Falling Rates and Rising Superstars *

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August 25, 2025

Abstract

Using high-frequency interest rate shocks, we find that falling rates in a low interest rate environment favor industry leaders: a fall in the interest rate leads to a stronger rise in market value for industry leaders. At the quarterly level, industry leaders also respond by borrowing more, investing more, and acquiring more assets. These advantages from falling rates for industry leaders diminish in a higher rate environment.

*We thank Sam Barnett, Keelan Beirne, Sebastian Hanson, Julio Roll, Sergio Nascimento, and Michael Varley for excellent research assistance, the Julis-Rabinowitz Center for Public Policy and Finance at Princeton for financial support, Michael Bauer and Eric Swanson for generously sharing their data, and participants at U.C. Berkeley Haas, London School of Economics, Northwestern University Kellogg, USC Marshall, and the Q Group Spring 2022 conference for comments. Kroen: tkroen@imf.org; Liu: ernestliu@princeton.edu; Mian: atif@princeton.edu; Sufi: amir.sufi@chicagobooth.edu.

1 Introduction

Over the past three decades, two significant economic trends have reshaped the U.S. economy: a dramatic decline in interest rates and a marked increase in market concentration (Autor et al., 2020). This paper uses high-frequency identification to provide an empirical analysis of how interest rate shocks differentially affect industry leaders versus followers. The key finding is that falling rates in the low interest rate environment of recent times have consistently favored industry leaders, or superstar firms belonging to the top 5% of publicly listed firms. The results inform the broader literature on the possible links between interest rate and market power.

We analyze the impact of interest rate on firms using high-frequency interest rate shocks at FOMC announcements as exogenous shifters to the interest rate over the period 1994 to 2024. Our identification strategy follows the important work of Gürkaynak et al. (2005), Nakamura and Steinsson (2018), and Bauer and Swanson (2023a). We estimate a firm's high-frequency market value response to the high-frequency interest rate shock, and test how this response varies for industry leaders versus followers. A key advantage of evaluating the high-frequency stock market response to FOMC interest rate shocks is that it isolates the causal impact of interest rate shock on firm value.

The high-frequency analysis shows that the proportional impact of a change in the interest rate on market value *rises* with firm size, *especially* in the low interest rate environment of post-2007. In other words, industry leaders have significantly higher interest rate sensitivities than industry followers in a low rate environment. This result is particularly striking given that the interest rate sensitivity is measured in proportional terms, i.e., as change in the log of market value in response to a one percentage point change in interest rate.

Since firm size distribution is highly skewed, higher proportional valuation gains for industry leaders translate into even more extreme dollar value gains. Industry leaders—which we define as the top 5% of firms by market value within an industry—have a dominant presence in the market and collectively represent about two-thirds of total value in our sample. We find that a typical industry leader gains about an additional 360 million dollars in market value (in real 2015 dollars) for every 10 basis points reduction in the one-year zero-coupon rate in the low interest rate environment of 2007-2024 relative to the high interest rate environment of 1994-2006.

The relative gain in market value for industry leaders in response to falling rates in the low rate environment is very large according to the high-frequency stock market analysis. But does this effect also show up in real outcomes in subsequent quarters? We answer this question by aggregating high-frequency shocks, as in Ottonello and Winberry (2020), and merging them to quarterly firm-level Compustat data on publicly listed U.S. firms.

We estimate the impulse response function of industry leaders relative to industry followers in a local-projections difference-in-differences framework. Our outcome variables include the cost of borrowing, as well as real outcomes including firm investment, acquisitions, revenue growth, and asset growth. The key empirical test is to compare the differential response of industry leaders versus followers to interest rate shocks, and see how this differential response varies by the initial level of the interest rate.

Consistent with our high-frequency analysis, we find that industry leaders benefit significantly more from lower rates in a low interest rate environment in terms of quarterly firm-level outcomes, and this leader-advantage dissipates in a higher rate environment. For example, when the initial federal funds rate is near the zero lower bound, a 10 basis point reduction in the interest rate lowers the cost of borrowing for industry leaders by 27 basis points relative to industry followers. If the initial federal funds rate is 2%, the effect is 6 basis points.

The leader advantage of falling rates translates into real outcomes as well, with industry leaders investing more and growing at a faster rate. A negative 10 basis point interest rate shock when the economy is near the zero lower bound leads to a 7% stronger increase in Property, Plant, and Equipment of leaders relative to followers. Relative to followers, leaders' revenues, capital expenditures, and acquisitions also rise significantly more when there is a decline in the interest rate in a low rate environment.

On the financing side, industry leaders raise additional debt financing and increase their leverage ratio relative to industry followers. A 10 basis point reduction in the interest rate when the economy is close to the zero lower bound leads to a 14% larger increase in issuance of debt and a 1 percentage point increase in the book leverage ratio. As with borrowing costs, the industry leader advantage in response to a negative interest rate shock is reduced at a higher level of the interest rate.

Overall, the results imply that interest rate shocks are not market neutral in terms of competition in a low rate environment. In particular, a decline in the interest rate from an already low level boosts industry leaders relative to followers across all the outcomes we consider. This relative advantage grows larger as the interest rate approaches the lower bound.

Although the interest rate shocks used in the empirical analysis are high-frequency, they are likely relevant for longer-term considerations for three reasons. First, the high-frequency interest rate shocks affect interest rates even at the longer end of the yield curve. Second, the shocks generate persistent effects of at least three years on borrowing costs faced by firms, and the differential borrowing costs faced by industry leaders versus followers. Finally, as shown in Hillenbrand (2025), a substantial portion of the overall decline in interest rates since the 1980s has occurred around FOMC meetings. While we do not attempt to estimate a long-run causal relationship of the decline in interest rates since the 1980s on the rise in market power, the evidence suggests that the estimates capture more than short-term business cycle effects that quickly revert.

All of these effects that favor industry leaders in response to a decline in the interest rate are mitigated if the economy is in a higher rate environment. This suggests the existence of a "competition-neutral" interest rate, a level at which interest rate changes have symmetric effects on leaders and followers. A back-of-envelope calculation places this competition-neutral rate in the range of 3% to 5%. Since federal funds rate has been persistently below this range for significant part of the last couple of decades, the results of this study suggest that negative shocks to the interest rate have boosted industry leaders relative to industry followers. Interestingly, this is consistent with time-series evidence on the rise in concentration since 2000.

The difference-in-differences methodology using quarterly data differences out any macro-level news effects that may be spuriously correlated with high-frequency FOMC shocks. For example, Bauer and Swanson (2023a) and Bauer and Swanson (2023b) show that the high-frequency changes in interest rates around FOMC meetings can be in part predicted by changes in macroeconomic news that occur prior to the meetings. The level effect of this macroeconomic news is differenced out by the empirical strategy; however, a remaining concern is that the changes in macroeconomic news released before the meetings differentially affect industry leaders versus followers.

Two results help mitigate this identification concern. First, estimation of a specification that directly controls for the measures of macroeconomic news that predict interest rate changes around FOMC announcements yields similar results. Second, and more importantly, as already discussed, high-frequency stock market returns show the same result. The high-frequency stock market analysis does not suffer from identification concerns given that all effects from the macroeconomic news released before the FOMC announcement should already be compounded into stock prices prior to FOMC announcements.

Our results are also robust to alternative industry leader definitions and the inclusion of firm-level control variables. For example, classifying leaders by sales instead of market capitalization or using the top 4 firms in each industry instead of the top 5% leads to similar results. We also consider the possibility that there may be a spurious "time-trend" with the following characteristics: industry leaders were not more responsive to interest rate shocks than industry followers early on, but over time have become more responsive for unknown reasons. This is a difficult possibility to rule out since the broader decline in r is naturally correlated with time. However, it is not perfectly correlated, and we show that even when we saturate a linear time trend and all its relevant interactions with the industry leader dummy and r, the results are similar.

The primary objective of this paper is to document new facts on how interest rate shocks differentially impact industry leaders versus followers. While we do not seek to determine which particular mechanism may be behind the empirical results, there are possible theoretical mechanisms that connect falling interest rate (r) to market competition. For example, Liu et al. (2022)

show that industry leaders gain a progressively more powerful *strategic advantage* when r falls. Intuitively, a decline in r makes persistent market power more valuable, giving the industry leader an incentive to "fight off" the industry follower more aggressively. This strategic effect becomes more powerful as r falls toward zero. Second, the presence of financial frictions brings an additional *financial advantage* that favors industry leaders as r falls. A natural implication of progressively strengthening strategic and financial advantages for industry leaders is that as r falls toward zero, markets ultimately become more concentrated.

Our results suggest that declining interest rates in an already low interest rate environment favor industry leaders. This has potentially important implications for the economy in the long run which we hope will be explored more in the future. For example, common explanations of very low interest rates focus on changes to the demand-side of the economy that reduce the equilibrium rate of interest, potentially leading the economy into a liquidity trap. The results here open the possibility of a feedback mechanism, where the reduction in the interest rate in turn makes the economy more monopolistic. A more monopolistic economy may in turn lower growth and hence put further downward pressure on the interest rate. Our hope is that the micro-economic estimates provided in this study can help inform future research focused on these longer-term issues.

The findings of this study are related to the large body of research exploring the rise in market concentration and market power in the United States since the 1980s (e.g., Grullon et al., 2019, Philippon, 2019, Syverson, 2019, De Loecker et al., 2020). Scholars have proposed that the rise in concentration may be a reason behind weak investment and low productivity growth (e.g., Gutiérrez and Philippon, 2017a, Gutiérrez and Philippon, 2017b, Crouzet and Eberly, 2019, Liu et al., 2022). A closely related area focuses on the rise of superstar firms, and the implications of superstar firms for the labor share and productivity patterns (e.g., Andrews et al., 2019, Olmstead-Rumsey, 2019, Autor et al., 2020, Berlingieri et al., 2024). This paper suggests that falling interest rates may be one of the factors behind the important patterns documented in this extensive literature. The findings are also related to the empirical literature in asset pricing exploring the effects of interest rates on asset returns (e.g., Koijen et al., 2017, Van Binsbergen, 2020).

There is also a related literature exploring the role of financial frictions in the transmission of monetary policy to firm investment (e.g., Gertler and Gilchrist, 1994, Ippolito et al., 2018, Weber, 2018 Ottonello and Winberry, 2020, Vats, 2020), and the determinants of low rate environment (e.g. Bauer and Rudebusch, 2020). Ozdagli (2018) and Morlacco and Zeke (2021) show that large firms benefit more than small firms in response to interest rate decline. To the best of our knowledge, the empirical demonstration that leaders benefit disproportionately from negative interest rate shocks as the level of the interest rate approaches the lower bound is new to the literature.

2 The Effect of Interest Rate on Firm Value

We begin by outlining a simple framework that motivates our empirical investigation into how firm value responds to unanticipated interest rate shocks in high versus low interest rate environments. Let V denote the market value of a representative firm. The effect of an unanticipated change in interest rate r on firm value, expressed in percentage terms, is captured by the derivative $\frac{\mathrm{d}\ln V}{\mathrm{d}r}$, which we refer to as the *interest rate sensitivity*. To build intuition, consider the standard Gordon growth model, which expresses firm value as $V = \frac{E}{r-g}$, where E is current net earning and g is the expected earnings growth rate going forward. Differentiating this expression with respect to r yields the following expression for interest rate sensitivity:

$$\frac{\mathrm{d}\ln V}{\mathrm{d}r} = -\frac{(1 - \frac{\mathrm{d}g}{\mathrm{d}r})}{(r-g)} \tag{1}$$

Despite being highly stylized, the Gordon growth valuation formula demonstrates three important takeaways. First, the response of firm value to change in interest rate depends on the level of interest rate, with the firm value rising faster for a given decline in r in a low rate environment. This echoes the concept of "convexity" in asset pricing, which captures the second derivative of (log) asset valuation with respect to the interest rate. Second, the effect of interest rate changes on firm value is not necessarily uniform across firms: firms with stronger growth prospects, g, respond more strongly to changes in interest rates. Third, the response of firm value to interest rate change also depends on possible feedback effects on cashflow growth represented by $\frac{\mathrm{d}g}{\mathrm{d}r}$. For example, if a fall in interest rate disproportionately favors larger firms, they might out-compete smaller firms, thus raising their own expected growth rate at the expense of smaller firms (Liu et al., 2022). More generally, how interest rate affects larger versus smaller firms is an empirical question that we turn to next.

2.1 High-Frequency Approach to Identifying Interest Rate Sensitivity

The key empirical challenge in identifying equation (1) is to generate unanticipated exogenous change in r and then estimate its impact on firm value V. We follow recent literature and use high-frequency changes in interest rates around FOMC announcements to generate unanticipated changes in r (e.g., Gürkaynak et al., 2005, Hanson and Stein, 2015, Gorodnichenko and Weber, 2016, Nakamura and Steinsson, 2018, Acosta and Saia, 2020, and Bauer and Swanson, 2023b). Our specific measure follows Nakamura and Steinsson (2018) and Bauer and Swanson (2023b), who calculate the first principal component of changes in the federal funds rate and Eurodollar futures contracts around FOMC announcements between 1994 and 2019,[1] and we extend their measure through the end of 2024.

