Monetary Policy, Industry Leaders and Growth*

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July 30, 2025

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Abstract

We provide novel evidence on heterogeneity in the transmission of monetary policy shocks to firms' financing conditions and investment, highlighting systematic differences between industry leaders and followers. Our key insight centers on differences in firms' profitability risk over the business cycle. Industry leaders - firms with larger market shares - generate profits that are relatively stable and less sensitive to aggregate economic fluctuations. When monetary policy tightens, aggregate risk is repriced, prompting investors to disproportionately raise the required rates of return for follower firms, whose profits are more cyclical and thus riskier. Following monetary tightening, industry leaders experience significantly smaller increases in financing costs, enabling them to sustain relatively higher growth expenditures in the form of physical investment and research and development. A stylized model featuring heterogeneous profit cyclicality rationalizes our empirical findings. Our results highlight previously unexplored distributional consequences of monetary policy, emphasizing its persistent effects on industry competition and firm investment dynamics.

Keywords: Monetary Policy, Corporate Finance, Market Power, Intangible Capital

JEL Codes: E22, E44, E52

*This draft has benefited from comments by Simon Gilchrist, Song Ma, Kelly Shue, Alp Simsek, and from seminar presentations at Yale University and New York University.

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1. Introduction

Firms exhibit heterogeneous responses to aggregate shocks, reflecting differences in their underlying characteristics and market positions. An extensive literature emphasizes financial constraints as a primary source of this heterogeneity, demonstrating that firms facing tighter financial constraints are more sensitive to monetary policy shocks (Gertler and Gilchrist, 1994; Ottonello and Winberry, 2020; Cloyne et al., 2023). However, even among large, financially unconstrained firms, significant dispersion in investment responses persists. Consider, for example, the recent U.S. monetary tightening cycle of 2023, during which dominant industry leaders, notably the "Magnificent 7", substantially expanded, while other firms faltered. This phenomenon raises a fundamental question: How does monetary policy differentially benefit industry leaders relative to followers, and what are the aggregate implications of this heterogeneous responsiveness?

To illustrate this mechanism clearly, consider the evolution of firm-level market shares during two distinct monetary regimes: the 2014Q1–2019Q1 tightening period, in which the Federal Reserve raised interest rates by approximately 2.4 percentage points, and the subsequent 2019Q3–2021Q3 easing period, in which interest rates declined by a similar magnitude. Within the industry comprising computing infrastructure, data processing, and web hosting services (NAICS 518), Alphabet Inc. (Google) and Intellicheck Inc. provide an instructive case study. Between 2014Q1 and 2019Q1, Alphabet - the industry leader at the outset - expanded its share of industry sales from 30.6% to 43.6%, representing a relative increase of over 42%. In contrast, Intellicheck, the firm with the lowest initial market share, saw its market share shrink by nearly 30% relative to its starting level. Conversely, during the subsequent monetary easing period (2019Q3–2021Q3), Intellicheck significantly increased its market share by roughly 76%, while Alphabet's share grew more modestly by about 13%. These starkly divergent patterns pose an intriguing puzzle: Why did Alphabet disproportionately benefit from a period characterized by rising financing costs, and conversely, why did a follower firm's market share accelerate during an easing cycle?

This paper introduces and empirically validates a novel "leader channel" for monetary policy transmission, through which industry leaders disproportionately benefit from contractionary monetary policy shocks relative to followers. In our framework, dominant firms are not only more productive on average, but also exhibit less cyclically sensitive profits. This lower cyclicality reduces risk, and therefore, the exposure of leaders' financing costs to monetary shocks, insulating their investment decisions during tightening cycles. Our proposed mechanism complements and provides a distinct perspective relative to the recent work by Liu et al. (2022), who emphasize that industry leaders are particularly advantaged by monetary easing due to their proximity to sustained market dominance, making discount rate reductions especially valuable. Taken together, leaders may benefit during tightening and loosening regimes, albeit through distinctly different mechanisms.

We document two novel empirical facts in support of this channel. First, industry-leading firms systematically increase their market shares relative to followers during periods of rising interest rates. Second, monetary tightening induces persistent increases in industry concentration, with the strongest effects arising in industries characterized by initially powerful market leaders. These findings suggest a compelling mechanism in which tighter monetary policy exacerbates existing competitive disparities, disproportionately favoring dominant firms at the expense of industry followers. Moreover, we find that these shifts in industry competition exhibit substantial persistence that arises primarily during contractionary episodes but is absent when policy loosens. Such nonlinearity indicates long-lasting structural consequences on industry competition due to monetary policy changes.

We present a standard model of firm investment and financing decisions that explicitly incorporates two facets of heterogeneous firm productivity. In our model, industry leaders not only have higher average productivity but also productivity that is significantly less cyclical and less risky compared to followers. This key structural difference directly lowers the sensitivity of leaders' required returns—and thus their financing costs—to monetary policy shocks, even absent conventional financial constraints. We derive explicit conditions under which market leaders' investment responses are less negatively impacted or even positively stimulated by monetary tightening, emphasizing the crucial role of the stochastic discount factor's volatility in driving these outcomes. Our mechanism highlights a previously underappreciated dimension of monetary transmission: heterogeneous productivity risk across firms can fundamentally alter firms' financing cost sensitivities, with important implications for industry competition and aggregate growth dynamics.

Empirically, we begin by documenting how monetary policy shocks propagate differentially through firms' financing conditions, introducing a robust mechanism we term the "leader premium". Specifically, we find substantial heterogeneity in the sensitivity of firms' cost of capital to monetary policy shocks, systematically dependent on their relative market share within their industry. Industry-leading firms — those commanding larger shares of industry sales — exhibit significantly lower passthrough of monetary shocks to their cost of capital. We establish that firms in the highest quantiles of industry market share experience markedly reduced sensitivity to tightening shocks, underscoring the insulation effect associated with market leadership.

We then analyze how these financing conditions translate into real investment and innovation outcomes. Consistent with differential financing sensitivities, we document that the tangible and intangible expenditures of industry leaders respond less dramatically to monetary tightening relative to followers. While follower firms significantly curtail their investment activities in response to contractionary monetary shocks, leaders exhibit a more muted response. Crucially, our analysis further demonstrates that this heterogeneous investment response is largely attributable to differences in firms' cost of capital sensitivity. The reduced exposure of industry leaders to adverse financing conditions during monetary tightening episodes effectively allows them to expand their market dominance precisely when aggregate credit conditions deteriorate. In this sense, industry leaders become relative beneficiaries of tighter monetary policy environments, reinforcing and amplifying existing market concentration.

Taken together, our empirical evidence highlights the importance of market structure and relative productivity positions as key determinants of firms' heterogeneous sensitivity to monetary policy shocks. The "leader premium" mechanism we identify provides a new dimension to the literature on monetary transmission, which has traditionally emphasized financial frictions or market structure near the zero lower bound. By emphasizing that the advantage of market leaders emerges systematically over conventional business cycles — not just near the zero lower bound — we contribute a significant and complementary perspective to ongoing discussions in macrofinance. Our findings highlight the role of industry leadership as a persistent and economically meaningful channel influencing both firm-level investment behavior and aggregate industry dynamics in response to monetary policy actions.

Contribution to the literature. Our paper studies the effects of monetary policy on firm expenditure through heterogeneity in the firm distribution.

First, we add to the literature on the heterogeneous capital investment response to monetary policy (Gertler and Gilchrist, 1994; Ottonello and Winberry, 2020; Cloyne et al., 2023). In much of existing literature, firms are differentially exposed to policy rate changes because of financial frictions: credit constrained firms react more strongly to changes in financial conditions due to a greater reliance on collateral price changes. In contrast to such work that inspect size as a form cross-sectional heterogeneity in credit constraints, we incorporate difference between firms across their market share distribution, controlling for size and leverage as possible explanations. We show market leaders feature less cyclical profits, which lowers their riskiness, and hence their required returns, in response to monetary tightening. More broadly, we add to literature on the differences between financial conditions of across firms over the business cycle.[1] Our paper builds on earlier insights on heterogeneity across firms to explore consequences of monetary policy shocks on investment decisions of firms across the market share distribution, and its consequences on industry competition.

Second, we add to the literature on capital reallocation over the business cycle. Capital reallocation (mergers, acquisitions, innovation, and purchases of tangible assets) is procyclical while the benefit of reallocation is countercyclical. Eisfeldt and Rampini (2006) explain this through countercyclical liquidity costs for a representative firm. Our findings suggest that the heterogeneous passthrough of monetary policy across the firm distribution can offer another potential explanation for procyclical reallocation.

Third, we add to the literature on the effects of monetary policy on productivity (Moran and Queralto, 2018; Ma and Zimmermann, 2023). Interest rate hikes are followed by decreases in

[1] See, for instance, Whited (1992), Kashyap et al. (1994), Oliner and Rudebusch (1996), Buera and Moll (2015), Gopinath et al. (2017), Crouzet and Mehrotra (2020), and Chodorow-Reich et al. (2022).

the profitability of innovation investment due to reductions in aggregate demand and tighter financial conditions. We add to this literature by showing that rate hikes passthrough to both tangible and intangible components of productivity and offer a novel mechanism explaining these findings.

Fourth, we add to the literature that explores the recent secular decline of productivity growth (Fernald, 2015; Summers, 2015; Philippon, 2023).[2] Liu et al., 2022 suggest that strategic investment behavior after monetary policy shocks affects the firm distribution. They argue that lower interest rates increase incentives for market leaders to invest in innovation, thereby benefiting leader firms. In Kroen et al. (2024), they argue that expansionary monetary policy shocks at the zero lower bound (ZLB) benefit industry leaders. We present the distributional changes due over the business cycle, studying a period of three decades beyond the recent ZLB episode. Notably, in line with earlier work, we find that interest rate increases benefit leaders more in monetary loosening regimes, thereby reducing competition which may affect productivity growth in the long run.

The paper proceeds as follows. Section 2 presents stylized facts of how monetary policy affects industry competition. Section 3 develops a stylized model to rationalize these facts and provide testable predictions. Section 4 describes our micro data. Section 5 provides empirical micro evidence for how market power matters for firm financing and investment decisions in response to monetary policy, informed by our stylized model. Section 6 concludes.

2. Stylized facts on business cycle competition

In this section we document industry outcomes over the business cycle. We show that industry leaders (relatively large firms) are expanding and that industry concentration increases after an interest rate tightening. We provide suggestive evidence that this decline in competition is due to the fact that ex ante large firms are expanding relatively more. Finally, rate changes have asymmetric effects on competition.

The data used in this section is based on large public firm data from Compustat assembled

[2] The literature suggests a plethora of explanations: demographic changes, foreign savings demand, rising markups and industry concentration.

in Section 4. We collapse the firm level panel by 3-digit NAICS industry and quarter and focus on sales or revenues (`saleq`) in the form of sale shares: $s_{i,j,t} = \texttt{saleq}_{i,t}/\texttt{saleq}_{j,t}$ is the share of sales of firm i in industry j at time t. The industry data covers 86 3-digit NAICS industries from 1991Q1 to 2023Q4.

2.1 Beneficiaries

We study the beneficiaries of increased interest rates. In each industry, we calculate the sales share of the 80th percentile firm $\mathrm{s}^{80}_{\mathrm{ind},t}$. Then, we run a local projection of the following form:

$$\mathrm{s}^{80}_{\mathrm{ind},t+h} - \mathrm{s}^{80}_{\mathrm{ind},t-1} = \alpha_{\mathrm{ind}} + \beta_h \Delta r_{f,t-1} + \varepsilon_{\mathrm{ind},t+h}$$

for h quarters ahead. β_h indicates the percent increase in the 80th percentile sale share between $t+h$ and $t-1$ due to a 1% rise in interest rates at time $t-1$. Figure 1 plots β_h for 15 quarters.

Figure 1 shows that industry leaders expand their market share relative to followers after a rise in interest rates. This effect is significant and persistent. Furthermore, in Appendix A we show similar patterns for the 90th percentile firm as well as the sale share of the 2 largest firms in each industry. We also decompose the underlying nominal sales response into the response by leaders and followers, which shows that sales for both groups initially slightly increase (as rates increase in good times) then decline (as booms are followed by busts).

2.2 Industry competition

To study competition, we calculate industry HHI as the sum of squared industry sale shares: $\mathrm{HHI}_{j,t} = \sum_i s^2_{i,j,t}$ where $s_{i,j,t}$ is firm i's sales share in industry j at time t.

