Corporate Investment and the Risk Channel of Monetary Policy

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Abstract

We provide evidence that changes in risk are relevant in the transmission of monetary policy to corporate investment. Positive risk premium shocks, occurring on FOMC announcement days and driven by increases in future cash flow uncertainty, are associated with a decline in tangible capital investment over the next four quarters and beyond, particularly for firms with high leverage. Two key mechanisms explain this vulnerability. First, when cash flow uncertainty rises after announcements, debt reallocates toward low-leverage firms, forcing high-leverage firms to increase precautionary cash holdings and reduce capital investment. Second, the negative investment response is concentrated among firms with high rollover risk—those with both high leverage and high refinancing intensity—suggesting that refinancing constraints further limit their investment capacity. The relevance of the risk channel in monetary policy transmission to firm investment is more pronounced when the proportion of high-rollover-risk firms in the economy is larger during the sample period. However, the aggregate investment response is muted relative to the firm-level response, primarily because high-rollover-risk firms tend to be smaller in terms of tangible capital and thus contribute less to aggregate investment.

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

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1. Introduction

A growing body of research documents extensive evidence that monetary policy significantly influences risk premia in financial markets, reflecting shifts in risk perception and risk attitudes. However, relatively little is known about the extent to which monetary-policy-driven risk shifts affect economic activity.[1] Understanding this relationship is not only valuable for academic research but also crucial from a policy perspective. It provides an important justification for the extent to which central banks should engage in managing risk through economic outlook communication and future policy promises.

From an asset pricing perspective, a crucial channel through which central banks influence risk premia is by altering investors' perceptions of uncertainty about future economic conditions, thus affecting the quantity of risk. Typically, this occurs during monetary policy announcements—for instance, when central banks unexpectedly adjust nominal interest rates or disclose private information regarding future economic conditions. When monetary policy increases aggregate economic uncertainty, firms encounter heightened uncertainty in their future cash flows. Concurrently, investors—whose consumption relies on equity returns—face increased uncertainty in their future consumption.[2] Consequently, investors require greater compensation for bearing this additional risk, raising firms' cost of capital. According to Q-theory , this rise in the cost of capital leads firms to reduce their capital investment, especially for firms whose cash flow uncertainty is closely linked to aggregate economic fluctuations.

In this paper, we empirically test whether monetary-policy-driven changes in aggregate economic uncertainty influence subsequent firm investment, using a panel dataset of U.S. public firms. We further explore how investment responses vary across firms and identify channels driving this heterogeneity. A central empirical challenge is isolating unexpected economic uncertainty change caused by monetary policy. Following the asset pricing methodology of Cieslak and Pang [2021], we identify daily aggregate cash flow risk shocks from bond and equity market data using a structural VAR approach. We use shocks on FOMC announcement days (hereafter referred to as *FOMC cash flow risk shocks*) as proxies for changes in economic uncertainty driven by monetary policy. The rationale for this identification is that FOMC announcements represent major daily events drawing significant attention from financial markets. Consequently, cash flow risk shocks occurring on these days primarily reflect unexpected information from monetary policy. In robustness

[1] Bauer et al. [2023] summarize recent findings in financial markets supporting the risk shift channel but highlight the gap in understanding its effects on the real economy: "... 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... At this stage, we know too little about the effects of the risk-taking channel on both financial stability and the real economy to offer useful quantitative advice to policymakers..."

[2] This relationship holds provided investors diversify through market claims, which exposes them directly to aggregate uncertainty.

tests, we verify our results using alternative proxies based on daily changes in risk premia and find consistent support for our main findings.

We examine firms' investment responses using the local projection method, which offers a flexible and robust estimation framework. This approach allows us to explicitly control for other economic shocks occurring on FOMC announcement days, including shocks identified from structural VAR analyses and other high-frequency monetary policy shocks. Thus, we mitigate potential confounding effects arising from alternative monetary transmission channels. Our empirical findings indicate that an increase in the FOMC cash flow risk shock significantly predicts a decline in firms' tangible capital investment. Quantitatively, a one-unit positive shock—equivalent to one standard deviation of the cash flow risk shock across all trading days—leads to an average investment decrease of -0.496% over a one-year horizon. This reduction corresponds to approximately 3% of the typical annual investment rate.We further demonstrate the critical role of financial risk in shaping firms' heterogeneous investment responses. Specifically, the investment reaction varies significantly depending on a firm's leverage. Following prior accounting literature Penman et al. [2007], we measure financial risk by the net debt-to-market value ratio, representing a firm's net market leverage. This measure aligns with the findings of Lian and Ma [2021], who show that about 80% of U.S. public firms' debt is secured primarily by cash flows rather than physical collateral. Our analysis reveals that firms with higher leverage respond more strongly to positive FOMC cash flow risk shocks. Firms in the top 5% of the net debt-to-market ratio distribution experience, on average, investment reductions roughly three times larger than firms in the bottom 95%.

We further explore the empirical mechanisms driving the heterogeneous investment responses observed across firms. Specifically, we investigate why firms with higher leverage exhibit greater sensitivity to FOMC cash flow risk shocks and consequently reduce investment more substantially. Our analysis focuses initially on the liquidity management channel, motivated by theoretical studies on investment under uncertainty and financial frictions (e.g., Bolton et al. [2019], Alfaro et al. [2024]). Consistent with these theories, we find that higher FOMC cash flow risk shocks lead firms—particularly those with higher leverage—to increase precautionary cash holdings. Moreover, these shocks trigger debt reallocation: high-leverage firms decrease their debt growth, while low-leverage firms expand it. This evidence indicates that increased monetary-policy-driven aggregate uncertainty raises external financing premiums disproportionately for high-leverage firms, restricting their borrowing capabilities and ability to smooth production amid uncertainty. Consequently, their cash flows become more volatile, compelling them to hold more cash and limit investment in tangible capital.

We further demonstrate that, in addition to liquidity management, rollover risk significantly influences firms' investment responses. We quantify rollover risk using refinancing intensity, defined as the ratio of debt maturing within one year to total debt. Our results reveal that the predictive effect of FOMC cash flow risk shocks on future investment is especially pronounced among firms with high rollover risk—firms characterized by both high leverage and substantial short-term refinancing needs. This finding remains robust after excluding firms with negligible debt to focus exclusively on indebted firms, and after controlling for other monetary policy shocks that might disproportionately impact high-rollover-risk firms. These empirical results align with the theoretical predictions of Acharya et al. [2011], which emphasize that firms facing collateral constraints encounter increased difficulty in rolling over short-term debt when refinancing needs are high. Consequently, their default risk rises, borrowing capacity decreases further, and uncertainty has a greater negative impact on investment. Collectively, our analysis of liquidity management and rollover risk channels clarifies why high-leverage firms exhibit heightened sensitivity to monetary-policy-induced cash flow uncertainty.

Based on the firm-level results, we examine the aggregate implications from two perspectives. First, given our finding that the negative investment response is concentrated among high-rollover-risk firms, we show that the transmission of monetary-policy-driven economic uncertainty to firm investment varies over time, depending on the aggregate share of high-rollover-risk firms. Since our leverage measure is market-based, the percentage of high-rollover-risk firms is countercyclical, leading to a larger share of such firms during recessions. Consequently, FOMC cash flow risk shocks result in a stronger decline in firm investment during economic downturns. Second, the share of high-rollover-risk firms also induces industry-level debt and capital reallocation. Industries with a higher proportion of these firms experience larger declines in both investment and debt following a positive FOMC cash flow risk shock. This industry-level effect is particularly pronounced after 2008 but less significant during periods of conventional monetary policy.

However, the transmission of monetary-policy-driven cash flow uncertainty to aggregate investment is weaker and delayed. Following the literature, we compute aggregate investment by weighting firm-level investment by 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 compared to firm-level estimates, though its responsiveness strengthens over a two-year horizon. To better understand this pattern, we conduct a counterfactual analysis following Crouzet and Mehrotra [2020]. While high-rollover-risk firms exhibit greater sensitivity to the shock at the firm level, their contribution to aggregate investment remains limited due to their relatively smaller capital size. Moreover, within the low-risk firm group—which accounts for a larger share of total capital—smaller firms are disproportionately more affected by the shock compared to their larger counterparts. These findings help explain 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[3]. 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 stimulating 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[4]. 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.

[3]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.

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

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. Section 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 a model from Pflueger et al. [2020] that serves as a conceptual framework for our empirical analysis. Although simple in structure, it highlights the key economic factors in risk-centric theories of the business cycle[5]. We extend this framework by incorporating a basic monetary policy rule to illustrate how monetary-policy-driven cash flow uncertainty affects firm investment decisions.

2.1. Model

Risk and Monetary Policy

Following Pflueger et al. [2020], we model the log aggregate consumption growth as a stochastic process defined by $x_t = v_t$, where v_t represents an aggregate demand shock that follows a mean-zero independently and identically distributed (i.i.d.) normal distribution with time-varying heteroskedastic variance, $v_t \sim N(0, \sigma^2_{v,t})$. The term $\sigma^2_{v,t}$ captures the risk or uncertainty associated with the demand shock[6]. This framework assumes that the economy operates in a steady state, with the consumption process reflecting deviations from the steady-state level[7].

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

[5] Earlier works in this area include Gourio [2012], Fernández-Villaverde et al. [2015], and Caballero and Simsek [2020].

[6] Throughout this paper, the terms "risk" and "uncertainty" are used interchangeably, as they are equivalent in this context.

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

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 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[8]. These deviations capture unexpected policy errors or temporary shifts in the policymaker's preferences[9].

By substituting the monetary policy rule into the consumption growth process, we express x_t in terms of the aggregate shock and the monetary policy shock as $x_t = \omega\theta\epsilon_t + \omega v_t$, where ω is a constant given by $\omega = \frac{1}{1-\theta\phi}$. The perceived aggregate uncertainty for the next period, defined as 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 $\sigma_{v,t+1}^2$, representing the perceived risk of future demand shocks, evolves as:

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

where a and b are constants, with $b > 0$. This specification is consistent with the literature, which documents the countercyclicality of the risk premium and the tendency for perceived future uncertainty to rise during recessions[10].