We focus on scheduled FOMC announcements. There are a total of 247 scheduled FOMC announcements during our sample period. We follow the literature and remove unscheduled FOMC announcements as they are by construction driven by specific world events like 9/11 or the 2008 financial crisis. These unusual events are likely to contain news and information beyond just the expected path of interest rates, and consequently add additional noise to the estimates. The first principal component reflects the unanticipated shift in the yield curve around the 30-minute FOMC announcement window starting at 10 minutes prior to the FOMC press release. On average there is a FOMC meeting every 6 weeks.[2] The unit of measure of the first principal component does not have an underlying economic meaning. We therefore normalize the interest rate shock similar to Nakamura and Steinsson (2018) so that a one unit change in the interest rate shock represents a 10 basis point change in the zero-coupon 1 year Treasury note. We denote the high-frequency interest rate news shock for an FOMC announcement on day t by ω_t.

There are two key advantages of using the high-frequency shock ω_t to identify firms' interest rate sensitivity. First, the interest rate shocks ω_t around FOMC announcements are unanticipated by market participants and provide an exogenous source of variation for identifying the effect on a firm's asset valuation. For example, Bauer and Swanson (2023b) show that while ω_t can be partially predicted by changes in economic conditions before the Fed meetings, such high-frequency shocks can nonetheless "be used without correction for estimating asset price responses".

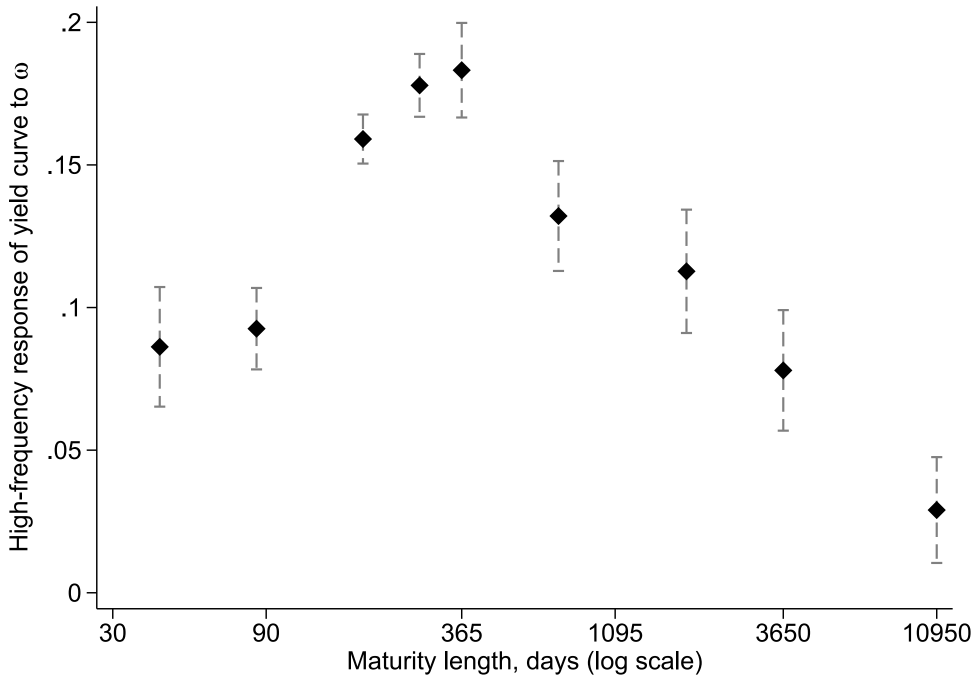
Second, the high-frequency FOMC interest rate shock is remarkably effective in moving the longer-end of the yield curve. As such, ω_t should not be viewed merely as a temporary shock to the very short end of the yield curve (like the federal funds rate) that quickly dissipates. There is significant evidence showing both that FOMC news shocks move the longer-end of the yield curve, and that these shocks have durable long term impact on interest rates. For example, Gürkaynak et al. (2005), Hanson and Stein (2015), and Nakamura and Steinsson (2018) show that FOMC news shocks have a persistent effect on interest rates. Relatedly, Hillenbrand (2025) shows that the long-run secular decline in U.S. Treasury yields since 1980 is captured almost entirely by changes in interest rates around Federal Reserve meetings. Thus, FOMC shocks contribute

[1] FOMC announcements started being communicated directly through a press release in 1994; therefore, post-1994 FOMC announcements provide the cleanest opportunity for high-frequency analysis. We shift from using Eurodollar futures to SOFR futures from January 2022 onward following Acosta et al. (2024).

[2] More specifically, we obtain the relevant measures of interest rates and Eurodollar futures contracts from Gürkaynak et al. (2022) and construct the first principal component, which is highly correlated with the measure from Nakamura and Steinsson (2018). It is the first principal component of the change in the following five interest rates over a 30-minute FOMC window: market expectation of the federal funds rate over the remainder of month, the expected federal funds rate following the next FOMC meeting, and the expected Eurodollar interest rates at two, three, and four quarter horizons.

significantly toward the long-term trends in U.S. interest rates.

Figure 1: Response of interest rates along the yield curve to ω_t shock



Note: Figure 1 displays coefficients from regressions of MP1, MP2, ED2, ED3, ED4, 2-year, 5-year, and 10-year US Treasury non-callable notes yields, and 30-year non-callable bond yields, all calculated using a 30-minute window around the FOMC announcement, on the PCA monetary policy shock ω_t for the 247 scheduled FOMC dates from 1994-2024. MP1 is the change in expectation of the Fed Funds Rate for the remainder of the month. MP2 is the change in expectation of the Fed Funds Rate for the month of the next FOMC. ED2, ED3, and ED4 are the change in Eurodollar future prices two, three, and four quarters ahead, respectively; this corresponds to the expectation of the three-month interest rate at the expiration date of the Eurodollar contract. For more details on how these variables are constructed see Appendix A of Nakamura and Steinsson (2018). Error bars are 95 percent confidence intervals from robust SEs.

To provide direct evidence that the FOMC shock ω_t shifts long-maturity interest rates in addition to the short-maturity ones, Figure 1 shows the high-frequency movement of interest rates across the yield curve over the same 30-minute FOMC window in response to the ω_t shock. The maturities of interest rates range from around thirty days (for federal funds rate futures) to thirty years. The first five interest rates—federal funds rate and Eurodollar futures contracts—are the same rates that are used to construct the first principal component ω_t. So these five rates naturally move in-sync with ω_t in Figure 1. The more interesting result is how the long-maturity interest rates, that were not used in the construction of ω_t, respond to the ω_t shock.

Figure 1 shows that all longer maturity interest rates, 2-year, 5-year, 10-year, and 30-year, respond strongly to the ω_t shock. In particular, 2-year, 5-year, 10-year, and 30-year interest rates move by 13, 11, 8, and 3 basis points respectively for a one unit change in ω_t. The magnitude of these shifts is similar to the shorter-end interest rate shifts, and the shifts are highly statistically significant. The vertical bars reflect the 95% confidence interval. Thus, a substantial portion of the short end movement in the yield curve associated with ω_t also shows up at the longer-end of the yield curve. This fact will be important for interpreting the real effects of these shocks that we investigate later.

The evidence that high-frequency shocks move the long-end of the yield curve as well, is also consistent with broader shifts in interest rates over our sample period. For example, the average federal funds rate dropped by 2.8 percentage points from the high interest rate environment of 1994-2006, to the very low interest rate environment in post-2007. The magnitude of the decline in the very short rate is remarkably similar to the decline in 5-year rate of 2.9 percentage points between the same periods.

2.2 Empirical Results

We estimate a firm's response to FOMC interest rate shocks by measuring the firm's high-frequency stock market response using the New York Stock Exchange Trade and Quote (TAQ) high-frequency trading data. We construct 30-minute stock market return around FOMC announcements by computing the return from 10 minutes prior to 20 minutes after the FOMC announcement,[3] and run various versions of the following regression to estimate firms' interest rate sensitivity:

$$\begin{aligned} R_{it} \quad = \quad & \alpha_i + \beta_1 \omega_t + \beta_2 (\mathbf{1}_{post2007} \cdot \omega_t) + \beta_3 \mathbf{1}_{post2007} \\ & + \beta_4 (\bar{X}_i \cdot \omega_t) + \beta_5 (\mathbf{1}_{post2007} \cdot \bar{X}_i \cdot \omega_t) + \epsilon_{it} \end{aligned} \tag{2}$$

where R_{it} is firm i's gross stock market return around the FOMC window, $\mathbf{1}_{post2007}$ is a dummy to capture post-2007 sample, and $\bar{X}_i$ is the percentile (between 0 and 1) of firm i's average market value rank across FOMC dates over the sample period. α_i denotes firm-level fixed effects. Table 1 builds sequentially on this specification: column (1) includes only the baseline effect of ω_t, capturing the average response across firms and time; column (2) adds interactions with the post-2007 period to allow the response to differ across interest rate regimes; column (3) replaces the single post-2007 dummy with separate indicators for the zero lower bound (ZLB) and non-ZLB periods post-2007 to flexibly capture time variation; column (4) incorporates firm size heterogeneity by interacting ω_t with firm size percentile $\bar{X}_i$; column (5) includes the full set of interactions in equation (2), allowing the effect of monetary shocks to vary flexibly across firm size and interest rate regime; finally, column (6) replaces the post-2007 dummy with ZLB and non-ZLB period dummies in the triple interaction terms.

We now discuss the results of these regressions in turn.

[3] We follow the convention in the literature by picking the last available traded price 10 minutes prior and the first available traded price 20 minutes after, for computing the return. The TAQ data is available at 5-min intervals.

Table 1: High-frequency stock price response to ω_t shock

	R_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
ω_t	-0.632***	-0.333***	-0.333***	-0.373***	-0.180**	-0.180**
	(0.0904)	(0.0756)	(0.0756)	(0.0994)	(0.0908)	(0.0908)
$\omega_t *$ post		-0.704***			-0.399*	
		(0.186)			(0.225)	
post		0.0909*			0.0916*	
		(0.0520)			(0.0520)	
$\omega_t *$ post (ZLB)			-0.899**			-0.176
			(0.441)			(0.526)
$\omega_t *$ post (non-ZLB)			-0.704***			-0.440*
			(0.189)			(0.235)
post (ZLB)			0.180***			0.182***
			(0.0654)			(0.0655)
post (non-ZLB)			-0.00257			-0.00212
			(0.0630)			(0.0632)
$\omega_t * \bar{X}_i$				-0.429***	-0.249**	-0.249**
				(0.126)	(0.107)	(0.107)
$\omega_t * \bar{X}_i *$ post					-0.519***	
					(0.189)	
$\omega_t * \bar{X}_i *$ post (ZLB)						-1.167**
						(0.530)
$\omega_t * \bar{X}_i *$ post (non-ZLB)						-0.455**
						(0.204)
N	795,059	795,059	795,059	795,059	795,059	795,059
R2	0.060	0.063	0.063	0.060	0.063	0.064
FEs	Firm	Firm	Firm	Firm	Firm	Firm

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$. R_{it} denotes the high-frequency stock price response for firm i at FOMC date t calculated using a 30-minute window. ω_t denotes the PCA shock using only scheduled dates; $\bar{X}_i$ is firm rank by average market value percentile across scheduled dates; and "post" denotes either the period 2007-2019, the periods 2009-2015 and 2020-2021, where the effective federal funds rate was near the zero lower bound (less than 0.25 for most months out of the year), or the periods 2007-2008, 2016-2019, and 2022-2024, where the federal funds rate was away from the ZLB. Standard errors are clustered at the FOMC date level.

How powerful are interest rate shocks for firm value on average? We begin by estimating the average interest rate sensitivity of firms' value over the entire 1994-2024 period. To do so, we run regression (2) by including only variables in the first line on the right-hand side. Column (1) of Table 1 shows that the average firm's interest rate sensitivity is estimated to be -0.63, which means that a one unit increase in ω_t (equivalent to 10 basis point increase in the one-year treasury) leads to a decline in firm value of 0.63 percentage points.[4]

This is a financially powerful effect, highlighting the importance of pure interest rate shocks. For example, the implied change in firm value for the one percentage point change in one-year

[4]Section A.1 in the appendix also conducts a placebo experiment to illustrate the significance of the estimated interest rate sensitivity.

rate equals 6.3 percentage points. Our estimate of -0.63 is close to the estimate of -0.65 in Nakamura and Steinsson (2018).

Are interest rate shocks more powerful in a low rate environment? We estimate the impact of interest rate shocks on firm valuation separately in high and low interest rate environments. To start, we define the 1994-2006 period as high interest rate environment with an average federal funds rate of 4.1 percentage points, and 2007-2024 as low interest rate environment with an average federal funds rate of 1.3 percentage points. We estimate regression (2) by including variables in the first and second lines on the right-hand side.

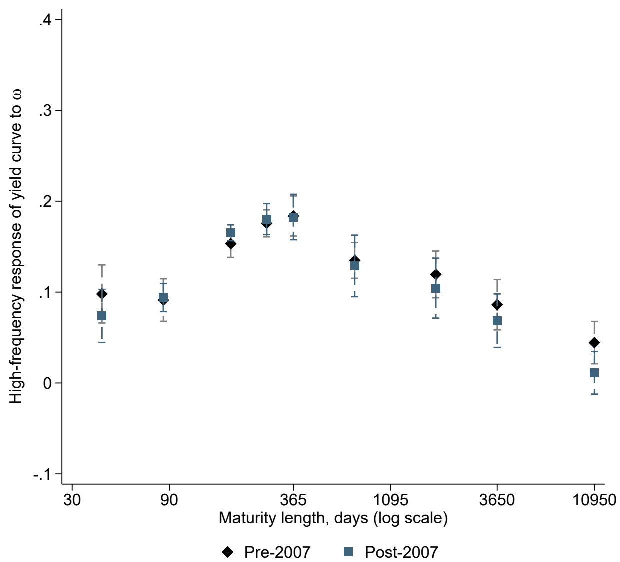
Table 1 column (2) estimates the average interest rate sensitivity separately for high and low rate environments. There is a significant increase in the magnitude of interest rate sensitivity by 0.7 in the low rate environment, implying that the equivalent of a one percentage point decline in the one-year rate leads to an additional 7 percentage point increase in firm valuation on average.