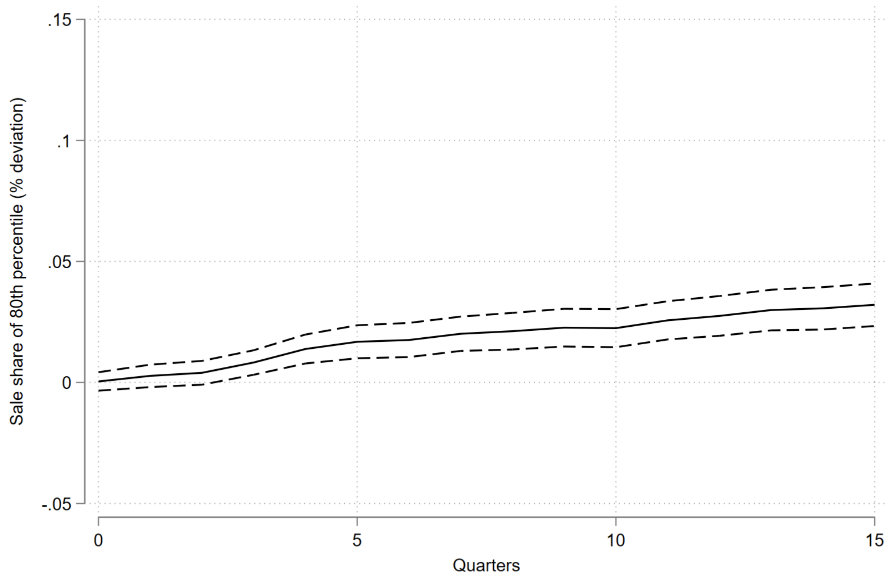
2.2.1 Interest rates on competition

To show the effect of interest rate changes on industry concentration, we run a local projection:

$$\mathrm{HHI}_{\mathrm{ind},t+h} - \mathrm{HHI}_{\mathrm{ind},t-1} = \alpha_{\mathrm{ind}} + \beta_h \Delta r_{f,t-1} + \varepsilon_{\mathrm{ind},t+h}$$

Figure 1: Sales share of 80th percentile firms due to interest rate increase in a local projection.

Notes: Dashed lines indicate the 95% confidence intervals.



for h quarters ahead. β_h indicates the percent increase in HHI between $t+h$ and $t-1$ due to a 1% rise in interest rates at time $t-1$. Figure 2 plots β_h for 15 quarters.

Figure 2 shows that industry competition falls after an interest rate increase. In particular, about 10 quarters ahead, industry HHI is 5% higher due to the monetary shock. The effect is also very persistent and does not disappear 15 quarters ahead.

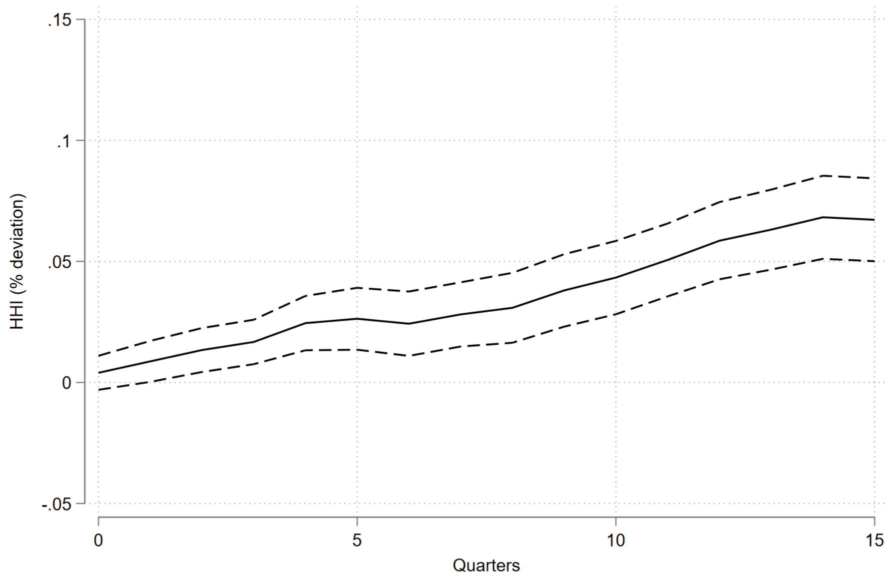
2.2.2 Interest rates on competition due to leaders benefiting

We interpret this fall in competition (or increase in HHI) as arising due to industry leaders benefiting disproportionally. However, another explanation focuses on firm entry and exit: when rates increase, new entrants are making less profit and therefore enter less. Similarly firms on the bottom of the distribution may be more likely to exit. Our data focuses on large public firms where new entry is less cyclical, so this is less of a concern. Nevertheless, we proceed by showing that this result is driven by industry leaders proportionally expanding.

To show that the change in competition is driven by our mechanism, we define an indicator $L_{ind,t-1}$ which corresponds to industries where the top 20% firms are larger than in the

Figure 2: HHI increase due to interest rate increase in a local projection.

Notes: Dashed lines indicate the 95% confidence intervals.



median industry at time $t-1$. These industries have larger top firms and should be more exposed to our mechanism. Then, we again run a local projection where we include the interaction of this indicator with rate changes:

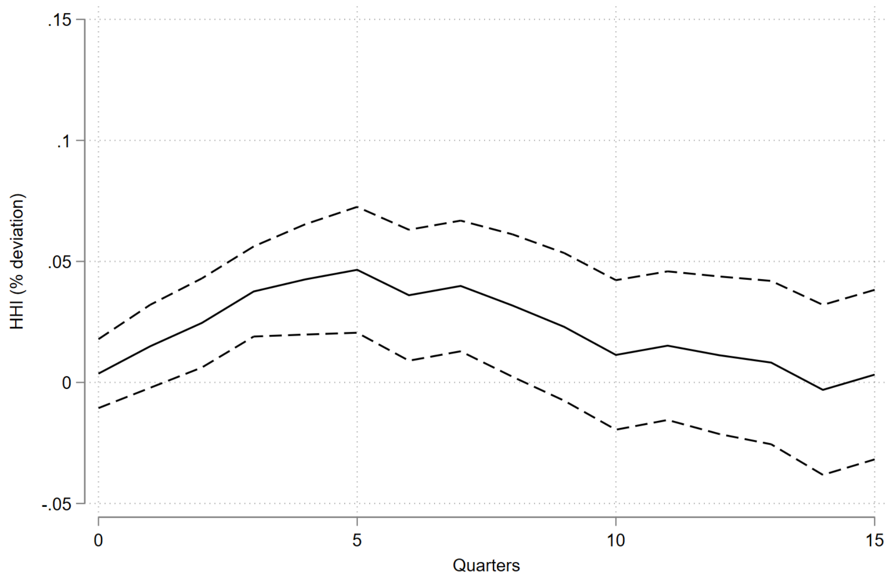
$$\mathrm{HHI}_{\mathrm{ind},t+h} - \mathrm{HHI}_{\mathrm{ind},t-1} = \alpha_{\mathrm{ind}} + \beta_h \times \Delta r_{f,t} \times L_{ind,t-1} + \gamma_h \Delta r_{f,t-1} + \zeta_h L_{ind,t-1} + \varepsilon_{\mathrm{ind},t+h}$$

for h quarters ahead. Now, β_h shows the percent increase in HHI that is driven by top heavy industries.

Indeed, Figure 3 highlights that the increase in HHI due to rate changes happens exactly in industries with relatively large top firms, suggesting that it is the large firms that disproportionally drive the results. The results suggest that the entire 5% HHI change is driven by larger than median top firms, although the standard errors in the regression are larger. In Appendix A we further show that this holds when defining industries with large firms differently: as industries where the top 40% firms are larger than the median industry or as industries where the top 2 firms control at least 30% market share.

Figure 3: HHI increase due to interest rate increase when top firms are large in a local projection.

Notes: Dashed lines indicate the 95% confidence intervals.



2.2.3 Nonlinear effect

The previous subsection highlights how the leader channel affects competition through interest rate changes. If this effect is linear, rate hikes lead to competition declines whereas rate lowerings lead to competition increasing, resulting in cycle of less competitive to more competitive forces. However, it might not be true that smaller firms are equally more likely to expand during looser monetary policy and take advantage of the opposite forces. To study this, we look at the non linear effect of rate changes on competition. We run the regression:

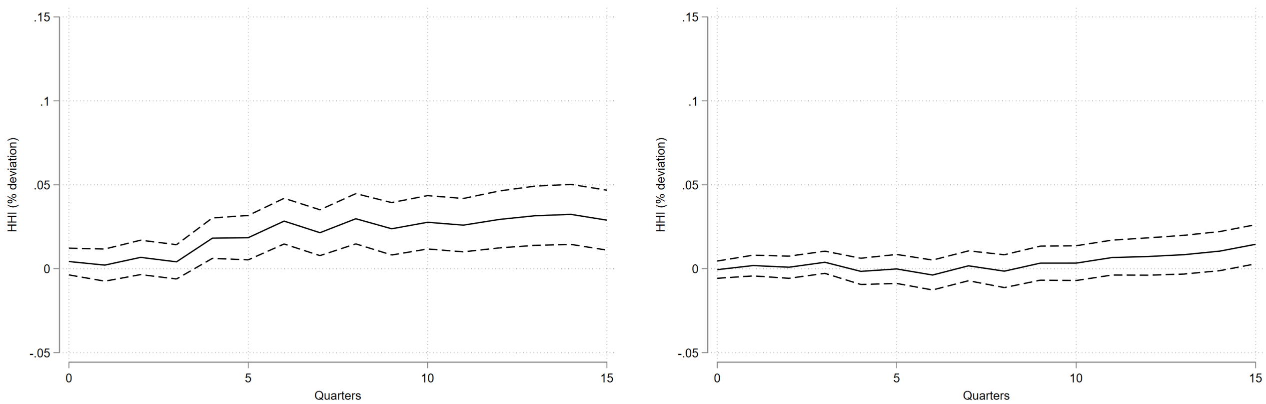
$$\text{HHI}_{\text{ind},t+h} - \text{HHI}_{\text{ind},t-1} = \alpha_{\text{ind}} + \kappa_{0,h} + \kappa_h I_{\Delta r_{f,t-1}>0} + \varepsilon_{\text{ind},t+h}$$

for h quarters ahead. $\kappa_{0,h}$ is the percent change h qyuarters ahead when rates stay constant or decline, κ_h is the additional percent increase due to a rate hike.

Figure 4 shows that the effect is only present during rate hikes. The left panel shows the additional effect due to positive hikes. This effect is positive and quantitatively large. The right panel shows the effect due to negative rate changes, which is insignificant. Thus, times when monetary policy is loose cannot offset the effect on competition when rates increase.

Figure 4: Nonlinear effect of interest rate increase on HHI.

Notes: Left: additional effect of a hike. Right: base effect of a rate decline. Dashed lines indicate the 95% confidence intervals.



While we do not have a compelling raison d'être for such a nonlinearity in theory, a possible explanation may be due to market share hysteresis that can create a "ratcheting" effect of monetary cycles on industry concentration. This is a promising field of research that we are encouraged to explore.

3. Stylized model

We demonstrate the market leader premium mechanism in a standard firm optimization problem augmented with a cyclical profit function. Consider a firm operating in a dynamic, stochastic, and discrete time environment. The only choice is firms next period capital stock K' (hence its investment rate), it discounts future profits using the economy wide SDF M' and importantly, its profits are a function of the SDF. We characterize industry leaders based on two attributes: first, industry leaders profits have a low cyclicality (they are less risky). Second, leaders have a higher average profitability.[3]

A firms optimization problem can be written recursively as a Bellman equation for any

[3] The key for our mechanism is the cyclicality of profits, which generates both the differential risk premium response and differential investment response. Including average productivity heterogeneity amplifies such heterogeneous response but cannot by itself generate such heterogeneous response.

general profit function π:

$$V = \max_{K'}\{\pi - (K' - (1-\delta)K) + \mathbb{E}[M'V']\} \tag{1}$$

where δ is the firms capital depreciation rate. Optimal choice leads to a general Euler equation for any form of profits π:

$$1 = \mathbb{E}[M'(MPK' + 1 - \delta)] \tag{2}$$

where we denote the marginal product of capital as $MPK' = \frac{\partial \pi'}{\partial K'}$. We can rewrite the euler equation using $r_f = R_f - 1$ as the net risk free rate and $R_f = 1/\mathbb{E}[M']$ as the gross risk free rate:

$$\mathbb{E}[MPK'] = r_f + \delta - R_f \mathrm{Cov}(M', MPK') \tag{3}$$

Thus, firms invest such that their expected marginal product (or required return) equals a user cost $(r_f + \delta)$ plus a risk premium. The risk premium depends on the covariance of the marginal product and the SDF. A firm whose profits are cyclical (or risky) will have a high risk premium, conversely a firm with low cyclical profits will have a low risk premium.

We specify a form for the profit function to show the effects of profit cyclicality on expected marginal products and investment rates. Consider a Cobb-Douglas production function $\pi = \phi K^{\gamma}$ with a cyclical productivity $\phi = \bar{\phi} - \varrho M$ where $\bar{\phi}$ is the average productivity and ϱ represents the cyclicality of productivity.[4] A high ϱ implies high cyclical profits.[5] $\gamma \in (0,1)$ is the elasticity of production with respect to capital. The marginal product becomes: $MPK' = \frac{\partial \pi'}{\partial K'} = (\bar{\phi} - \varrho M')\gamma(K')^{\gamma-1}$.

The expected marginal product then simplifies to:

$$\mathbb{E}[MPK'] = r_f + \delta + R_f \varrho \gamma K'^{\gamma-1} \mathrm{Var}(M') \tag{4}$$

where the risk premium is a function of the sensitivity ϱ and implicity the average produc-

[4] In the following, we will consider productivity and profitability to be synonymous as the size of the firm is deterministic.

[5] Since M is low when the economy is doing good.

tivity $\bar{\phi}$ (through the optimal size of the firm K'). Interest rate changes affect risk premia of firms with different characteristics differentially. We can see the impact of rate changes from: $\frac{d\mathbb{E}[MPK']}{dr_f} = 1 + \varrho\gamma K'^{\gamma-1}\mathrm{Var}(M')$. A firm with more cyclical productivity has a more sensitive expected marginal product.

