP follows the aggregate 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 the firm's exposure to aggregate consumption growth. The term $-\frac{1}{2}s_i^2\sigma^2_{x,t+1}$, which arises from Jensen's inequality, ensures that the expected value of TFP remains constant (equal to 1) across all firms. As a result, heterogeneity across firms stems solely from differences in their cash flow uncertainty driven by exposure to aggregate risk[20].

Capital evolves according to the standard accumulation equation, $K_{it+1} = I_{it} + (1-\delta)K_{it}$, where I_{it} represents investment and δ denotes the depreciation rate. To derive a closed-form solution for investment, we assume adjustment costs follow a standard quadratic form:

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

Firm dividends are given by the difference between output and adjustment costs, $D_{it} = Y_{it} - \Phi_{it}$. To obtain a closed-form solution, we impose two additional assumptions. First, capital fully depreciates within each period ($\delta = 1$), meaning the capital available for production in period $t+1$ equals the investment made in period t. Second, firms operate for a single period before exiting, with a new cohort of firms entering the market each period. These assumptions simplify each firm's problem into a two-period framework, similar to those commonly used in investment-based asset pricing models (e.g., Lin and

[19]This follows from the Euler equation:

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

[20]Since x_{t+1} follows a normal distribution with mean zero, $\exp(s_i x_{t+1})$ follows a log-normal distribution. We impose $s_i > \frac{\gamma}{2}$ 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, leading to lower aggregate investment.

Zhang [2013], Hou et al. [2015]). Under this setup, a firm that enters at time t earns dividends in periods t and $t+1$ as follows:

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

The firm maximizes the risk-adjusted present value of its dividends. The optimization problem is given by:

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

Risky Return and Real Investment

A key insight from Q-theory is that the market return on a financial claim to the firm, denoted by 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, which corresponds to the next-period productivity of that investment divided by its marginal cost. Formally, the marginal benefit of one additional unit of investment is given by:

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

The 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 equation $1 = E_t[M_{t+1} R_{it+1}]$ must hold. Since both the return and the stochastic discount factor (SDF) have been derived[21], combining the Euler equation with the quadratic adjustment cost function in Equation 4, we obtain:

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

where the left-hand side represents the investment rate. This equation indicates that investment declines as aggregate risk $\sigma_{x,t+1}^2$ increases, provided the firm is sufficiently risky ($s_i > \frac{\gamma}{2}$). The effect is more pronounced for firms with greater risk exposure (s_i), as their cost of capital becomes more sensitive to changes in risk. Additionally, the corresponding excess return is given by:

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

[21] The Euler equation for the risky asset is given by

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

2.2. Equilibrium

In this simple model, changes in perceived aggregate risk constitute the sole channel through which monetary policy affects asset prices and capital investment. The key insights that guide our empirical analysis are summarized in the following propositions. We begin by characterizing the model's equilibrium.

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

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

Proposition 2. *When x_t is small (close to zero), a positive monetary policy shock increases aggregate risk:*

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

The expression $-b\omega^3\theta\exp(a)$ captures the sensitivity of aggregate risk to monetary policy shocks. This result implies that such shocks have an approximately linear effect on perceived risk. The intuition is that a contractionary monetary policy shock lowers current consumption, which raises agents' uncertainty about future states of the economy. Log-linearizing the expression for aggregate risk yields the following result:

Lemma 1. *Suppose aggregate growth x_t, the monetary policy shock ϵ_t, and the consumption shock v_t are small and close to zero. Then, aggregate risk can be approximated linearly as:*

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

Thus, aggregate risk decomposes into three components: a constant term c, a component driven by the current demand shock κ^v_{t+1}, and a component driven by the monetary policy shock κ^ϵ_{t+1}, which captures monetary-policy-induced risk shifts. Taking the derivative of firm investment with respect to κ^ϵ_{t+1} yields the following result:

Proposition 3. *Given Lemma 1, 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 monetary-policy-induced risk shifts on investment is stronger for firms with greater exposure s_i.

Proposition 3 shows that a contractionary monetary policy shock raises aggregate risk, increasing the cost of capital by amplifying firms' cash flow uncertainty. This leads to a decline in investment on average. Cross-sectionally, firms with greater exposure (s_i) experience a larger increase in cash flow uncertainty and respond with more pronounced investment reductions. Taking the first derivative of the risk-free rate with respect to κ^{ϵ}_{t+1}, we obtain the next proposition:

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

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

Proposition 4 shows that as monetary policy increases aggregate risk, households respond by raising precautionary savings. This increased demand for safe assets depresses the risk-free rate and raises the price of risk-free securities. Since monetary-policy-induced risk shift is in an approximately linear fashion when x_t is near zero, the following corollary holds:

Corollary 1. *Given Lemma 1, the first derivatives of investment with respect to both the monetary-policy-induced risk shift κ^{ϵ}_{t+1} and the monetary policy shock ϵ_t,*

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

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

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

also share the same sign. In other words, the qualitative effects of monetary-policy-induced risk shifts on both investment and the risk-free rate remain consistent whether expressed in terms of risk shift κ^{ϵ}_{t+1} or the underlying monetary policy shock ϵ_t.

2.3. Empirical Implications

The risk channel of monetary policy transmission Proposition 3 yields a key empirical implication that we test:

Prediction 1: A positive monetary-policy-induced risk shift reduces firms' capital investment in the subsequent period.

We label this mechanism the "risk channel" of monetary-policy transmission. In the model, a positive risk shift raises firms' cash-flow uncertainty; investors then demand higher risk compensation, which increases firms' cost of capital and lowers investment. To capture this link, we also test whether positive risk shifts predict higher future equity returns, which serve as ex-post measure of the cost of capital.

Empirical methodology. In the simple conceptual framework, the risk channel is the only mechanism through which monetary policy affects capital investment. Under this idealised setting, the elasticity of investment with respect to a monetary policy shock provides direct evidence of the risk channel, as stated in Corollary 1. In practice, however, monetary policy influences investment through several channels, including the classical short-term discount-rate channel, so estimates of this elasticity may be confounded by other transmission mechanisms. A further concern is that monetary-policy-induced risk shifts may not originate solely from changes in interest rates. Previous studies show that non-rate information released at policy announcements also changes risk premia[22].

A practical strategy is therefore to measure unexpected changes in aggregate risk around policy announcements while controlling for the other information conveyed by the central bank. This approach requires a forward-looking indicator that captures revisions in perceived risk. A natural candidate is the risk premium embedded in asset prices. Accordingly, our empirical analysis uses market-level risk shocks, extracted from asset-pricing data on FOMC days, as a proxy for monetary-policy-induced risk shifts.

Identification of risk shocks. Propositions 3 and 4 provide empirical guidance on the properties that monetary-policy-induced risk shifts must satisfy to conform to the model's risk channel. We therefore seek risk shocks that increase uncertainty about firms' cash flows—uncertainty that is priced in equity markets, raises excess returns, and lowers the risk-free rate. Such shocks are embedded in expected equity returns but can be hedged by holding safe assets. This distinction is crucial. If equity prices are viewed as the sum of a long-term bond and a claim on cash-flow risk, an unexpected rise in discount-rate uncertainty would also lift expected returns, yet it would simultaneously raise safe-asset yields and leave cash-flow uncertainty unchanged. Although discount-rate uncertainty is priced in risk premia, it does not operate through the model's risk channel and is therefore not the focus of our identification strategy[23].

Financial constraints and the risk channel Proposition 3 posits that the investment effect of a monetary-policy-induced risk shift is stronger when a firm's cash flows are more exposed to aggregate risk, as captured by the coefficient s_i. This provides an abstract representation of cross-sectional heterogeneity in the risk channel. Empirically, the rich variation in firms' balance-sheet characteristics in our data allows us to explore

[22]For example, the Federal Reserve may issue a policy commitment to support the economy in a future recession, thereby reducing tail risk and uncertainty without changing the policy rate.

[23]According to standard asset-pricing theory, expected excess returns are determined by the negative covariance between asset returns and the stochastic discount factor (SDF). As noted by Hanson and Stein [2015], this covariance depends on three key components: uncertainty in future returns, uncertainty in the SDF, and their correlation. Consequently, when an unexpected increase in SDF uncertainty occurs, equity premia are expected to rise. However, this effect also extends to bonds, leading to a positive comovement between the two asset classes driven by heightened uncertainty in the SDF.

this heterogeneity once we identify the relevant dimension. Our study focus on financial constraints 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 constrained households and firms being most affected[24]. Second, earlier work—including Ottonello and Winberry [2020]—finds that financially constrained firms respond less to the conventional interest-rate channel; understanding whether these firms react more or less to monetary-policy-induced risk shifts therefore has important implications for policy design, particularly for how risk shifts and rate adjustments should be combined when financial constraints bind. Recent empirical results also suggest that financial constraints shape the investment response to cash-flow-risk shocks: Alfaro et al. [2024] document that, following a firm-level uncertainty shock, ex-ante constrained firms reduce investment more than unconstrained firms[25]. Guided by these observations, we state our second empirical prediction:

Prediction 2: Financially constrained firms respond more strongly to a positive monetary-policy-induced risk shift, reducing capital investment by more than unconstrained firms.

3. Empirical Strategy

Our empirical strategy builds on recent studies that examine monetary-policy shocks and firm investment with micro-level data, such as Ottonello and Winberry [2020] and Wong et al. [2019], and it closely follows the framework in Cloyne et al. [2023]. Mirroring Cloyne et al. [2023], we implement a two-stage procedure: first, we identify monetary-policy-related shocks with a structural VAR; second, we estimate their effects using firm-level panel data. The key distinction concerns the type of shock we identify. Following Cieslak and Pang [2021], we use asset-pricing data to extract aggregate *cash-flow-risk shocks* on FOMC announcement days. These shocks capture unexpected changes in aggregate cash-flow risk surrounding the policy announcement. By imposing sign restrictions in the structural VAR, we ensure that a positive shock raises expected equity returns, increases safe-Treasury prices, and remains orthogonal to other announcement-day shocks—properties required by the risk channel in our conceptual framework. We therefore treat this cash-flow-risk shock as a proxy for the monetary-policy-induced risk shift and use it as the main independent variable in the panel regressions that test the risk channel.

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

[25] Their findings align with our intuition that uncertainty/risk shocks suppress investment and emphasise the role of financial constraints; our study, by contrast, concentrates on aggregate monetary-policy-induced risk shifts rather than firm-specific uncertainty.

3.1. Identifying the Cash Flow Risk Shock Around FOMC Announcements

Cieslak and Pang [2021] propose a method to extract economic shocks from stock returns and changes in Treasury yields using a structural VAR. The method is grounded in macro-finance models that incorporate exogenous shocks to the endowment process, risk premia, and short-term interest rates to explain asset price dynamics. Below, we outline the key intuition of their approach; further details on the estimation procedure and results are available in Appendix D.

Suppose asset prices evolve according to the following structural VAR:

$$X_{t+1} = \mu + \Phi X_t + B\omega^f_{t+1}, \tag{11}$$

where X_t denotes the vector of daily asset price changes, defined as $X_t = (\Delta y^{(2)}_t,\ \Delta y^{(5)}_t,\ \Delta y^{(10)}_t,\ r^e_t)$. This vector includes changes in zero-coupon Treasury yields for 2-, 5-, and 10-year maturities, along with the market return. Here, μ represents a constant term, Φ is the matrix of dynamic coefficients, and B is the impact matrix governing contemporaneous structural relationships between shocks and asset prices. The vector of four structural shocks to the state variables is given by: $\omega^f_{t+1} = (w^c_t,\ w^d_t,\ w^{cr}_t,\ w^{dr}_t)$ [26]. By imposing restrictions on the impact matrix B, guided by the economic intuition of macro-finance models, we can assign the following interpretations to these shocks: (i) The cash flow growth shock (ω^c_{t+1}) reflects changes in investors' expectations about future equity cash flow growth. (ii) The discount rate shock (ω^d_{t+1}) captures shifts in the risk-free component of the discount rate. (iii) The discount rate risk premium shock (w^{dr}_t) reflects the compensation adjustment required by investors for bearing discount rate uncertainty. (iv) The cash flow risk premium shock (w^{cr}_t) captures the compensation adjustment demanded by investors for exposure to aggregate cash flow uncertainty, where bonds act as a hedge and move inversely to equities in response to this shock[27].

Two sets of restrictions are imposed on the impact matrix B. The first comprises cross-maturity restrictions inspired by the affine term-structure literature. Shocks tied to the short rate—namely, cash-flow-growth and discount-rate shocks—affect Treasury yields less as bond maturity increases. Conversely, risk-premium shocks exert larger effects at longer maturities. We therefore impose that the impact of the two risk-premium shocks on Treasury yields rises with maturity, which helps isolate these shocks from two short-rate shocks.

The second set of restrictions are sign restrictions that pin down the contemporaneous responses of asset prices to each structural shock and thereby separate cash-flow risk from discount-rate risk. A positive cash-flow-risk-premium shock (w^{cr}_t) lowers equity prices by

[26] All shocks are standardized to have zero mean and unit variance over the estimation period (i.e., $\mathrm{Var}(\omega^f_t) = I$).

[27] The two risk premium structure align with the view that an equity claim can be decomposed into a combination of a long-term bond and exposure to cash flow risk

raising expected returns to compensate investors for greater cash-flow uncertainty. At the same time, it raises bond prices (i.e., lowers yields) because investors flee to safety, and Treasuries hedge this type of uncertainty. By contrast, a positive discount-rate-risk-premium shock (w_t^{dr}) increases both bond yields and expected equity returns, reducing the prices of both asset classes as investors demand compensation for unhedgeable discount-rate uncertainty.[28] Because the sign restrictions, together with the orthogonality imposed in the VAR, render the shocks mutually independent, the identified cash-flow-risk shock satisfies the properties needed to test the risk channel in our conceptual framework [29].

We estimate the structural VAR on a sample that begins in 1983, mirroring the start date in Cieslak and Pang [2021], and extends through 2023[30]. Consistent with standard practice in the literature, including Wong et al. [2019], Ottonello and Winberry [2020], and Jeenas and Lagos [2024], we extract daily cash-flow-risk shocks on FOMC announcement days and aggregate them to the quarterly frequency to match the firm-level balance-sheet data. The resulting series, denoted ϵ_t^{cr} and referred to as the *FOMC cash-flow-risk shock*, serves as our empirical proxy for monetary-policy-induced risk shifts in testing the risk channel.

3.2. Cash Flow Risk Shock and Firm level Investment

We estimate the average investment response to monetary-policy-induced risk shifts with the panel local-projection method of Jordà [2005]:

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

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 captures firm 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. In this specification, we cannot include quarterly fixed effects[31]; instead, we use year fixed effects, α_y[32]. These dummies absorb annual macroeconomic trends common to all firms. The vector A_{t-1} collects lagged macroeconomic controls to further control quarterly macroeconomic fluctuations, including: real GDP growth, the unemployment rate, and four-quarter in-

[28]For the remaining two shocks, a positive cash-flow-growth shock (ω_{t+1}^c) lifts both bond yields and equity returns, consistent with stronger fundamentals, whereas a positive discount-rate shock (ω_{t+1}^d) lowers both, reflecting heavier discounting of future cash flows.

[29]Cieslak and Pang [2021] show that monthly or quarterly sums of daily risk premium shocks, have strong explanatory power for a range of bond and equity risk-premium proxies.

[30]We begin the sample in 1983 to follow Cieslak and Pang [2021] as closely as possible, ensuring that our parameter estimates are comparable to theirs. 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.

[31]Quarterly fixed effects would absorb the variation introduced by aggregate shocks.