The higher sensitivity of firm value to interest rate shocks in a low-rate environment in column (2) is consistent with our derivation (1) based on the Gordon growth formula and the general concept of asset convexity. An alternative explanation is that FOMC interest rate shocks in the post-2007 low-rate environment may have disproportionately affected the longer end of the yield curve due to unconventional monetary policies—such as quantitative easing and forward guidance—particularly during periods at the zero lower bound (ZLB). To investigate this alternative hypothesis, we split the post-2007 low-rate sample into two subsamples: (1) a ZLB sample, covering years when the federal funds rate was below 0.25 percent (2009-2015 and 2020-2021), and (2) a non-ZLB sample, covering all remaining years post-2007.

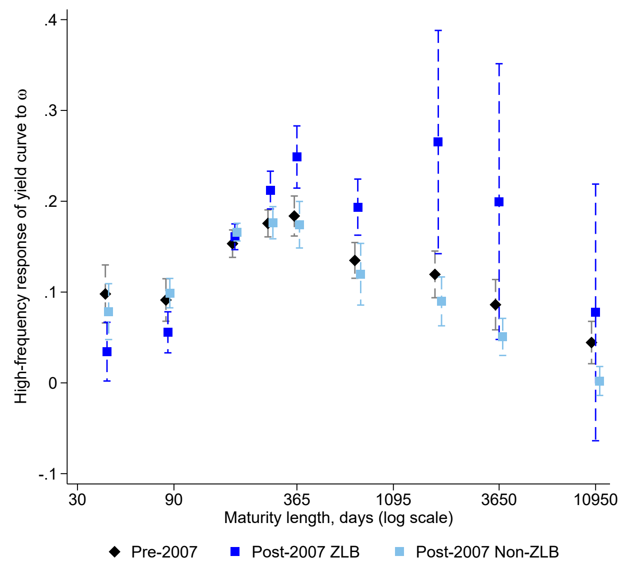
Figure 2 panel (a) compares how the yield curve responds to the high-frequency interest rate shock in the high-rate and low-rate environments. The responses across the two periods are not statistically distinguishable from one another. Panel (b) further decomposes the yield curve response within the low-rate environment, distinguishing between periods at the zero lower bound (ZLB) and non-ZLB periods. It reveals that, consistent with unconventional monetary policy, the yield curve's longer end is more responsive during ZLB periods, but not significantly more responsive during non-ZLB periods compared to the pre-2007 high-rate environment.

Table 1 column (3) presents estimates of the average interest rate sensitivity separately for three distinct sample periods: pre-2007 (high-rate), post-2007 ZLB, and post-2007 non-ZLB. We find the average sensitivity in the post-2007 non-ZLB period to be 0.7 units higher than in the pre-2007 high-rate environment. This estimate is statistically indistinguishable from the baseline result reported in column (2), supporting our baseline evidence of convexity. The point estimate of the sensitivity is even higher in the post-2007 ZLB period, consistent with the stronger impact of unconventional monetary policies.

Figure 2: By-period response of interest rates along the yield curve to ω_t shock



(a) Split by pre- and post-2007



(b) Split into three periods by FFR level

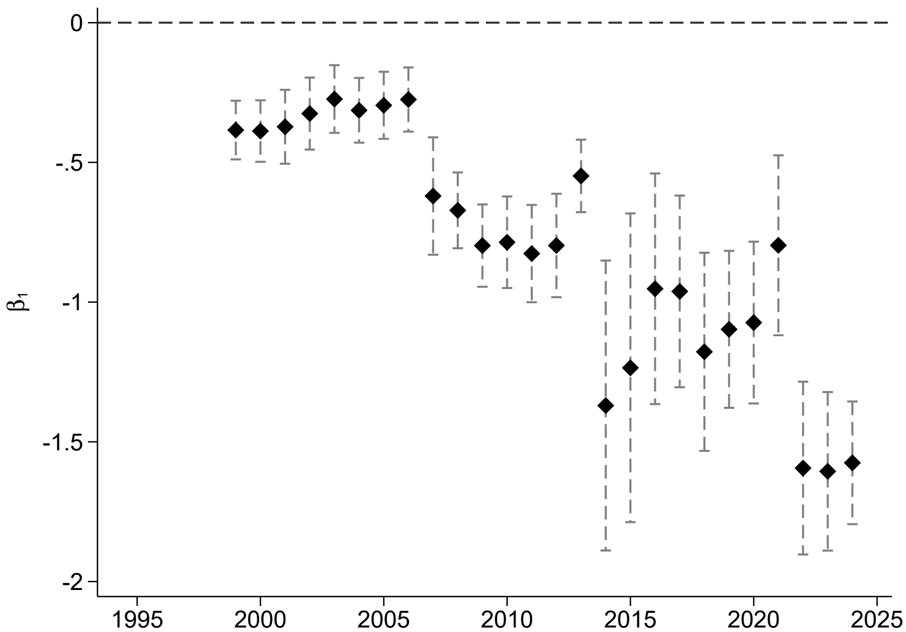
Note: Panel (a) of Figure 2 displays coefficients and standard errors from regressions of MP1, MP2, ED2, ED3, ED4, 2-year, 5-year, and 10-year yields for US Treasury non-callable notes, and 30-year yields for non-callable bonds on the PCA monetary policy shock ω_t, where black diamonds display coefficients for 1994-2006 and blue-gray squares display coefficients for 2007-2024. Panel (b) splits the regression into three periods: 1994-2006 in black; the periods 2009-2015 and 2020-2021, where the effective federal funds rate was near the zero lower bound (less than 0.25 for most months out of the year), in blue; and the periods 2007-2008, 2016-2019, and 2022-2024, where the federal funds rate was away from the ZLB, in light blue. Error bars are 95 percent confidence intervals from robust SEs. A horizontal jitter was applied to panel (b) for visualization.

Figure 3 examines interest rate sensitivity estimates across shorter, overlapping windows between 1994 and 2024. Using a rolling six-year window to ensure sufficient data points within each sub-period, we observe that sensitivity progressively increases in magnitude as interest rates decline after 2007 and the economy moves to a low interest environment in general.[5].

Does a fall in interest rate benefit larger firms more? Equation (1) indicates that it is not obvious a priori whether larger firms (by market value) necessarily benefit more from an interest rate decline. The net effect hinges on two key factors: whether larger firms tend to be high-growth firms, and whether they experience disproportionately greater future cash flow growth when rates fall. We empirically examine the relationship between firm-level interest rate sensitivity and firm size by measuring each firm's average size rank by market value over FOMC meeting dates. This average rank represented in percentiles from 0 to 1 is denoted by $\bar{X}_i$. We then estimate regression (2) using the complete set of right-hand-side variables.

[5]While nominal interest rate increased in the most recent years, so did inflation on average - pushing real rates down. Moreover, given that interest rate sensitivity can only be estimated over a sufficiently long enough time period, we cannot estimate short-term movements in interest rate sensitivity well.

Figure 3: Rolling interest rate sensitivity



Note: The black diamonds in Figure 3 display the estimated sensitivity of stock prices to ω_t over the years. To avoid small-sample issues, we estimate the coefficient using a rolling window of 6 years. For instance, the coefficient of 1999 was calculated by running the regression of equation (2), $R_{it} = \alpha_i + \beta_1\omega_t + \epsilon_{it}$, between 1994 and 1999. Error bars are standard errors clustered at the FOMC date level.

Table 1 column (4) shows that larger firms exhibit stronger sensitivity to interest rate changes—moving from smallest to largest firm in an industry more than doubles interest rate sensitivity. Column (5) shows that this relationship intensifies considerably in the low-rate environment. Specifically, moving from the smallest to the largest firm-size percentile increases a firm's interest rate sensitivity by 0.52 in the low-rate environment of 2007-2024 relative to the high-rate environment of 1994-2006. Quantitatively, this implies that the largest firms experience a 5.2 percentage-point greater increase in value than the smallest firms following a one-percentage-point reduction in interest rates.

Column (6) further divides the post-2007 low-rate period into ZLB and non-ZLB subsamples. The results show that the relationship between interest rate sensitivity and firm size during the non-ZLB period remains quantitatively similar to the findings based on the full post-2007 sample.[6]

Figure 4 panel (a) visually illustrates these findings by plotting the average firm-level interest rate sensitivity against firm-size percentiles grouped into twenty 5-percentile bins, separately for the high- and low-rate environments. The key observation is that the slope between interest rate sensitivity and firm size is substantially steeper during the low-rate environment of 2007-2024.

Finally, rather than using period dummies to implicitly capture different interest rate environ-

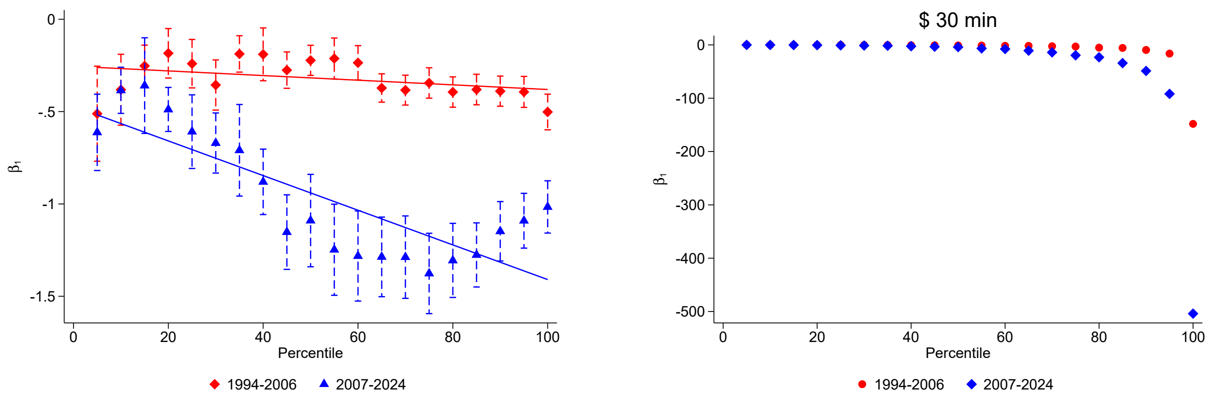
[6] Section A.3.2 of the appendix shows that results in Table 1 are robust to using within-industry percentile ranking of firms instead of overall percentile ranking.

ments, we can also explicitly parametrize each period by the average federal funds rate ($\overline{FFR_t}$) and test whether interest rate sensitivity is stronger in a low interest environment, and differentially so for larger firms. Specifically, we run:

$$R_{it} = \alpha_i + \beta_1 \omega_t + \beta_2 \overline{FFR_t} + \beta_3(\omega_t \cdot \overline{FFR_t}) + \beta_{ZLB}(\omega_t \cdot \bar{X}_i) + \beta_{\Delta}(\omega_t \cdot \bar{X}_i \cdot \overline{FFR_t}) + \epsilon_{i,t} \quad (3)$$

Columns (1) and (2) of Table 2 perform this test, and confirm our earlier results with respect to this parametrization as well.

Figure 4: Interest rate sensitivity by ventile



(a) Interest rate sensitivity

(b) Levels sensitivity

Note: Panel (a) of Figure 4 bins firms in the sample into ventiles by average percentile by market value across scheduled FOMC dates, then presents results from estimating equation (2), $R_{it} = \alpha_i + \beta_1 \omega_t + \epsilon_{it}$, on each ventile. Red diamonds depict coefficient estimates for the 1994-2006 subsample; blue triangles depict coefficient estimates for 2007-2024. Error bars are standard errors clustered at the FOMC date level. Panel (b) presents the same statistic in levels, measured in millions of December 2015 dollars.

The concentration of the valuation effect on the top 5 percent. Figure 4 panel (a) and Table 1 demonstrate that interest rate sensitivity—defined as the proportional change in firm value per unit change in interest rates—increases significantly with firm size. Given the highly skewed firm size distribution, the heightened sensitivity of large firms in proportional terms translates into substantial absolute advantages for these firms as interest rates decline. For instance, the top 5% firms constitute approximately 66% of total market value. Consequently, since the largest firms benefit disproportionately from declining interest rates, the dollar value gains from interest rate reductions are even more concentrated among these top firms.