Next, we solve for optimal investment. We can show that:[6]

$$\log K' = \frac{1}{\gamma - 1}\left[\log(1-(1-\delta)\mathbb{E}[M']) - \log(\gamma) - \log \mathbb{E}[M'(\bar{\phi} - \varrho M')]\right] \tag{5}$$

which yields a semi-elasticity of capital to interest rates of:

$$\frac{d\log K'}{dr_f} = \frac{1}{\gamma - 1}\left[\frac{1-\delta}{R_f(r_f+\delta)} - \frac{-\frac{\bar{\phi}}{R_f^2} + \frac{2\varrho}{R_f^3}}{\frac{\bar{\phi}}{R_f} - \varrho\mathrm{Var}(M') - \frac{\varrho}{R_f^2}}\right] \tag{6}$$

where the profit cyclicality ϱ and the average profitability $\bar{\phi}$ affect the semi-elasticity.

Indeed, we can show that the volatility of the SDF matters for the sensitivity of the semi-elasticity to both profit cyclicality and average profitability. We show in Appendix B that a very volatile SDF $(\mathbb{E}[M'])^2 < \mathrm{Var}(M')$) implies a larger magnitude investment semi-elasticity as ϱ increases and a smaller magnitude investment semi-elasticity as $\bar{\phi}$ increases. Changes in interest rates are then having a differential impact on firm investment rates depending on a firms ϱ and/or $\bar{\phi}$.

We can see that heterogeneity in the average profitability $\bar{\phi}$ affects the semi-elasticity, but only as long as there is some cyclicality of profits ϱ which does not need to be heterogeneous. On the other hand, heterogeneity in the cyclicality ϱ affects the semi-elasticity even if productivities are normalized to one.

In our empirical analysis, we will show that industry leaders (which have stable and high profit rates) are both differentially exposed to monetary policy changes through their expected returns which we will proxy using cost of capital rates and through their investment rates in tangible and intangible capital even in the absence of financial frictions.

[6] Please consult Appendix B for derivations.

4. Data and variable construction

We construct a firm level dataset with firm expenditure and firm financing choices. Our data is compiled at a quarterly frequency for US firms, running from 1991Q1-2019Q4. In what follows, we describe our data construction and present summary statistics of our variables-of-interest.

4.1 Firm fundamentals and growth expenditures

We start with the universe of Compustat firms.[7] Compustat provides financial and accounting variables, in particular, we are interested in expenditure data on PP&E (`ppentq`) and on capitalized R&D (`xrdq`). For every firm-quarter in our sample, we construct symmetric (midpoint) growth rates to account for both the intensive and extensive margins (Davis and Haltiwanger, 1992). We define growth in R&D and PP&E expenditure as:

$$\Delta Y_{i,t} = \frac{Y_{i,t} - Y_{i,t-1}}{0.5 \cdot (Y_{i,t} + Y_{i,t-1})}$$

where $Y_{i,t}$ is the net expenditure for firm i in quarter t.

In line with the literature, we drop firms in finance and insurance (NAICS code 52), real estate renting and leasing (NAICS code 53), public administration (NAICS code 92) and utilities (NAICS code 22). These firms have limited effect on the real economy, are usually subject to political and administrative considerations, and receive subsidies or preferential tax treatments. We also drop firms with negative assets (`atq`) or sales (`saleq`) as well as duplicates at the `gvkey` and quarter level.

4.2 Cost of capital

Our analysis relies on a comprehensive measure of firms' marginal cost of capital (COC). We add pricing data on firms' outstanding liabilities across different capital markets. Specifically, we estimate the weighted average of the cost of newly issued bonds, loans, and equities each quarter, weighted by the current value share for each asset class in the firms' newly issued

[7] We download Compustat from WRDS.

liability each quarter.[8] Our measure of COC is defined as:

$$\text{COC}_{i,t} = \sum_{\substack{L \in \{\text{Bonds, Loans,} \\ \text{Equity}\}}} r^L_{i,t} \times \frac{L_{i,t}}{\text{Bonds}_{i,t} + \text{Loans}_{i,t} + \text{Equity}_{i,t}} \tag{7}$$

where $r^L_{i,t}$ is the cost of newly issued securities L (bonds, loans, equity) by firm i in quarter t. Figure A6 shows the evolution of average COC for the firms in our sample period. Over the past two deacdes, we notice a secular decline in COC. Notably, since the GFC, we find a decline during the monetary loosening of the 2010 decade, and a tightening in recent years. Next, we turn to a component-wise discussion of the data sources employed in constructing $r^L_{i,t}$.

4.2.1 Cost of bonds

We estimate cost of bonds using bond price data from WRDS Bond Database. WRDS' Bond Database incorporates FINRA's TRACE (Trade Reporting and Compliance Engine) data for bond transactions and Mergent FISD data for bond issue and issuer characteristics. For each bond, we calculate the current yield as a function of the price of each current outstanding bond. The current yield is a measure of a firms marginal borrowing cost for a given maturity. We further adjust each yield by the treasury yield of the corresponding maturity to take out duration effects. Finally, we define the cost of bonds as the average adjusted yield, where we weight by outstanding bond volume.

4.2.2 Cost of loans

We estimate cost of loans using the syndicated loan data from Dealscan. Dealscan provides the borrowing history of firms that have accessed the syndicated loan market. This data contains loan-level information mainly based on Securities and Exchange Commission (SEC) filings and company statements. It provides borrower and lender identity, loan purpose, and loan terms at the time of origination. Following Chodorow-Reich (2014), we only use loans

[8] This assumes that a firms liability structure is expected to be fixed at its concurrent level.

with primary purpose listed as "working capital" or "corporate purposes". Since a firm may borrow from several different syndicates in any given quarter, our measure for the cost of loans takes a volume-weighted average of interest rates at the firm and quarter level.

4.2.3 Cost of equity

We estimate the cost of equity using equity price and return data from CRSP. The cost of equity is the return a firm is expected to generate for its equity investors based on the five-factor model proposed by Fama and French (2015) plus the momentum factor from Carhart (1997). We proceed in three steps. First, we define realized quarter-on-quarter equity return for each firm after adjusting for dividends (`dvpsxq`) and stock splits (`ajexq`). Second, using time series regressions for each firm in our sample over a rolling window of twelve quarters, we estimate the factor loadings for every firm each quarter as $\beta^F_{i,t-12,t}$ for each factor F. Specifically, we estimate,

$$\mathrm{ER}_{i,t} = \sum_F \beta^F_{i,t-12,t} \cdot \lambda^F_t + \epsilon_{i,t} \quad \forall\ i$$

where $\mathrm{ER}_{i,t}$ are equity returns in excess of the risk-free rate RF_t and λ^F is the time series for each factor. Finally, we estimate the cost of equity as follows:

$$\mathrm{COE}_{i,t} = \mathrm{RF}_t + \sum_F \widehat{\beta}^F_{i,t-12,t} \cdot \lambda^F_t.$$

4.2.4 Alternative measures of cost of capital

We construct several alternative measures for the cost of capital to test the robustness of our findings.

Implied cost of equity from Lee et al. (2020)

Lee et al. (2020) construct the composite expected-return proxies (ERP) for US firms. This is a commonly used proxy for implied cost of equity in literature.

Perceived cost of capital from Gormsen and Huber (2024)

Gormsen and Huber (2024) provide a firm-level measure of perceived cost of capital, hand-collected from annual reports, manager disclosures, and other corporate reports.

Average interest expense ratio from Kroen et al. (2024)
An alternative cost of debt is the ratio of interest expenses (`xintq`) to total interest-bearing debt (current liabilities (`dlcq`) and long-term liabilities (`dltttq`) calculated in Compustat. This is a measure of historical expenses and therefore measures a weighted sum of average cost of capital, rather than the cost of capital on newly-issued debt or equity.

4.3 Monetary policy shocks

To present causal evidence, we must rely on surprise changes in monetary policy that are unexpected by firms. To this end, we rely on a standard measure of monetary policy shocks from the literature. Specifically, this measure condenses the monetary policy surprise into a single dimension by taking the first principal component of rate changes in short-maturity federal funds futures contracts and two- to four-quarter-ahead Eurodollar futures contracts in a narrow, 30-minute window surrounding each FOMC announcement. The resultant time series reflects the monetary surprise at both the short-horizon and along the longer-maturity yield curve. Bauer and Swanson (2023) then purge these monetary surprises of any remaining explainable time-variation by orthogonalizing the surprises on a vector of economic news to create a series of monetary policy surprises. Utilizing a high-frequency approach for identification of monetary shock transmission is increasingly common in the empirical literate.[9] We follow Ottonello and Winberry (2020) and sum up shocks into a quarterly measure. To facilitate economic interpretation of our findings, we normalize the monetary policy shock by the standard deviation of the 90-day treasury bill, as is common in literature. We will subsequently describe our assumptions for identification when discussing our empirical specifications.

[9]See, for example, Ottonello and Winberry (2020), Swanson (2021), Ma and Zimmermann (2023), and Kroen et al. (2024).

4.4 Summary statistics

For our sample over 1990-2020, we provide summary statistics of the key variables in our data in Table 1. We present statistics for the full sample of firms in Panel A, and further disaggregate statistics by market followers (Panel B) and leaders (Panel C). Notably, there are striking differences between market leaders and followers across both levels and growth rates of key investment variables. Market leaders (top quartile firms) exhibit substantially lower cost of capital levels, with an average COC of 8.97% compared to 12.04% for market followers (bottom quartile firms), suggesting that market position translates into lower financing costs. At the same time, the change in COC has smaller left- and right-side tails for leaders, indicating a smaller change in their financing costs despite having similar means and SD.

The investment patterns also reveal pronounced differences. In terms of tangible investment, PP&E investment levels are dramatically higher for market leaders, averaging \$34.38 million compared to just \$0.48 million for followers - a difference of over 70-fold. Similarly, intangible investment through R&D shows market leaders investing \$22.24 million on average versus only \$3.27 million for followers, representing nearly a 7-fold difference. These level differences are complemented by notable variations in growth rates: while PP&E growth rates are similar across groups (around 0-1%), R&D growth rates show market leaders at 1% compared to 2% for followers, potentially reflecting the larger base effect for established market leaders. The overall pattern suggests that market leaders not only invest more heavily in both tangible and intangible assets but also benefit from lower costs of capital. In the next section, we present evidence of how market leaders are in a unique position of reinforcing their advantage after contractionary monetary shocks.

5. Empirical Evidence on the Leader Channel

In this section, we provide empirical support for the "leader channel" by demonstrating the differential effects of monetary policy shocks on firm-level financing costs and subsequent investment outcomes. Our central hypothesis is that market-leading firms—those commanding

Table 1: Summary statistics.

	Obs	Mean	Std. Dev.	P10	P50	P90
Panel A: Full sample						
ΔMPS	120	-0.02	0.42	-0.49	0	0.47
COC^{GW} (pp)	226171	10.43	5.38	4.24	9.53	18.02
ΔCOC^{GW}	214200	-0.06	2.38	-2.62	-0.02	2.48
PP&E investment ($ mn)	290145	12.07	168.88	-4.23	0.24	26.97
PP&E growth	286164	0.00	2.40	-2.85	0.01	2.77
R&D investment ($ mn)	295531	10.64	42.47	0.00	0.00	16.43
R&D growth	133324	0.02	0.85	-0.67	0.02	0.64
Panel B: Bottom quintile of industry sales (Q1)						
COC^{GW} (pp)	38557	12.04	5.78	5.01	11.46	20.04
ΔCOC^{GW}	36240	-0.06	2.36	-2.99	-0.02	2.95
PP&E investment ($ mn)	57604	0.48	8.97	-0.50	0.00	1.25
PP&E growth	56151	0.01	2.42	-2.91	0.00	2.85
R&D investment ($ mn)	57947	3.27	8.18	0.00	0.79	8.53
R&D growth	45111	0.02	0.59	-0.34	0.02	0.37
Panel C: Top quintile of industry sales (Q5)						
COC^{GW} (pp)	50047	8.97	4.74	3.73	8.06	15.48
ΔCOC^{GW}	48370	-0.06	2.27	-2.22	-0.02	2.03
PP&E investment ($ mn)	57400	34.38	312.99	-24.75	4.11	113.49
PP&E growth	57022	-0.00	2.41	-2.89	0.02	2.80
R&D investment ($ mn)	57946	22.24	72.32	0.00	0.00	45.31
R&D growth	12542	0.01	1.26	-2.00	0.00	2.00

a higher share of industry sales—face financing costs that are not only systematically lower, but also less responsive to contractionary monetary policy shocks compared to their smaller counterparts. This differential sensitivity facilitates higher relative growth for industry leaders, manifesting in both tangible and intangible capital expenditures.