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:

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

[8] 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."

[9] See Cieslak and McMahon [2023].

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

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:

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

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 $r_{ft} = -\ln\beta - \frac{1}{2}\gamma^2\sigma_{x,t+1}^2$[11].

Production

Firm production follows a simple Q-theory framework, where output is determined by a linear production technology in capital, given by $Y_{it} = Z_{it}K_{it}$. Here, Y_{it} denotes the output of firm i in period t, K_{it} represents the firm's capital stock, and Z_{it} captures the firm's total factor productivity (TFP). The TFP evolves according to the aggregate process:

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

The firm-specific parameter s_i determines the firm's exposure to aggregate growth. The term $-\frac{1}{2}s_i^2\sigma_{x,t+1}^2$, arising from Jensen's inequality, ensures that the expected total factor productivity remains constant (equal to 1) across all firms. Consequently, firms differ only in their exposure to aggregate uncertainty.[12]

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

[11] This follows from the Euler equation:

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

[12] 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.

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 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,[13] 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

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

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

excess return is given by:

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

2.2. Equilibrium

In this simple model, changes in perceived future aggregate uncertainty serve as the sole channel influencing asset prices and capital investment. The key insights that guide our empirical analysis are outlined in the following propositions. We begin by characterizing the 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 relation given in 9.*

Under the model's assumptions, future aggregate uncertainty is positively linked to monetary policy shocks:

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

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

Here, $-b\omega^3\theta\exp(a)$ represents the parameters governing the relationship between monetary policy shocks and future aggregate uncertainty. This proposition implies that monetary policy shocks have an approximately linear effect on future aggregate risk. The intuition is that a contractionary monetary policy shock reduces current consumption, which in turn raises agents' perception of future uncertainty. Log-linearizing aggregate uncertainty in the next period yields the following result:

Lemma 1. *Suppose the aggregate growth x_t, the monetary policy shock ϵ_t, and the consumption shock v_t are small and close to zero. Then, aggregate uncertainty 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, future aggregate uncertainty decomposes into three components: a constant term c, a term driven by the current demand shock κ^v_{t+1}, and a term driven by the current monetary policy shock κ^ϵ_{t+1}. Taking the first 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 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 impact of monetary policy-driven uncertainty on investment is stronger for firms with greater exposure s_i.

Proposition 3 implies that a contractionary monetary policy shock increases future uncertainty, raising the cost of capital for firms as their cash flow uncertainty grows. As a result, investment declines on average across all firms. Cross-sectionally, firms with greater exposure (s_i) face a larger increase in cash flow uncertainty and exhibit more pronounced investment contractions. Taking the first derivative of the risk-free rate with respect to κ^{ϵ}_{t+1}, we obtain the following proposition:

Proposition 4. *Given Lemma 1, a positive 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 as monetary policy increases the uncertainty of aggregate growth, households respond by increasing precautionary savings. This heightened demand for safe assets pushes down the risk-free rate and raises the price of risk-free assets. Since monetary policy shocks drive future uncertainty in a linear manner when x_t is close to zero, the following corollary holds:

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

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

share the same sign. Similarly, the first derivatives of the risk-free rate with respect to both 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 uncertainty on investment and the risk-free rate remain consistent, whether expressed in terms of κ^{ϵ}_{t+1} or ϵ_t.

2.3. Empirical Implications

Proposition 3 outlines the model's key empirical implication, which we aim to test: monetary-policy-driven increases in future aggregate uncertainty can reduce firms' capital investment.

We refer to this mechanism as the "risk channel" of monetary policy transmission. In the model, higher future aggregate uncertainty raises firms' cash flow uncertainty, which also affects investors, as their consumption becomes exposed to the same uncertainty. Consequently, investors demand higher risk compensation, increasing firms' cost of capital and leading to lower investment. Cross-sectionally, firms with greater exposure to this risk experience larger investment declines. In our empirical analysis, we test whether perceived changes in cash flow uncertainty due to monetary policy predict higher future returns—serving as an ex-post measure of the cost of capital—and lower investment rates.

In this simple framework, the risk channel is the sole mechanism through which monetary policy affects capital investment. Under this idealized setting, the elasticity of investment with respect to a monetary policy shock provides direct evidence of the risk channel, as shown in Corollary 1. However, in reality, monetary policy influences investment decisions through multiple channels, including changes in short-term discount rates and revisions to expected growth paths. As a result, estimating the elasticity of investment to monetary policy shocks may be confounded by these additional factors[14].

A more practical approach is to measure unexpected changes in aggregate cash flow uncertainty driven by monetary policy while controlling for other information released by the central bank. To identify these uncertainty shocks, we require a forward-looking measure that reflects changes in perceived risk. A natural choice is the risk premium embedded in asset prices. In our empirical analysis, we use aggregate cash flow risk shocks derived from asset pricing data on FOMC days as a proxy for unexpected changes in cash flow uncertainty induced by monetary policy. Our main identification strategy relies on a structural VAR approach to isolate risk shocks on FOMC days. For robustness, we also consider alternative risk measures to proxy monetary-policy-driven uncertainty.

We primarily focus on cash flow uncertainty in our empirical analysis, as Propositions 3 and 4 guide the identification of the relevant type of uncertainty necessary for consistency with the model's implied risk channel. Specifically, we seek to identify risk shocks that increase uncertainty in firms' cash flows—uncertainty that is priced into equity markets, raises excess returns, and lowers the risk-free rate. These shocks are embedded in expected equity returns but can be hedged by holding safe assets. This distinction is crucial because if equity prices are interpreted as a combination of a long-term bond and a claim on cash flow risk, an unexpected increase in discount rate uncertainty could also raise expected returns. However, such a shock would simultaneously drive up the yield on safe assets and does not alter firms' cash flow uncertainty. While discount rate uncertainty is also priced into the risk premium, it does not align with the risk channel in our model and is therefore

[14]Another potential concern is that monetary-policy-driven uncertainty in practice may not stem solely from changes in interest rates. For example, the Federal Reserve could issue policy promise responses to a future recession, thereby reducing tail risk and uncertainty without directly altering interest rates. Such policy communication can effectively lower uncertainty without affecting short-term rates.

not the focus of our identification strategy[15].

3. Empirical Strategy

Our empirical strategy builds on recent literature that examines the impact of monetary policy shocks on firm investment using micro-level data, including Ottonello and Winberry [2020] and Wong et al. [2019], and is particularly aligned with Cloyne et al. [2023]. Similar to Cloyne et al. [2023], we first employ a structural VAR to identify monetary-policy-related shocks and then analyze their effects on micro-level panel data. The key distinction lies in the type of shock we estimate: following Cieslak and Pang [2021], we use asset pricing data to identify cash-flow-risk shocks on FOMC announcement days, which serve as a proxy for monetary-policy-driven changes in 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 Treasury yields using a structural VAR with sign and magnitude restrictions. Below, we briefly outline the main intuition and structure of their approach, with further details on the estimation procedure provided in Appendix D.

Suppose asset prices evolve according to the following structural VAR:

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

where X_t is the vector of daily asset price changes, defined as: $X_t = (\Delta y_t^{(2)},\ \Delta y_t^{(5)},\ \Delta y_t^{(10)},\ r_t^e)$, which includes changes in zero-coupon Treasury yields for maturities of 2, 5, and 10 years, along with the market return. Here, μ is a constant, Φ is the matrix of dynamic coefficients, and B is the impact matrix that governs the contemporaneous structural relationships between shocks and asset prices. The vector of four structural shocks to the state variables is:$\omega^f_{t+1} = (w_t^c,\ w_t^d,\ w_t^{cr},\ w_t^{dr})$. By imposing restrictions on the impact matrix B, we assign economic interpretations to these shocks: (i) ω^c_{t+1} (cash flow growth shock) reflects changes in investors' expectations about future cash flow growth; (ii) ω^d_{t+1} (discount rate shock) influences the risk-free component of the discount rate; (iii) w_t^{dr} (discount rate risk premium shock) captures the compensation investors require for exposure to discount rate uncertainty, causing bond and stock prices to move in the same direction; (iv) w_t^{cr} (cash flow risk premium shock) reflects the compensation investors demand for exposure to equity cash flow risk, where bonds act as a hedge and therefore move in the opposite direction from

[15] 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 returns 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.

equities. These two risk premium shocks 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. Each shock is standardized to have unit variance, i.e., $\mathrm{Var}(\omega_t^f) = I$[16]. The diagonal matrix Σ^f contains the variances of these shocks.

The shock identification method proposed by Cieslak and Pang [2021] relies on restrictions imposed on the impact matrix B, which are 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. Two main sets of restrictions are applied to the impact matrix B: The first set consists of cross-maturity restrictions. These restrictions are motivated by the affine term structure model literature and supported by empirical evidence. The key intuition is that shocks related to the short rate—such as cash flow growth shocks and discount rate shocks—should have a diminishing impact as bond maturity increases. In contrast, holding long-term bonds exposes investors more to risk premium shocks. Therefore, cross-maturity restrictions ensure that the impact of risk premium shocks on Treasury yields increases with maturity, while the effects of discount rate and cash flow growth shocks decrease with maturity.

The second set consists of sign restrictions, which regulate the direction of each shock's simultaneous impact on asset prices, allowing us to distinguish cash flow risk shocks from discount rate risk shocks. To separate these two risk shocks, the impact matrix B assumes that a positive cash flow risk premium shock, w_t^{cr}, lowers equity prices by raising expected returns to compensate for increased risk, while simultaneously increasing bond prices (lowering yields), reflecting a flight-to-safety effect, as bonds serve as a hedge. Conversely, a positive discount rate risk premium shock, w_t^{dr}, raises both bond yields and expected equity returns, thereby depressing current asset prices, as investors demand compensation for this unhedgeable risk across asset classes[17]. The sign restrictions are particularly important in ensuring that the identified cash flow risk shock aligns with the type of uncertainty change needed to test the risk channel implied by the conceptual framework[18].