Figure 4 panel (b) illustrates interest rate sensitivity measured in level terms ($\mathrm{d}V/\mathrm{d}r$) across twenty five-percentile firm-size groups, separately for the high-rate (pre-2007) and low-rate (post-2007) periods. The y-axis reflects firm-value changes in real 2015 dollars in response to a one-unit

Table 2: Differential interest rate sensitivity with respect to average federal funds rate

	R_{it}		$\$R_{it}$
	(1)	(2)	(3)
ω_t	-1.710***	-0.873**	-34.83***
	(0.320)	(0.400)	(7.668)
$\overline{\text{FFR}}$	-0.0505***	-0.0508***	-3.549***
	(0.0170)	(0.0170)	(1.145)
$\omega_t * \overline{\text{FFR}}$	0.319***	0.152	7.237***
	(0.0840)	(0.103)	(1.940)
$\omega_t * \bar{X}_i$		-1.387***	
		(0.385)	
$\omega_t * \bar{X}_i * \overline{\text{FFR}}$		0.277***	
		(0.103)	
ω_t * Overall Leader			-770.7***
			(170.7)
ω_t * Overall Leader * $\overline{\text{FFR}}$			143.6***
			(43.87)
N	795,059	795,059	794,801
R2	0.063	0.063	0.021
FEs	Firm	Firm	Firm

Note: Standard errors in parentheses, * $p < 0.10$, ** $p \leq 0.05$, *** $p < 0.010$. $\$R_{it}$ is the high-frequency stock price response in December 2015 U.S. dollars calculated using a 30-minute window. $\overline{\text{FFR}}$ is the period average federal funds rate in each of the three periods used in Table 1: pre-2007 ($\overline{\text{FFR}} = 4.116$), post-2007 ZLB ($\overline{\text{FFR}} = 0.0336$), and post-2007 non-ZLB ($\overline{\text{FFR}} = 2.616$). Overall Leader is an indicator variable for a firm being in the top 5% by average percentile by market value across all scheduled FOMC dates. Standard errors are clustered at the FOMC date level.

change in ω_t, normalized as a 10-basis-point shift in the one-year treasury rate. The graph highlights how the dollar impact of interest rate movements is heavily skewed towards the largest firms, particularly in the low-rate environment. Specifically, during the high-rate period (pre-2007), firms in the lowest decile experience average value increases of approximately twenty thousand dollars per unit increase in ω_t. The impact gradually rises across deciles, reaching around 9 million dollars for firms in the 85th-90th percentile. However, the impact sharply escalates for larger firms—reaching 16 million dollars for the 90th-95th percentile and surging to approximately 144 million dollars for the top 5%.

In the low-rate period (post-2007), the absolute dollar impact further intensifies, particularly among the largest firms. The value gain for top 5% firms jumps dramatically from 144 million dollars during the 1994-2006 high-rate environment to 500 million dollars post-2007. By contrast, smaller firms experience relatively modest gains, underscoring the highly uneven distribution of benefits from falling interest rates. The pronounced skewness in the dollar-weighted impact of interest rate changes motivates the additional analysis provided in column (3) of Table 2. The column quantifies the level-based interest rate sensitivity specifically for the top 5% of firms. The industry leaders realize an additional 770 million dollars in value relative to other firms for each unit decline in ω_t when the effective federal funds rate is near the ZLB. This level effect significantly declines in magnitude during periods with higher rates.

Taking stock. The high-frequency analysis of stock market responses to interest rate shocks yields two key insights: (a) larger firms experience stronger proportional impacts, particularly in a low interest rate environment, and (b) these effects are overwhelmingly concentrated among the top 5 percent of firms in dollar terms. Our subsequent analysis emphasizes the comparison between the top 5 percent of firms ("industry leaders") and the remaining firms. Given that the absolute dollar size of the effect matters for competition across firms in an industry, the ability of a firm to leverage an additional billion dollars of value due to falling interest rates likely has far greater competitive implications than smaller increments of a few million dollars.

3 Real and Balance Sheet Effects of Interest Rate Changes on Firms

High frequency analysis has the important advantage that it isolates the causal effect of unanticipated changes in interest rates on firm value around FOMC announcements. The results indicate that very large firms benefit disproportionately from interest rate declines, especially in the low interest rate environment following the Great Recession. Does this differential benefit of lower interest rates for larger firms show up in firm outcomes such as investment and sales revenue over time? This section develops the empirical methodology for answering this question.

3.1 Data Construction

Constructing firm-level outcomes. In order to analyze the real effects of interest rate changes on firms, we build a firm-level quarterly data set using the merged CRSP-Compustat data from 1994 to 2024, aligning with the availability of high-frequency interest rate shocks ω_t. Starting from the full quarterly data set of US-incorporated public firms, we apply the filters that are standard in the literature (e.g. Gutiérrez and Philippon, 2017b and Ottonello and Winberry, 2020).[7] We measure a firm's cost of borrowing at the quarterly level by dividing interest expenses by the level of interest-bearing debt.

[7] Specifically, we drop the financial sector (SIC between 6000 and 6999) and public administration (SIC between 9000 and 9999). We also drop firms with 10 or fewer observations. We drop firms with leverage, defined as current debt (dlcq) plus long-term debt (dlttq) divided by assets (atq), exceeding 10. Furthermore, we drop firms with net current asset ratio, defined as current assets (actq) minus current liabilities (lctq) over total assets (atq), exceeding 10 or below -10 and firms with real sales growth, defined as growth in nominal sales (saleq) adjusted by the CPI, exceeding 100% or below -100%. Finally, we winsorize the distribution of leverage at the 0.5th and 99.5th percentile and we linearly interpolate missing values of assets.

We continue to draw the critical distinction between industry "leaders" and "followers". The baseline definition of industry leaders is according to size as measured by market value. For each firm, we compute the average within-industry market value percentile across quarters, $\tilde{X}_i$, and then classify a firm as an industry leader if it is in the top 5 percent of firms by $\tilde{X}_i$. Robustness results in the appendix show similar results for alternative leader definitions based on sales, the top 5 firms within each industry and for SIC instead of Fama-French industries.

Table 3 provides summary statistics for the firm-level panel data. We report summary statistics for a firm's borrowing cost, assets, revenue, capital expenditures, acquisitions, debt, and leverage. Variable construction for each of these variables in Compustat sample is described in Table 3's footnote. The last row provides the summary statistics for the quarterly interest rate shock series. A one standard deviation interest rate shock is a 3.6 basis point change in the one-year zero-coupon T-bill.

Table 3: Summary statistics of main variables

	N	Mean	SD	p25	p50	p75
Borrowing Cost	278,394	6.82	3.50	4.54	6.55	8.65
Assets	431,008	3,521.27	18,075.86	57.57	274.01	1,402.92
Property, Plant, and Equipment	430,003	1,202.42	6,548.53	6.33	45.38	328.00
Revenue	429,850	690.77	3,543.06	10.84	62.06	304.82
Capital Expenditure	345,115	6.32	15.29	1.69	3.65	7.34
Acquisitions Expenditure	327,456	3.60	14.19	0.00	0.00	1.48
Debt	411,628	1,158.84	7,290.10	1.67	31.89	388.50
Leverage	411,577	24.18	23.80	3.11	20.00	37.11
MP shock	124	0.01	0.36	-0.15	0.05	0.22

Note: Table 3 reports summary statistics for our main variables. Borrowing Cost is defined as the annualized quarterly interest expenses (xintq) over interest-bearing debt (dlcq + dlttq). Assets is the total value of assets (atq). Property, Plant, and Equipment is the total value of tangible fixed property net of depreciation (ppentq). Revenue is total revenue (revtq). Capital Expenditure is the sum of capital expenditure over 4 quarters (capxy) divided by its lagged assets (atq). Acquisitions Expenditure is the sum of funds used for company acquisitions over 4 quarters (acqy) divided by its lagged assets (atq). Debt is defined as current debt (dlcq) plus long-term debt (dlttq). Leverage is current debt (dlcq) plus long-term debt (dlttq) divided by assets (atq). Borrowing Cost, Leverage, Capital Expenditure, and Acquisitions Expenditure are in percentage points. Revenue, Debt, Assets, and Property, Plant, and Equipment are in millions of dollars. The monetary policy shock was constructed in the same way as Gürkaynak et al. (2022), and was rescaled to have an instantaneous unit impact of 10 bps on the one-year zero-coupon treasury. We follow the procedure of Ottonello and Winberry (2020) to aggregate ω at the quarterly level.

Constructing interest rate shocks at quarterly frequency. Since firm outcomes are measured at the quarterly frequency, we need to aggregate the high-frequency FOMC interest rate shocks ω_t accordingly to quarterly frequency. Following the approach in Ottonello and Winberry (2020), we construct a quarterly shock using a weighted average of intra-quarter FOMC shocks, which gives greater weight to shocks occurring earlier in the quarter, reflecting firms' longer exposure to these events. As a robustness check, we also consider a simpler method that sums all 30-minute FOMC shocks within a quarter, and our results remain materially unchanged. For convenience, we continue to refer to the resulting quarterly shock as ω_t, where t indexes the quarter.

Sanity check. As a validation of our data construction, we first test if the FOMC news-based quarterly ω_t shock impacts firms' borrowing costs (defined as the annualized quarterly interest expenses over interest-bearing debt; see the footnote of Table 3). The relationship is expected: most loans made to U.S. corporations by banks and non-bank financial institutions are floating rate loans linked to a short-term interest rate such as LIBOR or SOFR. Consistent with this, our firm-level borrowing cost measure aligns closely with measures of firm financial strength as shown in Table A.1. For example, industry leaders pay 162 basis points lower borrowing costs (column 1), as do large firms in general (column 2). More levered firms pay higher rates (column 3), while firms with higher price-to-earnings ratios, higher interest coverage, higher distance to default, higher earnings, and higher ratings pay lower rates (columns 4-8).[8]

Figure 5 estimates the impulse response function for the average borrowing cost across firms to the interest rate shock ω_t. Over the four quarters following a shock, borrowing costs rise gradually until they rise by 46 basis points for a 10 basis point interest rate shock. The gradual rise reflects the fact that fixed-rate debt instruments do not reset rates immediately. The shock also has a persistent effect on borrowing costs, which remain elevated even three years after the shock.

3.2 Empirical Methodology

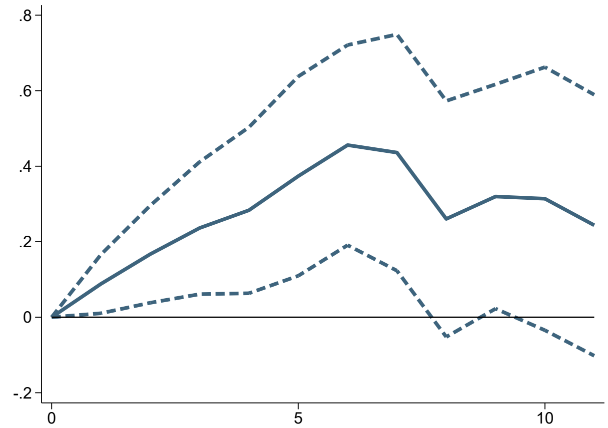
Our main goal is to test how FOMC-news driven interest rate shocks impact industry leaders versus followers. We do by running the following local-projections empirical specification,

$$\begin{aligned} \Delta y_{i,j,t+h-1} \quad = \quad & \alpha^h_{j,t} + \beta^h_{ZLB}\left(\omega_t \cdot L_{i,j}\right) + \beta^h_{\Delta}\left(\omega_t \cdot L_{i,j} \cdot FFR_{t-1}\right) \\ & + \delta'_h z_{i,j,t} + \sum_{\ell=1}^{3} \Gamma'_h \theta_{i,j,t-\ell} + \epsilon_{i,j,t+h-1}, \end{aligned} \tag{4}$$

where $\Delta y_{i,j,t+h-1} = y_{i,j,t+h-1} - y_{i,j,t-1}$ is the cumulative change in the outcome variable of interest for firm i in industry j from quarter $t-1$ to $t+h-1$, $L_{i,j}$ is an indicator variable equal to 1 if firm i's average within-industry market value rank across quarters over the sample period

[8] We code ratings numerically from 1 (for AAA) to 9 (for C). Moving down one rung on the rating ladder, say from BBB to BB, is associated with a 102 basis points increase in the cost of borrowing.

Figure 5: Response of average borrowing cost to monetary policy shocks (ω)



Note: The solid line in Figure 5 shows the impulse response function of borrowing cost to an interest rate shock. The estimating equation is: $\Delta y_{t+h-1} = \alpha_h + \beta_h \omega_t + \sum_{\ell=1}^{3} \Gamma_h' \omega_{t-\ell} + \sum_{\ell=1}^{3} \Theta_h' \Delta y_{(t-\ell)+h-1} + \epsilon_{t+h-1}$, where Δy denotes the average change in borrowing costs across firms and ω_t is the FOMC interest rate shock. The plot shows β_h going from h = 1 to h = 11. The shocks are normalized such that the impact on instantaneous response of zero-coupon one year treasury notes is 10 bps. Note that our procedure is different than taking the average borrowing cost for each period, and then calculating the changes; this is because the latter method creates biases due to firms entering/leaving the sample. The dotted lines depict 95 percent confidence intervals around $\beta_k$from standard errors clustered at the quarterly level.

is in the top 5 percent of firms, FFR_{t-1} is the lagged level of the nominal federal funds rate, ω_t is the measure of interest rate shocks between $t-1$ and t discussed above in Section 3.1, $z_{i,j,t} = \{L_{i,j,}, L_{i,j} \cdot FFR_{t-1}\}$ is a vector of market leadership controls while $\theta_{i,j,t-l} = \{\Delta y_{i,t-l}, \omega_{t-l} \cdot L_{i,j}, \omega_{t-l} \cdot L_{i,j} \cdot FFR_{t-l}, z_{i,t-l}\}$ is a vector containing lagged values of all variables in the system. We also control for industry-time fixed effects $\alpha_{j,t}^h$, which removes all cross-industry variation in response to FOMC shocks.