5.1 Monetary Policy and Firm Financing Costs

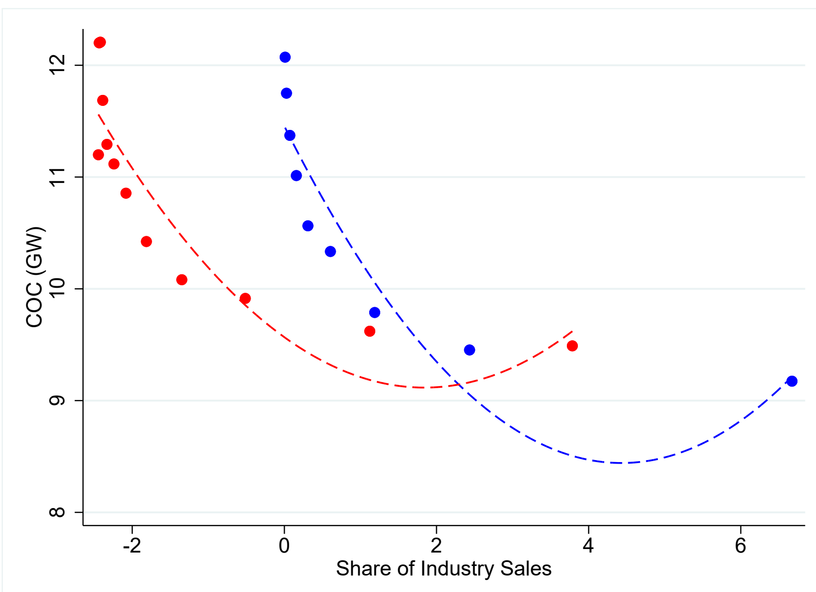
We first document that industry leaders exhibit consistently lower unconditional costs of capital relative to follower firms. We providing motivational evidence in support of our stylized model that market leaders have lower profit cyclicality risk, which can explain the a lower required return for these firms. Finally, we provide causal evidence that leaders' financing conditions are less sensitive to contractionary monetary policy shocks, reflecting a pronounced insulation against adverse credit conditions.

5.1.1 Cost of Capital across Firms

Figure 5 provides empirical support for this hypothesis by plotting a binned scatterplot of the unconditional average cost of capital against firm-level industry sales share across all U.S. firms from 1990 to 2020. A clear downward-sloping relationship emerges: firms commanding a greater share of industry sales systematically enjoy lower financing costs. Further, this is true even after controlling for assets: cost of capital is a function of sales or earnings, not of assets.

Figure 5: Cost of capital and firms' industry sales share.

Notes: The figure plots a binned scatterplot of the unconditional average cost of capital against the share of industry sales at the three-digit NAICS level. Both axes are measured in percentage points. Blue dots represent the raw data; red dots show residualized values after controlling for firm assets.



We confirm the robustness of this relationship using alternative components of the marginal cost of capital measure, disaggregated into equity, bonds, and loans (Figure A7). The negative relationship between industry leadership and financing cost persists strongly across these sub-components. Furthermore, alternative measures of the cost of capital, such as the implied cost proposed by Lee et al. (2020) (Figure A8), reveal similarly robust findings. By contrast, we find no relationship between a firm's existing debt servicing cost and its market position within an industry (Figure A9). This discrepancy suggests that the advantage enjoyed by leaders primarily manifests in terms of newly raised external financing, rather than existing commitments.

5.1.2 Profit cyclicality risk across Firms

Our stylized model in Section 3 assumes that market leaders have more stable profits over the business cycle. To confirm this hypothesis in data, we construct an analog to the profit cyclicality term in our model, ϕ. For each firm in our sample, we estimate a firm-level market beta of its annual revenues to the aggregate annual market revenue, as follows:

$$\pi_{i,t} = \beta_i \cdot \pi_t^M + \varepsilon_{i,t} \ \ \forall \ i$$

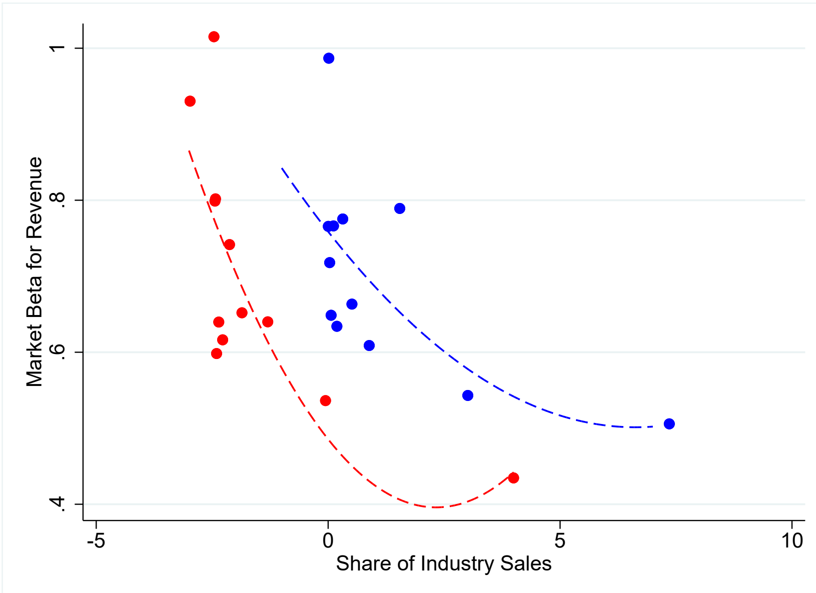
where we proxy π^M using total annual revenues across all firms in our sample.[10] The term β_i captures the comovement between profits for the macroeconomy and any individual firm i over the business cycle - our proxy for the profit cyclicality term, ϕ.

Figure 6 plots a binned scatterplot of firm-level market betas. The cyclicality of profits ranges from slightly above 1 (more than a one-for-one change with aggregate profits) to 0.4 (a 40% change in firm-level profits for every 100% change in profits for the aggregate economy). Indeed, market leaders have lower profit cyclicality than followers.

[10]We find similar results when we proxy for π^M using aggregate GDP, for robustness.

Figure 6: Profit cyclicality risk and firms' industry sales share.

Notes: The blue dots depict the relationship between the observed market share and market beta for firm revenue, $\frac{Cov(\pi^i,\pi^M)}{Var(\pi^M)}$. The red dot depicts the relationship for market share that is residualized on firm assets and age each time period.

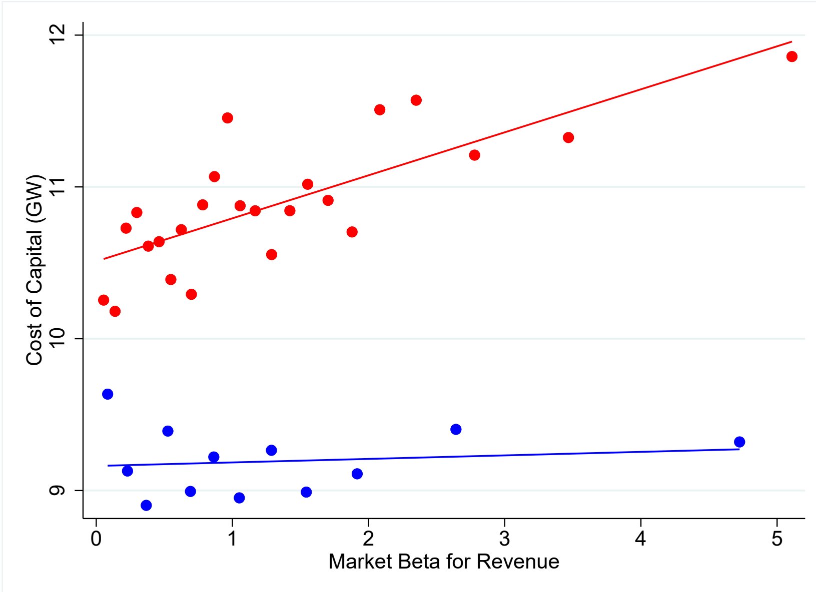


Finally, we turn to the risk-return tradeoff. Intuitively, we would expect that a firm with higher profit cyclicality should face higher require rate of return. This would imply a positively sloped line in the two-dimensional space spanned by cost of capital and market beta. We present the risk-return tradeoff separately for leaders and followers in Figure 7, where leaders are classified as firms above the 80th percentile of sales share in their industry.

We document three compelling findings. First, in general, firms with more profit cyclicality have higher cost of capital. Second, this relationship is stronger for followers than for leaders. Third, leaders are more clustered towards the origin (bottom-left region) than followers, implying they feature both lower required returns and lower profit cyclicality.

Figure 7: Profit cyclicality risk and required return tradeoff.

Notes: Return (y-axis) is captured by cost of capital; Risk (x-axis) is captured by market beta for firm revenue, $\frac{Cov(\pi^i,\pi^M)}{Var(\pi^M)}$. Leaders are in blue and followers are in red.



5.1.3 Monetary Policy Transmission to the Cost of Capital

Next, we examine how monetary policy shocks (MPS) differentially affect firms' cost of capital (COC) according to their industry market shares. To quantify this differential sensitivity, we estimate the following specification:

$$\Delta\text{COC}_{i,t} = \alpha_i + \alpha_{ind,t} + \beta_1 \cdot (\Delta\text{MPS}_{t-1} \times \text{Share}_{i,t-1}) + \Upsilon' X_{i,t-1} + \epsilon_{i,t} \tag{8}$$

where $\text{Share}_{i,t-1}$ denotes firm i's standardized share of industry sales in the preceding quarter. Firm fixed effects, α_i, control for permanent differences in the level of financing costs across firms, while industry-time fixed effects, $\alpha_{ind,t}$, absorb industry-specific cyclical variation. We include firm-level characteristics commonly associated with financial constraints in literature - specifically size, leverage, and liquidity - as well as lagged industry sales share as additional controls.

The identification in this empirical approach relies crucially on the orthogonality of our aggregate monetary shocks to firm-level determinants of capital costs. Given our monetary shocks are derived from high-frequency changes around Federal Open Market Committee (FOMC) announcements, and that we explicitly orthogonalize them against macroeconomic news contemporaneously released, we are confident interpreting the estimates causally. This confidence is further bolstered by our comprehensive set of fixed effects and firm-level controls.

Table 2 summarizes our main findings. A 100 basis point (bp) contractionary monetary policy shock results in a significantly smaller passthrough to the COC for firms with larger industry market shares: specifically, firms with one standard deviation higher market share experience a 56 bp smaller increase in their COC. These results remain robust upon inclusion of our full set of firm-level controls (column 2).

Table 2: Effect of monetary policy shocks on cost of capital.

	ΔCOC_i	
	(1)	(2)
MPS × Share_i	-0.597***	-0.620***
	(0.151)	(0.143)
Lagged controls	N	Y
Firm FE	Y	Y
Industry × Time FE	Y	Y
F stat.	15.65	16.54
Observations	213395	204964
R^2	0.151	0.156

* p < 0.1, ** p < 0.05, *** p < 0.01.

Heteroskedasticity-robust standard errors clustered by firms are in parentheses.

We decompose the effects across alternative components of the marginal cost of capital measure, disaggregated into equity and bonds,[11] as well as the implied cost measure by Lee et al. (2020). Finally, we also study the transmission to existing debt servicing cost (interest expenses measure), where we expect to find a null result. Our results are reports in table A1. We find that the leader premium in cost of capital is observed robustly across all columns (1)-(4) and is missing in column (5), as anticipated. Notably, the leader premium is thrice as large in the bond market pricing as compared to the equity market.

[11] We omit loans due to the low sample size after first-differencing.

Is this differential response linear across the distribution of firms' industry sales shares? To explicitly investigate this, we adapt equation (8) by interacting the MPS with indicators for each quintile of industry sales share, estimated separately for each period. Formally, we estimate:

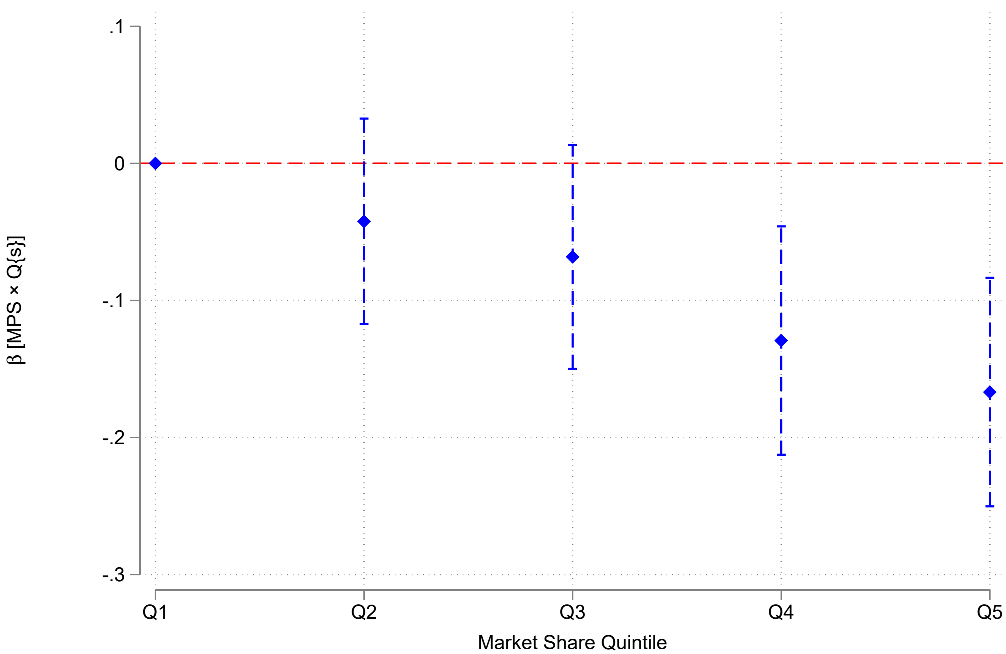
$$\Delta\text{COC}_{i,t} = \alpha_i + \alpha_{ind,t} + \sum_{s\in\{2,\ldots,5\}} \beta_1^j \cdot (\Delta\text{MPS}_{t-1} \times \text{Q}_{s,t-1}) + \Upsilon' X_{i,t-1} + \epsilon_{i,t} \tag{9}$$

where we omit the lowest quintile (Q1) to avoid perfect collinearity.