We estimate the structural VAR starting in 1983, following Cieslak and Pang [2021] to adhere as closely as possible to their specification, and extend it through the end of 2023. In line with common practice in the literature, including Wong et al. [2019], Ottonello and Winberry [2020], and Jeenas and Lagos [2024], we retain daily cash flow risk shocks from FOMC days and aggregate them to the quarterly level to align with firm-level balance sheet data. The resulting quarterly sum, ϵ_t^{cr}, which we refer to as the FOMC cash flow risk

[16]Each shock is normalized to have zero mean and unit standard deviation over the entire estimation period by construction.

[17]A positive cash flow growth shock, denoted by ω_{t+1}^c, increases both bond yields and equity returns, as fundamentals are expected to improve. In contrast, a positive discount rate shock, ω_{t+1}^d, reduces bond yields and equity returns, reflecting a heavier discounting of future cash flows.

[18]Cieslak and Pang [2021] show that the identified economic shocks strongly explain FOMC-day responses to various monetary policy shocks. Additionally, the monthly and quarterly sums of daily risk shocks exhibit strong explanatory power for different bond and equity risk premium proxies.

shock, serves as a proxy for monetary-policy-driven cash flow uncertainty implied by the conceptual framework and is the primary independent variable in our empirical analysis.

3.2. Cash Flow Risk Shock and Firm level Investment

We use the local projection method of Jordà [2005] to assess the average investment response to monetary-policy-driven changes in uncertainty:

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

where $k_{j,t}$ represents the book value of tangible capital stock for firm j at time t, and $h = 0, 1, \ldots, H$ denotes the time horizon over which the effects are estimated. The term α_j captures firm fixed effects, while $Z_{j,t-1}$ represents a vector of lagged firm-level controls that may simultaneously affect investment, including financial position, total assets, sales growth, liquid assets, total asset returns, and operational leverage, all measured prior to the shock. Since we use quarterly panel data, t refers to the quarter. When estimating the average effect, including quarterly time fixed effects is not feasible[19], so we instead include year fixed effects α_y[20]. Additionally, we include lagged macroeconomic controls A_{t-1}, consisting of the lagged GDP growth rate, unemployment rate, and inflation over the previous four quarters. Our primary coefficient of interest, β^h, measures how cumulative investment from quarter t to $t + h$ responds to the shock ϵ_t^{cr}. This coefficient can also be interpreted as the semi-elasticity of investment with respect to the shock.

To analyze the heterogeneous investment response driven by cross-sectional variation in firm characteristics, we follow Ottonello and Winberry [2020] and Jeenas and Lagos [2024] and estimate the following specification:

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

where the key independent variable is the interaction between firms' lagged characteristics, $X_{j,t-1}$, and the FOMC cash flow risk shock, ϵ_t^{cr}. This interaction term captures how a firm's cumulative investment response depends on its characteristics. In this specification, quarterly time fixed effects can be included, removing the need for year fixed effects and macroeconomic controls. The non-interacted terms are also included in the regression.

The above specification assumes a linear interaction effect, and the coefficient of the interaction term primarily reflects cross-sectional differences in investment responses. To relax this assumption, we adopt an alternative approach, following Cloyne et al. [2023] and

[19] Quarterly fixed effects would absorb all aggregate-level shock effects.

[20] We also consider specifications where year fixed effects are replaced with industry-year or industry-time fixed effects (α_{sy} and α_{st}), which control for time-varying investment opportunities at the broad sector level.

Anderson and Cesa-Bianchi [2024], by using a dummy variable approach:

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

Here, the indicator function $I[X_{j,t-1} \in g]$ equals 1 if the firm characteristic falls within a particular category, which defines the firm's group. These categories can be multidimensional, such as firms that are both small in size and highly leveraged. The dummy variable approach provides a semi-parametric method for estimating conditional average responses, where the coefficients $\beta_g^h \cdot I[X_{j,t-1} \in g]$ capture the average response within each subgroup. The key advantage of specification 14 over 13 is that it does not impose a linearity assumption on the interaction term, allowing for flexible estimation of subgroup-level average responses[21].

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[22]. Additionally, our analysis focuses on pre-scheduled FOMC meetings. We exclude unscheduled meetings due to significant noise in these events, as they often

[21] A potential concern with the linear interaction approach is that extreme values in the distribution of firm characteristics may disproportionately influence the estimated coefficient. However, since firms in the tails of the distribution—such as those with a high debt-to-market capitalization ratio, which we examine in the section below—are precisely the ones of interest, simply dropping them is not an option. The dummy variable approach provides a more robust way to capture the average behavior of firms in these tails.

[22] 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.

coincide with periods of heightened uncertainty, making it difficult to attribute cash flow uncertainty driven by monetary policy on those days[23]. 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[24]. We then extract all daily shocks occurring on regularly scheduled FOMC meeting days, denoted as w^{dr}_{fomc}, aggregate them to the quarterly level to match firm-level data, and use the resulting quarterly FOMC cash flow risk shock, ϵ^{cr}_t, as our primary dependent variable. The equity market index and Treasury yield data are sourced from Bloomberg.

[Figure 1 around here]

Figure 1 presents the identified cash flow risk premium shocks on scheduled FOMC meeting days. By construction[25], the daily cash flow risk shocks have a mean of zero and a unit standard deviation 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 the average daily volatility of cash flow risk. The figure highlights several patterns: cash flow risk shocks tend to be more negative on FOMC announcement days, indicating that these announcements generally reduce 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 exhibit extreme shock magnitudes. 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 cash flow risk.

[Table 1 around here]

[23]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.

[24]We follow the original sample period in Cieslak and Pang [2021], which begins in 1983 and extends through the end of 2023. The choice of 1983 ensures that the estimated parameters remain comparable to those in the original study. One rationale provided in Cieslak and Pang [2021] for using data from 1983 onward is that the Federal Reserve transitioned to an interest rate targeting framework in the early 1980s. This shift allows for a more precise measurement of short-term discount rate shocks.

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

Table 1 presents summary statistics for cash flow risk shocks across all trading days and scheduled FOMC days. The column labeled 'MAV' reports the mean of the absolute values of the shocks. The table highlights two key findings. First, cash flow risk shocks on FOMC days tend to be larger in magnitude and exhibit a more negative median compared to those on all trading days, suggesting that FOMC announcements are more frequently associated with reductions in cash flow risk. Additionally, the dispersion of shocks, as indicated by the interquartile range and extreme percentiles (P5 and P95), is greater on FOMC days. Second, in the post-2008 period, cash flow risk shocks display both larger absolute magnitudes and greater dispersion compared to the full sample, reflecting heightened cash flow uncertainty change during the era of unconventional monetary policy.

5. Empirical Results

This section presents the two main findings of our analysis. First, we examine the average response of firm tangible capital investment to FOMC cash flow risk shocks. Second, we show that the magnitude of this response varies depending on firms' net market leverage.

5.1. Average Investment Response

Table 2 reports the estimated average firm-level response of tangible capital investment over the following four quarters, based on the specification in equation 12. All firm-level panel regressions employ standard errors clustered by firm and quarter, following Driscoll and Kraay [1998] to account also for potential serial correlation in the error term. Column (1) includes firm fixed effects, year fixed effects, and macroeconomic controls. The results indicate that the quarterly FOMC cash flow risk shock, ϵ_t^{cr}, significantly reduces investment over a one-year horizon, with statistical significance at the 5% level. This finding suggests that greater monetary-policy-driven future cash flow uncertainty leads firms, on average, to reduce investment, aligning with the prediction in Proposition 3 of the motivating framework. To interpret the magnitude, we define one ϵ_t^{cr} as a one-unit FOMC cash flow risk shock, which quantitatively corresponds to one standard deviation of daily cash flow risk shocks across all trading days. The estimated coefficient of -0.496 implies that a one-unit positive shock leads to a 0.496% decline in one-year investment[26]. Given that the average one-year investment rate in our sample is approximately 17.52%, this effect accounts for about 3% of the annual investment rate—an economically significant impact, particularly considering that ϵ_t^{cr} represents a quarterly shock.

[Table 2 around here]

[26] Investment rates are multiplied by 100 for interpretability.

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] [27]. 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 allows us to estimate the dynamic investment response following a shock, capturing how tangible capital investment evolves over time. Figure 2 plots the estimated coefficients using the same specification as Column (2) of Table 2, along with confidence intervals, for up to eight quarters after the shock. The results indicate that FOMC cash flow risk shocks negatively predict average firm-level investment starting from the second quarter, with the effect peaking around the fourth quarter. This dynamic impact remains persistently negative but gradually dissipates after reaching its peak, becoming statistically less significant over longer horizons. In summary, the average firm-level investment response to cash flow risk shocks on FOMC days is both negative and significant, with the strongest effect observed at a one-year horizon. This result provides a clear benchmark for evaluating the heterogeneous effects conditional on firm net market leverage in the next section.

[Table 3 around here]

Our motivating framework suggests that the decline in investment following monetary-policy-driven cash flow uncertainty is accompanied by an increase in the cost of capital. Therefore, we expect to observe a similar response pattern in the cost of capital as in investment. To test this, we adopt the same specification as in Equation 12, replacing the dependent variable with future realized returns, which serve as an ex-post measure of the cost of capital, following Pflueger et al. [2020]. Table 3 presents the results. The coefficient of ϵ_t^{cr} is positive and significant across all specifications, with a magnitude that remains

[27]We sum all shocks from daily to quarterly frequency to align with firm-level data.

highly robust[28]. This finding suggests that when the FOMC cash flow risk shock increases, future equity returns also rise, indicating an increase in the cost of capital. Figure 3 illustrates the dynamic effect of the shock on the cost of capital over eight quarters. The cumulative impact peaks in the fourth quarter and remains persistent at a similar level through the eighth quarter, highlighting the prolonged effect of monetary-policy-driven cash flow uncertainty on the cost of capital.