Regarding standard errors, Montiel Olea and Plagborg-Møller (2021) show that augmenting the local projection with lags of each variable (as in our specification) removes the need to correct standard errors for autocorrelation, meaning heteroskedasticity robust standard errors are appropriate when estimating equation (4). Almuzara and Sancibrián (2025) show that this result extends to our panel data setting as well. Our standard errors are always clustered by time in this paper since all firms face the same ω_t shock. The specification also has the advantage of appropriately handling the issue of dynamic heterogeneous treatment effects as highlighted by Dube et al. (2025).

Finally, h indicates the time horizon in quarters of the local projection. For our main results, we will estimate equation (4) for $h = 1, 2, 3, ..., 11$. The coefficients at $h = 1$ therefore capture the contemporaneous response of the dependent variable, and the coefficient at $h = 0$ is zero by construction.

The two main coefficients of interest in equation (4) are β_{ZLB}^h and β_{Δ}^h. This can be seen by comparing estimated equation (4) for industry leaders (with $L_{i,j} = 1$) versus industry followers (with $L_{i,j} = 0$). The differential response to interest rate shock ω_t for leaders versus followers can be written as:

$$\beta^h_{ZLB}\omega_t + \beta^h_{\Delta}(\omega_t \cdot FFR_{t-1}). \tag{5}$$

If the lagged interest rate is equal to zero ($FFR_{t-1} = 0$), then the differential effect of a shock to the interest rate on the leader's outcome relative to the follower's is fully captured by β^h_{ZLB}. This is why we refer to the coefficient as the zero lower bound coefficient; it is the effect of a shock to the interest rate when interest rates are already at the zero lower bound. As the lagged interest rate moves above zero, the effect of an interest rate shock changes with the lagged level of the interest rate, which is captured by β^h_{Δ}.

Identification concern regarding macroeconomic news. It is important to note here that the firm-level analysis in this section does not attempt to distinguish whether changes in interest rates around Fed meetings reflect a "news" effect as in Nakamura and Steinsson (2018) or an updating of the Fed reaction function as in Bauer and Swanson (2023b). The goal of the analysis here is to exploit the change in interest rates around Fed meetings, regardless of the underlying economic mechanism. However, from an identification perspective, it is a concern that the shocks are predictable by macroeconomic news if the same macroeconomic news has a differential effect on outcomes for industry leaders versus followers.

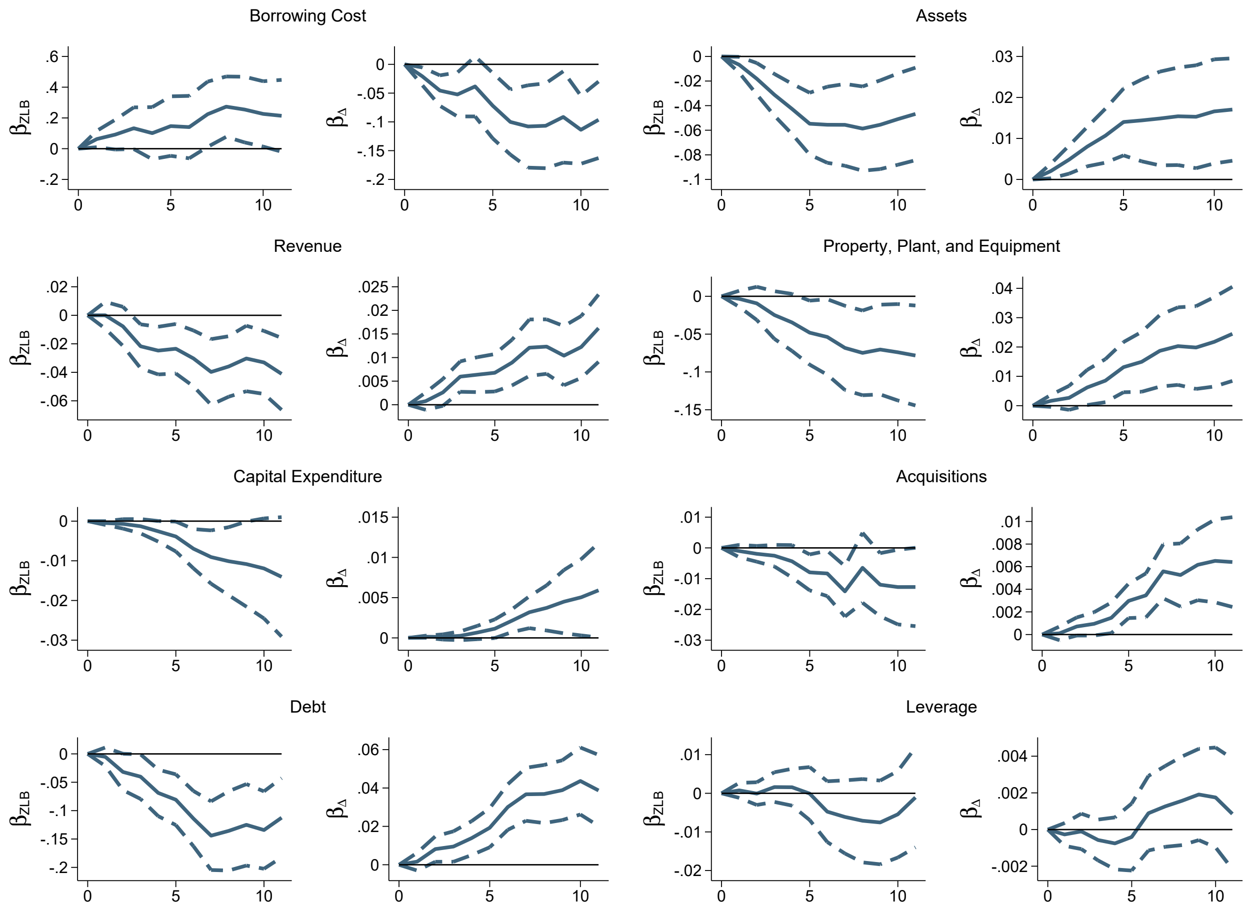
This issue does not arise in Section 2 since it used high-frequency stock return outcomes on the left-hand side as well, but when estimating quarterly impulse responses, we must ensure that prior macroeconomic news is not differentially impacting outcomes for leaders versus followers. We conduct a number of tests in Section 3.4 below to mitigate this concern, including the use of control variables for the macroeconomic news that predicts the monetary policy shocks. These tests suggest that the differential response of leaders versus followers is due to changes in interest rates around the Fed meetings, and not due to differences in macroeconomic news that occur before the meetings.

3.3 Empirical Results

This section reports results from estimating equation (4) for a range of firm-level outcome variables. We estimate local projections at horizons of up to 10 quarters after a shock and plot the main coefficients of interest, β^h_{ZLB} and β^h_{Δ} with their 95 % confidence bands.

Firm cost of capital. How does a decline in interest rates affect the cost of capital for industry leaders versus followers? Figure 6 panel (a) reports coefficients β^h_{ZLB} and β^h_{Δ} from estimating

Figure 6: Local projection results for firm outcomes



Note: The solid lines in Figure 6 display coefficient estimates of β^h_{ZLB} and β^h_{Δ} from equation (4) for each outcome variable defined in Table 3, $h = 1, ..., 11$. The dotted lines depict 95 percent confidence intervals around β_{ZLB} and β_{Δ} from standard errors clustered at the quarter level.

equation (4), with cost of borrowing in percentage points as the outcome variable. Dotted lines represent the 95% confidence interval. The estimates of β_{ZLB} are positive and the estimates of β_{Δ} are negative. Positive β_{ZLB} implies that when the federal funds rate is close to the zero lower bound,[9] a decline in the interest rate favors industry leaders more by lowering their borrowing cost more than industry followers. The coefficient β^h_{Δ} with the opposite sign implies that the advantage that industry leaders enjoy at very low rates gets diminished in a higher interest rate environment. We will see this pattern to be consistently repeated for all firm outcomes.

In terms of magnitudes, a decline in the interest rate by 10 basis points near ZLB leads to a 27 basis point relative decline in the borrowing cost faced by leaders versus followers two years later. The point estimate for β_{Δ} eight quarters out is about -0.11. This implies that the differential decline in the leaders' borrowing cost advantage for a 10 basis points negative interest rate shock at the zero lower bound shrinks by about seventy-five percent when the level of the interest rate

[9]Recall that ω_t is the first principal component and therefore reflects the decline in the longer-end of the yield curve via forward guidance when federal funds rate is at or near zero.

is at 2%. The fact that the leaders' financing advantage shrinks at a higher level of the initial interest rate (i.e., $\beta^h_\Delta < 0$) implies that there is a level of the interest rate that would be neutral for the leader's financing advantage. We will return to this idea in our conclusion.

Firm growth. Figure 6 panels (b) and (c) plot β^h_{ZLB} and β^h_Δ from equation (4) with measures of firm growth—log assets size and log sales revenue, respectively—as outcome variables. The results show that a decline in interest rates leads to a relative increase in firm size and firm revenue for leaders versus followers when the initial federal funds rate is near zero, and this relative increase gets diminished in higher interest rate environments.

In terms of magnitude, a 10 basis point decline in interest rates near ZLB leads to about 4 to 6 percentage points stronger asset and revenue growth for industry leaders relative to industry followers after two years. β_Δ has the opposite sign as before, showing that the relative advantage for industry leaders in response to interest rate decline diminishes in higher rate environment. In particular, the magnitude of β_Δ implies that the effect of interest rate decline at ZLB mentioned above diminishes by about one-third to a half when the federal funds rate is 2% instead of 0%.

Firm investment and acquisitions. Figure 6 panels (d) through (f) plot β^h_{ZLB} and β^h_Δ from equation (4) with log property, plant, and equipment (PPE), the cumulative sum of capital expenditure (CAPX) flows over h quarters as a share of assets, and the cumulative sum of acquisitions as a share of assets as outcome variables. The outcome variables measure firm investment, either as new capital formation, or through buying existing capital via acquisitions. The β^h_{ZLB} estimate shows that a decline in interest rates leads to a relative increase in firm investment - across all three variables - for leaders versus followers when the federal funds rate is near zero. However, as before β_Δ has the opposite sign, showing that this relative increase gets diminished in higher interest rate environments.

The cumulative Capital and Acquisitions Expenditures for leaders is 1pp and 0.6pp larger than for followers at the ZLB after eight quarters. The stronger effect for industry leaders is diminished at higher interest rates, with the relative impact on capital expenditure dropping by about two-thirds when the level of federal funds rate is 2%, and the relative impact on acquisitions disappearing entirely.

Firm financing. Figure 6 panels (g) and (h) plot β^h_{ZLB} and β^h_Δ from equation (4) with log total debt and firm leverage in percentage points as outcome variables. These variables measure how the interest rate shock affects firms' external financing. We have already seen that a fall in interest rate disproportionately lowers borrowing cost for industry leaders, especially in low interest rate environment – does the borrowing cost advantage also translate into greater borrowing?

The negative β_{ZLB} estimate shows that near the ZLB, a fall in interest rate increases relative borrowing for industry leaders, and increases their leverage as well. The magnitude of the increase is significant, and in fact shows that the magnitude of the impact of interest rate shocks on industry leaders versus followers is strongest for the stock of debt outstanding. A one unit decline in ω_t results in a 14pp rise in the stock of debt two years out for industry leaders versus followers at the ZLB. Similarly firm leverage also rises relatively for industry leaders. β_Δ has the opposite sign, showing that these effects get diminished in higher interest rate environment, with the relative effect declining by about one-third to a half when the federal funds rate rises by 2pp. Overall, the results on firm borrowing and leverage are also consistent with the recent work of Chatterjee and Eyigungor (2023), who argue that a lower risk-free rate benefits bigger firms because they can increase leverage by more than smaller firms, and therefore acquire more of the new product varieties arriving into the economy.

Robustness checks. We performed a number of robustness checks for the main results documented in this section. The details are all mentioned in online appendix A.3, but we enumerate the robustness checks here. First, we show robustness to alternative definitions of the shock ω_t, including using the period average federal funds rate as in Table 2 and using a longer one-hour window for ω_t instead of a 30-minute window. Second, we show that our results are robust to alternative definitions of leader variable, including using sales to rank firms. Third, the results are also robust to alternative industry definitions used in the literature. Fourth, we estimate the local projections in levels. Section 3.4 performs additional tests relating to potential identification concerns with estimating equation (4).

3.4 Addressing Identification Concerns

This section presents a series of tests to address three identification concerns in the analysis: (1) that monetary policy shocks may be predictable based on macroeconomic information, as highlighted by Bauer and Swanson (2023b); (2) that the results may be driven by a spurious time trend; and (3) that the firm-level leader indicator variable may be spuriously correlated with underlying firm attributes that are the true drivers of the observed effects.

Macroeconomic news and predictability. The identification strategy used in the quarterly firm-level analysis compares the differential effect of interest rate shocks on industry followers versus leaders. As mentioned earlier, one identification concern is whether the macroeconomic news that predicts interest rate shocks also has a differential effect on industry leaders and borrowers, *and* that this spurious effect of macroeconomic news gets stronger when the level of interest rates is lower.

There are two tests that mitigate this concern. First, as Bauer and Swanson (2023b) show, the concern regarding spurious news effect goes away if one looks at high-frequency stock market response, and we have already done that in Section 2.

Second, if the concern is that macroeconomic news has a differential effect on leaders versus followers, then control variables for the macroeconomic news can be added to the specification in equation (4). It is important that the control variables be interacted with the leader indicator variable to allow leaders and followers to have a differential response to the macroeconomic news.