Figure 8 plots these estimated coefficients. The results illustrate a nearly monotonic and economically substantial pattern across quintiles of industry sales share. The insulating effect of industry leadership against monetary tightening is strongest among firms in the highest quintiles of industry market share and significantly weaker among lower market share firms.

Figure 8: Differential sensitivity of cost of capital by quintile.

Notes: The blue dots represent estimates from equation (9). The y-axis is in percentage points. 95% confidence intervals are depicted.



5.1.4 Dynamic Transmission of Monetary Policy to the Cost of Capital

We further assess the dynamic implications of monetary policy shocks on firms' cost of capital through a local projection framework following Jorda (2005). Specifically, we estimate:

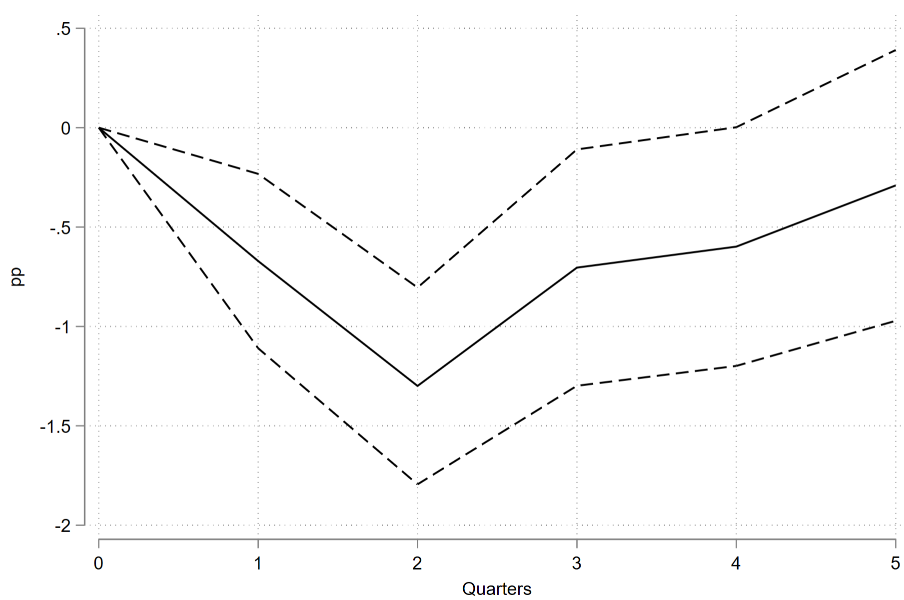
$$\Delta \text{COC}_{i,t+h} = \alpha_i + \alpha_{ind,t} + \beta_{1,h} \times (\Delta \text{MPS}_{t-1} \times \text{Share}_{i,t-1}) + \Upsilon' X_{i,t-1} + \epsilon_{i,t+h}, \tag{10}$$

for horizons $h = 1, ..., 5$ quarters.

Figure 9 plots the estimated dynamic responses, $\beta_{1,h}$. Our results indicate a significant differential passthrough effect lasting up to three quarters after the shock, with the strongest magnitude observed approximately two quarters after the initial tightening. Thereafter, both the magnitude and statistical significance of the differential response gradually dissipate.

Figure 9: Dynamic response of cost of capital to monetary policy shocks.

Notes: Dashed lines indicate the 95% confidence intervals.



5.1.5 Robustness

A potential alternative explanation for our results is that the differential sensitivity of financing costs to monetary shocks, as documented above, simply reflects standard factor-based asset pricing explanations rather than a unique "leader channel". Indeed, if our measured effects of industry market share are merely proxies for traditional firm-level asset-pricing factors - such as size, value or profitability - our proposed channel may lack independent economic significance. In that case, being a market leader is inconsequential for explaining the required returns of firms once we control for their factor-structure. To assess the validity of such a concern, we conduct a comprehensive analysis in the appendix by explicitly controlling for firm-level factor loadings derived from well-established asset-pricing models. Our detailed results indicate that the leader channel remains economically large and statistically significant, confirming that industry market share captures a distinct and economically meaningful dimension of monetary policy transmission. Additional details on our approach is presented in Appendix C.4.

5.2 Effects on real outcomes

Next, our goal is to study the response of real investment outcomes due to monetary policy shocks. We proceed in two steps. First, we present reduced form evidence on firms' growth sensitivity to monetary policy shocks across the industry sales share distribution, analogous to the estimation of their COC sensitivity in equation (9). Ideally, following from our COC results, we expect to find that growth expenditure is relatively higher for market leaders than for followers following a surprise monetary contraction.[12] Second, we study the responsiveness of growth expenditures to monetary policy shocks in a two-stage instrumented variable setting: the first component of the mechanism is the passthrough of monetary shocks to cost of capital; the second is the passthrough of these instrumented cost of capital shocks to growth expenditure. Such an estimation purges real changes from any factors that are not through the "leader channel" in response to a monetary policy shock.

[12] These effects are relative since we compare the low market share firm with the high market share firm. However, on aggregate, we still expect a monetary contraction to lower investment for all firms, just by less for leaders.

5.2.1 Reduced form growth responses

To explicitly investigate this, we interact the MPS with indicators for each quintile of industry sales share, estimated separately for each period. Formally, we estimate:

$$\Delta \mathrm{y}_{i,t} = \alpha_i + \alpha_{ind,t} + \sum_{s \in \{2,\ldots,5\}} \gamma_1^j \cdot (\Delta \mathrm{MPS}_{t-1} \times \mathrm{Q}_{s,t-1}) + \Upsilon' X_{i,t-1} + \epsilon_{i,t} \tag{11}$$

The setting above follows equation (9) closely. We omit the lowest quintile (Q1) to avoid perfect collinearity.

Figure 10 presents coefficients for MPS by quintile from equation (11). We find a monotonically increasing effect of a contractionary monetary policy shock on growth spending across the distribution of firm sales share: firms in a higher quintile invest relatively more to firms in the lower quintile. Furthermore, this effect seems larger for tangible investment than for intangible investment. Most interestingly, the effects observed in investment growth is monotonically inverse of the COC effect observed in Figure 8.

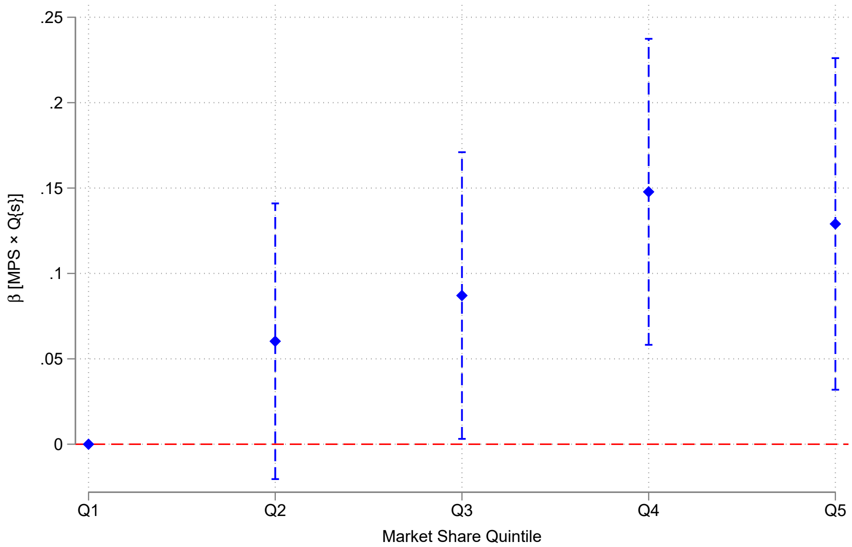
5.2.2 Growth response to cost of capital shocks

Firms change their investment behavior after shocks to their financial conditions. In particular, we analyze the sensitivity of growth in tangible (PP&E) and intangible (R&D) investment to COC shocks, where the COC shocks are instrumented using equation (8). The $\widehat{\Delta COC}_{i,t}$ measure captures changes in COC that are explained by the interaction of MPS and industry sale share, as well as our array of fixed effects and controls. Our first-stage F statistic is above 15 as presented in Table 2, and is well above the critical value of 4.05 for rejecting the null of weak instruments at the 5 percent level (Stock and Yogo, 2005, table 5.2).

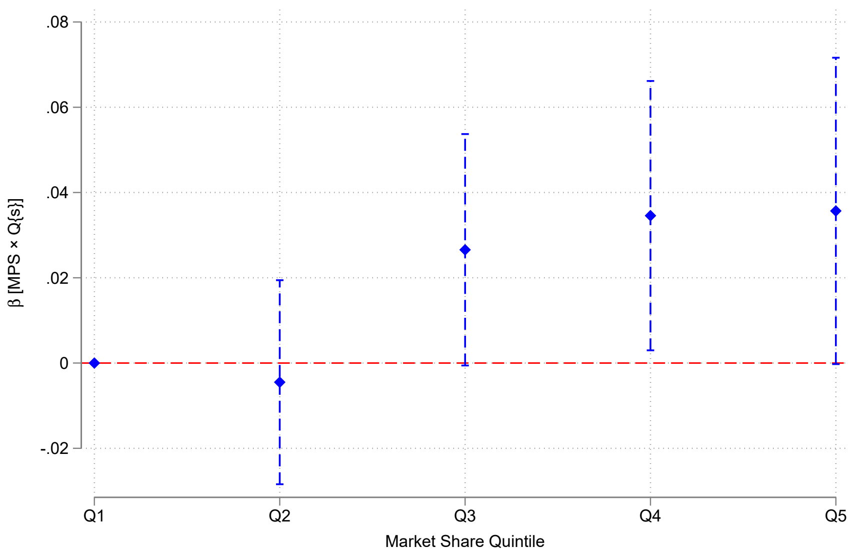
Furthermore, per our previous section, COC changes due to contractionary monetary shocks are smaller for firms with higher industry sale share. This implies that a value of negative 100 bp for $\widehat{\Delta COC}_{i,t}$ for a high industry sales share firm implies a much larger monetary tightening regime than for a low industry sales share firm, given the lower sensitivity of COC to monetary shocks for the former. Given our focus in this section on the sensitivity of

Figure 10: Differential sensitivity of growth expenditure by quintile.

Notes: The blue dots represent estimates from equation (11). The y-axis is in growth rates, i.e., 0.05 = 5%. 95% confidence intervals are depicted.



(a) PP&E



(b) R&D

growth expenditures by firms to MPS via the COC mechanism, where the COC mechanism relies upon the "leader channel" from the first-stage, we estimate the sensitivity of R&D and

PP&E growth to instrumented COC shocks using the following specification:

$$\Delta \mathrm{Y}_{i,t} = \alpha_i + \alpha_{ind,t} + \gamma_1 \widehat{\Delta \mathrm{COC}}_{i,t} + \Upsilon' X_{i,t-1} + \epsilon_{i,t} \tag{12}$$

where we control again for firm fixed effect α_i, industry/time fixed effect $\alpha_{ind,t}$, and the previous vector of controls $X_{i,t-1}$. In addition, we control for the lagged level of expenditure $Y_{i,t-1}$ to control for heterogeneity in initial investment levels across firms as is often conventional in growth literature. Given large time coverage of our data at the firm-level, we are confident of a negligible bias induced in dynamic models with fixed effects (Nickell, 1981; Acemoglu et al., 2019).[13]

Table 3 produces the results of running regression (12) for R&D and PP&E growth using both estimated changes in COC and estimated changes in industry COC. We find that growth rates for each expenditure type decrease after a 100 bp COC shock: PP&E growth falls by 93 bp (column 1) and R&D falls by 50 bp (column 2).

Table 3: Real outcome response to COC shock.

	PP&E growth	R&D growth
	(1)	(2)
$\widehat{\Delta \mathrm{COC}}_i$	-0.621**	-0.336**
	(0.294)	(0.168)
Lagged controls	Y	Y
Firm FE	Y	Y
Industry × Time FE	Y	Y
Observations	255307	116817
R^2	0.056	0.298

* p < 0.1, ** p < 0.05, *** p < 0.01.

Heteroskedasticity-robust standard errors clustered by firms are in parentheses.

The sample of firm-quarters that have non-missing R&D growth is smaller than that for

[13]We replicate our analysis for the subset of firms with at least 50 quarters of data over the 1990-2020 period and find similar results as those reported in the paper.