[Figure 3 around here]

5.2. Heterogeneous Investment Responses Based on Net Market Leverage

In the motivating framework, firms with greater exposure s_i exhibit stronger responses to monetary-policy-driven cash flow uncertainty shocks, reducing their investment more significantly than firms with lower exposure[29]. Which firms have higher exposure? A natural consideration is those with greater financial risk. Early literature, such as Hamada [1972], suggests that a firm's exposure to aggregate risk increases with its debt-to-equity ratio, as higher leverage amplifies the financial risk of equity and cost of capital[30]. Based on this insight, we investigate whether firms' investment responses to cash flow risk shocks on FOMC days vary with their financial risk.

Several recent empirical findings also hint that firms' financial risk may play a crucial role in shaping their investment response to cash flow risk shocks on FOMC days.Alfaro et al. [2024] find that following an uncertainty shock, ex-ante financially constrained firms reduce investment more than unconstrained firms[31]. Moreover, Gürkaynak et al. [2022] show that stock price reactions to monetary policy announcements on FOMC days depend on firms' debt characteristics, including the amount, type, and maturity of outstanding debt. Given that we extract monetary-policy-driven cash flow uncertainty from market price indices, their findings suggest that a similar mechanism may also influence the transmission of monetary policy driven uncertainty shocks to tangible capital investment.

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

[29]In the motivating framework, uncertainty shocks are the sole driver of the risk premium for all firms. When monetary-policy-driven cash flow uncertainty rises, high-exposure firms display greater comovement with the market and experience a more pronounced decline in stock prices.

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

[31]Alfaro et al. [2024] use aggregate exchange rate, policy, and energy price volatility as instruments for firm stock price volatility to examine how firms adjust investment in response to volatility changes. Their findings align with our intuition that uncertainty shocks lead to investment reductions, but our study specifically focuses on monetary-policy-driven cash flow uncertainty.

[Table 4 around here]

We measure firms' financial risk following the accounting literature in Penman et al. [2007], which decomposes the book-to-market ratio into asset and leverage components, consistent with Hamada [1972]. This decomposition separates equity risk into two distinct sources: asset (operational) risk and financing risk. We use net market leverage, defined as the net debt-to-market equity ratio ($netDMR$), to capture financial risk:

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

where net debt is defined as financial liabilities minus financial assets. Financial liabilities include 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 calculated as the number of common shares outstanding multiplied by the share price (from CRSP). Net debt can be negative when a firm holds excess cash, making it a more precise indicator of financial risk as it accounts for liquidity. This market-based measure is particularly relevant given recent findings by Lian and Ma [2021], which document that 80% of U.S. nonfinancial corporate debt is collateralized against cash flows rather than physical assets. Since market value directly reflects cash flow potential, it serves as an appropriate proxy for financing risk. For robustness, we also test a simpler measure—total debt divided by market equity—and find that our main results remain unchanged.

Table 4 presents the results for the heterogeneous investment response based on cross-sectional variation in leverage. We employ a local projection approach with interaction terms, as specified in Equation 13. The key independent variable is the interaction between the net debt-to-market ratio ($netDMR$) and the FOMC cash flow risk shock (ϵ_t^{cr}), which captures the relevance of market leverage in predicting investment responses. Column (1) follows the same specification as in Table 2, including firm fixed effects, year-industry fixed effects, and macroeconomic controls. However, we can apply stricter quarter-by-industry fixed effects while still identifying the interaction coefficient. Column (2) replaces year-industry fixed effects with quarter-by-industry fixed effects while maintaining firm fixed effects. Column (3) further introduces firm-level controls, all interacted with the shock variable, and additionally includes interactions between $netDMR$ and business cycle proxies to account for potential differences in the cyclical sensitivity of financing risk. Across all specifications, the coefficient of $\epsilon_t^{cr} \times netDMR_{t-1}$ remains negative and statistically significant at the 1% level, indicating that firms with leverage exhibit a stronger decline in investment in response to monetary-policy-driven uncertainty.

The conditional effect is also economically significant. Since the lagged $netDMR$ is standardized, the interaction term in column (3)—which includes the most controls—is estimated at −0.68. This implies that, for two firms differing by one standard deviation in $netDMR$, the firm with higher leverage experiences a 0.68% larger reduction in one-year investment in response to a one-unit positive shock[32]. This effect is particularly pronounced for firms with extremely high leverage. In our sample, firms in the top 0.5 percentile of the $netDMR$ distribution differ from median firms by 2.62 standard deviations[33]. As a result, firms in the top 0.5 percentile reduce their one-year investment by approximately 1.78% more than the median firm in response to a one-unit positive shock. Additionally, a comparison between columns (3) and (4) shows that this conditional effect becomes even stronger after 2008, coinciding with the adoption of unconventional monetary policy.

[Figure 4 around here]

The results in Table 4 rely on a linear interaction term. Figure 6 provides a complementary perspective using the dummy interaction specification in Equation 14, which estimates the average subsample effect. In each regression, we divide the full sample into two subgroups—"higher" and "lower"—based on whether a firm's net debt-to-market ratio exceeds the 50th, 75th, 90th, or 95th percentile. Panel A presents the full sample estimation, and the findings are consistent with those from the linear interaction approach. As the percentile threshold increases, firms classified as "higher" exhibit a more pronounced negative investment response to FOMC cash flow risk shocks. In each case, higher-leverage firms experience a greater decline in investment compared to their lower-leverage counterparts, with the gap widening at higher thresholds. Moreover, in the post-2008 period, firms in the higher leverage subgroups display even stronger negative investment responses, further amplifying the divergence between lower- and higher-risk firms. These results indicate that firms with greater leverage are more vulnerable to monetary-policy-driven cash flow uncertainty, and this effect intensifies under the unconventional monetary policy regime introduced after 2008.

6. Mechanism of Heterogenous Investment Response

In the previous section, we established that market leverage is a strong predictor of heterogeneity in firms' investment responses to cash flow uncertainty induced by monetary policy. In this section, we further investigate the empirical mechanisms that drive these

[32] This magnitude is approximately $0.68/17.52 = 3.89\%$ of the average annual investment rate.

[33] Firms in the tail of the $netDMR$ distribution exhibit particularly high values. We retain these observations because their behavior is relevant to our study, following the reasoning in prior research on financial frictions in monetary policy transmission Ottonello and Winberry [2020]. However, these large values could bias OLS estimates if the relationship is nonlinear. To address this concern, we employ a semi-parametric dummy regression to estimate subgroup average effects.

heterogeneous responses, extending beyond the scope of our conceptual framework[34]. Our empirical analysis takes two approaches. First, drawing on the liquidity management literature—originating from Keynes' *General Theory*—which suggests that firms hoard cash as a precaution when uncertainty rises and external financing frictions exist, leading them to allocate fewer resources toward investment and production expansion, we test this channel by examining the heterogeneous responses of cash holdings and debt growth based on cross-sectional variation in leverage. Second, we assess the role of rollover risk in shaping investment responses. Specifically, we test whether the negative impact of FOMC cash flow risk shocks on investment is concentrated among firms that have both high market leverage and high refinancing intensity.

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 rise in the shock. 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

[34] Exploring these mechanisms also helps us understand why firms with high leverage are more exposed to monetary-policy-driven cash flow uncertainty.

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[35]. Consequently, highly leveraged firms, which already face elevated financing premiums before the shock[36], 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.

[35] 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.

[36] 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].

[Table 6 around here]

Figure 6 reports the estimated coefficients for the average subgroup debt response. The figure reveals an interesting effect that the previous table does not fully capture: the debt reallocation effect. For a one-unit increase in cash flow risk on FOMC days, firms in the top 50% of the net debt-to-market ratio increase their debt by 5.11%, while those in the bottom 50% decrease their debt by 1.82%. This effect becomes even more pronounced at higher leverage levels. Specifically, firms in the top 5% of the debt-to-market ratio reduce their debt by 3.43% over a one-year horizon, whereas firms in the bottom 95% experience a marginal increase of around 1%. This debt reallocation effect suggests that monetary-policy-driven cash flow uncertainty leads to a differential debt response between high- and low-financial-risk firms. The debt response complements 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[37]. 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]

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

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[38]. We estimate an interaction-term regression (specification 13) with a 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%[39].

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].

[38] 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.

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

The results remain consistent, confirming that the observed effects are driven by highly indebted firms rather than those with negligible debt levels.[40].

[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 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

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

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.[41] 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

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

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 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}.[42] 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-

[42] 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.

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 indicate that the aggregate investment response to the FOMC cash flow risk shock is substantially weaker than the firm-level average response over a one-year horizon. From Table 2, a one-unit increase in ϵ_t^{cr} reduces firm-level investment by 0.496% over one year. In contrast, the one-year aggregate investment response across all firms remains close to zero, with an insignificant positive effect of 0.04%. A similar pattern emerges when focusing on high-rollover-risk firms. As shown in Figure 8, the average firm-level investment response for high-rollover-risk firms is -0.96% over one year. However, 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 increase in ϵ_t^{cr} leads to a decline of -0.330%, which, while not highly significant, is consistent with the firm-level results 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[43]. These results indicate that the effect 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

[43] The firm-level average investment response for firms with a high net debt ratio and high RI is -0.991 over a two-year horizon.

and other firms, respectively. The term $\hat{\text{cov}}_{t+8}$ further decomposes as:

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

This covariance term accounts for the fact that aggregate investment is a size-weighted average of firm-level capital growth. The components $\hat{\text{cov}}^{\text{low}}_{t+8}$ and $\hat{\text{cov}}^{\text{high}}_{t+8}$ 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 counterfactuals are:

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

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:

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

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)[44].