In order to implement this test, we follow Bauer and Swanson (2023a), who show that interest rate shocks can be predicted with macroeconomic news that occurs before the Fed meeting. We begin with univariate tests, and we find four macroeconomic variables that predict the interest rate shocks in a statistically robust manner: (a) the surprise in real GDP relative to consensus forecasts, (b) the surprise in the BBK index which summarizes all major macroeconomic indices, (c) the return on the S&P 500, and (d) the return on an index of commodity prices.[10] For each of these four variables, we estimate equation (4) with an additional control of the news variable interacted with the leader indicator variable and an additional control of the news variable interacted with the leader variable and the level of the initial interest rate. Finally, we also estimate this specification using as a control variable the first principal component of all of the macroeconomic news variables used in the Bauer and Swanson (2023a) specification.

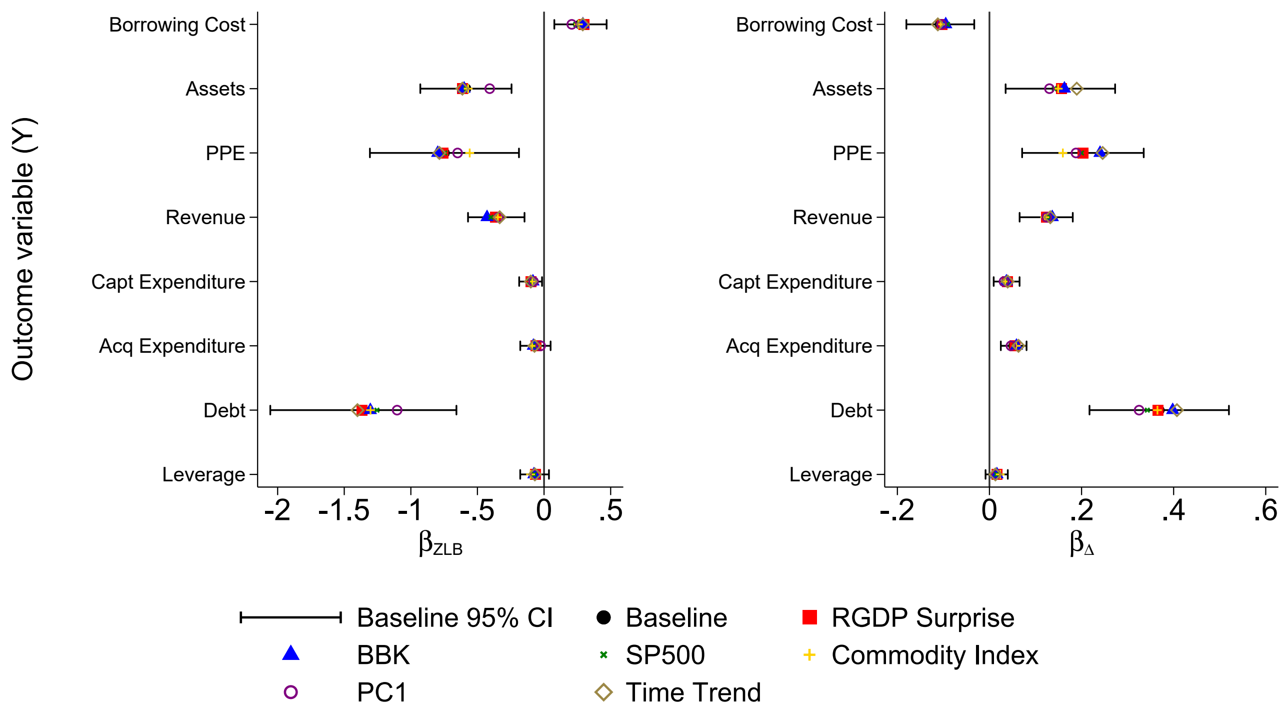
The results are shown in Figure 7. For each outcome variable, the figure shows the original 95% confidence interval of the baseline estimate of β_{ZLB} (left panel) and β_{Δ} (right panel), and then it shows the estimate once the macroeconomic news variable in question is included. As the figure shows, the control variables do not change the core estimate significantly. For all of the outcome variables, the estimates from a specification using the control variables lies within the 95% confidence interval of the original estimate.

Controlling for time trend. One of the core results is that the advantage gained by industry leaders in response to an interest rate decline is stronger in a low interest rate environment. This is captured by the coefficient β_{Δ}. Since there has been a general tendency for the interest rate to decline over recent decades, there may be a concern that the strengthening of the leader advantage in response to an interest rate decline is driven by some other spurious time trend.

This is a difficult possibility to rule out since the broader decline in r is naturally correlated with time. However, it is not perfectly correlated. Figure 7 also plots β_{ZLB} (left panel) and β_{Δ} (right panel) coefficients (in diamond-shaped marker) after controlling for a linear time trend, its interactions with the leader dummy as well as with the leader dummy times the level of interest rate interaction. The specification with the time trend controls is quite demanding as it identifies

[10] Please see Bauer and Swanson (2023b) for more details on these macroeconomic news variables.

Figure 7: Robustness to macro news and time trend



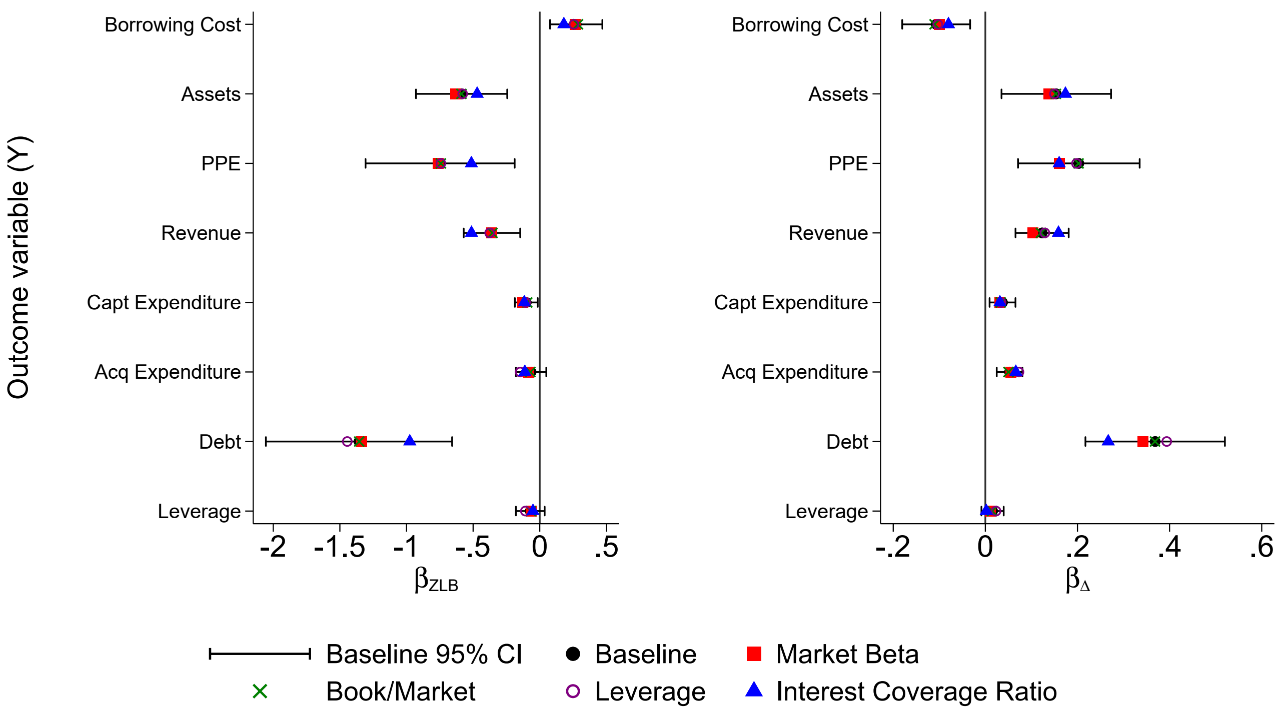
Note: The left panel of Figure 7 plots estimates of β^8_{ZLB}, while the right panel plots estimates of β^8_{Δ}, estimated from the local projection $\Delta y_{i,j,t+8-1} = \alpha^8_{j,t} + \beta^8_{ZLB}(\omega_t \cdot L_{i,j}) + \beta^8_{\Delta}(\omega_t \cdot L_{i,j} \cdot FFR_{t-1}) + \gamma^8_{ZLB}(n_t \cdot L_{i,j}) + \gamma^8_{\Delta}(n_t \cdot L_{i,j} \cdot FFR_{t-1}) + \delta'_8 z_{i,t} + \sum_{\ell=1}^{3} \Gamma'_8 \theta_{i,t-\ell} + \epsilon_{i,t+h-1}$, where n_t is a news control and y is the outcome. Baseline coefficient estimates and 95% confidence intervals are plotted in black.

coefficients from differences in the level of interest rates beyond the secular downward trend in rates. As an example, there are large tightening cycles in the mid 1990s and again in the mid 2000s. The results indicate that even after controlling for a linear time trend and its interactions, the core results broadly hold across the eight dependent variables.

Firm-level controls. We have so far controlled for variables that might be spuriously correlated with the interest rate shock ω_t, or the level of interest rate FFR_{t-1} in equation (4). We now control for firm-level variables that might be spuriously correlated with the industry leader dummy $L_{i,j}$. The black dot in Figure 8 indicates the baseline estimate for the 7-quarters-ahead local projection estimate for β_{ZLB} or β_{Δ} respectively, along with their 95% confidence interval.

Figure 8 then reports how the estimates of β_{ZLB} and β_{Δ} change when adding a specific firm-level control $x_{i,t-1}$, both on its own and interacted with the interest rate shock, the initial level of the interest rate, and the interest rate shock times the initial level of interest rate. The firm-level controls we consider include a firm's market beta, interest coverage ratio, book-to-market value, price-to-earnings ratio, and leverage. The idea is to test whether factors correlated with being a leader are responsible for the differential effect of interest rate shocks on outcomes.

Figure 8: Robustness to various firm-level controls



Note: The left panel of Figure 8 plots estimates of β^8_{ZLB}, while the right panel plots estimates of β^8_{Δ}, estimated from the local projection $\Delta y_{i,j,t+8-1} = \alpha^8_{j,t} + \beta^8_{ZLB}(\omega_t \cdot L_{i,j}) + \beta^8_{\Delta}(\omega_t \cdot L_{i,j} \cdot FFR_{t-1}) + \gamma^8(x_{i,t-1}) + \gamma^8_{ZLB}(\omega_t \cdot x_{i,t-1}) + \gamma^8_{FFR}(x_{i,t-1} \cdot FFR_{t-1}) + \gamma^8_{\Delta}(\omega_t \cdot x_{i,t-1} \cdot FFR_{t-1}) + \delta'_8 z_{i,t} + \sum_{\ell=1}^{3} \Gamma'_8 \theta_{i,t-\ell} + \epsilon_{i,t+h-1}$, where $x_{i,t}$ is a firm level control and y is the outcome. Baseline coefficient estimates and 95% confidence intervals are plotted in black.

One concern is that leaders and followers differ by their sensitivity to the aggregate market movements—that is, their market betas. While industry-time fixed effects absorb cross-industry differences in market beta, within-industry differences remain. The first robustness check controls for each firm's market beta and its interaction with the interest rate shock. The red squares show that the point estimates when controlling for market beta interacted with the interest rate shock lies close to the baseline estimates.

Next, a control for the book-to-market ratio is added (green crosses in Figure 8). High book-to-market is typically associated with value stocks as compared to growth stocks with low book-to-market ratios. If, within each industry, leaders are disproportionately growth stocks, this would be an alternative potential explanation for the results above. Moreover, the book-to-market ratio is a common proxy for Tobin's Q and controlling for Q therefore also attempts to control for differences in investment opportunities. Including market-to-book ratios leaves all point estimates nearly unchanged.

The next set of results controls for firms' ex-ante financial position, again interacted with the interest rate shock. The different responses across leaders and followers could be driven by ex-ante differences in leverage or interest coverage. For instance, if leaders are less levered, they have more ex-ante remaining debt capacity when an interest rate shock occurs and this might be driving the differential financing responses. The purple circles show the point estimates when including leverage interacted with the interest rate shock. The point estimates lie within the baseline 95% confidence band.

Finally, a control for the interest coverage ratio interacted with the interest rate shock is added. Even if differences in leverage do not explain the results, there is a concern that if leaders are financially less vulnerable because they can more easily cover their interest expenses, these differences could explain the differential financing response across leaders and followers. The interest coverage ratio is computed as earnings over interest expenses at the firm-level. The blue triangles in Figure 8 show that most point estimates are very similar to the baseline estimates. Results are quantitatively slightly smaller for PPE, borrowing cost, and debt but statistically indistinguishable from the baseline point estimates. Overall, the baseline results are robust to the inclusion of various firm-level controls that address specific alternative hypotheses.

4 Conclusion

Using high-frequency interest rate shocks and stock market response, as well as response of quarterly firm outcomes over the longer run from 1994 to 2024, we find that declines in the interest rate disproportionately benefit industry leaders relative to industry followers. Leaders use this advantage to raise additional debt financing, increase leverage, boost capital investment, and conduct acquisitions. All of these effects become stronger as the level of the interest rate declines; that is, a decline in interest rates has a stronger effect on all of these outcomes of leaders relative to followers when the initial level of the interest rate is already low. The findings provide empirical support to the idea that extremely low interest rates may be a contributing factor in explaining the rise of superstar firms in the U.S. economy.