PP&E. To rule out sample selection issues, we estimate for the first stage in equation (8) and the second stage of equation (12) holding fixed the sample of firm-quarters as those with non-missing R&D growth. Table A3 reports the analog to the table above for that sample. We find similar results. Although statistically significant and of a similar direction, the economic magnitude of our effects is larger for PP&E growth and smaller for R&D growth in this new sample of firm-quarters. Finally, our step-wise instrument approach allows us to predict COC out-of-sample for firm-quarters with non-missing explanatory variables. This enlarges our sample from 213,395 (column (1) of Table 2) to approximately 255,307 (column (1) of Table 3), by adding firm-quarters where COC is predicted out-of-sample.

Finally, to underpin the economic magnitude of our monetary policy transmission to firm growth, we ask the following question: What is the effect of a 100 bp surprise monetary contraction on a firm that has one standard deviation higher industry sales share? Using our estimates, we can compute this in two stages:

1. First stage (for a firm with one $\sigma(\text{Share}_i)$ higher industry sales share):

$$\frac{dCOC_i - dCOC_0}{dMPS} = \beta_1$$

2. Second stage (average effect for a representative firm):

$$\frac{dI_i}{dCOC_i} = \gamma_1$$

3. This yields (for a firm with one $\sigma(\text{Share}_i)$ higher industry sales share):

$$\frac{dI_i - dI_0}{dMPS} = \gamma_1 \times \beta_1$$

4. Our back-of-the-envelop estimates are provided in the table below:

	PP&E	R&D
$\gamma_1 \times \beta_1$	0.384	0.208

We find that a 100 bp surprise monetary contraction results in higher PP&E investment growth by 38.4 bp for a firm that has one standard deviation higher industry sales share. Similarly, it results in a 20.8 bp higher R&D investment growth.

6. Conclusion

Industry leaders have less cyclical profitability and higher average profits. Hence, required returns are less sensitive for rate hikes for industry leaders, which translate into a less muted investment following to contractionary rate shocks. Using micro data, we verify that leaders cost of capital is less exposed to monetary shocks and that their real investment rates fall by less than those of followers following tighter policy. The findings in this paper emphasize the need to account explicitly for the competitive structure and market leadership positions of firms when evaluating the full impact of monetary policy interventions on aggregate economic outcomes.

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Online Appendix
Monetary Policy, Industry Leaders and Growth

Pranav Garg, Julien Weber

A. Additional stylized facts

A.1 Beneficiaries

Figure A1: Sales share of 90th percentile firms due to interest rate increase in a local projection.

Notes: Dashed lines indicate the 95% confidence intervals.

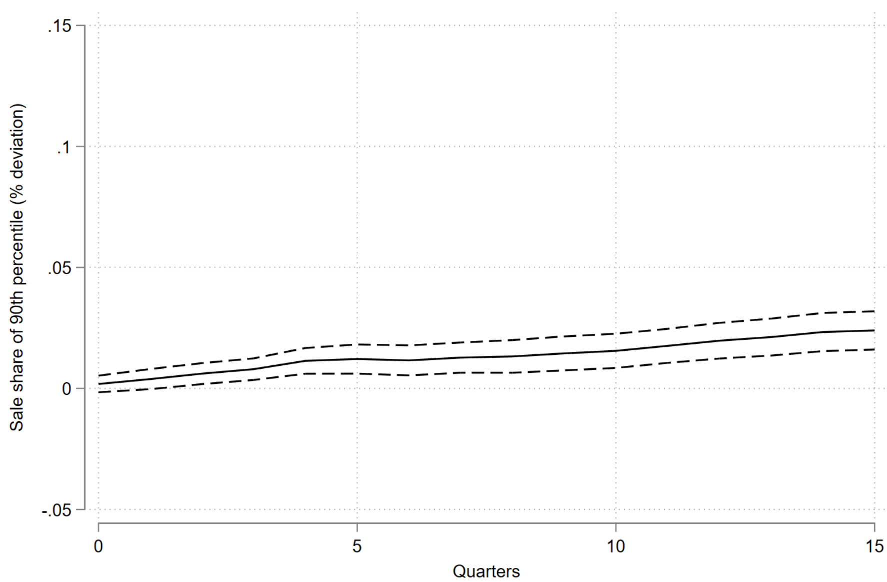


Figure A2: Sales share of largest 2 firms due to interest rate increase in a local projection.

Notes: Dashed lines indicate the 95% confidence intervals.

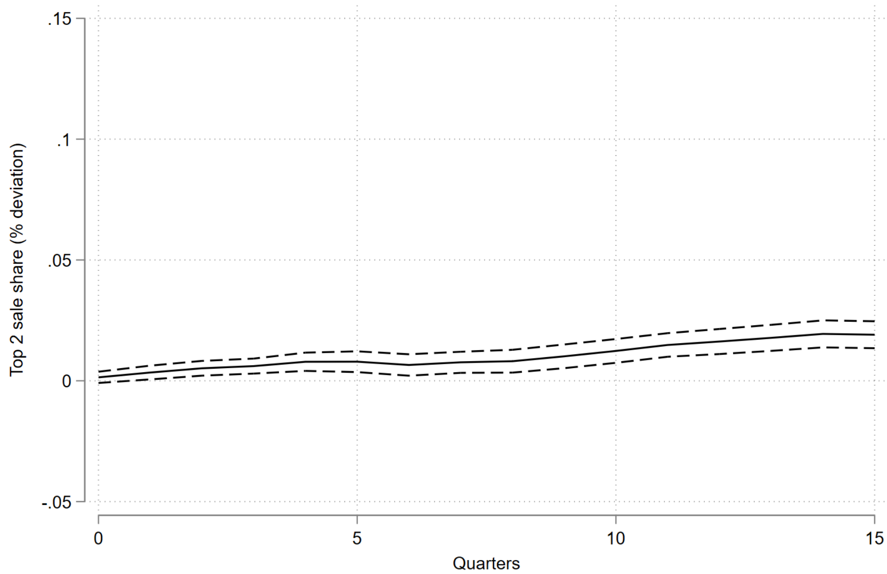
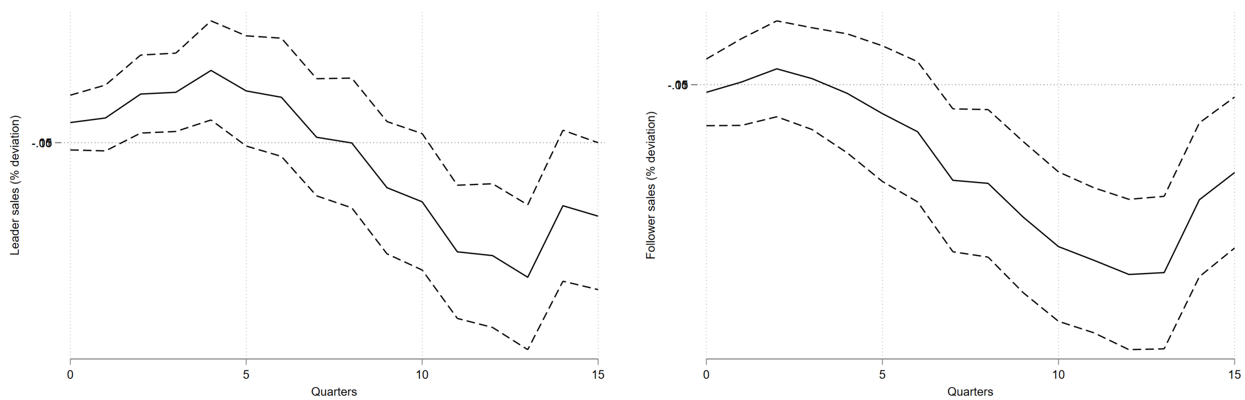


Figure A3: Sales of leaders (top 20 percentile; left) and followers (right) due to interest rate increase in a local projection.

Notes: Dashed lines indicate the 95% confidence intervals.



A.2 Interest rates on competition due to leaders benefiting

Figure A4: HHI increase due to interest rate increase in top heavy (top 40% firms are big) industries in a local projection.

Notes: Dashed lines indicate the 95% confidence intervals.

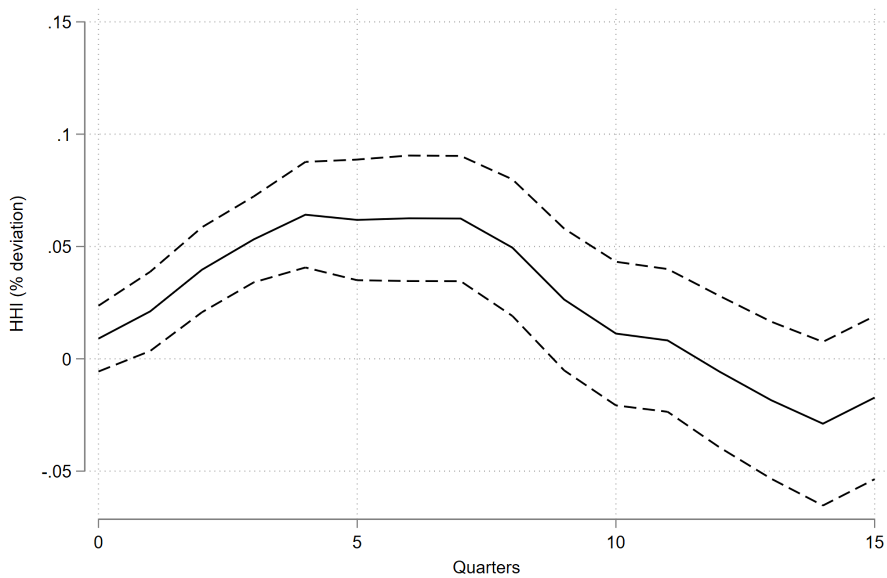
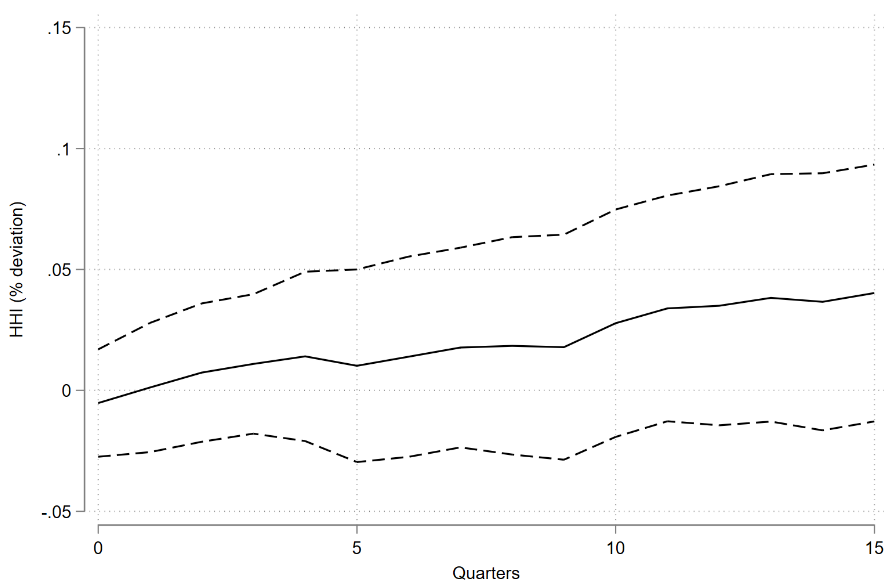


Figure A5: HHI increase due to interest rate increase in top heavy (top 2 firms are big) industries in a local projection.

Notes: Dashed lines indicate the 95% confidence intervals.



B. Model derivations

B.1 Elasticities

Derive elasticity of $\mathbb{E}[MPK']$ and semi-elasticity of investment. Start with two equations:

- $MPK' = \frac{\partial \pi'}{\partial K'} = (\bar{\phi} - sM')\gamma(K')^{\gamma-1}$
- $\mathbb{E}[MPK'] = r_f + \delta - R_f \mathrm{Cov}(M', MPK')$ or $1 = \mathbb{E}[M'(MPK' + 1 - \delta)]$

Can solve for a "Cost of capital" equation:

$$\begin{aligned}
\mathbb{E}[MPK'] &= r_f + \delta - R_f \mathrm{Cov}(M', MPK') \\
&= r_f + \delta - R_f \mathrm{Cov}(M', (\bar{\phi} - sM')\gamma(K')^{\gamma-1}) \\
&= r_f + \delta + R_f s\gamma(K')^{\gamma-1}\mathrm{Var}(M')
\end{aligned}$$

Elasticity follows easily.