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

flation. Our coefficient of interest, β^h, measures the cumulative response of investment from t to $t+h$ to the FOMC cash-flow-risk shock ϵ_t^{cr}; it can also be interpreted as the semi-elasticity of investment with respect to this shock.

To analyze heterogeneity in investment responses arising from cross-sectional variation in financial constraints, we follow Ottonello and Winberry [2020] and Jeenas and Lagos [2024] and estimate

$$\log k_{j,t+h} - \log k_{j,t} = \alpha_j + \alpha_t + \beta^h X_{j,t-1}\epsilon_t^{cr} + \Gamma_Z' Z_{j,t-1} + e_{j,t,h}, \tag{13}$$

where the key regressor is the interaction between the firm's lagged financial-constraint measure, $X_{j,t-1}$, and the FOMC cash-flow-risk shock, ϵ_t^{cr}. This term captures how a firm's cumulative investment response varies with its degree of financial constraint. This specification can incorporate quarterly time fixed effects, which subsume the year fixed effects and macroeconomic controls[33] .

The specification in (13) imposes a *linear* interaction, and its coefficient captures only average cross-sectional differences in the investment response. To check robustness, we follow Cloyne et al. [2023] and Anderson and Cesa-Bianchi [2024] and estimate a dummy-variable model:

$$\log k_{j,t+h} - \log k_{j,t} = \alpha_j + \sum_{g=1}^{G} \beta_g^h \, I\big[X_{j,t-1} \in g\big]\, \epsilon_t^{cr} + \sum_{g=1}^{G} \gamma_g^h \, I\big[X_{j,t-1} \in g\big] + \Gamma_Z' Z_{j,t-1} + \Gamma_A' A_{t-1} + e_{j,t,h}, \tag{14}$$

where the indicator $I\big[X_{j,t-1} \in g\big]$ equals one if the firm's financial-constraint proxy falls in group g. Groups can be multidimensional,for instance, firms that are both small and highly leveraged. Equation (14) provides a semiparametric estimation: Each coefficient β_g^h captures the mean response within subgroup g. Compared with (13), this dummy-variable approach relaxes the linearity assumption and delivers more flexible estimates for each subgroup[34].

3.3. Discussion on Identification Strategy

Our empirical specification aligns with a strand of macroeconomic studies that identifies plausibly exogenous policy variation and uses it to evaluate policy effects. In this literature, dynamic causal inference generally involves two steps: (i) constructing the series of policy shocks and (ii) estimating the impulse-response conditional on those shocks. Our specification is designed to implement precisely these two steps.

[33] The non-interacted terms are also included in the regression.

[34] A linear interaction may be distorted by extreme values of the conditioning variable, yet those tail observations—such as firms with exceptionally high debt-to-market ratios—are central to our analysis. The dummy-variable specification captures their average behaviour without discarding them.

A central empirical challenge is to isolate a policy component that is plausibly exogenous to future macroeconomic conditions and can therefore be used to assess its effect on investment. We focus on the unexpected change in perceived aggregate risk revealed by Federal Open Market Committee (FOMC) announcements. The asset-pricing–based structural VAR we employ is well suited to this purpose for two reasons. First, financial markets incorporate publicly available information almost instantaneously, so asset prices recorded before an announcement already embed any expected policy response. By using daily data and restricting the event window to the announcement day, we ensure that the price movements classified as shocks are truly unanticipated. These returns provide a market-based proxy for the shift in perceived cash flow risk driven primarily by the information released at the FOMC meeting.[35] Second, the structural VAR isolates the cash flow risk shock within the one-day window and enforces orthogonality across shocks. The resulting series is therefore uncontaminated by simultaneous surprises in the federal funds rate—on which most monetary-policy studies focus—or by the broader information effect on future output captured by the cash-flow-growth shock.[36] Consistent with the news shock literature, the FOMC cash flow risk shock from daily data should thus be interpreted as unexpected news about aggregate uncertainty.

High-frequency identification requires choosing an event window length. The methodology of Cieslak and Pang [2021] could, in principle, be applied with intraday windows of 30 or 60 minutes, as in Cieslak and Schrimpf [2019]. Window length presents a trade-off: 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], we adopt a one-day window for two main reasons. (i) In contrast to policy rate surprises, changes in perceived cash-flow uncertainty take longer for investors to absorb. Empirical evidence in Schmeling and Wagner [2016] shows that risk-premium adjustments after central bank announcements can persist until the next trading day. (ii) Very short windows produce extremely small shocks. This weak signal problem reduces statistical power and prevents tight standard error estimates for real-sector impulse responses.

However, using a daily window raises the concern that the cash-flow-risk shock may embed non-FOMC news. To gauge this background noise, Table 1 compares the shock's variance on all trading days with its variance on FOMC announcement days. Over the full sample, the announcement-day variance is roughly twice as large, and after 2008 it is almost three times as large. These ratios indicate that FOMC communications convey a substantial amount of information about risk. Some residual noise remains, however, so the shock should be viewed as an imperfect but informative proxy for the aggregate risk

[35] The VAR removes any remaining predictable component.

[36] Quarterly aggregation of the daily FOMC cash-flow-risk shocks rests on the assumption that these shocks are orthogonal to contemporaneous macroeconomic variables and other structural disturbances. The high-frequency asset price VAR satisfies this orthogonality by construction.

shift triggered by each FOMC announcement.

In the second step, we estimate the impulse response of firm investment to FOMC cash-flow-risk shocks. Following Wong et al. [2019] and Jeenas [2023], we run OLS local projections, treating the high-frequency shocks as exogenous regressors. A standard concern with this approach is limited statistical power, because high-frequency shocks might be small or transitory. Appendix D shows that this concern does not apply in our setting: a one-standard-deviation shock lowers equity prices by 66.5 basis points on impact, and the effects persist for several quarters. The quarterly sum of FOMC-day shocks often reaches multiple standard deviations, making the shocks both economically sizable and statistically informative. Our analysis emphasizes the heterogeneity of investments. Identification comes from interacting the shock series with firm-level characteristics, which vary across both time and firms. This cross-sectional variation sharpens the precision of the estimated heterogeneous responses; causal inference ultimately relies on differences in firms' reactions to large shocks.

Alternatively, since our shock captures aggregate risk shifts from unexpected news released on FOMC announcement days and is orthogonal to other economic information, it could serve as an instrument for quarterly aggregate risk changes. However, this strategy would instrument an endogenous regressor with a strong instrument; quarterly aggregate risk changes must also be extracted from asset price data, and the appendix D shows that stock and bond prices react strongly and persistently to these cash flow risk shocks. Consequently, the instrumental-variable approach would yield results very similar to those obtained from linear local projections that use the shocks directly. We therefore adopt the direct linear local projection method in our main empirical analysis.

4. Data

We construct a quarterly panel of firm balance sheet information from Compustat. Following Ottonello and Winberry [2020] and Jeenas [2023], the investment rate, $\log k_{j,t+h} - \log k_{j,t}$, represents the h-quarter log change in the book value of firm j's tangible capital stock from the end of period t. Tangible capital stock is measured using net property, plant, and equipment (PPENT). All investment rates are winsorized at the 1% level on both tails. We 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, we retain only firms with at least 40 quarters of observations. Appendix A provides details on variable construction and sample selection, while Appendix B.1 presents summary statistics for all variables.

Our panel spans 1995Q1 to 2023Q4 and includes a total of 321,268 firm-quarter observations. We begin our sample in 1995Q1 because our regression analysis controls for monetary policy shocks from Nakamura and Steinsson [2018], which measure monetary policy shocks using the entire term structure of interest rates. This measure is only available starting in 1995Q1[37]. Additionally, our analysis focuses on pre-scheduled FOMC meetings. We exclude unscheduled meetings due to significant noise in these events, as they often coincide with periods of heightened uncertainty, making it difficult to attribute aggregate risk shifts are only driven by monetary policy on those days[38]. Since pre-scheduled FOMC meetings began in 1994, our choice of sample period aligns with the availability of these events. Finally, we merge the Compustat data with the CRSP dataset to obtain firm-level equity returns.

We estimate the structural VAR model described earlier to obtain the daily cash-flow-risk shock. Next, we isolate the shocks that occur on pre-scheduled FOMC meeting days, w^{dr}_{FOMC}. Summing these shocks within each calendar quarter aligns their frequency with the firm-level data; the resulting quarterly FOMC cash-flow-risk shock, ϵ^{cr}_t, is our primary dependent variable. The equity-market index is retrieved from Bloomberg, whereas daily Treasury yields are taken from Gürkaynak et al. [2007], which is continuously updated on the Federal Reserve's website.

[Figure 1 around here]

Figure 1 presents the identified cash flow risk premium shocks on scheduled FOMC meeting days. By construction[39], the daily cash flow risk shocks have a mean of zero and a standard deviation of one over the estimation period. As a result, one unit in Figure 1 corresponds to one standard deviation of the cash flow risk shock across all trading days (or can be interpreted as the average daily volatility of cash flow risk). In Appendix D, we show that, quantitatively, a one-standard-deviation increase in the cash flow risk shock is associated with a simultaneous 66.5 basis point (0.665%) decline in the equity market index[40].In addition, Appendix D shows that the effects of the cash flow risk shock on the equity market and Treasury bond yields are highly persistent, remaining similar in magnitude to the initial impact over a one-year horizon. Figure 1 highlights several patterns: cash flow risk shocks tend to be more negative on FOMC announcement days, suggesting that these announcements generally shift aggregate risk lower, resolute uncertainty about future cash flows. Moreover, the dispersion of cash flow risk shocks increases in the post-financial-crisis period, particularly during the era of unconventional monetary policy. Several notable events are associated with extreme shock magnitudes.

[37]The tick-by-tick data on federal funds futures and Eurodollar futures, which are necessary for constructing these shocks, are only available after 1995. Consequently, the monetary policy shock series from Nakamura and Steinsson [2018] is also only available from 1995 onward.

[38]Some unscheduled FOMC meetings, such as the one on March 15, 2020, took place on a Sunday, making it difficult to capture stock market reactions in real time.

[39]Market returns and Treasury yields are demeaned before estimating the Structural VAR.

[40]A one-standard-deviation increase in the cash flow risk shock is also associated with a simultaneous 3.7 basis point decline in 10-year Treasury bond yield.

For example, the QE2 announcement led to a significant reduction in cash flow risk, whereas the Operation Twist program resulted in a sharp increase. Additionally, the July 26, 2023, FOMC announcement had the largest effect in reducing cash flow risk, despite coinciding with a widely anticipated rate hike that pushed interest rates to their highest level in over 22 years. A key factor may have been Fed Chair Powell's statement that the "Fed staff is no longer forecasting a recession," which likely contributed to the substantial decline in perceived aggregate risk.

[Table 1 around here]

Table 1 reports summary statistics for cash-flow-risk shocks computed for all trading days and, separately, for scheduled FOMC days[41]. Three findings emerge. First, shocks on FOMC days are, on average, larger in absolute value and have a more negative median than shocks on a typical trading day, indicating that FOMC announcements are frequently associated with sizable reductions in cash-flow uncertainty, consistent with Figure 1. Second, their dispersion—as measured by the interquartile range and the variance—is markedly higher on FOMC days. Third, in the post-2008 subsample both the absolute size and the dispersion of shocks increase further; the variance on FOMC days is roughly three times the unconditional average. These patterns support our identification strategy. Although some background noise inevitably remains in the FOMC cash-flow-risk shock, the evidence suggests that announcement days convey substantial new information about aggregate risk, particularly after 2008. In the empirical analysis that follows we therefore present results for both the full sample and the post-2008 subsample; the latter should more clearly capture investment responses to monetary-policy-induced shifts in risk.

5. Investment Responses to Monetary-Policy-Induced Risk Shifts

This section tests the two empirical predictions stated above. First, we estimate the average effect of monetary-policy-driven risk shifts on firms' tangible capital investment. Second, we investigate heterogeneity in this effect and show that its magnitude varies with firms' financial constraints.

5.1. Average Investment Response

Table 2 presents the estimated average firm-level response of tangible capital investment over the subsequent four quarters based on specification (12). All firm-level panel regressions employ standard errors two-way clustered by firm and quarter, following Driscoll and Kraay [1998] to accommodate potential serial correlation in the error term. In column (1)

[41] The column labeled "MAV" reports the mean of the absolute values of the shocks

the coefficient on the quarterly FOMC cash-flow-risk shock, ϵ_t^{cr}, is statistically significant at the 5% level (point estimate -0.496). Because the regression contains firm and year fixed effects, this estimate indicates that an increase in the quarterly monetary-policy shock relative to its annual mean, is associated with a reduction in firm investment growth over the next four quarters after we control for time-invariant firm heterogeneity and aggregate annual trends. This finding supports Proposition 3 in the conceptual framework, which predicts that positive monetary-policy-induced risk shifts lead firms, on average, to curtail investment. Quantitatively, a one-unit positive ϵ_t^{cr}—equivalent to one standard deviation of the daily shock series and corresponding to a 66.5-basis-point decline in the equity-market index—lowers the one-year investment rate by 0.496%[42]. Given the sample mean of 17.52%, the estimated decline corresponds to roughly 3% of the typical annual investment rate, a magnitude that is economically significant[43].

[Table 2 around here]

Columns (2) to (4) in Table 2 progressively incorporate additional fixed effects and controls. Column (2) replaces year fixed effects with year $\times$ industry fixed effects to account for time-varying industry-level differences in response to aggregate shocks. Column (3) introduces a set of firm-level balance sheet controls, including proxies for firm size, financing risk, profitability, sales growth, and liquidity. Column (4) further incorporates additional FOMC-related shocks, including the three other types of daily shocks on FOMC announcement days identified from the structural VAR, as well as the standard high-frequency monetary policy shock from Nakamura and Steinsson [2018] [44]. The baseline results from Column (1) remain robust across all specifications, maintaining statistical significance while exhibiting a slight decrease in magnitude as more controls are added.

[Figure 2 around here]

The local-projection specification in equation (12) allow us to trace the dynamic path of tangible-capital investment after a shock. Figure 2 plots the impulse-response coefficients estimated with the same controls as column (2) of Table 2, together with their confidence intervals, for horizons of up to eight quarters. The estimates show that an FOMC cash-flow-risk shock reduces average firm-level investment from the second quarter onward, with

[42]Investment rates are multiplied by 100 for interpretability.
[43]On average, each FOMC announcement day in our sample is associated with a cash-flow-risk shock of about one unit, and there are eight such announcements per year.
[44]We sum all shocks from daily to quarterly frequency to align with firm-level data.

the contraction reaching its maximum around the fourth quarter. Although the effect remains negative thereafter, it gradually declines in magnitude and becomes statistically insignificant at longer horizons. This benchmark response provides a reference point for the subsequent analysis of heterogeneity: in particular, it allows us to evaluate whether financial constraints amplify and prolong the investment slowdown.

[Table 3 around here]

The risk channel in the motivating framework posits that monetary-policy-induced risk shifts affect investment primarily by altering the cost of capital. Accordingly, the FOMC cash-flow-risk shock should be reflected in the cost of capital itself. We test this prediction with the specification in equation (12), replacing the dependent variable with subsequent realised equity returns, an ex-post proxy for the cost of capital following Pflueger et al. [2020]. Table 3 reports the estimates: the coefficient on ϵ_t^{cr} is positive, statistically significant, and remarkably stable across all columns[45]. Figure 3 depicts the impulse response over eight quarters. The cumulative effect peaks in quarter 4 and remains near that level thereafter, indicating that monetary-policy-driven risk shifts raise the cost of capital for an extended period. Taken together, the evidence reinforces the operation of the risk channel in the transmission of monetary policy.