The counterfactual analysis highlights two key economic findings. First, although high-rollover-risk firms are, on average, more responsive to the FOMC cash flow risk shock, their contribution to aggregate investment is limited. A key reason is their smaller tangible capital stock compared to low-risk firms, reducing their overall impact on aggregate investment transmission. Second, the FOMC cash flow risk shock affects firms of different sizes (in terms of tangible capital) disproportionately. Compared to low-rollover-risk firms, the shock makes the covariance between capital size and subsequent investment more negative for high-risk firms. In other words, within the high-risk group, the shock affects both large and small firms more evenly, whereas in the low-risk group, smaller firms are relatively more impacted.

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,

[44] 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.

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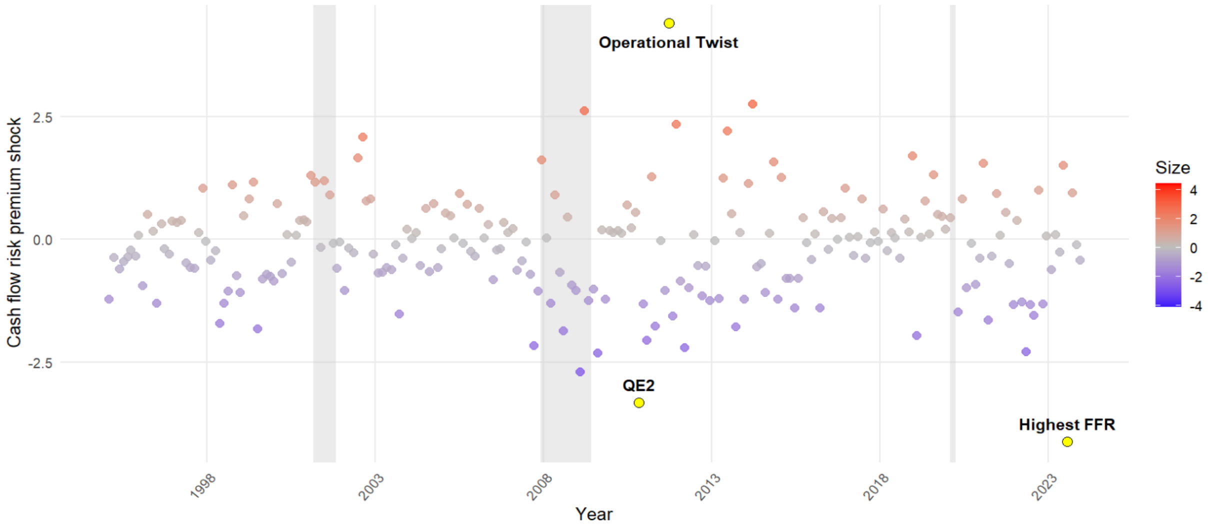
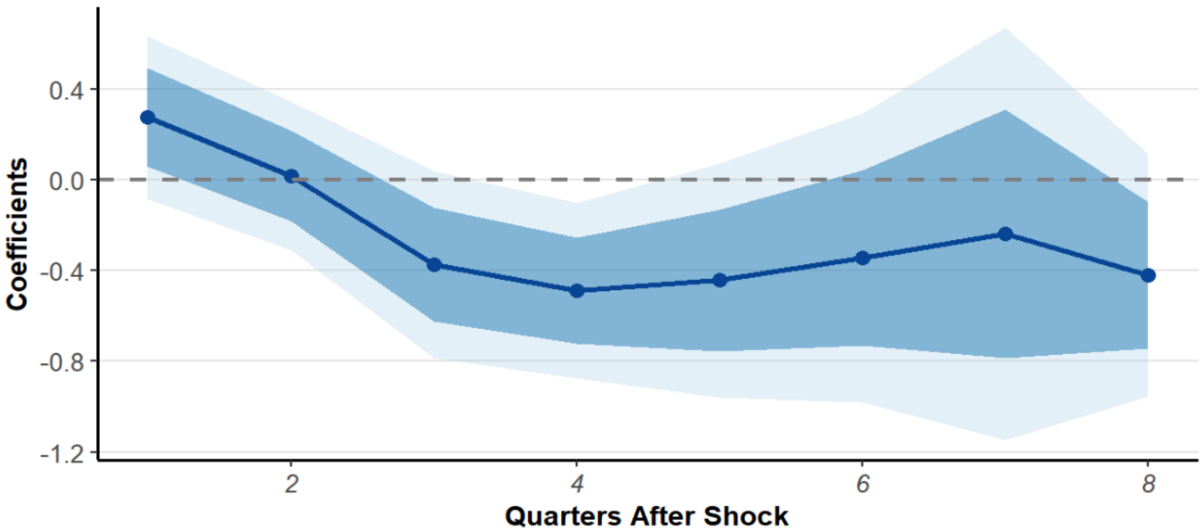
Figure 1: Cash Flow Risk Premium Shocks on Scheduled FOMC Meeting Days



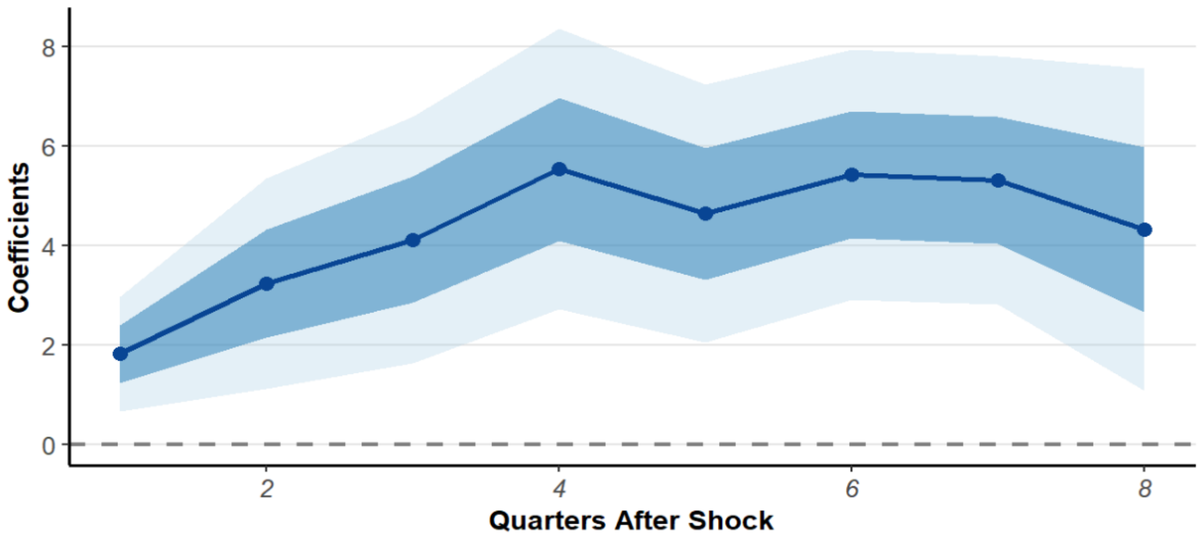
This figure shows the identified cash flow risk premium shocks on all scheduled FOMC meeting days from 1995 to 2023. The shocks are estimated using a structural VAR model with bond and equity data for all trading days during the period 1983–2023. The shocks are normalized to have a mean of zero and a 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



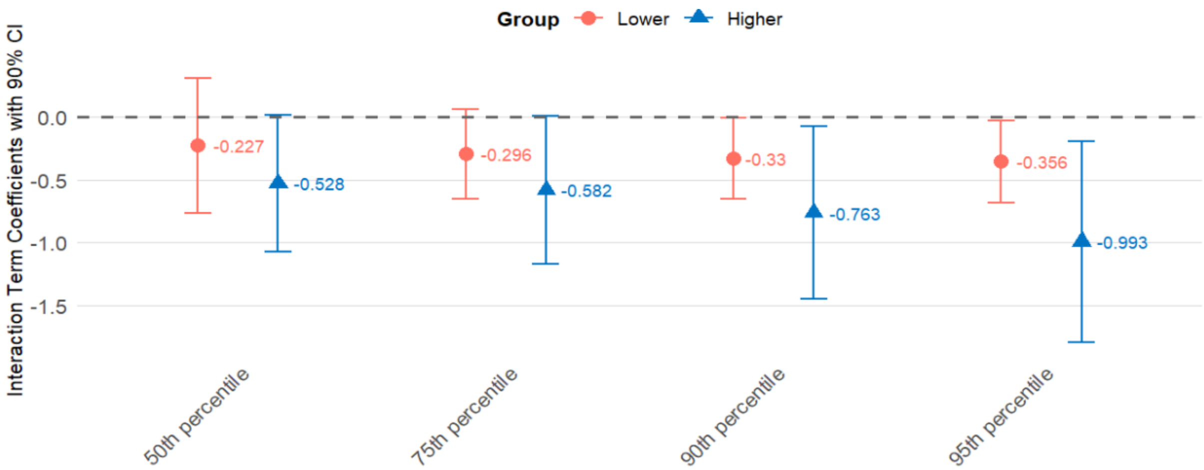
This plot illustrates the dynamic effects of FOMC cash flow risk shocks on investment. The regression is based on equation 12, with the dependent variable being the change in the log book value of tangible capital stock over next one to eight quarters. The sample consists of a quarterly panel of Compustat 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