Now solve for optimal K: Let $m_1 = \mathbb{E}[M']$ and $m_2 = \mathbb{E}[M'(\bar{\phi} - sM')]$.

$$m_1 = \frac{1}{R_f} = \frac{1}{r_f + 1}$$

$$m_2 = \mathbb{E}[\bar{\phi}M' - s(M')^2] = \bar{\phi}\mathbb{E}[M'] - s\mathbb{E}[(M')^2] = \frac{\bar{\phi}}{R_f} - s(\mathrm{Var}(M') + (\mathbb{E}[M'])^2) = \frac{\bar{\phi}}{R_f} - s\mathrm{Var}(M') - \frac{s}{R_f^2}$$

The Euler equation becomes:

$$1 = \gamma(K')^{\gamma-1}m_2 + (1-\delta)m_1 \tag{13}$$

$$(K')^{\gamma-1} = \frac{1 - (1-\delta)m_1}{\gamma m_2}$$

So, the optimal capital stock is:

$$K' = \left(\frac{1 - (1-\delta)m_1}{\gamma m_2}\right)^{\frac{1}{\gamma-1}} \tag{14}$$

$$\log K' = \frac{1}{\gamma - 1}\left[\log(1 - (1-\delta)m_1) - \log(\gamma) - \log m_2\right]$$

Then we can derive semi-elasticity:

$$\frac{d(\log K')}{dr_f} = \frac{1}{\gamma-1}\left[\frac{-(1-\delta)\frac{dm_1}{dr_f}}{1 - (1-\delta)m_1} - \frac{\frac{dm_2}{dr_f}}{m_2}\right]$$

where:

$$\frac{dm_1}{dr_f} = \frac{d}{dr_f}\left(\frac{1}{r_f+1}\right) = -\frac{1}{(r_f+1)^2} = -\frac{1}{R_f^2}$$

and:

$$\frac{dm_2}{dr_f} = \frac{d}{dr_f}\left(\frac{\bar{\phi}}{r_f+1} - s\mathrm{Var}(M') - \frac{s}{(r_f+1)^2}\right) = \bar{\phi}\left(-\frac{1}{(r_f+1)^2}\right) - 0 - s\left(-\frac{2}{(r_f+1)^3}\right) = -\frac{\bar{\phi}}{R_f^2} + \frac{2s}{R_f^3}$$

So, the semi-elasticity is:

$$\frac{d(\log K')}{dr_f} = \frac{1}{\gamma-1}\left[\frac{1-\delta}{R_f(r_f+\delta)} - \frac{-\frac{\bar{\phi}}{R_f^2} + \frac{2s}{R_f^3}}{\frac{\bar{\phi}}{R_f} - s\mathrm{Var}(M') - \frac{s}{R_f^2}}\right] \tag{15}$$

B.2 Sensitivity of investment elasticity

The semi-elasticity as derived:

$$E_s = \frac{d\log K'}{dr_f} = \frac{1}{\gamma-1}\left[T_1 - T_2(s)\right] \tag{16}$$

where:

- $T_1 = \frac{1-\delta}{R_f(r_f+\delta)}$ (This term is positive and independent of s).
- $T_2(s) = \frac{N_2(s)}{D_2(s)}$, with:

$$N_2(s) = -\frac{\bar{\phi}}{R_f^2} + \frac{2s}{R_f^3}$$

$$D_2(s) = \frac{\bar{\phi}}{R_f} - s\mathrm{Var}(M') - \frac{s}{R_f^2} = \mathbb{E}[M'(\bar{\phi} - sM')]$$

We note $R_f = r_f + 1$. For an optimal $K' > 0$, we require $D_2(s) > 0$. Under the standard condition $2s < \bar{\phi}R_f$, $N_2(s) < 0$, which makes $T_2(s) < 0$. Given $T_1 > 0$, the term $[T_1 - T_2(s)]$ is positive. Since $\frac{1}{\gamma-1} < 0$, E_s is negative.

To find how E_s changes with s, we calculate $\frac{\partial E_s}{\partial s}$:

$$\frac{\partial E_s}{\partial s} = \frac{\partial}{\partial s}\left(\frac{1}{\gamma-1}\left[T_1 - T_2(s)\right]\right)$$

Since T_1 is independent of s, $\frac{\partial T_1}{\partial s} = 0$.

$$\frac{\partial E_s}{\partial s} = -\frac{1}{\gamma-1}\frac{\partial T_2(s)}{\partial s}$$

The term $-\frac{1}{\gamma-1}$ is positive (since $0 < \gamma < 1$, $\gamma - 1 < 0$). Thus, the sign of $\frac{\partial E_s}{\partial s}$ is the same as the sign of $\frac{\partial T_2(s)}{\partial s}$.

We use the quotient rule for $T_2(s) = \frac{N_2(s)}{D_2(s)}$:

$$\frac{\partial T_2(s)}{\partial s} = \frac{\frac{dN_2}{ds} D_2(s) - N_2(s)\frac{dD_2}{ds}}{(D_2(s))^2}$$

The derivatives are:

- $\frac{dN_2}{ds} = \frac{\partial}{\partial s}\left[-\frac{\bar{\phi}}{R_f^2} + \frac{2s}{R_f^3}\right] = \frac{2}{R_f^3} > 0.$
- $\frac{dD_2}{ds} = \frac{\partial}{\partial s}\left[\frac{\bar{\phi}}{R_f} - s\left(\text{Var}(M') + \frac{1}{R_f^2}\right)\right] = -\left(\text{Var}(M') + \frac{1}{R_f^2}\right) < 0.$ Let $V_{term} = \text{Var}(M') + \frac{1}{R_f^2}$. Then $\frac{dD_2}{ds} = -V_{term}$.

The numerator of $\frac{\partial T_2(s)}{\partial s}$ is $\frac{dN_2}{ds} D_2(s) - N_2(s)\frac{dD_2}{ds}$:

$$\begin{aligned}
\text{Num}_{\partial T_2/\partial s} &= \left(\frac{2}{R_f^3}\right) D_2(s) - N_2(s)(-V_{term}) \\
&= \frac{2}{R_f^3}\left(\frac{\bar{\phi}}{R_f} - sV_{term}\right) + V_{term}\left(-\frac{\bar{\phi}}{R_f^2} + \frac{2s}{R_f^3}\right) \\
&= \frac{2\bar{\phi}}{R_f^4} - \frac{2sV_{term}}{R_f^3} - \frac{\bar{\phi}V_{term}}{R_f^2} + \frac{2sV_{term}}{R_f^3} \\
&= \frac{2\bar{\phi}}{R_f^4} - \frac{\bar{\phi}V_{term}}{R_f^2} = \frac{\bar{\phi}}{R_f^2}\left(\frac{2}{R_f^2} - V_{term}\right) \\
&= \frac{\bar{\phi}}{R_f^2}\left(\frac{2}{R_f^2} - \left(\text{Var}(M') + \frac{1}{R_f^2}\right)\right) \\
&= \frac{\bar{\phi}}{R_f^2}\left(\frac{1}{R_f^2} - \text{Var}(M')\right)
\end{aligned}$$

Since $R_f = 1/\mathbb{E}[M']$, we have $1/R_f^2 = (\mathbb{E}[M'])^2$.

$$\text{Num}_{\partial T_2/\partial s} = \frac{\bar{\phi}}{R_f^2}\left((\mathbb{E}[M'])^2 - \text{Var}(M')\right)$$

The denominator $(D_2(s))^2$ is positive. The term $\frac{\bar{\phi}}{R_f^2}$ is positive. Thus, $\text{sign}\left(\frac{\partial T_2(s)}{\partial s}\right) = \text{sign}\left((\mathbb{E}[M'])^2 - \text{Var}(M')\right)$.

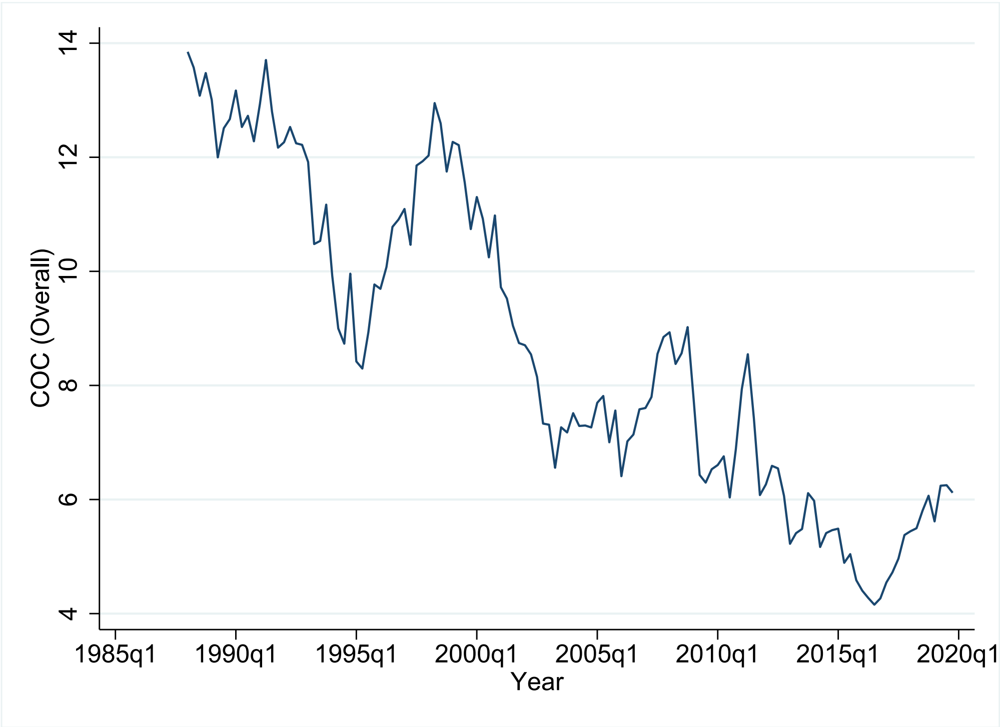
- If SDF is very volatile: $(\mathbb{E}[M'])^2 < \text{Var}(M')$
  - Then $(\mathbb{E}[M'])^2 - \text{Var}(M') < 0$, so $\frac{\partial T_2(s)}{\partial s} < 0$.
  - This implies $\frac{\partial E_s}{\partial s} < 0$.
  - Since E_s is negative, a negative derivative $\frac{\partial E_s}{\partial s}$ means that as s increases, E_s becomes *more negative* (moves further from zero).
  - Therefore, the **magnitude (absolute value) of the investment semi-elasticity increases** as profit sensitivity s increases.

C. Additional empirical results

C.1 Evolution of cost of capital

Figure A6: Firms' cost of capital over the sample period.

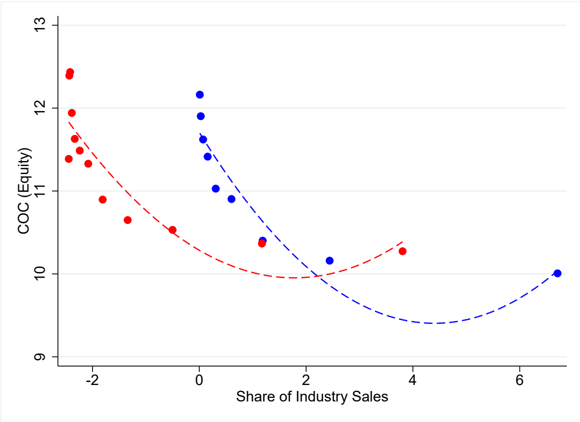
Notes: The line is the average cost of capital weighted by firm assets.



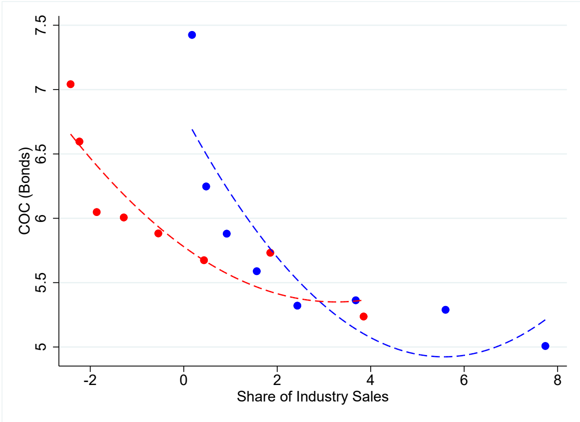
C.2 Share of industry sales and cost of capital

Figure A7: Cost of capital and firms' industry sale share.

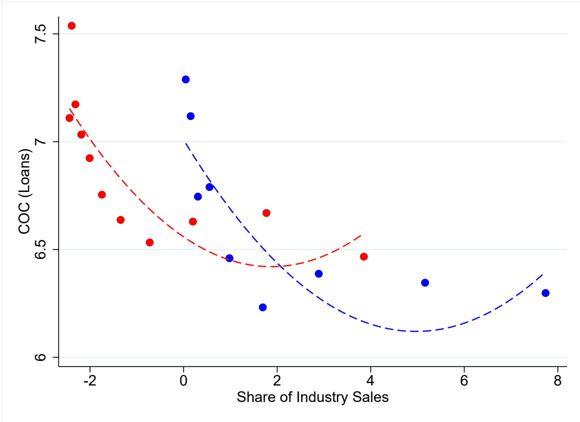
Notes: The blue dots depict the relationship between the observed industry sale share and cost of capital. The red dot depicts the relationship for industry sale share that is residualized on firm assets each time period.



(a) Equity



(b) Bonds



(c) Loans

Figure A8: Cost of capital (Lee et al. (2020)) and firms' industry sale share.

Notes: The blue dots depict the relationship between the observed industry sale share and cost of capital. The red dot depicts the relationship for industry sale share that is residualized on firm assets each time period.