[Figure 3 around here]

5.2. Financial constraints and investment response heterogeneity

We next test our second empirical prediction—that financial constraints amplify the investment response to monetary-policy-induced risk shifts. Following the accounting literature Penman et al. [2007], we use net market leverage, defined as the ratio of net debt to the market value of equity ($netDMR$), as our proxy for financial constraints[46]. We adopt $netDMR$ for three reasons. First, because it nets debt against cash holdings, it reflects both liquidity and leverage, providing a more precise measure of financing capacity. Second, its market-value basis is appropriate in light of Lian and Ma [2021], who show that roughly 80% of U.S. non-financial corporate debt is collateralised by cash flows rather than physical assets; market value directly captures this cash-flow potential, making $netDMR$ a suitable proxy for financing constraints.Third, early work beginning with Hamada [1972] shows that a higher debt-to-equity ratio magnifies a firm's exposure to aggregate risk by

[45] This result is expected, as our shock is identified from market returns.

[46] This measure is from decomposition of the book-to-market ratio into separate asset and leverage components.

raising both equity risk and the cost of capital[47]. Consequently, firms with different debt-to-equity ratios should respond heterogeneously to aggregate-risk shocks[48]. The measure $netDMR$ allows us to capture this heterogeneity. The construction of $netDMR$ is as follows:

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

where net debt equals financial liabilities minus financial assets. Financial liabilities comprise long-term debt (Compustat quarterly item `DLTTQ`), debt in current liabilities (`DLCQ`), and the carrying value of preferred stock (`PSTKQ`). Financial assets consist of 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. For robustness, we also employ a simpler measure—total debt divided by market equity—and find that our main results are unchanged.

[Table 4 around here]

Table 4 summarises how investment responses vary across firms with different degrees of financial constraint. We estimate Equation 13 using a local-projection framework that includes interaction terms. The key regressor is the product of the lagged net debt-to-market ratio ($netDMR_{t-1}$) and the FOMC cash-flow-risk shock (ϵ_t^{cr}); this interaction tests whether tighter financing capacity amplifies the effect of monetary-policy-induced risk shifts on investment. Column (1) reproduces the baseline specification from Table 2, with firm fixed effects, year-industry fixed effects, and the full set of macroeconomic controls. Column (2) substitutes quarter-by-industry fixed effects for the year-industry effects while retaining firm fixed effects. Column (3) adds firm-level covariates—each interacted with ϵ_t^{cr}—and further interacts $netDMR_{t-1}$ with business-cycle proxies to allow for differential cyclical sensitivities of financing constraints. In every specification, the coefficient on $\epsilon_t^{cr} \times netDMR_{t-1}$ is negative and significant at the 1% level. Thus, firms with higher $netDMR$—and therefore tighter financial constraints—curtail investment more sharply when monetary policy raises aggregate risk, supporting our empirical prediction that financial constraints amplify this effect.

The conditional effect is economically meaningful. Because lagged $netDMR$ is standardised, the interaction coefficient in column (3)—our most saturated specification—is

[47] Hamada [1972] demonstrates that borrowing, regardless of its source, amplifies risk when the amount of equity is fixed. Conceptually, the asset beta (β_A) measures the aggregate risk of total assets (financed by both debt and equity). The equity beta (β_E) depends on financial leverage through the relationship $\beta_E = \beta_A(1 + D/E)$, where D/E denotes the debt-to-equity ratio. As D/E increases, β_E rises proportionally, making the firm's stock more sensitive to aggregate risk.

[48] The cost of capital is central to our framework linking risk shocks to investment.

-0.68. Thus, when two firms differ by one standard deviation in $netDMR$, the more leveraged firm cuts its one-year investment by an additional 0.68% following a one-unit increase in the FOMC cash-flow-risk shock[49]. The effect is even larger for highly leveraged firms. In our sample, firms in the top 0.5 percentile of the $netDMR$ distribution lie 2.62 standard deviations above the median[50]. Consequently, these firms reduce one-year investment by about 1.78% more than the median firm when the shock rises by one unit. A comparison of columns (3) and (4) further shows that this conditional effect intensifies after 2008, coinciding with the shift to unconventional monetary policy.

[Figure 4 around here]

The estimates in Table 4 are based on a linear interaction term. Figure 6 provides a complementary view using the dummy–interaction specification in Equation 14, which recovers average effects for subsamples. In each regression, we divide the full sample into "higher" and "lower" groups according to whether a firm's net debt-to-market ratio exceeds the 50th, 75th, 90th, or 95th percentile. Panel A reports the full-sample results, which closely match those obtained from the linear specification. As the percentile cutoff rises, firms in the "higher" group exhibit a progressively larger negative investment response to positive shocks. In every case, more-leveraged firms reduce investment by more than their less-leveraged counterparts, and this gap widens at stricter thresholds. The pattern intensifies after 2008: firms in the high-leverage subsamples show even stronger negative responses, further widening the divergence between low- and high-risk firms. These findings suggest that financially constrained firms are especially vulnerable to monetary-policy-induced risk shifts, and that this vulnerability grows under the post-2008 unconventional policy regime, when FOMC announcement days convey more information about aggregate risk than do ordinary trading days[51].

6. Mechanism Behind Heterogeneous Investment Responses: Flight to Quality

Why do financial constraints amplify the investment response to monetary-policy-induced risk shifts? One plausible mechanism involves the well-documented *flight-to-quality* phenomenon:when aggregate risk is elevated, heightened risk aversion leads investors to shed assets perceived as risky and to accumulate assets perceived as safe, thereby widening

[49]This figure equals $0.68/17.52 = 3.89\%$ of the sample mean annual investment rate.

[50]Observations in the extreme right tail of $netDMR$ are retained because, following Ottonello and Winberry [2020], their behaviour is informative for studying financial frictions in monetary-policy transmission. However, such extreme values can bias OLS estimates if the relationship is nonlinear, so we also estimate subgroup-specific averages using a semi-parametric dummy regression.

[51]Hence, identification is cleaner after 2008 because the signal is less obscured by background noise.

the premium between them. Flight-to-quality episodes can occur across asset classes—for example, investors favour bonds over equities in turbulent periods—but they also arise within a single class, as when the AAA–BBB credit-spread widens countercyclically during times of heightened risk. This behaviour offers a natural explanation for our heterogeneous investment results.hen monetary policy raises aggregate risk, investors demand a higher premium from financially constrained firms, which typically face higher credit risk and hold weaker collateral. The larger external-finance premium tightens their access to credit. With less external funding, these firms must rely on internal cash: liquidity falls first, and investment is cut. Because internal cash flows are volatile, investment go ahead only when cash flow is strong; when cash flow is weak, external funds are scarce. This dependence on fluctuating cash flows, in turn, heightens uncertainty about future growth.

Empirical studies document flight-to-quality episodes in credit markets and show that they carry sizable real effects. Lang and Nakamura [1995] report that the share of new loans priced at less than *prime* + 1%—a proxy for "safe" lending—is counter-cyclical. Similarly, Bernanke et al. [1994] find that financial constraints on lower-quality borrowers tighten in recessions and that the resulting contraction in credit has quantitatively important macroeconomic consequences. In this section we test whether the risk shifts triggered by monetary policy can induce a comparable flight to quality, thereby raising the external-finance premium for financially constrained firms. Because conventional policy-rate tightening and the state of the business cycle can themselves provoke similar episodes, all of our specifications explicitly control for aggregate conditions and for policy-rate shocks.

We cannot observe the external-finance premium directly in our firm-level panel. Instead, we furnish indirect evidence that a monetary-policy-induced rise in risk triggers a flight to quality, thereby raising the premium for financially constrained firms. We offer two pieces of evidence. First, the corporate–liquidity literature, originating with Keynes's *General Theory*, argues that when external finance becomes costly, firms hoard cash and scale back net borrowing. Consistent with this view, we show that financially constrained firms increase cash holdings and reduce net external financing after an positive FOMC cash-flow-risk shock. Second, the rollover-risk literature predicts that tighter credit conditions hurt firms that are both highly leveraged and heavily reliant on near-term refinancing. We find that, following a positive risk shock, the contraction in investment is concentrated precisely among firms with high net leverage and high refinancing intensity. This pattern suggests that the shock tightens their access to credit, exacerbates rollover risk, and leaves these firms the most vulnerable.

6.1. Liquidity Management

Precautionary Cash Holding

Extensive theoretical work (e.g., Riddick and Whited [2009]) and empirical evidence (e.g., Bates et al. [2009]) show that cash flow uncertainty and financing risk play a crucial role in determining corporate cash holdings. Recent studies (e.g., Bolton et al. [2019], Bloom [2014]) further reveal that a sudden rise in cash flow uncertainty, when combined with financial frictions, leads firms with high financing risk to reduce investment more sharply. These firms choose to hoard cash as a precaution rather than invest in expanding production. Therefore, if the precautionary liquidity management channel helps explain why high-financial-risk firms cut investment more in response to FOMC cash flow risk shocks, we should also expect these firms to increase their cash holdings.

[Table 5 around here]

We test the precautionary cash hoarding mechanism using the same interaction term regression based on specification 13, with the dependent variable defined as the cash growth rate over the next four quarters. Column (1) of Table 5 shows that both the coefficient on the risk shock and its interaction with the net debt-to-market ratio are positive and statistically significant at the 5% level. This finding suggests that an FOMC cash flow risk shock leads to an increase in cash hoarding over the following year, with the effect becoming more pronounced for firms with higher leverage. The magnitude of the effect is economically meaningful: a one-standard-deviation increase in the net debt-to-market ratio amplifies the precautionary cash hoarding response by 3% for a one-unit unexpected rise in the aggregate cash flow risk. In Columns (2) and (3), where we include stricter quarter $\times$ industry fixed effects, the interaction term remains positive. Column (4) further shows that in the post-2008 period, the heterogeneous response in cash hoarding is even stronger, aligning with our findings on the investment response.

Figure 5 presents the average cash holding responses for different subgroups using the dummy regression approach in Equation 14. The figure confirms the findings from the linear interaction regression. All subgroups exhibit a positive elasticity of cash holdings with respect to FOMC cash flow risk shocks. However, firms with higher leverage show a significantly stronger cash holding response compared to firms with lower leverage. Additionally, as the threshold for defining the high-risk group increases, indicating that these firms, on average, face greater financing risk, the magnitude of the cash holding response becomes even more pronounced.

[Figure 5 around here]

Debt Reallocation

The heterogeneous cash holding response suggests that firms with high leverage are more exposed to monetary-policy-driven cash flow uncertainty. As a result, these firms increase precautionary cash holdings to a greater extent, leading to a larger reduction in capital investment for production expansion. However, this explanation alone does not fully capture the underlying mechanism. In the absence of financial frictions, firms could smooth investment by issuing additional debt, meaning higher cash holdings would not necessarily constrain investment. When financial frictions are present, external financing premiums rise with uncertainty[52]. Consequently, highly leveraged firms, which already face elevated financing premiums before the shock[53], struggle even more to expand their debt capacity to sustain investment when monetary policy increases uncertainty. To further investigate this mechanism, we examine whether the FOMC cash flow risk shock also generates a heterogeneous debt growth response.

We repeat the interaction term regression using one-year debt growth as the dependent variable. Table 6 shows that firms with higher leverage, reduce their debt borrowing more in response to an increase in the FOMC cash flow risk shock. This finding is consistent with the liquidity management under financial frictions. The coefficient on the interaction term remains negative and statistically significant at the 1% level across all specifications.

[Table 6 around here]

Figure 6 presents the estimated coefficients for average subgroup debt responses, revealing an important effect not fully captured by the previous table: the debt reallocation effect. Specifically, after a one-unit unexpected increase in aggregate cash flow risk on FOMC days—quantitatively equivalent to a 66.5 basis point drop in the equity market index—firms in the top 50% of the net debt-to-market ratio respond by increasing their debt by 5.11%, whereas firms in the bottom 50% decrease their debt by 1.82%. This pattern becomes even more pronounced at higher leverage levels. Firms in the top 5% of the debt-to-market ratio reduce their debt by 3.43% over a one-year horizon, while those in the bottom 95% experience a marginal increase of around 1%. Overall, this debt reallocation effect indicates that monetary-policy-driven cash flow uncertainty leads to distinct debt responses among firms with differing levels of financial risk. The debt response complements

[52] Several studies also support this view. For instance, Gilchrist et al. [2014] demonstrates that uncertainty significantly influences investment, primarily through changes in credit spreads. Additionally, studies such as Acharya et al. [2011] and Lian and Ma [2021] highlight that firms use discounted future cash flows as collateral for external funding. Uncertainty shocks reduce equity prices, signaling weaker future cash flows and raising financing costs. Our empirical evidence also shows that the ex-post cost of capital increases with FOMC cash flow risk shocks.

[53] Highly leveraged firms tend to have lower net worth and higher agency costs, leading to higher external financing premiums. This concept originates in the financial accelerator literature Bemanke and Gertler [1989], Bernanke [1999].

the liquidity management mechanism underlying the heterogeneous investment response and highlights why financial risk determines a firm's exposure to uncertainty. When monetary policy increases cash flow uncertainty, highly leveraged firms face a higher external financing premium, limiting their ability to borrow to mitigate uncertainty and making them more reliant on internal cash flows. As a result, these high-leverage firms increase their cash holdings as a precaution, constraining their capacity for capital investment.

[Figure 6 around here]

6.2. Rollover Risk

We further demonstrate that, beyond the liquidity management mechanism, rollover risk plays a crucial role in shaping the heterogeneous investment response to monetary-policy-driven cash flow uncertainty. As previously documented, rising uncertainty lowers equity prices, weakens discounted future cash flows, and constrains debt borrowing. Theoretical work such as Acharya et al. [2011] shows that firms relying on short-term debt to finance long-term assets face heightened rollover risk when borrowing capacity declines, making it more difficult to refinance maturing debt[54]. This increased rollover risk raises default risk and further restricts borrowing, leading to a sharp reduction in debt financing. The resulting liquidity shortfall limits capital investment and production, amplifying the negative impact of uncertainty on investment.

[Table 7 around here]

To test the rollover channel, we measure firms' refinancing intensity (RI) following Friewald et al. [2022]:

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

where $dlcq$ represents debt maturing within one year, and $dlttq$ represents long-term debt. A higher RI indicates greater reliance on short-term debt, increasing firms' exposure to rollover risk[55]. We estimate an interaction-term regression (specification 13) with a

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

[55] Friewald et al. [2022] show that firms with high RI earn higher returns due to increased exposure to systemic risk. Our approach differs from theirs, as they define RI based on debt maturing within three years relative to total debt, whereas we focus on shorter-term debt to align with Acharya et al. [2011], who argue that rollover risk intensifies as average debt maturity shortens.

triple interaction between the FOMC cash flow risk shock, RI, and $netDMR$, to examine whether high refinancing intensity amplifies the impact of leverage on investment responses. To facilitate interpretation, we define the dummy indicator $\mathbf{1}\{RI_{t-1}^{high}\}$, which equals one for firms whose RI exceeds the sample median.

Table 7 presents the results of the triple interaction regression. In Column (1), we compare the triple interaction term with the double interaction term and find that the negative investment impact of ϵ_t^{cr} intensifies with leverage only for firms with high refinancing intensity; this effect is not present for firms with low refinancing intensity. Column (2) shows that the triple interaction coefficient is larger in the post-2008 sample, suggesting that the rollover risk channel became more pronounced during this period. In Columns (3) and (4), we replace the continuous $netDMR$ variable with the dummy indicator $\mathbf{1}\{netDMR_{t-1}^{high}\}$, which identifies firms whose $netDMR$ exceeds the 75th percentile. Under this specification, the coefficient of the triple interaction term captures the relative difference in investment responses between firms with both high leverage and high refinancing intensity and those with low leverage and low refinancing intensity. The estimated coefficients indicate a substantial effect: for each one-unit increase in the FOMC cash flow risk shock, firms with high leverage and high refinancing intensity reduce their one-year investment by an additional 1.403%[56].