The finding that leader's advantage diminishes in a higher rate environment suggests the existence of a "competition-neutral" interest rate, a level at which interest rate changes have symmetric effects on leaders and followers. As a back-of-envelope calculation, consider β_{ZLB} and β_{Δ} in equations (3) and (4). The firm-level response to interest rate changes is neutral with respect to a firm's size when nominal federal funds rate equals $\eta = \frac{-\beta_{ZLB}}{\beta_{\Delta}}$. Table A.4 in the appendix reports estimates of η, which range from about 3% (based on local projection regressions using quarterly financial and real outcomes) to about 5% (based on high-frequency stock market responses). When the nominal federal funds rate falls below η, interest rate cuts disproportionately benefit industry leaders, and the differential benefit grows as the economy-wide nominal interest rate gets closer to zero.

The possibility of a competition-neutral interest rate—one at which monetary policy affects industry leaders and followers symmetrically—raises important questions for future research. In particular, if this rate differs meaningfully from the traditional natural rate of interest, then monetary policy may face a trade-off between aggregate efficiency and market competition. This suggests a potential role for complementary tools—such as antitrust enforcement or targeted fiscal interventions—to offset the pro-leader tilt of monetary easing when interest rates are persistently low.

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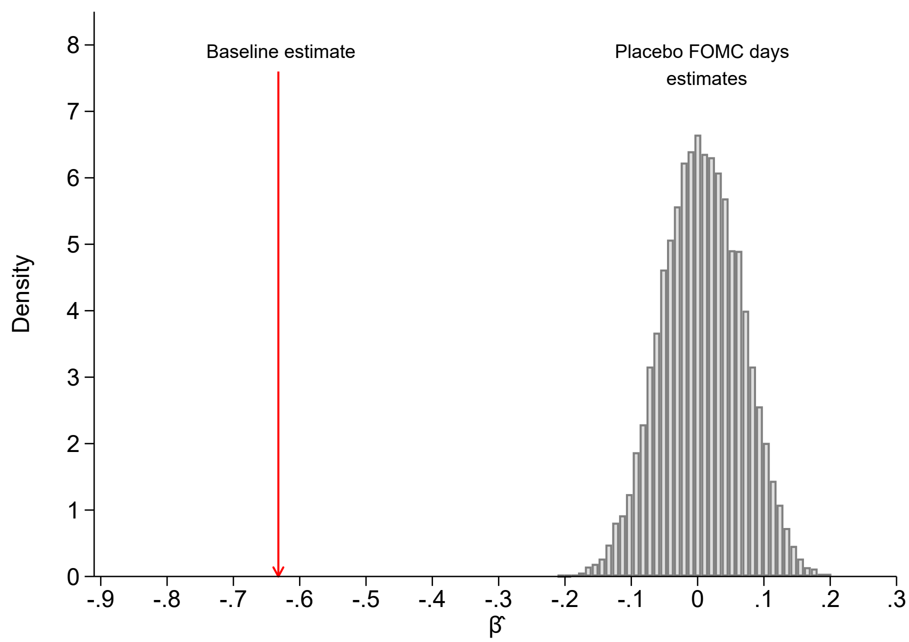
A Online Appendix

A.1 Placebo Interest Rate Sensitivity Estimates

What is the likelihood that the high-frequency estimate of a firm's stock market sensitivity to monetary policy shock is spuriously generated? The red arrow in Figure A.1 marks the estimated average sensitivity to monetary policy shocks (column 1 of Table 1). We run a set of placebo tests on non-FOMC days to show that this main effect is not driven spuriously. In particular, we pick a placebo FOMC day at random from one of the non-FOMC days in the intra-FOMC period prior to the FOMC-day in question. We assign the placebo FOMC day the ω_t shock of the FOMC day, and then recompute average sensitivity to these placebo shocks using the placebo day 30-minute high-frequency stock return for each firm. This procedure is bootstrapped many times, with the resulting distribution of estimated interest rate sensitivity shown in Figure A.1. The placebo estimates are centered around zero, and the estimated sensitivity is clearly way outside of the distribution generated by placebo estimates.

Figure A.1: Placebo baseline



A.2 Borrowing Cost Correlations

Table A.1 shows the correlates of firm borrowing cost with various measures of firm's risk and performance. It presents regression results for the specification $y_{i,t} = \alpha_t + \beta x_{i,t} + \epsilon_{i,t}$, where $y_{i,t}$ is borrowing cost (in levels), α_t indicates quarter fixed effects, and $x_{i,t}$ is the firm-level attribute of interest. All of the correlations have the expected sign, with less risky firms having lower borrowing cost.

Table A.1: Borrowing cost

	(1) Leader	(2) Market Value	(3) Leverage	(4) P/E	(5) ICR	(6) Distance to Default	(7) Earnings / Assets	(8) S&P Ratings
X	-1.62***	-0.37***	1.81***	-1.03***	-0.13***	-0.16***	-5.18***	1.02***
	(0.078)	(0.014)	(0.15)	(0.083)	(0.0030)	(0.023)	(0.77)	(0.031)
N	267,117	277,148	278,817	204,433	200,094	124,956	263,793	76,368
R2	0.197	0.237	0.198	0.218	0.294	0.219	0.199	0.364

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$. Standard errors are clustered at the firm and FOMC date level. P/E estimates are multiplied by 100.

A.3 Further Robustness Checks

This section provides a number of additional robustness checks of the main results.

A.3.1 Window Length Controls

The high-frequency analysis measures stock returns over a 30-minute window around FOMC announcement. However, the actual window length for stock return can be longer for firm-date observations when the stock is not traded at sufficiently high frequency. Table A.2 tests whether variation in the window length over which stock return is computed spuriously affect our core results. Column (1) repeats the baseline estimate in column (5) of our main results in Table 1 for ease of comparison. Column (2) then includes as control the length, in minutes, of the window used to compute firm-date high-frequency returns, together with an interaction with ω_t. Columns (3), (4), and (5) include additional interactions with the post-2007 dummy, rank by average percentile, and the triple interaction term $\omega_t * \bar{X}_i *$ post, respectively. The important observation is that none of these controls have a significant impact on our coefficients of interest. In particular, the triple interaction coefficients do not change significantly with the addition of window length and its various interactions as controls.

Column (6) shows the same robustness in a different way. It drops all firm-date observation above the 90th percentile by window length (130 minutes). Naturally we lose variation in firm size when dropping observations with longer window length: smaller firms tend to be less liquid and hence more likely to have longer window length. Given that one important coefficient of interest is the triple interaction with firm size percentile, our preference is to test for robustness

Table A.2: Robustness to window length

	R_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
ω_t	-0.180**	-0.510***	-0.503***	-0.504***	-0.431***	-0.249**
	(0.0908)	(0.119)	(0.118)	(0.118)	(0.119)	(0.106)
$\omega_t *$ post	-0.399*	-0.297	-0.310	-0.310	-0.416*	-0.479**
	(0.225)	(0.207)	(0.205)	(0.205)	(0.216)	(0.224)
post	0.0916*	0.0922*	0.144**	0.143**	0.141**	0.106*
	(0.0520)	(0.0518)	(0.0623)	(0.0623)	(0.0625)	(0.0543)
$\omega_t * \bar{X}_i$	-0.249**	-0.00721	-0.0126	-0.0115	-0.0647	-0.179
	(0.107)	(0.103)	(0.104)	(0.104)	(0.104)	(0.123)
$\omega_t * \bar{X}_i *$ post	-0.519***	-0.593***	-0.577***	-0.577***	-0.718***	-0.404**
	(0.189)	(0.178)	(0.176)	(0.176)	(0.185)	(0.195)
window$_{it}$		0.0000415	0.000361**	0.0000803	0.0000572	
		(0.000150)	(0.000176)	(0.000299)	(0.000300)	
window$_{it} * \omega_t$		0.00244***	0.00240***	0.00240***	0.00186***	
		(0.000546)	(0.000533)	(0.000533)	(0.000534)	
window$_{it} *$ post			-0.000910***	-0.000848***	-0.000804**	
			(0.000305)	(0.000317)	(0.000322)	
window$_{it} * \bar{X}_i$				0.000687	0.000742	
				(0.000539)	(0.000539)	
window$_{it} * (\omega_t * \bar{X}_i *$ post)					0.00682**	
					(0.00319)	
N	795,059	795,059	795,059	795,059	795,059	720,001
R2	0.063	0.063	0.063	0.063	0.064	0.084
FEs	Firm	Firm	Firm	Firm	Firm	Firm
Notes	Baseline	Window Control	Window Control	Window Control	Window Control	Drop WL > p90

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$. Standard errors are clustered at the FOMC date level.

by controlling for window length. Nonetheless, as seen in column (6), our main result survives even after dropping top 10% of firm-date observations by window length.

A.3.2 Within-Industry High-Frequency Results

Table A.3 presents the same specifications as Table 1, but using a within-industry definition of firm size percentile. In other words, $\bar{X}_i$ is the percentile of firm i's market value, ranked within each industry, averaged across FOMC dates over the sample period.

Table A.3: Within-industry percentile results

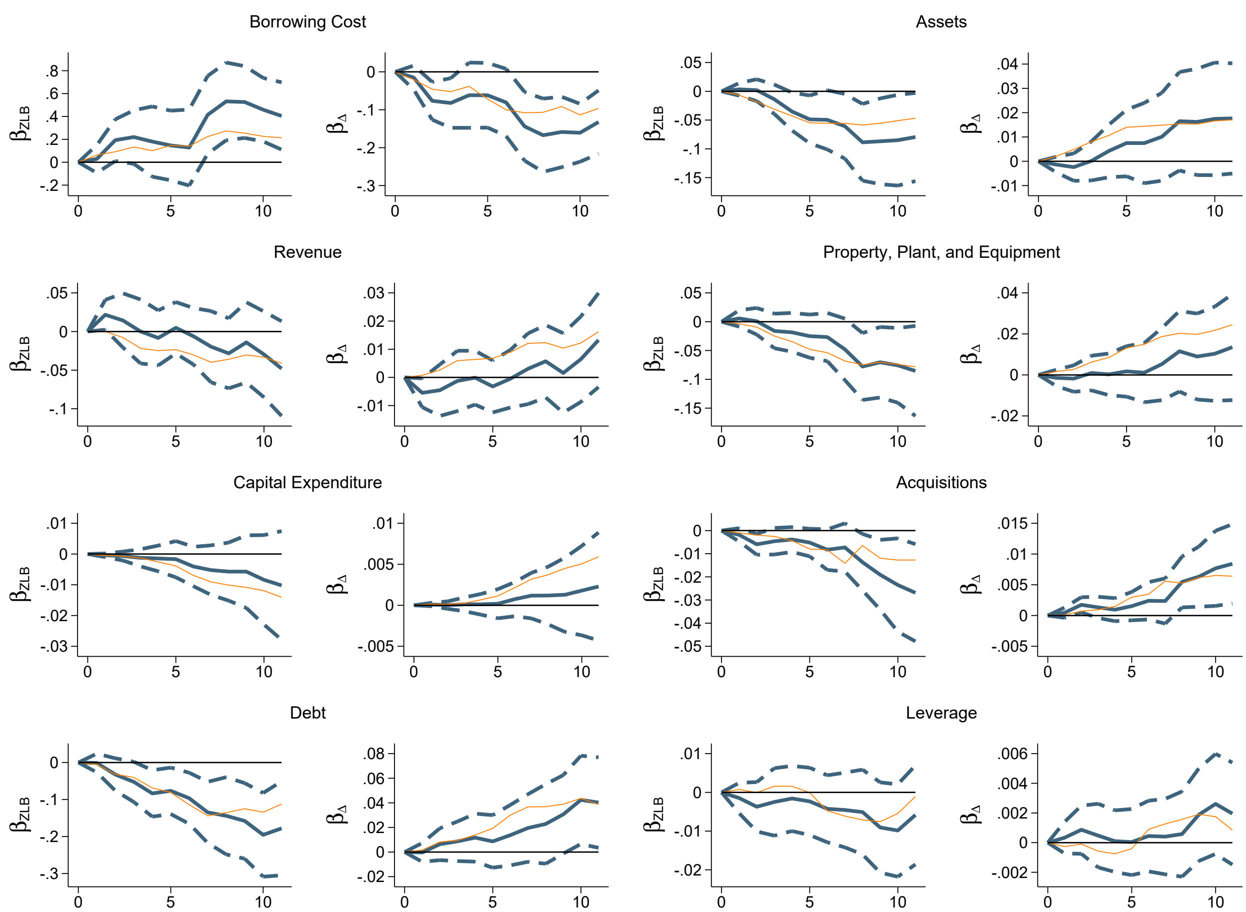
	R_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
ω_t	-0.632***	-0.333***	-0.333***	-0.366***	-0.173**	-0.171**
	(0.0904)	(0.0756)	(0.0756)	(0.0927)	(0.0869)	(0.0854)
$\omega_t *$ post		-0.704***			-0.410*	
		(0.186)			(0.216)	
post		0.0909*			0.0916*	
		(0.0520)			(0.0520)	
$\omega_t *$ post (ZLB)			-0.899**			-0.176
			(0.441)			(0.527)
$\omega_t *$ post (non-ZLB)			-0.704***			-0.438*
			(0.189)			(0.233)
post (ZLB)			0.180***			0.182***
			(0.0654)			(0.0655)
post (non-ZLB)			-0.00257			-0.00202
			(0.0630)			(0.0632)
$\omega_t * \bar{X}_i$				-0.443***	-0.263**	-0.267***
				(0.115)	(0.102)	(0.0958)
$\omega_t * \bar{X}_i *$ post					-0.501***	
					(0.169)	
$\omega_t * \bar{X}_i *$ post (ZLB)						-1.167**
						(0.531)
$\omega_t * \bar{X}_i *$ post (non-ZLB)						-0.455**
						(0.200)
N	795,059	795,059	795,059	795,059	795,059	795,059
R2	0.060	0.063	0.063	0.060	0.063	0.064
FEs	Firm	Firm	Firm	Firm	Firm	Firm

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$. Table A.3 presents the same regressions as Table 1, but using average within-industry percentile across all scheduled FOMC dates as $\bar{X}_i$. Standard errors are clustered at the FOMC date level.