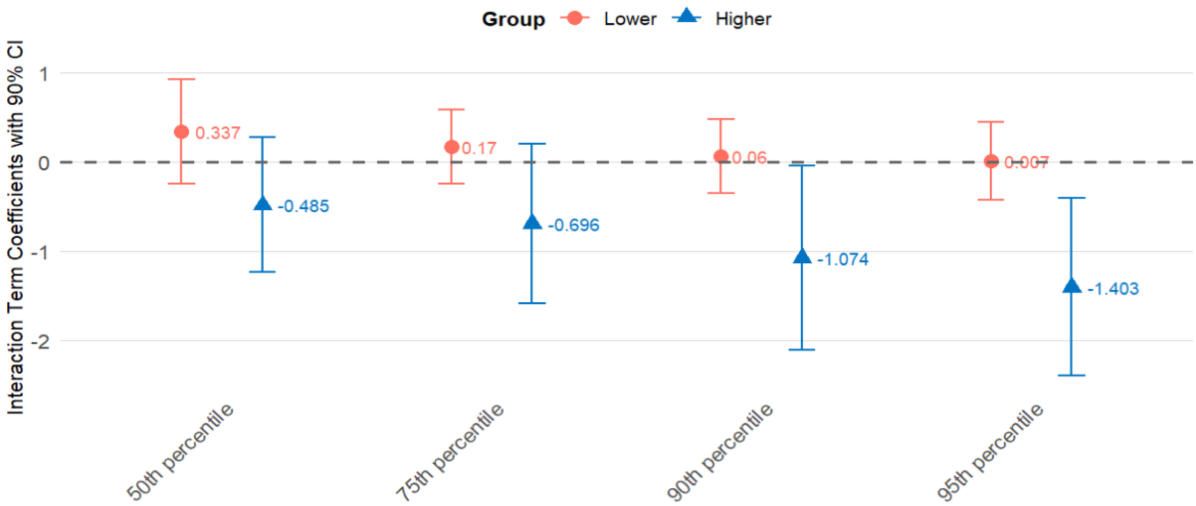


This plot illustrates the dynamic effects of the FOMC cash flow risk shock on scheduled FOMC days on Cost of Capital. The regression is based on equation 12, with the dependent variable being the change in the log equity price over next one to eight quarters. The sample consists of a quarterly panel 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 $\times$ 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



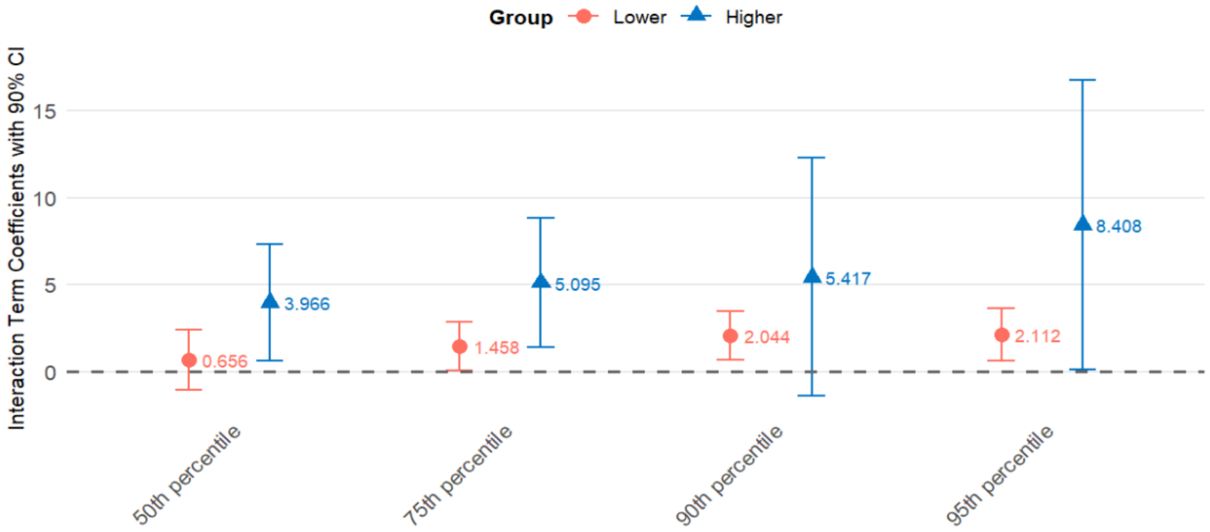
Panel A: Full Sample



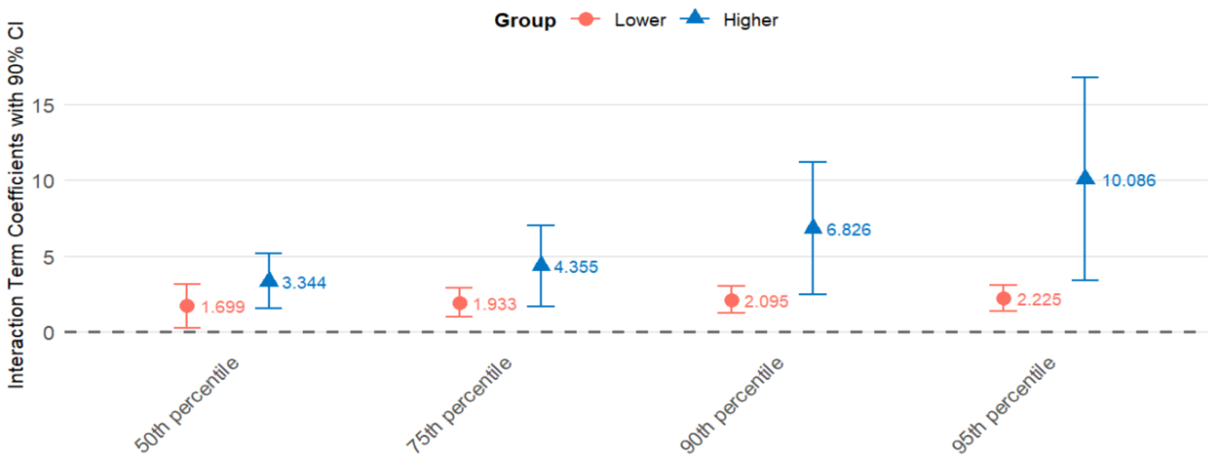
Panel B: Post-2008 Sample

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



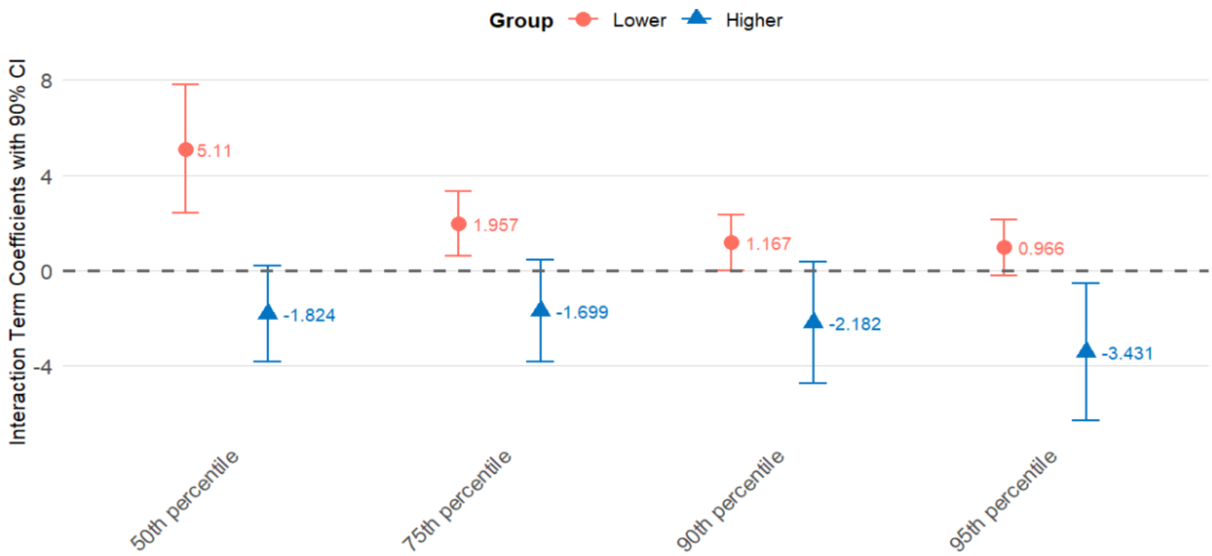
Panel A: Full Sample



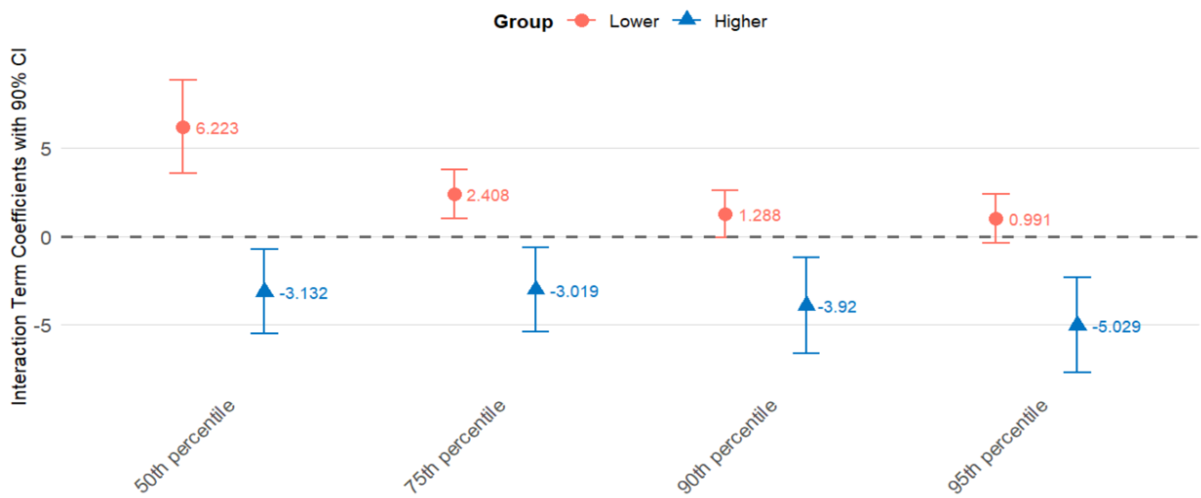
Panel B: Post-2008 Sample

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 × 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