Figure 7 illustrates the persistent effects of the investment response difference over an eight-quarter horizon. The figure plots the coefficient of the triple interaction term, following the same specification as in Columns (3) and (4) of Table 7. The results indicate that firms with high leverage and high refinancing intensity consistently maintain a significantly lower investment rate after a one-unit positive shock, with the effect persisting throughout the entire period. This impact is both substantial and cumulative, growing larger as the time horizon extends. To ensure robustness, we replicate the analysis in Appendix B.2 using a sample that excludes almost-zero-leverage (AZL) firms, which are not directly involved in the debt refinancing process. This approach follows Strebulaev and Yang [2013]. The results remain consistent, confirming that the observed effects are driven by highly indebted firms rather than those with negligible debt levels.[57].

[Figure 7 around here]

Figure 8 presents the average one-year-ahead investment response for firms grouped by whether their net debt-to-market ratio (netDMR) exceeds the 75$^{\text{th}}$ percentile and whether their refinancing intensity (RI) exceeds the median. Panel A shows substantial differences

[56] This one-year investment response to a one-unit risk shock (1.403%) corresponds to approximately 10% of the average annual investment rate.

[57] Follow Friewald et al. [2022], we define almost-zero-leverage (AZL) firms as those with book leverage ratios below 0.05.

across subgroups in the full sample. Specifically, the estimated coefficients of ϵ_t^{cr} over a one-year horizon are -0.412 for firms with low leverage and low refinancing intensity, close to zero for those with either low leverage and high refinancing intensity or high leverage and low refinancing intensity, but significantly lower at -0.950 for firms with both high leverage and high refinancing intensity. These results indicate that the decline in investment, driven by monetary-policy-related cash flow uncertainty, is primarily concentrated among firms with elevated leverage and refinancing needs, highlighting the critical role of rollover risk in shaping investment responses to monetary policy driven cash flow uncertainty. Moreover, when we increase the high-leverage threshold to the 90$^{\text{th}}$ percentile of netDMR, the coefficient for the high-leverage, high-refinancing-intensity group becomes even more negative, reinforcing the importance of rollover risk at higher leverage levels. This pattern is particularly pronounced in the post-2008 sample, suggesting that the interaction between leverage and refinancing needs has played an increasingly significant role in investment decisions following the financial crisis.

[Figure 8 around here]

One potential concern is that, on FOMC announcement days, other monetary policy shocks—beyond cash flow uncertainty—could disproportionately impact the investment of firms with high rollover needs, potentially driving our observed results. To address this issue, in Appendix B.3, we repeat the triple interaction regression from Columns (3) and (4) of Table 7, but additionally control for other monetary policy shocks identified from a structural VAR and the shocks from Nakamura and Steinsson [2018]. All shocks are included with triple interaction terms. The results show that the coefficient on the triple interaction with the FOMC cash flow risk shock remains negative and statistically significant, with its magnitude and significance largely unchanged. This finding suggests that other monetary policy shocks do not drive our results.In Appendix B.4, we further examine the ex-post cost of capital (equity return) response to the FOMC cash flow risk shock. The results indicate that all four firm groups experience an increase in the cost of capital. Consistent with the investment response, firms with both high leverage and high refinancing intensity exhibit a larger rise in financing costs. This finding suggests that heightened rollover risk, coupled with increased uncertainty, amplifies credit risk and raises the cost of capital more significantly for these firms.

6.3. Reconciling Two Channels

Our empirical results indicate that firms with different levels of leverage respond heterogeneously to cash-flow-uncertainty shocks driven by monetary policy. In our analysis, we identify two primary mechanisms—the liquidity management channel and the debt rollover channel—which are not mutually exclusive. Under the liquidity management channel, a rise in cash flow uncertainty prompts high-risk firms to reduce debt growth more sharply. This reallocation of debt toward lower-risk firms makes it more difficult for high-risk firms to roll over their short-term obligations, thereby increasing their credit risk, especially for those with significant rollover needs (as in Acharya et al. [2011]). The interaction of these channels helps explain why high-risk firms are especially vulnerable to cash flow uncertainty. Meanwhile, the heightened rollover risk also appears to drive an increase in cash holdings among high-risk firms. Because such firms face greater difficulty in obtaining new borrowing, holding additional cash becomes a buffer against the risk of being unable to refinance short-term debt. Consequently, the liquidity management and debt rollover channels reinforce each other, ultimately producing the patterns we observe in the data.

7. Further Discussion and Robustness

7.1. 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 our 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 our 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 our 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 we focus on cash-flow-risk shocks observed on FOMC days. Second, they measure risk using book leverage or default risk, while we 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 our analysis spans the period since 1995 and highlights especially strong effects after 2008. In unreported results, we 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 we 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 [2018], firms with higher default risk exhibit stronger responses to monetary policy announcements.

7.2. Additional Robustness Test

Alternative Measurements Our main empirical analysis relies on the structural VAR from Cieslak and Pang [2021] to identify the cash-flow-risk shock on FOMC days as our primary proxy for monetary-policy-driven cash flow uncertainty. In Appendix B.5, we assess the robustness of our results by using alternative risk measures, also use risk changes on FOMC announcement days. First, we draw on the principal component of 14 risk-sensitive financial indicators proposed by Bauer et al. [2023] (the "BBM Index"), which captures a broad range of market-based risk signals. Second, we consider $SVIX^2$, an option-implied risk premium measure from Martin [2017] based on six-month maturity options. Both proxies primarily reflect risk appetite or premia connected to future discount rate uncertainty and broader economic or cash flow uncertainty. While neither measure isolates pure cash flow uncertainty, this dimension should remain a key component within them. As shown in AppendixB.5, changes in both of these alternative measures on FOMC days are significantly correlated with our identified cash-flow-risk shock. Substituting these measures into our 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. Our 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, we show that our findings remain qualitatively robust when restricted to manufacturing firms (SIC codes 3000–3999).

Alternative Leverage Measure In Appendix B.8, we 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.

8. Aggregate Implication

In this section, we build on our firm-level estimation results to examine the aggregate implications of monetary-policy-driven cash flow uncertainty. We take two approaches. First, we highlight the time-varying conditional semi-elasticity between investment and the FOMC cash flow risk shock, which depends on the cross-sectional distribution of firms—particularly, the proportion of firms with high rollover risk. Additionally, the industry composition of such firms plays a role in capital reallocation across industries following a cash flow risk shock. Second, we document that the transmission of monetary-policy-driven cash flow uncertainty has a weaker effect on aggregate investment than on firm-level investment. To understand this phenomenon, we conduct a simple counterfactual analysis to explore potential explanations.

[Figure 9 around here]

8.1. Distribution and Time varying investment response

Figure 9 presents the percentage of firms classified as having high rollover risk, defined as those with a net debt-to-market ratio above the 75th percentile and a refinancing intensity exceeding the panel mean (calculated across all firms and quarters). The results indicate that the proportion of high rollover risk firms is strongly procyclical. This pattern is intuitive, as the net debt-to-market ratio tends to increase during economic downturns due to declining market valuations. As a result, firms with high rollover risk become more concentrated during recessions.

[Table 8 around here]

The results in Table 8 indicate that the transmission of monetary-policy-driven cash flow uncertainty to firm investment intensifies when a larger share of firms is exposed to rollover risk. In this table, we extend the analysis of the average investment response by interacting the FOMC cash flow risk shock with the percentage of firms classified as having high rollover risk. The interaction term is significantly negative, confirming that the investment impact of the FOMC cash flow risk shock strengthens as the proportion of firms with rollover risk increases. In Column (1), the coefficient on the non-interacted term is 1.1, while the coefficient on the interaction term is -0.178. To illustrate this effect, consider a normal period when approximately 6% of firms face rollover risk. Under these conditions, the FOMC cash flow risk shock has a negligible impact on the one-year average investment rate.[58] However, during a recession, when the proportion of high-rollover-risk firms rises to around 15%, a one-unit shock leads to an average investment decline of 3.77%, indicating a highly significant effect. Columns (3) and (4) further support this finding, showing that both the baseline non-interacted term and the interaction term exhibit larger coefficients in the post-2008 period, suggesting that the effect has intensified under the unconventional monetary policy regime.

[**Table 9 around here**]

FOMC cash flow risk drives industry-level reallocation of tangible capital and debt due to differences in the percentage of high rollover risk firms across industries. This effect is particularly strong after 2008, when investment becomes more sensitive to cash flow risk. To analyze this reallocation, we modify the regression in Table 8, replacing the aggregate percentage with the industry-level percentage, calculated based on the 2-digit SIC classification. Panel A of Table 9 reports results using the quarterly time-varying industry-level percentage of high rollover risk firms. The findings indicate that after 2008, the impact of a one-unit FOMC cash flow risk shock leads to a greater decline in investment as the industry-level percentage of high rollover risk firms rises, driving capital reallocation between industries with different exposure levels. The results are even stronger when using a time-invariant industry-level percentage, which assumes that rollover need is an inherent industry characteristic (Panel B).

8.2. Aggregate Investment

[**Figure 10 around here**]

The previous subsection demonstrates that the average investment response to monetary-policy-driven cash flow uncertainty varies over time, depending on the percentage of firms

[58] The percentage is multiplied by 100 for interpretability.

with high rollover risk. We now shift our focus to the aggregate level by examining how this uncertainty affects overall investment. Following Crouzet and Mehrotra [2020] and Lagos and Zhang [2020], we compute the total tangible capital in our Compustat sample at time t as

$$K_t = \sum_{i \in I} k_{i,t}, \quad K_{t+4} = \sum_{i \in I} k_{i,t+4},$$

where I includes all firms in the sample. The aggregate capital growth rate is then defined as

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

To examine the role of rollover risk, we also compute separate growth rates for firms classified as high rollover risk at time t, denoted I_{t+4}^{high}, and for all other firms, denoted I_{t+4}^{low}.[59] Figure 10 plots the quarterly time series of I_{t+4}^{high} and I_{t+4}^{low}. Aggregate investment growth is consistently lower for high-rollover-risk firms compared to their lower-risk counterparts, particularly during recessions. Although the two series exhibit comovement, I_{t+4}^{high} is noticeably more volatile, suggesting that rollover risk amplifies fluctuations in firm-level investment decisions and, in turn, aggregate investment dynamics.

[Table 10 around here]

We next investigate whether the aggregate investment response to the FOMC cash flow risk shock aligns with the firm-level average response and assess the contribution of high-rollover-risk firms to aggregate investment dynamics. To test the aggregate investment response, we estimate the following linear projection:

$$I_{t+n} = \alpha + \beta \epsilon_t^{cr} + G_{t-1} + e_t \tag{15}$$

where I_{t+n} denotes the n-period aggregate investment rate for a given sample, and G_{t-1} represents the set of lagged aggregate controls. We also include a simultaneous interest rate shock control to account for potential confounding factors.

Table 10 presents the results of this analysis. The findings show that the aggregate investment response to FOMC-induced cash flow risk shocks is substantially weaker than the average firm-level response over a one-year horizon. According to Table 2, a one-unit positive cash flow risk shock ϵ_t^{cr}—which translates into a 66.5 basis point decline in the equity market index—reduces firm-level investment by 0.496% over one year. In contrast,

[59] To ensure consistency with our previous findings in Figure 8, we restrict the sample to firms with non-missing net debt-to-market ratios and refinancing intensities at time t. Additionally, at each time t, we retain only firms with capital observations available for the next four quarters (or eight quarters for eight-quarter total investment growth), avoiding complications related to firm entry and exit. A firm is classified as "high rollover risk" if its net debt-to-market ratio exceeds the 75th percentile and its refinancing intensity is above the median in the full panel.

the one-year aggregate investment response to the same shock is a statistically insignificant increase of 0.04%.A similar pattern is observed when focusing on firms with high rollover risk. As shown in Table 8, the average firm-level investment response for these firms is −0.96% over one year, whereas their aggregate investment response to a one-unit increase in the FOMC cash flow risk shock is only −0.276%, and is less statistically significant.

Aggregate investment becomes more responsive over a two-year horizon. A one-unit positive ϵ_t^{cr} leads to a decline of −0.330%, which, although not highly significant, is consistent with the firm-level findings in Figure 2. Notably, the aggregate investment response for high-rollover-risk firms is both substantial and statistically significant. Although slightly smaller than the firm-level average, its magnitude remains comparable, with a coefficient of −0.832.[60] These results suggest that the impact of monetary-policy-driven uncertainty on aggregate investment strengthens over longer horizons.

Counterfactual Analysis We assess whether high-rollover-risk firms significantly contribute to the aggregate investment response through a counterfactual analysis following Crouzet and Mehrotra [2020]. We decompose aggregate investment growth into the contributions from firm-level investment growth of high-rollover-risk and low-risk firms, then construct counterfactuals to quantify each group's role in aggregate fluctuations. Given that the eight-quarter aggregate investment rate responds more strongly to FOMC cash flow risk shocks, we focus on this horizon. Following Crouzet and Mehrotra [2020], the eight-quarter aggregate investment rate decomposes as:

$$I_{t+8} = \hat{i}_{t+8}^{\text{low}} + s_t \left(\hat{i}_{t+8}^{\text{high}} - \hat{i}_{t+8}^{\text{low}} \right) + \hat{\text{cov}}_{t+8}, \tag{16}$$

where $s_t = \frac{K_t^{\text{high}}}{K_t}$ represents the initial capital share of high-rollover-risk firms, and $\hat{i}_{t+8}^{\text{high}}$ and $\hat{i}_{t+8}^{\text{low}}$ denote the cross-sectional average investment growth rates for high-rollover-risk and other firms, respectively. The term $\hat{\text{cov}}_{t+8}$ further decomposes as:

$$\hat{\text{cov}}_{t+8} = \hat{\text{cov}}_{t+8}^{\text{low}} + s_t \left(\hat{\text{cov}}_{t+8}^{\text{high}} - \hat{\text{cov}}_{t+8}^{\text{low}} \right). \tag{17}$$

This covariance term accounts for the fact that aggregate investment is a size-weighted average of firm-level capital growth. The components $\hat{\text{cov}}_{t+8}^{\text{low}}$ and $\hat{\text{cov}}_{t+8}^{\text{high}}$ capture the within-group cross-sectional covariance between firms' initial tangible capital size and subsequent capital growth. If smaller firms grow faster, these covariance terms make that aggregate investment growth lower than the unweighted average firm-level growth.

We construct counterfactual growth rates based on the decomposition. The first two

[60] The firm-level average investment response for firms with both high net debt ratios and high rollover risk is −0.991 over a two-year horizon.

counterfactuals are:

$$I^{(1)} = I_{t+8} - s_t\Big(\hat{i}^{\text{high}}_{t+8} - \hat{i}^{\text{low}}_{t+8}\Big),$$
$$I^{(2)} = I_{t+8} - (1 - s_t)\Big(\hat{i}^{\text{low}}_{t+8} - \hat{i}^{\text{high}}_{t+8}\Big).$$

Here, $I^{(1)}$ removes the contribution of high-rollover-risk firms' investment growth from aggregate growth, while $I^{(2)}$ removes the contribution of low-rollover-risk firms. We further construct counterfactuals that also exclude the size-investment covariance term:

$$I^{(3)} = I_{t+8} - s_t\Big(\hat{i}^{\text{high}}_{t+8} - \hat{i}^{\text{low}}_{t+8}\Big) - s_t\Big(\hat{\text{cov}}^{\text{high}}_{t+8} - \hat{\text{cov}}^{\text{low}}_{t+8}\Big),$$
$$I^{(4)} = I_{t+8} - (1 - s_t)\Big(\hat{i}^{\text{low}}_{t+8} - \hat{i}^{\text{high}}_{t+8}\Big) - (1 - s_t)\Big(\hat{\text{cov}}^{\text{low}}_{t+8} - \hat{\text{cov}}^{\text{high}}_{t+8}\Big).$$

Thus, $I^{(1)}$ and $I^{(3)}$ estimate aggregate growth assuming all firms behave like low-rollover-risk firms, while $I^{(2)}$ and $I^{(4)}$ assume all firms follow the investment behavior of high-rollover-risk firms.