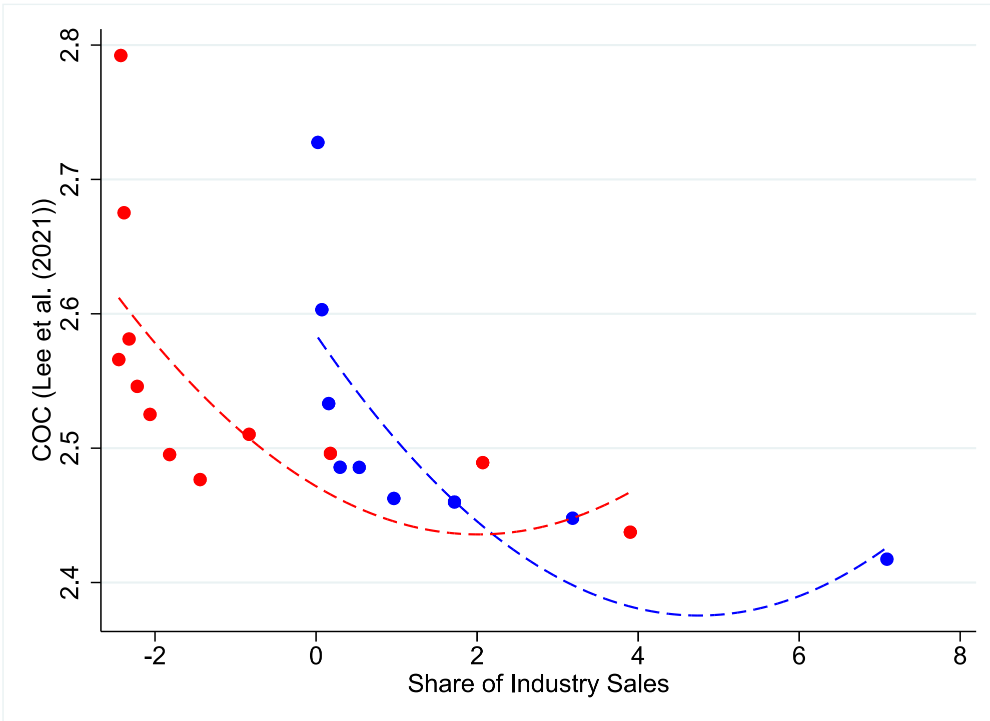
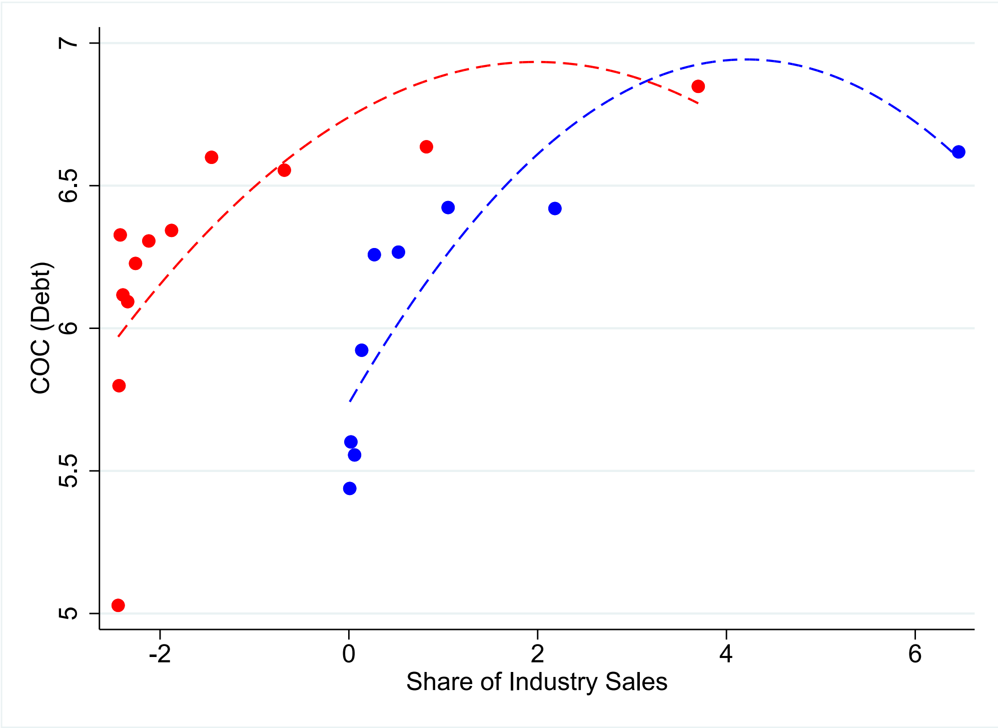


Figure A9: Average expense ratio (Compustat) and firms' industry sale share.

Notes: The blue dots depict the relationship between the observed industry sale share and cost of capital. The red dot depicts the relationship for industry sale share that is residualized on firm assets each time period.



C.3 Monetary Policy Transmission to the Cost of Capital

Table A1: Effect of monetary policy shocks on cost of capital.

	ΔCOC^{GW}	ΔCOC^{LSW}	ΔCOC^{Bonds}	ΔCOC^{Equity}	ΔCOC^{IntExp}
	(1)	(2)	(3)	(4)	(5)
MPS $\times$ Share$_i$	-0.612***	-0.141*	-1.485***	-0.540***	0.512
	(0.143)	(0.078)	(0.168)	(0.105)	(0.438)
Lagged controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Industry $\times$ Time FE	Y	Y	Y	Y	Y
Observations	204964	106814	32893	209678	225593
R^2	0.156	0.202	0.410	0.247	0.053

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Heteroskedasticity-robust standard errors clustered by firms are in parentheses.

C.4 Market share versus other factors

The asset-pricing literature provides extensive evidence that firms' implied cost of capital responds to firm-level characteristics and exposures to systematic risk factors (for a survey, see Lee et al. (2020)). It is therefore critical to distinguish our proposed "leader channel" from traditional explanations that rely on common asset-pricing factor loadings, such as those outlined by Fama and French (2015) and Carhart (1997). A valid concern is that our findings regarding the differential sensitivity of industry leaders' cost of capital to monetary shocks could be reduced to a combination of these standard factors. If so, controlling for firm-specific exposures to these factors would substantially attenuate the relationship between market leadership and monetary policy sensitivity.

To test the economic distinctiveness of our channel, we expand our baseline specification (8) to incorporate factor loadings derived from the six-factor model, comprising the Fama-French five factors plus the Carhart momentum factor. The augmented regression specification is:

$$\Delta \mathrm{COC}_{i,t} = \alpha_i + \alpha_{ind,t} + \beta_1 \cdot (\Delta \mathrm{MPS}_{t-1} \times \mathrm{Share}_{i,t-1}) + \Gamma'(\Delta \mathrm{MPS}_{t-1} \times \mathrm{F}_{s,t-1}) + \Upsilon' X_{i,t-1} + \varepsilon_{s,t}, \tag{17}$$

where $\mathrm{F}_{s,t-1}$ is the vector of the six firm-specific beta loadings from the Fama-French five factors plus momentum. It is derived from time-varying rolling regressions at the firm-quarter-level, as described in section 3.2.1.

Table A2 reports our results from estimating equation (17). Column (1) demonstrates that the coefficient on the interaction between monetary policy shocks and industry market share remains economically large (0.335) and statistically significant, even after controlling for the entire set of asset-pricing factor loadings. Notably, this effect is more than four times larger than the sensitivity associated with firms' exposure to the market beta factor (0.083). Columns (2)–(4) further confirm the robustness of our findings across various subcomponents of our cost-of-capital measure and alternative definitions.

These results strongly indicate that our identified "leader channel" is not subsumed by standard asset-pricing characteristics. We further illustrate this distinctiveness in Figure A10, which plots the relationship between average cost of capital (left y-axis, in blue) and factor loadings (right y-axis) across 20 quantiles of firm industry sales share. As expected, the size (SMB) factor exhibits positive correlations, while the profitability (RMW) factor displays a negative correlation with our observed relationship between sales share and cost of capital. This speaks to salient differences in firm size and the cyclical nature of profits across the distribution of within-industry market share. The remaining factors do not display systematic co-movement, barring momentum, which also exhibits strong positive correlation.

These patterns reinforce the intuition underlying our channel: smaller (larger SMB) and less profitable (lower RMW) firms—typical market followers—face systematically higher costs, whereas the unique and pronounced insulation effect of market leaders cannot be fully explained by common factor exposures alone. In sum, the robust and significant coefficient on our industry market share measure, even after incorporating standard asset-pricing factor loadings, underscores the unique role played by the leader channel in shaping firms' sensitivity to monetary policy shocks.

Table A2: Effect of monetary policy shocks on cost of capital.

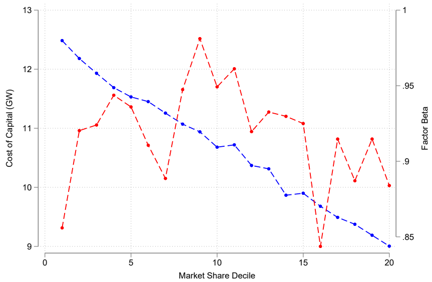
	ΔCOC^{GW}	ΔCOC^{LSW}	ΔCOC^{Bonds}	ΔCOC^{Equity}
	(1)	(2)	(3)	(4)
MPS × Share$_i$	-0.335**	-0.144*	-1.313***	-0.312***
	(0.141)	(0.080)	(0.168)	(0.101)
MPS × β_i^{MKT}	-0.083***	-0.005	0.099***	-0.101***
	(0.009)	(0.006)	(0.023)	(0.007)
MPS × β_i^{SMB}	0.059***	-0.003	0.041***	0.052***
	(0.007)	(0.004)	(0.015)	(0.005)
MPS × β_i^{HML}	0.051***	-0.000	0.045***	0.050***
	(0.007)	(0.005)	(0.017)	(0.005)
MPS × β_i^{RMW}	-0.015***	0.001	-0.026**	-0.013***
	(0.004)	(0.002)	(0.012)	(0.003)
MPS × β_i^{CMA}	0.022***	0.003	0.040***	0.026***
	(0.004)	(0.003)	(0.010)	(0.003)
MPS × β_i^{MOM}	0.021***	0.006	-0.061***	0.023***
	(0.007)	(0.005)	(0.022)	(0.006)
Lagged controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry × Time FE	Y	Y	Y	Y
Observations	202618	97715	31798	208305
R^2	0.176	0.207	0.419	0.277

* p < 0.1, ** p < 0.05, *** p < 0.01.

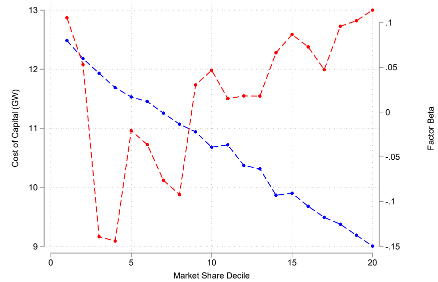
Heteroskedasticity-robust standard errors clustered by firms are in parentheses.

Figure A10: Firms' factor-based betas and firms' industry sale share.

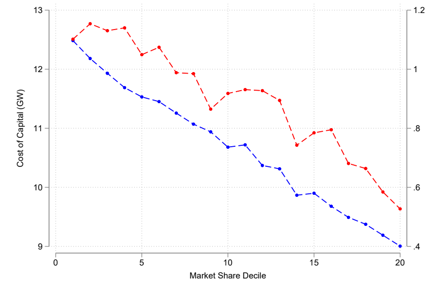
Notes: These panels plot the relationship between average cost of capital (left y-axis, in blue) and factor loadings (right y-axis) across 20 quantiles of firm industry sales share.



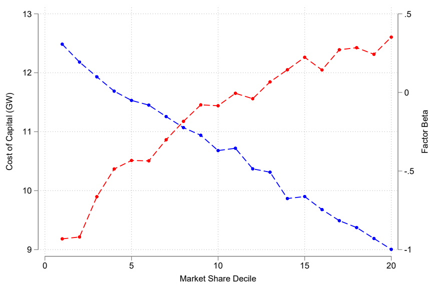
(a) MKT ($\rho = 0.161$)



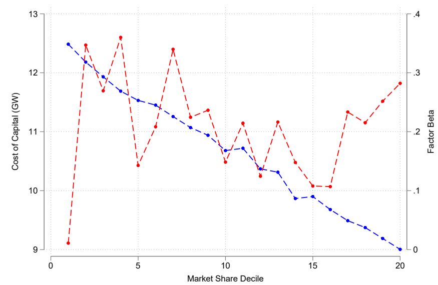
(b) HML ($\rho = -0.557$)



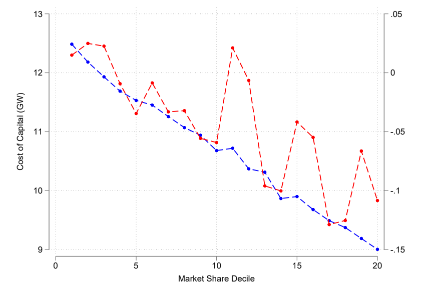
(c) SMB ($\rho = 0.961$)



(d) RMW ($\rho = -0.966$)



(e) CMA ($\rho = 0.080$)



(f) MOM ($\rho = 0.801$)

C.5 Growth response to cost of capital shocks

Table A3: Real outcome response to COC shock.

	PP&E growth	R&D growth
	(1)	(2)
$\widehat{\Delta \mathrm{COC}}_i$	-0.859***	-0.153**
	(0.280)	(0.076)
Lagged controls	Y	Y
Firm FE	Y	Y
Industry × Time FE	Y	Y
Observations	116817	116817
R^2	0.059	0.298

* p < 0.1, ** p < 0.05, *** p < 0.01.

Heteroskedasticity-robust standard errors clustered by firms are in parentheses.