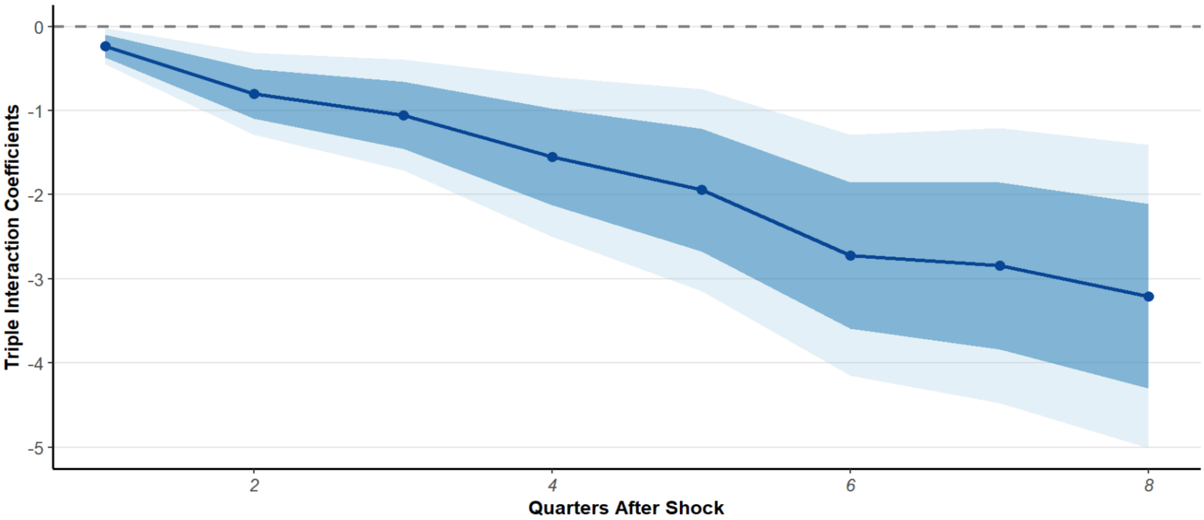
Panel A: Full Sample



Panel B: Post-2008 Sample

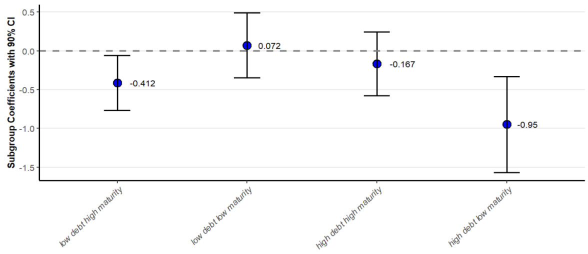
This table reports regression results based on equation 14. The dependent variable is the four-quarter change in the log total debt. The main independent variable is the FOMC cash flow risk shock, interacted with binary indicators for high or low firm-level lagged net debt-to-market ratio (netDMR). Firms 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 × 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

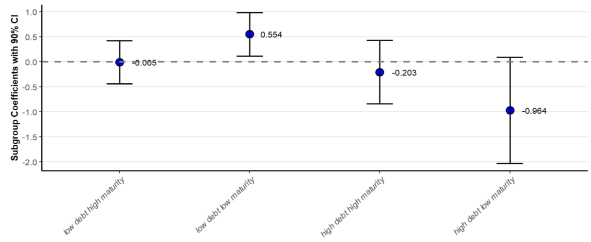


This plot illustrates the dynamic effects of High Net Debt and Low Maturity on the investment response to the FOMC cash flow risk shock. The regression is based on Equation 13, with the dependent variable defined as the change in the log book value of tangible capital stock over the next one to eight 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.

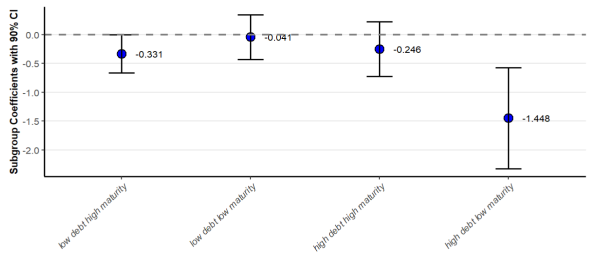
Figure 8: Subsample Firm-Level Investment Response Based on Net Market Leverage and Refinancing Intensity



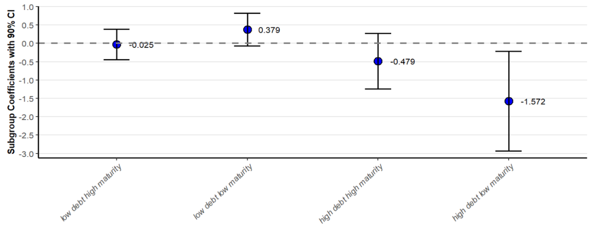
Panel A: Full sample with 75th Percentile of netDMR



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



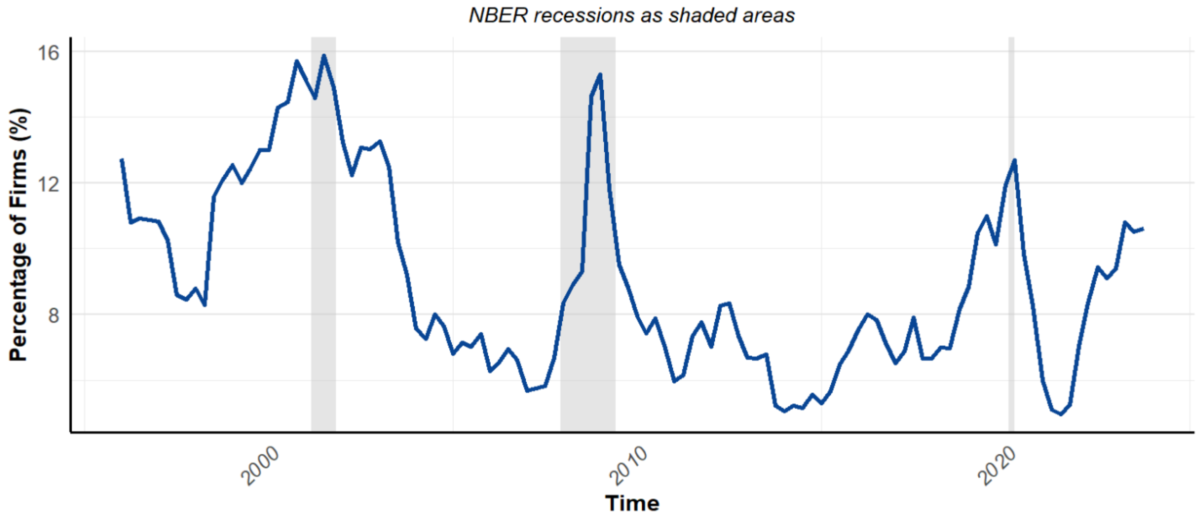
Panel C: Full sample with 90th Percentile of netDMR



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

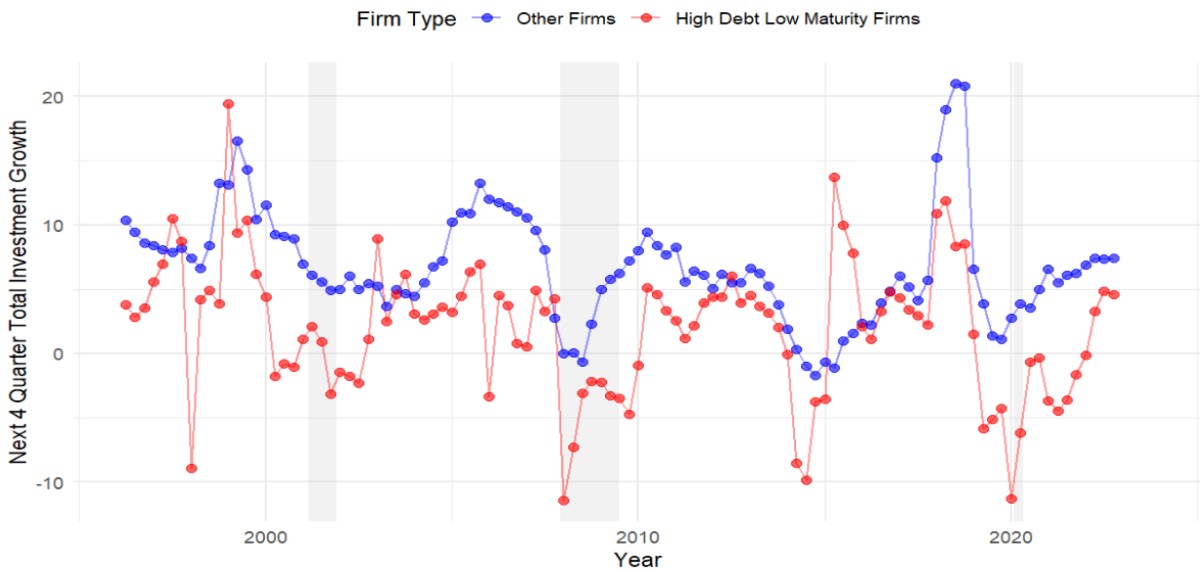
This plot reports regression results based on equation 14. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The main independent variable is a triple interaction term consisting of the FOMC cash flow risk shock, an indicator variable for high netDMR, $\mathbf{1}\{netDMR_{t-1}^{low}\}$, 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 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 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 $\mathbf{1}\{RI_{t-1}^{high}\} \times \mathbf{1}\{netDMR_{t-1}^{low}\}$. Macroeconomic controls include lagged values (one to four quarters) of inflation, GDP growth, and unemployment. The table also presents 90% point-wise 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**
FOMC Days (Full)	0.842	-1.999	-0.752	-0.180	0.443	1.239
All Trading Days (Full)	0.668	-1.373	-0.518	-0.028	0.478	1.504
FOMC Days (Post-2008)	1.007	-2.184	-0.853	-0.242	0.386	1.350
All Trading Days (Post-2008)	0.673	-1.408	-0.521	-0.051	0.473	1.527

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	✓	✓	✓	✓
ϵ_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 × Industry FE	✓	✓	✓	✓
Macro Controls	✓	✓	✓	✓
Firm Controls		✓		✓
Other MP Shocks × $\boldsymbol{p}_t$		✓		✓
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 ∈ [6000, 6799]) or utilities (SIC ∈ [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 ∈ [0, 999]; (ii) mining: SIC ∈ [1000, 1499]; (iii) construction: SIC ∈ [1500, 1799]; (iv) manufacturing: SIC ∈ [2000, 3999]; (v) transportation, communications, electric, gas, and sanitary services: SIC ∈ [4000, 4999]; (vi) wholesale trade: SIC ∈ [5000, 5199]; (vii) retail trade: SIC ∈ [5200, 5999]; (viii) services: SIC ∈ [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[45], 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

[45] 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 $x_t = 0$:

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

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 structural VAR model with sign and magnitude restrictions proposed in Cieslak and Pang [2021] aims to recover economic shocks. This model is based on the intuition that asset prices can be represented as an affine function of state variables. Assume asset prices evolve according to the following structural VAR:

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

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:

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

where w_t^c represents the cash flow growth shock, w_t^d the discount rate shock, w_t^{cr} the cash flow risk premium shock, and w_t^{dr} the discount rate risk premium shock. These shocks have unit variance, i.e., $\mathrm{Var}(\omega_t^f) = I$. The matrix Σ^f is diagonal and contains the variances of these shocks, while B is the impact matrix that governs the contemporaneous structural relationships between the shocks and asset prices.