[Table 11 around here]

Table 11 presents the counterfactual regression results based on specification 15. Column (1) reports the baseline using the 8-quarter aggregate investment rate, while the remaining columns use counterfactual aggregate investment rates. Comparing columns (1) and (2), removing the average investment rate of high-rollover-risk firms has little impact on the aggregate investment response to the FOMC cash flow risk shock, as the coefficient decreases only slightly from -0.33 to -0.315, suggesting a limited contribution from these firms. Comparing columns (1) and (3), further controlling for the covariance between initial capital size and investment rate slightly reduces the aggregate response (the coefficient drops to -0.271). Columns (4) and (5) conduct the same counterfactual analysis for low-rollover-risk firms. Removing their average investment rate makes the coefficient more negative (-0.434), and further removing their covariance leads to a highly negative and statistically significant coefficient (-0.824)[61].

The counterfactual analysis yields two main insights. First, although high-rollover-risk firms react more strongly to an FOMC cash-flow risk shock, their influence on aggregate investment is modest because they hold only a small share of tangible capital. Second, the shock redistributes investment unevenly across firm sizes. Among high-rollover-risk firms, the response is fairly uniform across the size distribution, leaving the covariance between capital size and subsequent investment close to zero. Among low-rollover-risk

[61]Interestingly, our counterfactual analysis, which nets out the average investment rate and covariance, produces similar results to those obtained using subgroup aggregate investment rates, as shown in Table 10.

firms, however, the response is concentrated in smaller firms, producing a more negative size–investment covariance. Because large low-rollover-risk firms own most of the economy's tangible capital—and are only weakly affected—the aggregate decline in investment remains limited.

9. Conclusion

This paper provides new evidence on the "risk channel" of monetary policy. Specifically, we show that aggregate cash flow uncertainty shocks on FOMC announcement days predict firm investment, suggesting that uncertainty induced by monetary policy transmits to corporate investment decisions.

Financial frictions play a crucial role in shaping this transmission. Firms with high debt relative to market value—experience a decline in debt growth following an increase in uncertainty. As a result, these firms accumulate more cash and scale back tangible capital investment. The investment decline is particularly concentrated among firms with high rollover risk, which not only exhibit high leverage but also face significant short-term refinancing needs. Consequently, the cross-sectional share of firms with high rollover risk is a key determinant of the transmission effectiveness of policy-induced cash flow uncertainty to the real economy.

Our findings provide important policy implications by highlighting a novel channel through which monetary policy and its communication affect the real economy, beyond adjustments in nominal interest rates. These results contribute to the literature on monetary policy communication by showing that policymakers must carefully manage perceived uncertainty during announcements, as this uncertainty can influence real economic outcomes, especially the effect is stronger in the post-2008 period. Moreover, our analysis suggests that the optimal timing for uncertainty management during monetary policy announcements should consider the cross-sectional distribution of firms' rollover risk.

Our study provides a first step in examining the risk channel of monetary policy on corporate operations using a reduced-form approach. Using an asset pricing approach, we seek to capture the aggregate cash flow uncertainty shock associated with FOMC announcements. A promising direction for future research is to disentangle the sources of this uncertainty—whether it stems from policy actions, information released by the central bank, or the tone of policy announcements, as documented in Schmeling and Wagner [2016] and Cieslak and McMahon [2023]. Understanding which source of uncertainty matters most for corporate decision-making remains an open question.Additionally, future research could employ general equilibrium models to examine the interaction between the risk channel and other monetary policy transmission mechanisms while incorporating additional economic agents, such as financial institutions. This approach would enhance our understanding of the aggregate effects of the risk channel and provide a structural explanation for the weaker short-term aggregate response to risk shocks documented in our paper.

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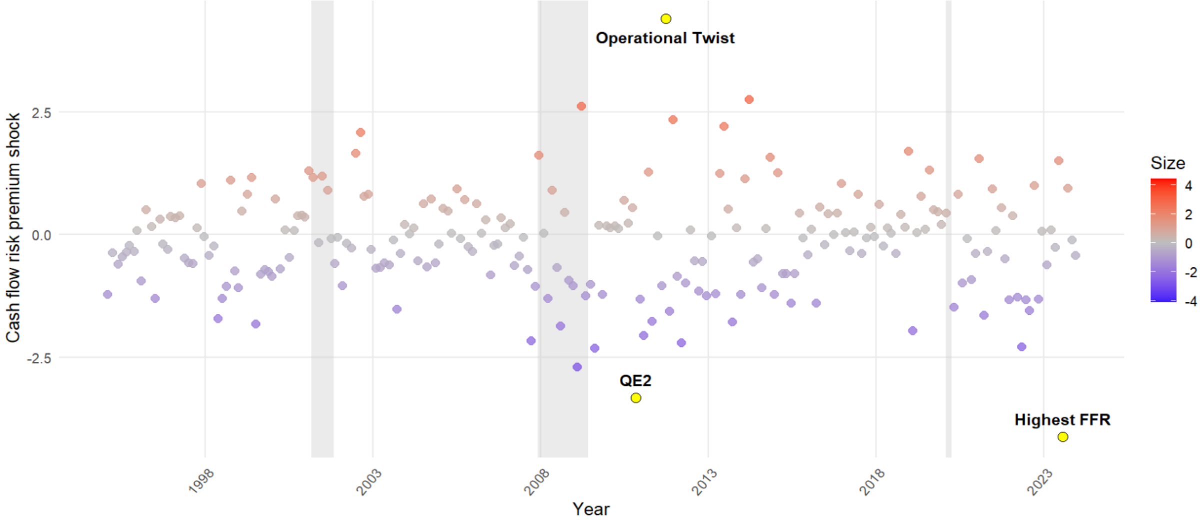
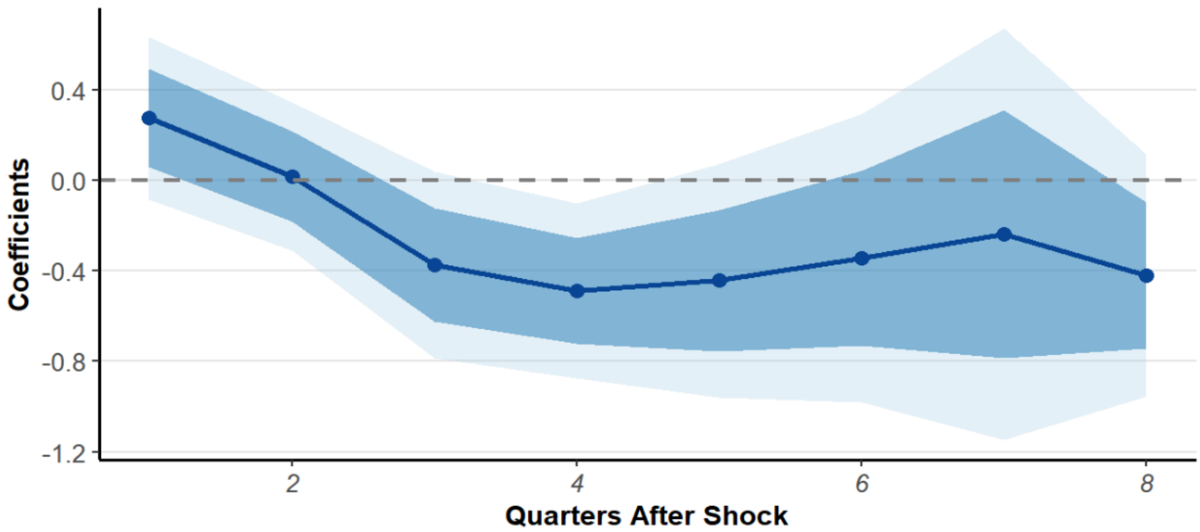
Figure 1: Cash Flow Risk Premium Shocks on Scheduled FOMC Meeting Days



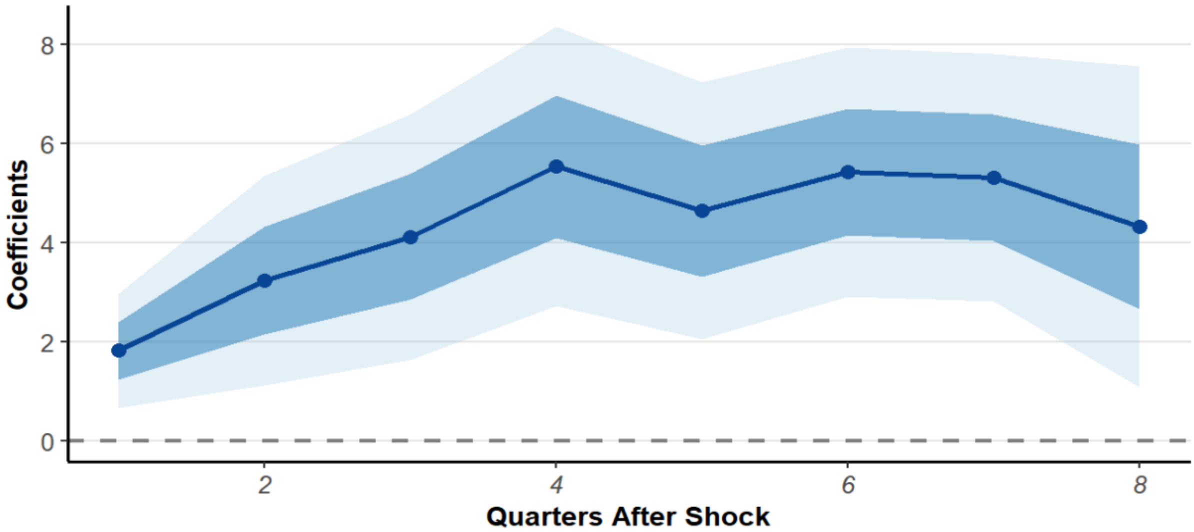
This figure shows the identified cash flow risk premium shocks on all scheduled FOMC meeting days from 1995 to 2023. The shocks are estimated using a structural VAR model with bond and equity data for all trading days during the period 1983–2023. The shocks are normalized to have a mean of zero and a standard deviation of one in the estimation sample. Thus, the quantities on the Y-axis represent units of standard deviation across all trading days.

Figure 2: Firm-Level Average Investment Response



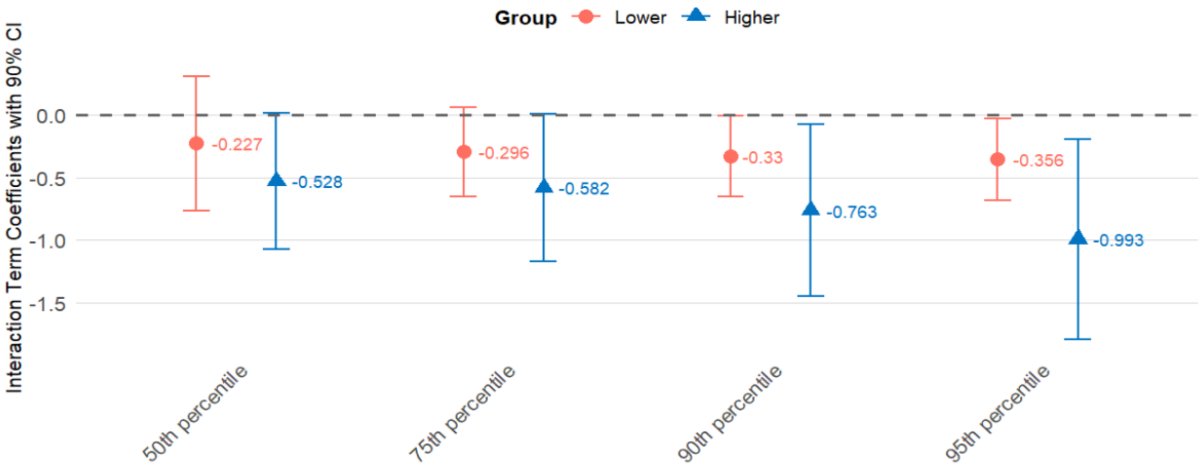
This plot illustrates the dynamic effects of FOMC cash flow risk shocks on investment. The regression is based on equation 12, with the dependent variable being the change in the log book value of tangible capital stock over next one to eight quarters. The sample consists of a quarterly panel of Compustat firms spanning 1995 to 2023. The regressions include macroeconomic controls (lagged values of inflation, GDP growth, and unemployment for one to four quarters) as well as firm and industry × year fixed effects. The inner and outer shaded areas represent 68% and 90% confidence intervals, respectively, based on standard errors computed using the Driscoll–Kraay method, accounting for clustering by firm and time.

Figure 3: Dynamic Ex-post Cost of Capital Response

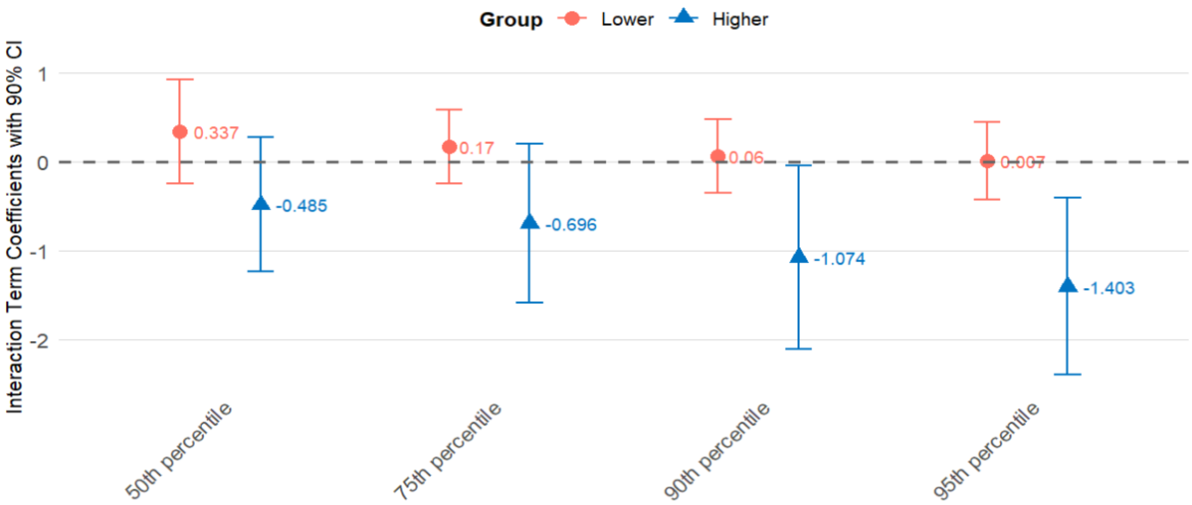


This plot illustrates the dynamic effects of the FOMC cash flow risk shock on scheduled FOMC days on Cost of Capital. The regression is based on equation 12, with the dependent variable being the change in the log equity price over next one to eight quarters. The sample consists of a quarterly panel of Compustat firms spanning 1995 to 2023. The regressions include macroeconomic controls (lagged values of inflation, GDP growth, and unemployment for one to four quarters) as well as firm and industry × year fixed effects. The inner and outer shaded areas represent 68% and 90% confidence intervals, respectively, based on standard errors computed using the Driscoll–Kraay method, accounting for clustering by firm and time.

Figure 4: Subgroup Firm-Level Investment Response Based on Net Market Leverage



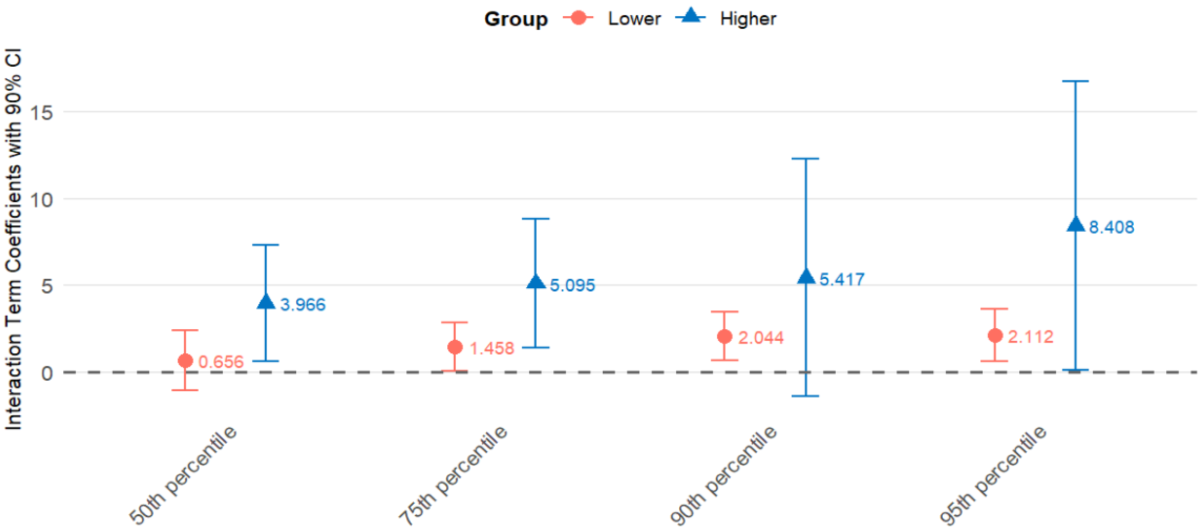
Panel A: Full Sample



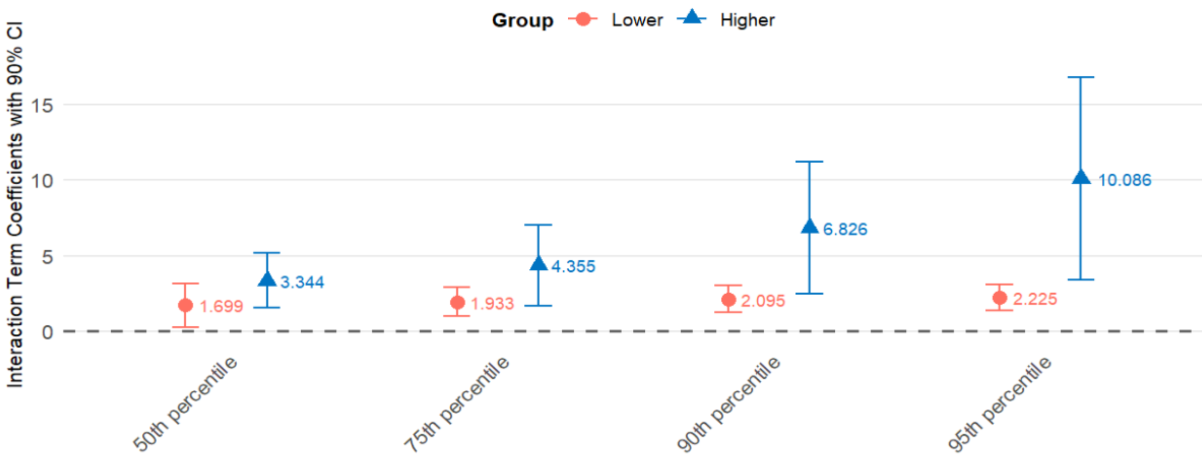
Panel B: Post-2008 Sample

This table reports regression results based on equation 14. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The main independent variable is the FOMC cash flow risk shock, interacted with binary indicators for high or low firm-level lagged net debt-to-market ratio (netDMR). Firms in the high group have lagged netDMR values above a specific percentile. The sample includes 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 binary indicator variable itself. 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.

Figure 5: Subgroup Firm-Level Cash Holding Response Based on Net Market Leverage



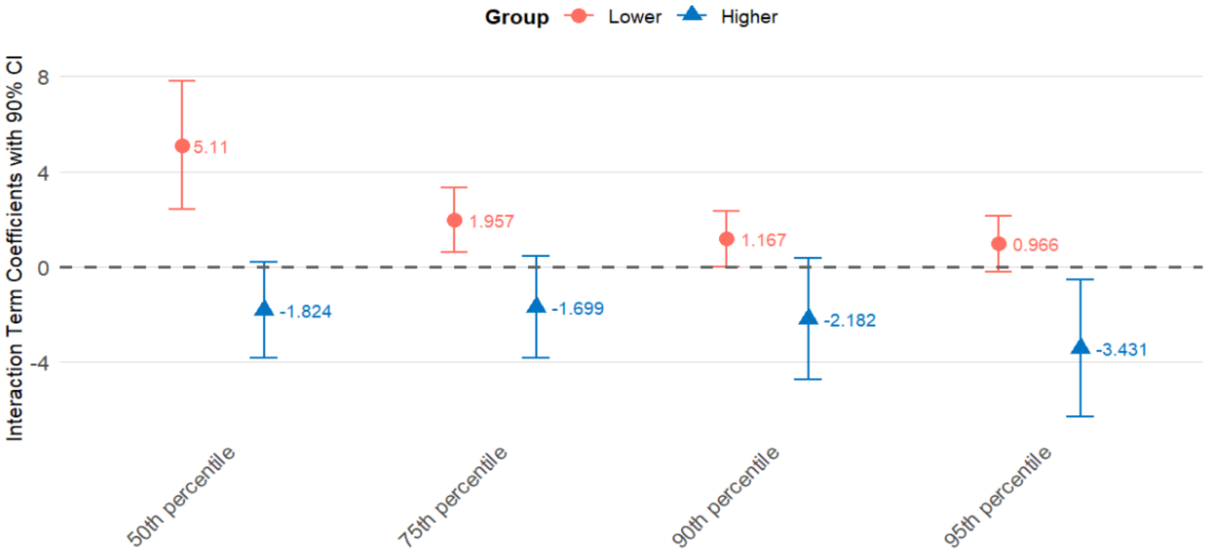
Panel A: Full Sample



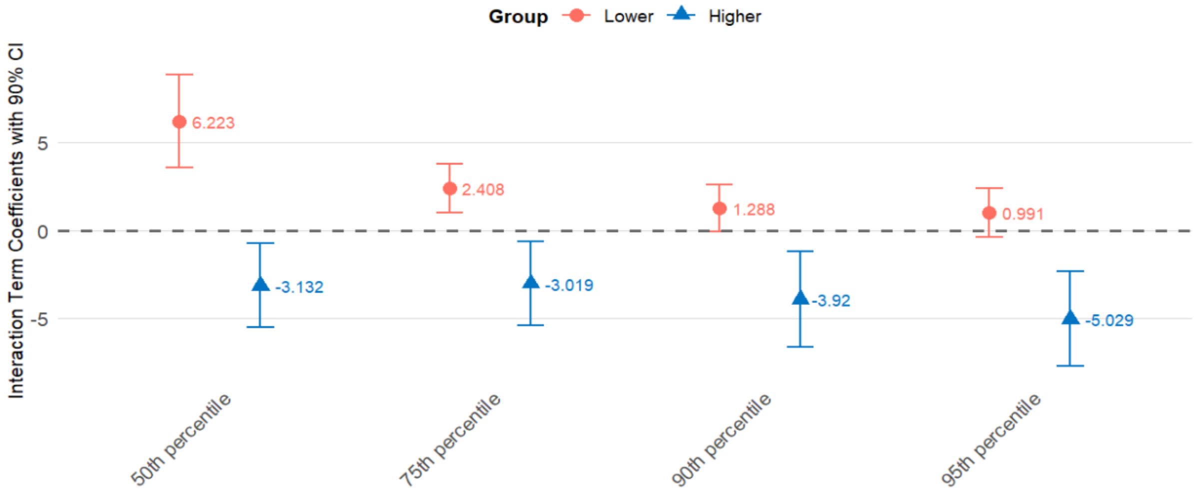
Panel B: Post-2008 Sample

This plot reports regression results based on equation 14. The dependent variable is the four-quarter change in the log cash holding. The main independent variable is the FOMC cash flow risk shock, interacted with binary indicators for high or low firm-level lagged net debt-to-market ratio (netDMR). Firms in the high group have lagged netDMR values above a specific percentile in the whole panel. The sample includes 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 binary indicator variable itself. 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.

Figure 6: Subsample Firm-Level Debt Response Based on Net Debt to Market Ratio



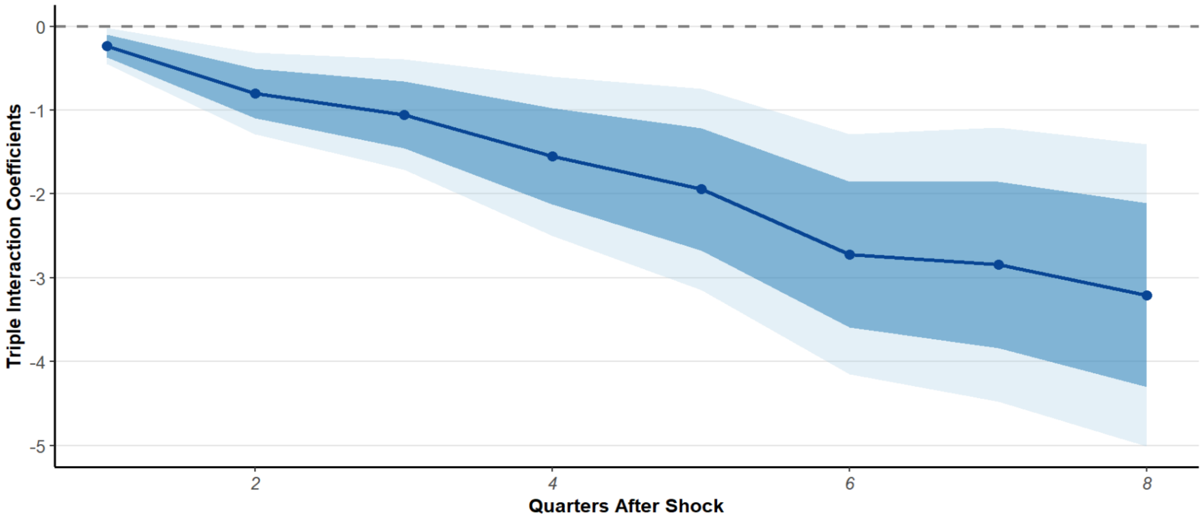
Panel A: Full Sample



Panel B: Post-2008 Sample

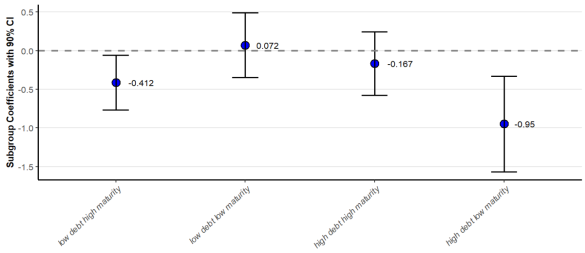
This table reports regression results based on equation 14. The dependent variable is the four-quarter change in the log total debt. The main independent variable is the FOMC cash flow risk shock, interacted with binary indicators for high or low firm-level lagged net debt-to-market ratio (netDMR). Firms in the high group have lagged netDMR values above a specific percentile across whole panel. The sample includes 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 binary indicator variable itself. 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.

Figure 7: Rollover Risk Effect on Firm-Level Investment Response

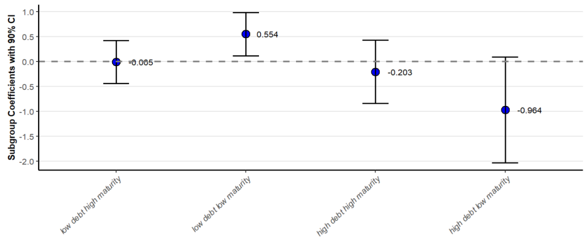


This plot illustrates the dynamic effects of High Net Debt and Low Maturity on the investment response to the FOMC cash flow risk shock. The regression is based on Equation 13, with the dependent variable defined as the change in the log book value of tangible capital stock over the next one to eight quarters. The main independent variable is a triple interaction term comprising the quarterly sum of cash flow risk premium shocks on scheduled FOMC days, an indicator variable for high netDMR, $\mathbf{1}\{netDMR_{t-1}^{high}\}$, and an indicator variable for high Refinancing Intensity, $\mathbf{1}\{RI_{t-1}^{low}\}$. The indicator $\mathbf{1}\{RI_{t-1}^{low}\}$ represents firms with a refinancing intensity (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 percentile of the sample. The sample consists of a quarterly panel of Compustat firms spanning the period from 1995 to 2023. The regressions include firm fixed effects and industry-by-quarter fixed effects. Non-interacted and double-interacted coefficients are omitted for brevity. The inner and outer shaded areas represent the 68% and 90% confidence intervals, respectively, based on standard errors computed using the Driscoll–Kraay method, which accounts for clustering by both firm and time.