Macro-finance models typically embed exogenous shocks to the endowment process, risk premia, and short-term interest rates to drive asset pricing dynamics. The shock identification in Cieslak and Pang [2021] follows this approach. By imposing restrictions on the impact matrix B (described later), the identified shocks in ω_{t+1}^f acquire distinct economic interpretations:

1. ω_{t+1}^c (cash flow growth shock) captures investors' expectations about future cash flow growth.

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

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

4. w_t^{cr} (cash flow risk premium shock) 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 and exposure to cash flow risk.

To identify the four economic shocks, two main sets of restrictions 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 based on the intuition from affine term structure models and empirical evidence: the impact of short-term rate-related shocks (such as the cash flow growth shock and discount rate shock) diminishes as maturity increases. However, long-term bonds are more exposed 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 different maturities, separating the two risk premium shocks from the other two shocks. Specifically, the 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 cross-maturity restrictions to isolate the risk shocks, the second set of sign restrictions draws on insights from macro-finance literature. These restrictions aim to further differentiate the cash flow risk shock from the discount rate risk shock, as 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 fundamentals. In contrast, a positive discount rate shock, ω_{t+1}^d, reduces bond yields and equity returns, as it leads to heavier discounting of future cash flows. A positive cash flow risk premium shock, w_t^{cr}, raises the expected rate of return to compensate for increased risk, which lowers equity prices but raises bond prices (thus lowering bond yields), as bonds provide a hedge. Meanwhile, a positive discount rate risk premium shock, w_t^{dr}, increases both bond yields and equity expected returns, but depresses current asset prices as investors demand compensation for this unhedgeable risk across asset classes. These opposite co-movements are essential for distinguishing the cash flow risk shock from the discount rate risk shock and ensuring that the identified cash flow risk shock aligns with the model's propositions.

In addition to the two main sets of restrictions, Cieslak and Pang [2021] imposes a third set of within-asset restrictions to constrain the relative contributions of each shock to the conditional volatility of treasury yields. These within-asset restrictions consist of two conditions: First, the contribution of the two risk premium shocks to the 10-year yields must be larger than the contribution of the other two shocks. Second, the contribution of the two risk premium shocks to the 2-year yields must be smaller than that of the other two shocks.

The estimation process starts 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 are then expressed as $u_t = P\omega_t^*$, where ω_t^* are uncorrelated shocks with $\mathrm{Var}(\omega_t^*) = I$. The economic interpretation of these shocks depends on the imposed ordering. To address this ordering issue, we generate alternative uncorrelated shocks by applying an *orthonormal rotation matrix* Q_i:

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

This rotation preserves orthogonality, as $Q_iQ_i' = I$. The corresponding reduced shock representation becomes:

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

The rotation matrices Q_i are generated using *QR decomposition*, with only those that satisfy the imposed *sign restrictions* being retained. This process is repeated 1,000 times, yielding 1,000 valid shock sets $\omega_t(Q_i)$. The final shocks, ω_t, are selected based on the median target (MT) solution, where the instantaneous asset price responses to these shocks are closest to the median response across the 1,000 valid shock sets.

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 × Industry FE	✓	✓
ϵ_t^{cr} × 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

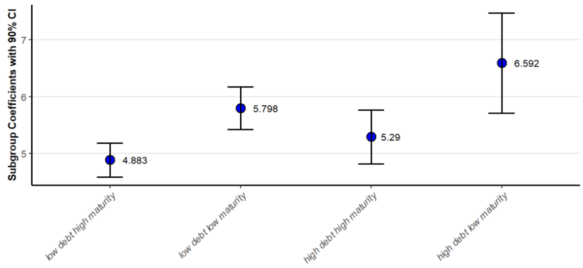
This table reports regression results based on Equation 13. The dependent variable is the four-quarter change in the log book value of tangible capital stock. The key independent variable is a triple interaction term comprising the FOMC cash flow risk shock, an indicator for high net debt-to-market ratio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

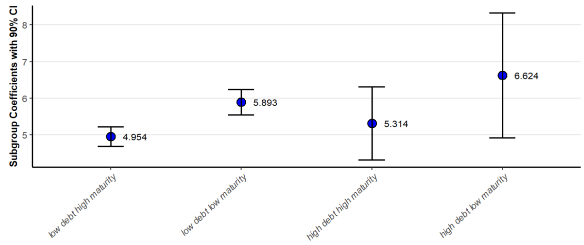
	$\log(k_{t+4}) - \log(k_t)$	
	(1)	**(2)**
$\epsilon_t^{cr} \times \mathbf{1}\{netDMR_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$	-1.522***	-1.388**
	(0.552)	(0.549)
$\epsilon_t^{ns} \times \mathbf{1}\{netDMR_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$	-3.071	8.871
	(12.482)	(14.173)
$\epsilon_t^{c} \times \mathbf{1}\{netDMR_{t-1}^{high}\} \times \mathbf{1}\{RI_{t-1}^{high}\}$		-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, $\mathbf{1}\{netDMR^{high}_{t-1}\}$, and an indicator variable for high refinancing intensity, $\mathbf{1}\{RI^{high}_{t-1}\}$. The indicator $\mathbf{1}\{RI^{high}_{t-1}\}$ represents firms with a short maturity ratio (debt maturing in less than one year to total debt) above the sample median. Similarly, $\mathbf{1}\{netDMR^{high}_{t-1}\}$ 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 $\times$ industry fixed effects, and the indicator variable $\mathbf{1}\{RI^{high}_{t-1}\} \times \mathbf{1}\{netDMR^{high}_{t-1}\}$. 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.

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

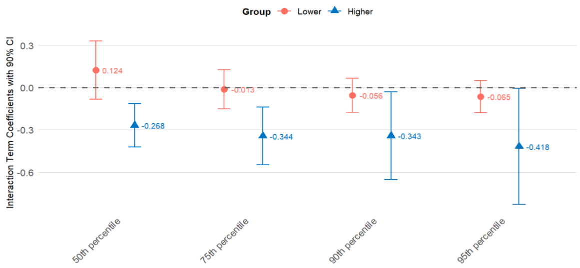
This table reports the correlation between changes in the risk index from Bauer et al. [2023] and changes in SVIX from Martin [2017] with the cash flow shock and discount rate shock. All four measures represent the quarterly sum of daily changes or shocks occurring on scheduled FOMC announcement days.

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

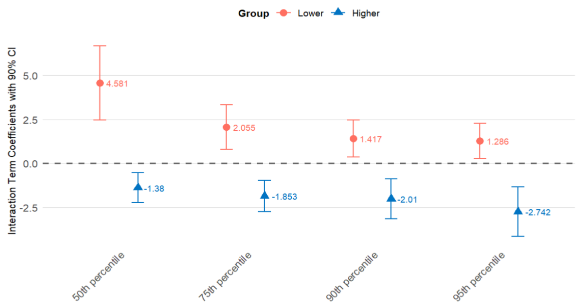
4 quarters growth rate	Capital	Capital	Debt	Cash	Capital	Capital
	(1)	(2)	(3)	(4)	(5)	(6)
ϵ_t^{risk}	-0.235					
	(0.250)					
$\epsilon_t^{risk} \times netDMR_{t-1}$		-0.881***	-3.47***	1.104*		
		(0.195)	(0.821)	(0.633)		
$\epsilon_t^{risk} \times netDMR_{t-1} \times \mathbf{1}\{RI_{t-1}^{high}\}$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

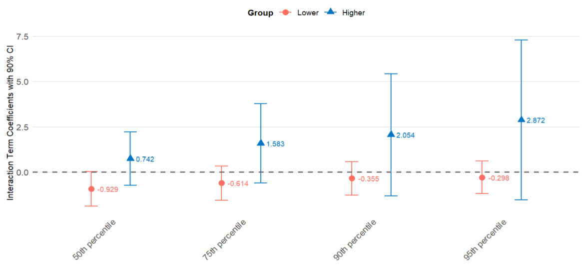
Figure 12: Subsample Firm-Level Investment Response Using the Risk Index from Bauer et al. [2023]



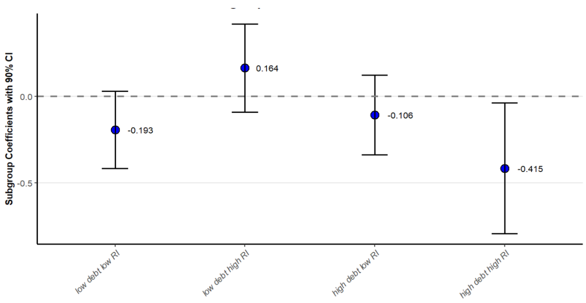
Panel A: Tangible Capital Investment Based on Net Market Leverage



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		✓	✓	✓	✓	✓
ϵ_t^{risk}× 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		✓	✓	✓	✓	✓
ϵ_t^{risk}× 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.