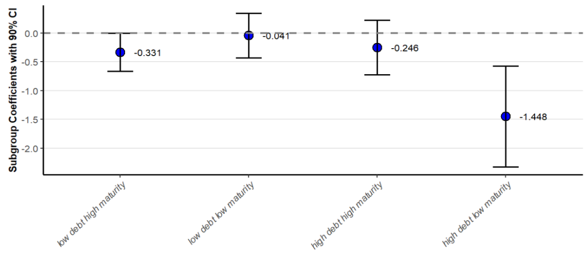
Figure 8: Subsample Firm-Level Investment Response Based on Net Market Leverage and Refinancing Intensity



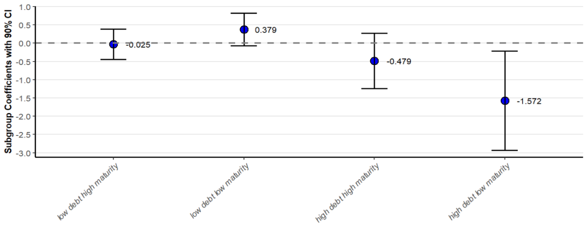
Panel A: Full sample with 75th Percentile of netDMR



Panel B: Post-2008 with 75th Percentile of netDMR



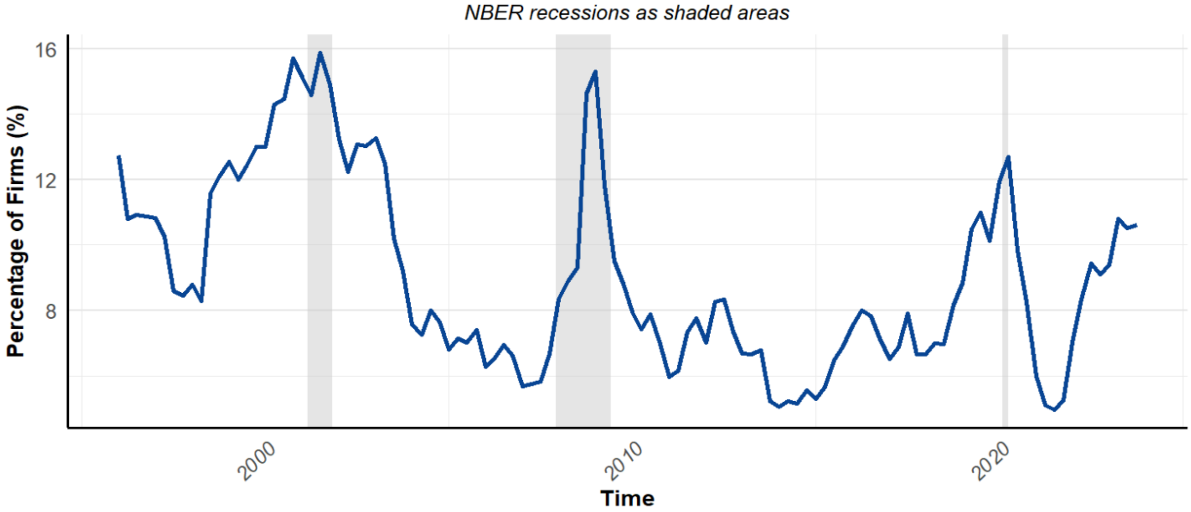
Panel C: Full sample with 90th Percentile of netDMR



Panel D: Post-2008 with 90th Percentile of netDMR

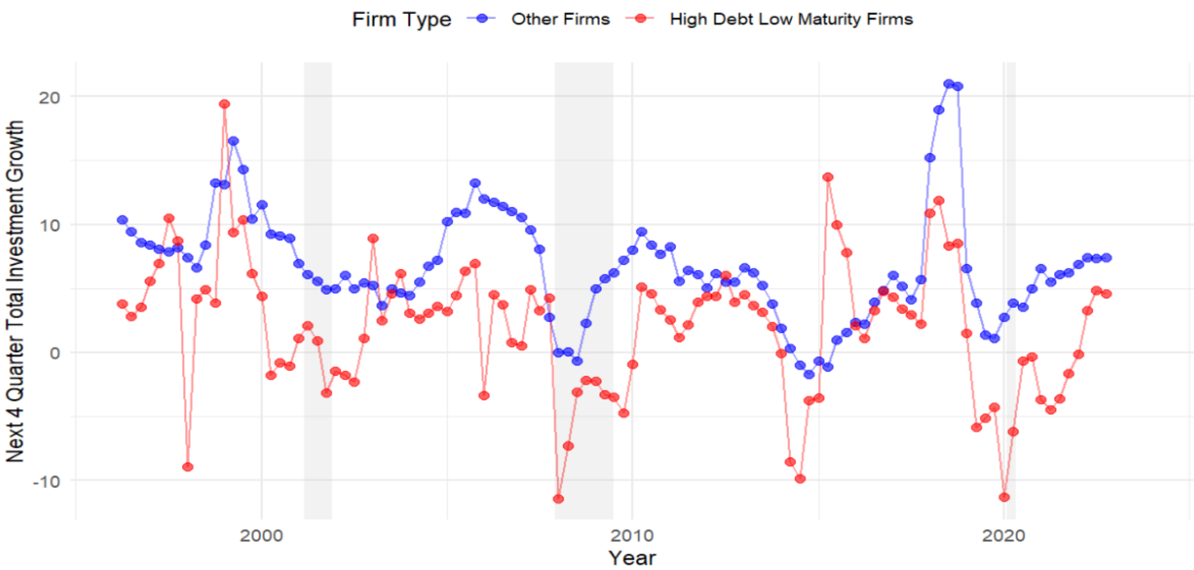
This plot reports regression results based on equation 14. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The main independent variable is a triple interaction term consisting of the FOMC cash flow risk shock, an indicator variable for high netDMR, $\mathbf{1}\{netDMR^{low}_{t-1}\}$, and an indicator variable for low debt maturity, $\mathbf{1}\{RI^{high}_{t-1}\}$. The indicator $\mathbf{1}\{RI^{high}_{t-1}\}$ represents firms with refinancing intensity(debt maturing in less than one year to total debt) above the sample median. Similarly, $\mathbf{1}\{netDMR^{high}_{t-1}\}$ 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 × industry fixed effects, and the indicator variable $\mathbf{1}\{RI^{high}_{t-1}\} \times \mathbf{1}\{netDMR^{low}_{t-1}\}$. 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.

Figure 9: Percentage of High Rollover Risk Firms



This figure presents the quarterly time series of the percentage of firms with high rollover risk. Firms are classified as high rollover risk if their net debt-to-market ratio exceeds the 75th percentile and their refinancing intensity is above the median, both measured across the full sample. The analysis is based on a quarterly panel of Compustat firms from 1995 to 2023. Shaded areas represent NBER-designated recessions.

Figure 10: Aggregate Capital Growth



This figure shows the quarterly aggregate growth rate for firms with high rollover risk and other firms.The sample includes a quarterly panel of Compustat firms spanning from 1995 to 2023. Shaded areas indicate NBER recessions.

Table 1: Summary Statistics of Cash Flow Risk Shocks

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

This table presents summary statistics for cash flow risk shocks from 1995 to 2023. 'FOMC Days' refers to scheduled FOMC announcement days. The shocks are estimated using a structural VAR model with bond and equity data for all trading days from 1983 to 2023. The shocks are normalized to have a mean of zero and a standard deviation of one over the estimation period. Thus, the values represent units of standard deviation across all trading day. 'MAV' denotes the mean of the absolute values of the shocks. 'P5,' 'P25,' 'Median,' 'P75,' and 'P95' correspond to the 5th percentile, 25th percentile, median (50th percentile), 75th percentile, and 95th percentile of the shocks, respectively.

Table 2: 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			✓	✓
Other MP Shocks				✓
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 12. The dependent variable is the next four-quarter change in the log book value of tangible capital stock. The main independent variable is the FOMC cash flow risk shock. The sample consists of a quarterly panel of Compustat firms from 1995 to 2023. Macro controls include lagged values (lag one to four quarter) of inflation, GDP growth, and unemployment. Firm-level controls include lagged (lag one quarter) size , net debt-to-market ratio, sales growth, asset return, operational leverage, and short-term asset ratio. Other monetary policy shocks include the discount rate shock, cash flow shock, discount rate risk shock (identified using structural VAR) on FOMC days, and the Nakamura-Steisson shock. 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 3: Firm 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			✓	✓
Other MP Shocks				✓
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 12. The dependent variable is the next four-quarter change in the log equity price. The main independent variable is the FOMC cash flow risk shocks. The sample consists of a quarterly panel of Compustat firms from 1995 to 2023. Macro controls include lagged values (lag one to four quarter) of inflation, GDP growth, and unemployment. Firm-level controls include lagged (lag one quarter) size , net debt-to-market ratio, sales growth, asset return, operational leverage, and short-term asset ratio. Other monetary policy shocks include the quarterly sum of discount rate shock, cash flow shock, discount rate risk shock (identified using structural VAR) on FOMC days, and the Nakamura-Steisson shock. 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 4: Firm-Level Investment Response Based on Net Market Leverage

	$log(k_{t+4}) - log(k_t)$			
	(1)	(2)	(3)	(4)
ϵ_t^{cr}	-0.432**			
	(0.193)			
$\epsilon_t^{cr} \times netDMR_{t-1}$	-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			✓	✓
$\Delta GDP_{t-1} \times netDMR_{t-1}$			✓	✓
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 13. The dependent variable is the next four-quarter change in the log book value of tangible capital stock. The main independent variable is the FOMC cash flow risk shock, interacted with the firm-level lagged net debt-to-market ratio (netDMR). The sample consists of a quarterly panel of Compustat firms spanning 1995 to 2023. Firm-level controls include lagged values (one-quarter lag) of size, net debt-to-market ratio, sales growth, asset return, operational leverage, and short-term asset ratio. The last two columns also include the lagged GDP growth rate interacted with the lagged net debt-to-market ratio to control for differences in cyclical sensitivities across firms. Non-interacted coefficients are omitted for brevity. Standard errors, shown in parentheses, are computed using the Driscoll–Kraay method, accounting for clustering by firm and time. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Firm-Level Cash Holding Response Based on Net Market Leverage

	$log(Cash_{t+4}) - log(Cash_t)$			
	(1)	(2)	(3)	(4)
ϵ_t^{cr}	2.446**			
	(0.976)			
$\epsilon_t^{cr} \times netDMR_{t-1}$	2.923**	2.43**	1.133	4.579**
	(1.141)	(1.067)	(0.886)	(1.768)
Firm FE	✓	✓	✓	✓
Year × Industry FE	✓			
Macro Controls	✓			
Quarter × Industry FE		✓	✓	✓
ϵ_t^{cr} × Firm Controls			✓	✓
$\Delta GDP_{t-1} \times netDMR_{t-1}$			✓	✓
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 13. The dependent variable is the next four-quarter change in log cash holding. The main independent variable is the FOMC cash flow risk shock, interacted with the firm-level lagged net debt-to-market ratio (netDMR). The sample consists of a quarterly panel of Compustat firms spanning 1995 to 2023. Firm-level controls include lagged values (one-quarter lag) of size, net debt-to-market ratio, sales growth, asset return, operational leverage, and short-term asset ratio. The last two columns also include the lagged GDP growth rate interacted with the lagged net debt-to-market ratio to control for differences in cyclical sensitivities across firms. Non-interacted coefficients are omitted for brevity. Standard errors, shown in parentheses, are computed using the Driscoll–Kraay method, accounting for clustering by firm and time. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Firm-Level Debt Response Based on Net Market Leverage

	$log(Debt_{t+4}) - log(Debt_t)$			
	(1)	(2)	(3)	(4)
ϵ_t^{cr}	0.750			
	(0.698)			
$\epsilon_t^{cr} \times netDMR_{t-1}$	-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			✓	✓
$\Delta GDP_{t-1} \times netDMR_{t-1}$			✓	✓
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 13. The dependent variable is the next four-quarter change in log total debt. The main independent variable is the FOMC cash flow risk shock, interacted with the firm-level lagged net debt-to-market ratio (netDMR). The sample consists of a quarterly panel of Compustat firms spanning 1995 to 2023. Firm-level controls include lagged values (one-quarter lag) of size, net debt-to-market ratio, sales growth, asset return, operational leverage, and short-term asset ratio. The last two columns also include the lagged GDP growth rate interacted with the lagged net debt-to-market ratio to control for differences in cyclical sensitivities across firms. Non-interacted coefficients are omitted for brevity. Standard errors, shown in parentheses, are computed using the Driscoll–Kraay method, accounting for clustering by firm and time. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Firm-Level Investment Response Based on Net Market Leverage and Refinancing Intensity

	$\log(k_{t+4}) - \log(k_t)$			
	(1)	**(2)**	**(3)**	**(4)**
$\epsilon_t^{cr} \times netDMR_{t-1}$	0.504**	0.158		
	(0.249)	(0.505)		
$\epsilon_t^{cr} \times netDMR_{t-1} \times \mathbf{1}\{RI_{t-1}^{high}\}$	-1.478***	-1.764***		
	(0.391)	(0.581)		
$\epsilon_t^{cr} \times \mathbf{1}\{netDMR_{t-1}^{high}\}$			0.678***	0.306
			(0.190)	(0.247)
$\epsilon_t^{cr} \times \mathbf{1}\{netDMR_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$			-1.403***	-1.499***
			(0.418)	(0.548)
Firm FE	✓	✓	✓	✓
Quarter $\times$ Industry FE	✓	✓	✓	✓
$\epsilon_t^{cr} \times$ Firm Controls	✓	✓	✓	✓
$\Delta GDP_{t-1} \times netDMR_{t-1}$	✓	✓	✓	✓
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 presents regression results based on Equation 13. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The main independent variable is a triple interaction term consisting of the FOMC cash flow risk shock, the firm-level lagged net debt-to-market ratio (netDMR), and an indicator variable for low debt maturity, $\mathbf{1}\{RI_{t-1}^{high}\}$. Columns (3) and (4) replace the continuous netDMR variable with an indicator variable for high netDMR, $\mathbf{1}\{netDMR_{t-1}^{high}\}$. The indicator $\mathbf{1}\{RI_{t-1}^{high}\}$ represents firms with a refinancing intensity (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 percentile of the sample. The sample consists of a quarterly panel of Compustat firms spanning 1995 to 2023. Firm-level controls include lagged values (one-quarter lag) of size, net debt-to-market ratio, sales growth, asset return, operational leverage, and the short-term asset ratio. The last two columns additionally include the lagged GDP growth rate interacted with the lagged net debt-to-market ratio to control for differences in cyclical sensitivities across firms. Non-interacted coefficients and other double interaction coefficients are omitted for brevity. Standard errors, shown in parentheses, are computed using the Driscoll–Kraay method, which accounts for clustering by firm and time. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Investment Response Conditional on Percentage of Firms with 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		✓		✓
Other MP Shocks $\times$ $\boldsymbol{p}_t$		✓		✓
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 presents 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 the FOMC cash flow risk shock, interacted with the percentage of firms classified as having high rollover risk at each time point. High rollover risk firms are defined as those with a net debt-to-market ratio above the 75th percentile and a refinancing intensity below the median, both calculated across all firms and time periods. The sample consists of a quarterly panel of Compustat firms spanning from 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. Additional monetary policy shocks include the discount rate shock, cash flow shock, and discount rate risk shock (identified using a structural VAR) on FOMC days, as well as the Nakamura-Steisson shock. 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 9: Industry Level Capital and Debt Reallocation

Panel A: Time varying industry level percentage				
	$log(k_{t+4}) - log(k_t)$		$log(Debt_{t+4}) - log(Debt_t)$	
	(1)	(2)	(3)	(4)
$\epsilon_t^{cr} \times \boldsymbol{p}_t^{Ind}$	-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	✓	✓	✓	✓
Other MP Shocks $\times$ $\boldsymbol{p}_t$	✓	✓	✓	✓
Observations	238,411	86,295	196,089	86,772
Sample	Full	Post-2008	Full	Post-2008

This table presents 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 the FOMC cash flow risk shock, interacted with the industry-level percentage of firms classified as having rollover risk. Firms with high rollover risk are defined as those with a net debt-to-market ratio above the 75th percentile and a refinancing intensity below the median, both calculated across all firms and time periods. **Panel A** uses a time-varying industry-level percentage, where the proportion of high-rollover-risk firms is computed at each time point. **Panel B** employs a time-invariant approach, using the average percentage over the entire sample period. The sample consists of a quarterly panel of Compustat firms from 1995 to 2023. Firm-level controls include lagged (one-quarter) values of size, net debt-to-market ratio, sales growth, asset return, operational leverage, and short-term asset ratio. Other monetary policy shocks include the discount rate shock, cash flow shock, discount rate risk shock (identified using a structural VAR) on FOMC days, and the Nakamura-Steisson shock. 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 10: Aggregate Investment Response

	(1)	(2)
Panel A	I_{t+4}	I_{t+8}
ϵ_t^{cr}	0.040	-0.330
	(0.209)	(0.409)
Adj. R^2	0.055	0.118
Panel B	I_{t+4}^{other}	I_{t+8}^{other}
ϵ_t^{cr}	0.084	-0.248
	(0.222)	(0.416)
Adj. R^2	0.066	0.127
Panel C	I_{t+4}^{high}	I_{t+8}^{high}
ϵ_t^{cr}	-0.276	-0.832**
	(0.239)	(0.396)
Adj. R^2	0.053	0.210
Observations	110	106
Macro controls	✓	✓
Interest rate shock	✓	✓

This table reports regression results for the aggregate investment response to FOMC cash flow risk shocks. All regressions include macro controls, which consist of one-to-four-quarter lags of inflation, GDP growth, unemployment, and the Nakamura-Steisson shocks. Standard errors, shown in parentheses, are calculated using Newey-West Newey and West [1986] with lags matching the forecast horizon. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Conuterfactual Aggregate Investment Analysis

	(1)	(2)	(3)	(4)	(5)
	I_{t+8}	$I^{(1)}$	$I^{(2)}$	$I^{(3)}$	$I^{(4)}$
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 shock	✓	✓	✓	✓	✓

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: Our 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, we 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], we 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 12 around here]

[Table 13 around here]

Table 12 presents the summary statistics for the full sample used in our analysis from 1995 to 2023. Table 13 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 our main analysis sample for the rollover risk channel and its aggregate implications.

B.2. Triple Interaction Excluding Almost Zero Debt Firms

[Table 14 around here]

We examine the relationship between rollover risk and investment response by employing the same triple interaction term regression as in our main analysis. To ensure the robustness of our results, we further exclude firms with negligible leverage (AZL, or "Almost Zero Leverage"). This exclusion ensures that our findings are not driven by low-leverage firms but rather by firms with higher rollover risk. Following the methodology of Strebulaev and Yang [2013], we first exclude all firms with a book leverage ratio below 0.05. We 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 14, this adjustment does not alter our 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 15 around here]

Table 15 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, we include triple interaction terms for the other three FOMC shocks, as well as the interest rate shock from Nakamura and Steinsson [2018], all interacted with dummy variables for high net market leverage and high refinancing intensity as controls. We 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 our primary channel remain unchanged, with no significant difference in significance or magnitude.

B.4. Triple interaction of cost of capital

[Figure 11 around here]

In this section, we 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 we 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

[Table 16 around here]

To assess the robustness of our main results, particularly whether they are driven by our identification of aggregate cash flow risk shocks on FOMC announcement days, we consider two alternative measures of aggregate cash flow uncertainty. The first measure is the risk index from Bauer et al. [2023], constructed using the principal component of risk-sensitive financial indicators, including market indices, equity market and Treasury index volatility, credit spreads, and exchange rates. The second measure is the option-implied market equity risk premium, SVIX2, from Martin [2017]. It is important to note that both of these risk measures incorporate information on both cash flow uncertainty and discount rate uncertainty[62], including uncertainty surrounding monetary policy itself (see a simple model in Cieslak and McMahon [2023]). Therefore, these measures do not purely capture cash flow uncertainty. However, cash flow uncertainty should still account for a significant component of these measures.

[Table 17 around here]

Table 16 presents the correlations between the two alternative risk measures and the cash flow risk shock and discount rate risk shock identified from the structural VAR. All four series are aggregated to the quarterly level by summing daily changes from scheduled FOMC announcement days. We also adjust the sign of the risk index to ensure that an increase reflects a rise in risk. As shown, both risk measures are highly correlated with the FOMC cash flow risk shock. While they are also correlated with the FOMC discount rate risk shock, the correlation is weaker—especially for the risk index, which exhibits a strong correlation with the cash flow risk shock (t-statistic = 5.224) but only a marginally significant correlation with the discount rate shock (t-statistic = 1.964).

[Figure 12 around here]

Table 17 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 12 examines the robustness of the subgroup average response to changes in the FOMC BBM risk index using the dummy interaction approach from equation 14. 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

[62] Assuming constant risk aversion.

high rollover risk. These findings confirm the robustness of the subgroup response across alternative risk measures.

[Table 18 around here]

Table 18 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 our main findings.

B.6. Control other monetary policy shocks

In this section, we 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. We aggregate both factors to the quarterly level and include them as control variables in our analysis.Table 19 presents the results. In column (1), we include both the target and path factors as controls. In columns (2) to (4), we interact these factors with the net debt-to-market ratio. In columns (5) and (6), we 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 us 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 our main findings. As shown in the table, our main results remain robust both qualitatively and quantitatively.

[Table 19 around here]

B.7. Sample Restricted to Manufacturing Firms

In this section, we test the robustness of our 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 20 presents the results for the manufacturing subsample.

We find that the results are similar to those of our 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 our previous results.

[Table 20 around here]

B.8. Using Debt-to-Market Ratio

Table 21 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 21 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, we obtain the equation for the excess return:

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

D. Detail of the Structural VAR

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

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

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

where X_t is the vector of daily asset price changes:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

The intuition behind these sign restrictions is as follows: A positive cash flow growth shock, denoted by ω_{t+1}^{c}, increases both bond yields and equity returns, reflecting improved economic fundamentals.[63] In contrast, a positive discount rate shock, ω^d_{t+1}, 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^{cr}_t, 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^{dr}_t, 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 our 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 our 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

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

reduced-form shocks becomes:

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

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

In our 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.

We 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 13 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 13 around here]

Moreover, our 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 our 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 22 around here]

Table 22 reports the correlations between the original shock series identified by Cieslak and Pang [2021], using data from 1983 to 2017, and our 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 14 plots our 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 our updated shock estimates relative to the original series.

[Figure 14 around here]

E. Decomposition of Aggregate Investment

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

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

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

where S_t^{high} represents the set of firms with high rollover risk at time t, and $w_{i,t} = \frac{k_t}{K_t}$ represents the share of each firm in the group. The covariance term captures the relationship between the initial size of a firm and its subsequent investment. Since aggregate investment can be viewed as the size-weighted investment of firms, we can decompose it as:

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

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

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

where s_t represents the share of high rollover risk capital in total capital, defined as $s_t = \frac{K_t^{\text{high}}}{K_t}$. Therefore, total growth can be further decomposed as:

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

Table 12: 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 our analysis. All variables are quarterly data from Compustat, covering the period from 1995 to 2023.

Table 13: 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 14: 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

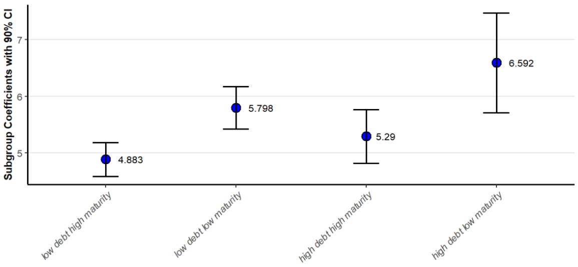
This table reports regression results based on Equation 13. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The key independent variable is a triple interaction term comprising the FOMC cash flow risk shock, an indicator for high net debt-to-market ratio (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.

Table 15: Firm-Level Investment Response Based on Net Debt and Maturity: Controlling Other Shocks

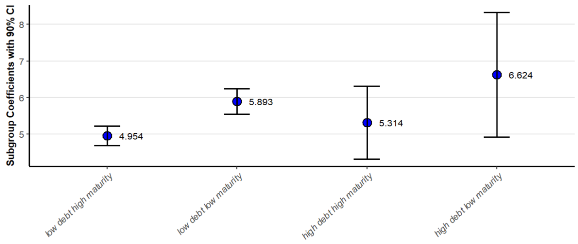
	$\log(k_{t+4}) - \log(k_t)$	
	(1)	**(2)**
$\epsilon_t^{cr} \times \mathbf{1}\{netDMR_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$	-1.522***	-1.388**
	(0.552)	(0.549)
$\epsilon_t^{ns} \times \mathbf{1}\{netDMR_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$	-3.071	8.871
	(12.482)	(14.173)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

This table presents regression results based on Equation 13. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The main independent variables are triple interaction terms consisting of the quarterly sum of different shocks on scheduled FOMC days, an indicator variable for high netDMR, $\mathbf{1}\{netDMR_{t-1}^{high}\}$, and an indicator variable for low debt maturity, $\mathbf{1}\{RI_{t-1}^{high}\}$. 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 percentile of the sample. The sample consists of a quarterly panel of Compustat firms spanning 1995 to 2023. Firm-level controls include lagged values (one-quarter lag) of size, net debt-to-market ratio, sales growth, asset return, operational leverage, the short-term asset ratio, and lagged GDP growth rate interacted with the lagged net debt-to-market ratio to control for differences in cyclical sensitivities across firms. Non-interacted coefficients and double interaction coefficients are omitted for brevity. Standard errors, shown in parentheses, are computed using the Driscoll–Kraay method, which accounts for clustering by firm and time. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 11: 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 14. 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 16: Correlation Between Risk Proxies

	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

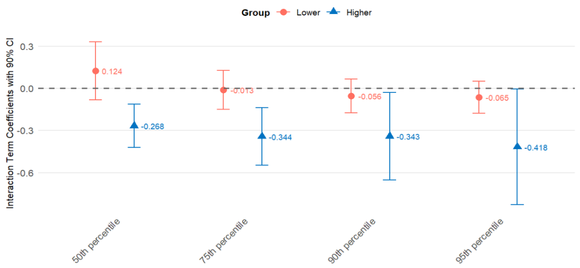
This table reports the correlation between changes in the risk index from Bauer et al. [2023] and changes in SVIX from Martin [2017] with the cash flow shock and discount rate shock. All four measures represent the quarterly sum of daily changes or shocks occurring on scheduled FOMC announcement days.

Table 17: Robustness: Main Results Using the Risk Index from Bauer et al. [2023]

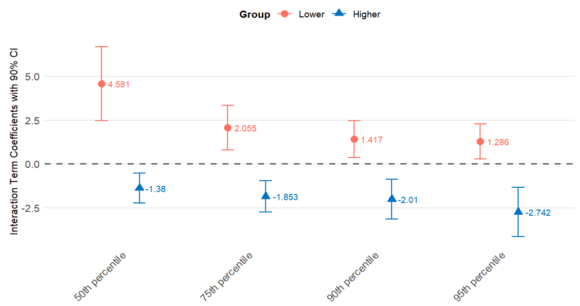
4 quarters growth rate	Capital	Capital	Debt	Cash	Capital	Capital
	(1)	(2)	(3)	(4)	(5)	(6)
ϵ_t^{risk}	-0.235					
	(0.250)					
$\epsilon_t^{risk} \times netDMR_{t-1}$		-0.881***	-3.47***	1.104*		
		(0.195)	(0.821)	(0.633)		
$\epsilon_t^{risk} \times netDMR_{t-1} \times \mathbf{1}\{RI_{t-1}^{high}\}$					-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.

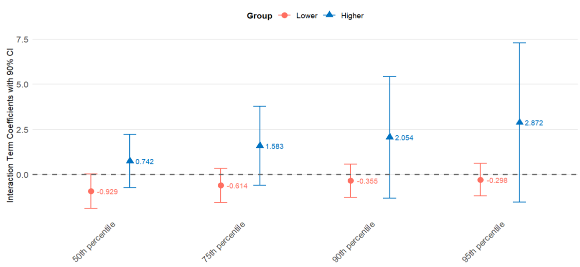
Figure 12: Subsample Firm-Level Investment Response Using the Risk Index from Bauer et al. [2023]



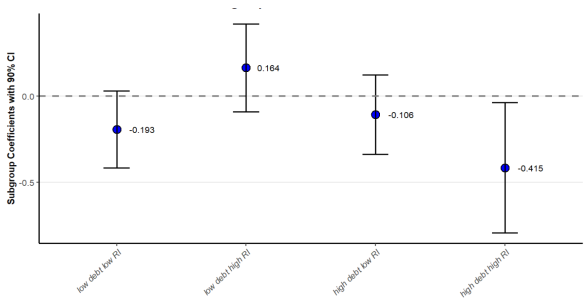
Panel A: Tangible Capital Investment Based on Net Market Leverage



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 14. 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 18: 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 × Industry FE	✓					
Macro Controls	✓					
Quarter × 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 19: 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 × Industry FE	✓					
Macro Controls	✓					
Quarter × 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 20: 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

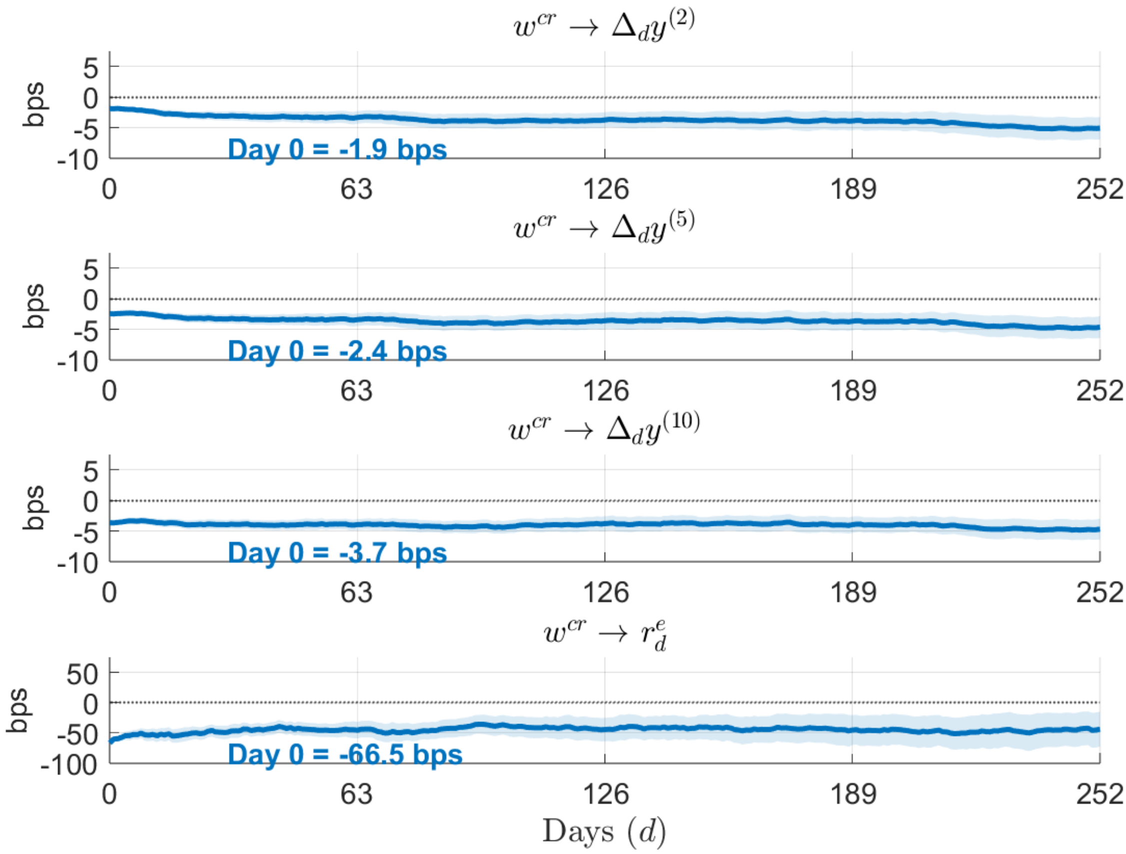
This table presents a robustness test of the main firm-level investment results using a sample restricted to manufacturing firms. The independent variable is the FOMC cash flow risk shock, while the dependent variable is the four-quarter-ahead change in tangible capital investment, cash growth, or debt 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 21: 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 13: 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 $d + 1$.

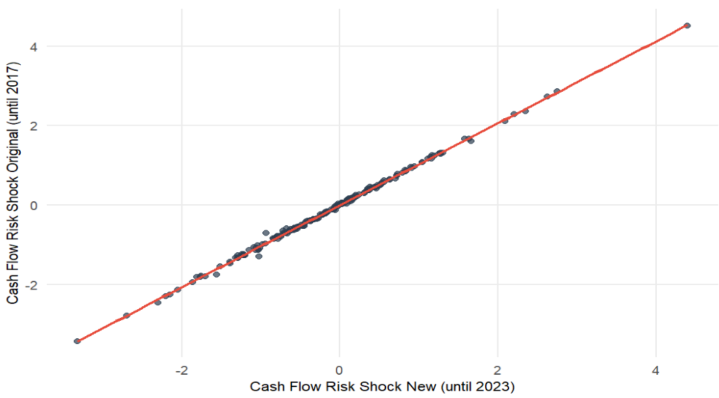
Table 22: Correlation Between Original and Updated Shock Series

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 14: 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.