A.3.3 Alternative Rate Specification: Average Federal Funds Rate

The solid blue-gray lines in Figure A.2 display coefficient estimates of β^h_{ZLB} and β^h_Δ from equation (4) for each outcome variable defined in Table 3, $h = 1, ..., 11$, using $\overline{\text{FFR}}$ in place of FFR_{t-1}, where $\overline{\text{FFR}}$ is the period average federal funds rate in each of the three periods used in Table 1: pre-2007 ($\overline{\text{FFR}} = 4.116$), post-2007 ZLB ($\overline{\text{FFR}} = 0.0336$), and post-2007 non-ZLB ($\overline{\text{FFR}} = 2.616$).

Figure A.2: LP robustness to using average federal funds rate by period



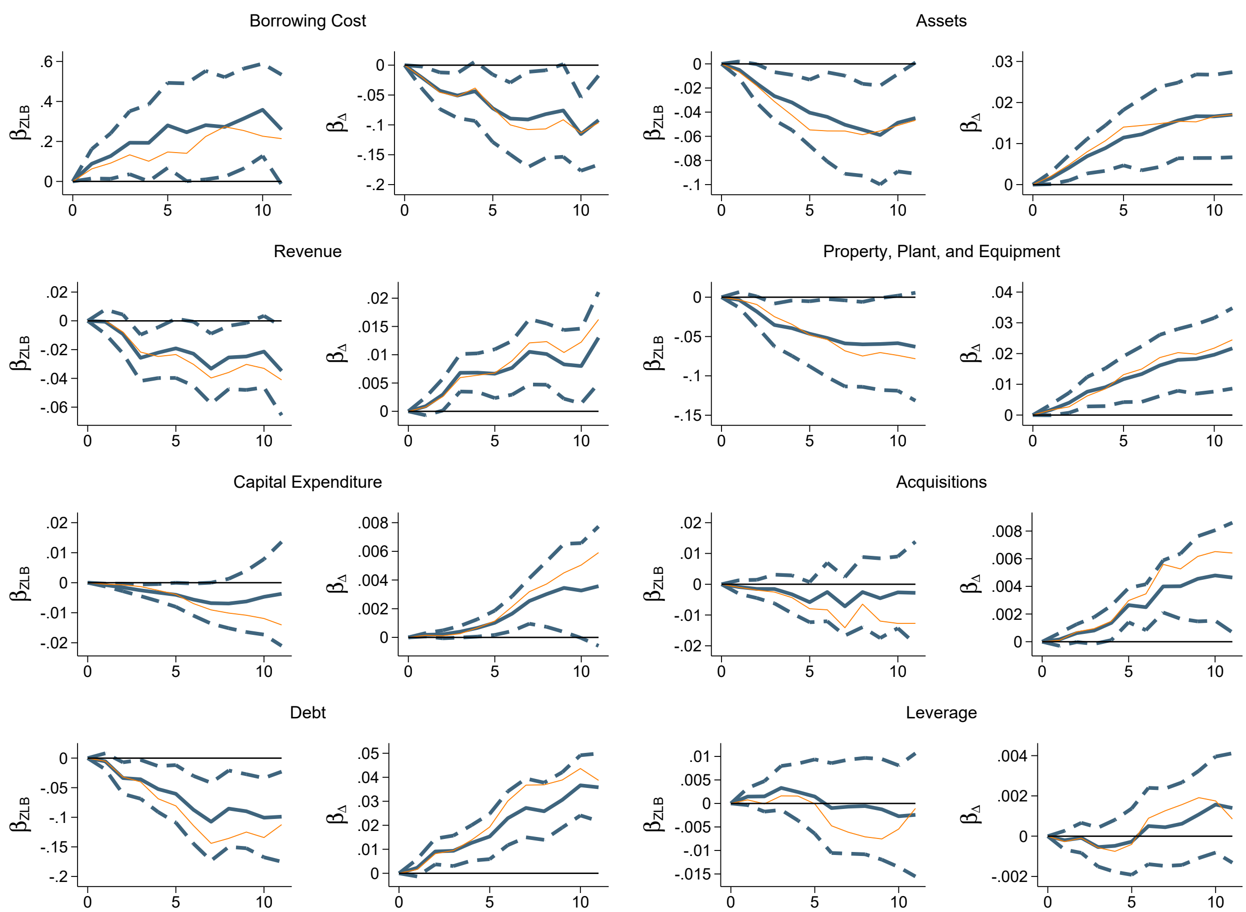
Note: The dotted lines depict 95 percent confidence intervals around β_{ZLB} and β_Δ from standard errors clustered at the quarter level. Coefficient estimates from the baseline estimation are plotted in orange.

A.3.4 Time Window for Federal Funds Shock

We investigate how sensitive our results are with respect to the definition of the time window for shocks to the federal funds rate. The identifying assumption for monetary policy shocks identified directly from movements in Fed Funds Futures is that no other macroeconomic news occur in the time window around the FOMC meeting. Under that assumption, the change in federal funds futures around the FOMC announcement is plausibly driven only by the change to monetary policy. In our main specifications, we use a 30-minute time window.

Figure A.3 re-estimates our main specification for our ω shocks but instead of constructing it over a 30-minute time window, the shock in Figure A.3 is identified over a 60 minute time window (-15 minutes to +45 minutes around the FOMC announcement). All our results are robust to this alternative definition.

Figure A.3: LP robustness to wide window

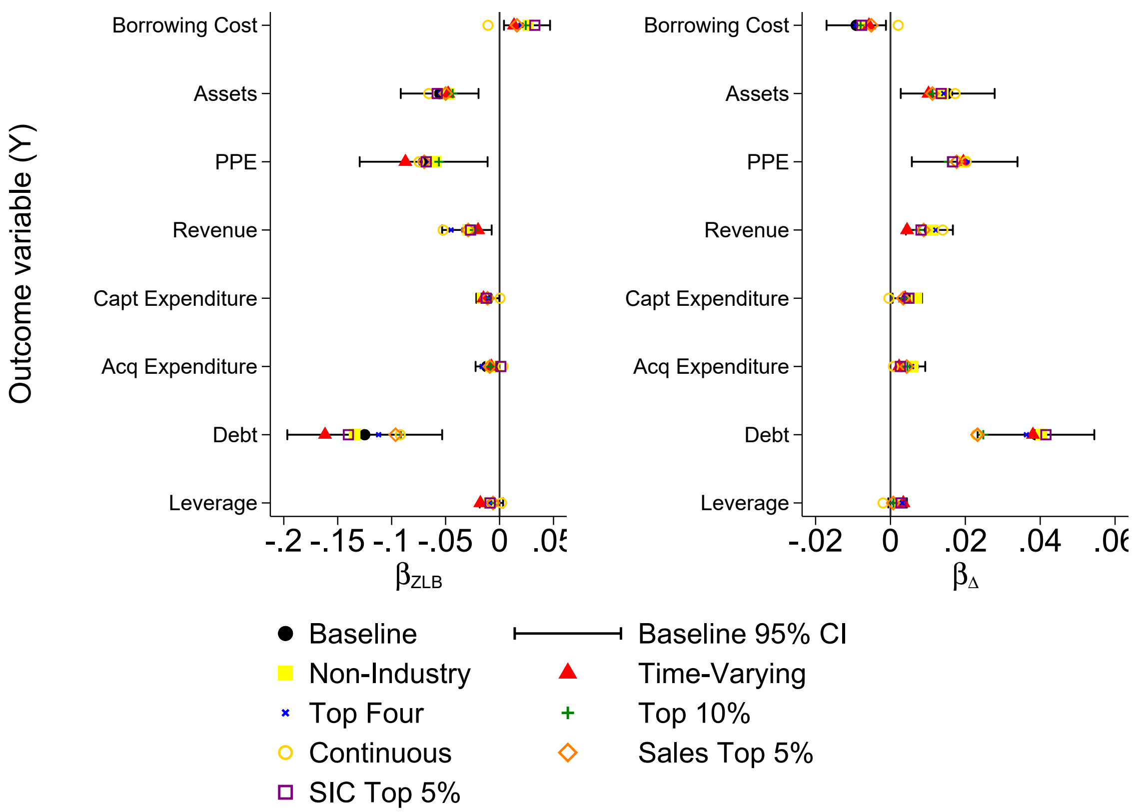


Note: The solid blue-gray lines in Figure A.3 display coefficient estimates of β^h_{ZLB} and $\beta^h_{\triangle}$ from equation (4) for each outcome variable defined in Table 3, $h = 1, ..., 11$, using a 1-hour window to compute the high-frequency monetary policy shock ω_t at each scheduled FOMC date and then aggregating to the quarterly level as before. The dotted lines depict 95 percent confidence intervals around β_{ZLB} and $\beta_{\triangle}$ from standard errors clustered at the quarter level. Coefficient estimates from the baseline estimation are plotted in orange.

A.3.5 Alternative Leader and Industry Definitions

One could be concerned that the previous results hinge on the specific definition of industry leaders. While the top 5% of firms by market value is a natural definition, it is not dictated by economic theory. We therefore perform various alternative sortings and show that they do not materially affect results.

Figure A.4: Robustness to alternative leader and industry definitions



Note: The left panel of Figure A.4 plots estimates of β^8_{ZLB}, while the right panel plots estimates of β^8_{Δ}, estimated from the local projection $\Delta y_{i,j,t+8-1} = \alpha^8_{j,t} + \beta^8_{ZLB}(\omega_t \cdot L_{i,j}) + \beta^8_{\Delta}(\omega_t \cdot L_{i,j} \cdot FFR_{t-1}) + \delta_8' z_{i,t} + \sum_{\ell=1}^{3} \Gamma_8' \theta_{i,t-\ell} + \epsilon_{i,t+h-1}$, using various alternative specifications of the leader definition $L_{i,j}$. The "non-industry" specification takes the top 5% of firms by $\bar{X}_i$, average overall market value percentile across all scheduled FOMC dates (used in Table 1 and throughout the high-frequency section) as industry leaders. "Time-varying" takes the top 5% of firm-quarters by time-varying industry percentile (so the leader definition $L_{i,j,t}$ is time-varying as well) as leaders. "Top four" takes the top four firms in each industry by average within-industry percentile across all scheduled FOMC dates as leaders, rather than the top 5%. "Top 10%" takes the top 10% by average within-industry percentile. "Continuous" takes the level of the average within-industry percentile in place of the leader dummy. "Sales top 5%" computes average within-industry percentile by sales instead of market value and then takes the top 5%. "SIC Top 5%" computes average within-industry percentile by market value within SIC industries, rather than Fama-French industries, and then takes the top 5%. Baseline coefficient estimates and 95% confidence intervals are plotted in black.

First, we sort firms by sales—instead of assets—and then define leaders as the top 5% of firms within each industry by sales. Estimates for β_{ZLB} and for β_{Δ} as reported in Figure A.4 again display a high degree of robustness.

Second, we retain the top 4 firms, instead of the top 5% of firms, as industry leaders. While the top 5% might be a growing (in the 1990s) or shrinking (in the 2000s and 2010s) number of firms within each industry, this measure keeps the number of leaders per Fama-French industry constant. Both measures have their pros and cons. Using the top 4 implies that firms do not just switch from being followers to being leaders because of their industry growing. On the other hand, the top 4 might be too small a set of firms in industries where several leaders compete neck-on-neck.

Figure A.4 reports results for the top 4 measure. Most point estimates (the blue "x") are very similar to the baseline point estimates (solid black line). For several variables (assets, PPE, capital expenditures, acquisitions), the point estimates are close to identical. Similarly, taking the top 10% as leaders instead of the top 5% does not substantially affect the results.

Third, we show robustness with respect to the definition of industries. Rather than using Fama-French industries as we do in our main specification, Figure A.4 reports results for leaders classified within 2-digit SIC industries. Point estimates derived from this alternative specification are almost identical to the baseline estimates and retain high statistical significance.

Fourth, instead of defining leaders within industries, we define leaders as the top 5% of firms by $\bar{X}_i$, the percentile of firm i's average market value rank across FOMC dates over the sample period. This is the percentile definition used throughout the high-frequency section. Figure A.4 shows that point estimates from this specification are similar, and are even stronger for some outcome variables (capital expenditures, debt).

Fifth, Figure A.4 also displays results for using the within-industry percentile in each quarter to define leaders. This time-varying leader definition does not materially affect the results.

Lastly, Figure A.4 displays results from using the continuous value of rank by average within-industry percentile $\tilde{X}_i$ directly in place of the leader indicator $L_{i,j}$. Introducing comparisons within the lower portion of the firm distribution reduces the point estimates in some cases (borrowing cost, capital expenditure, leverage), but the overall effect is ambiguous, as other results (assets, revenue) are strengthened.

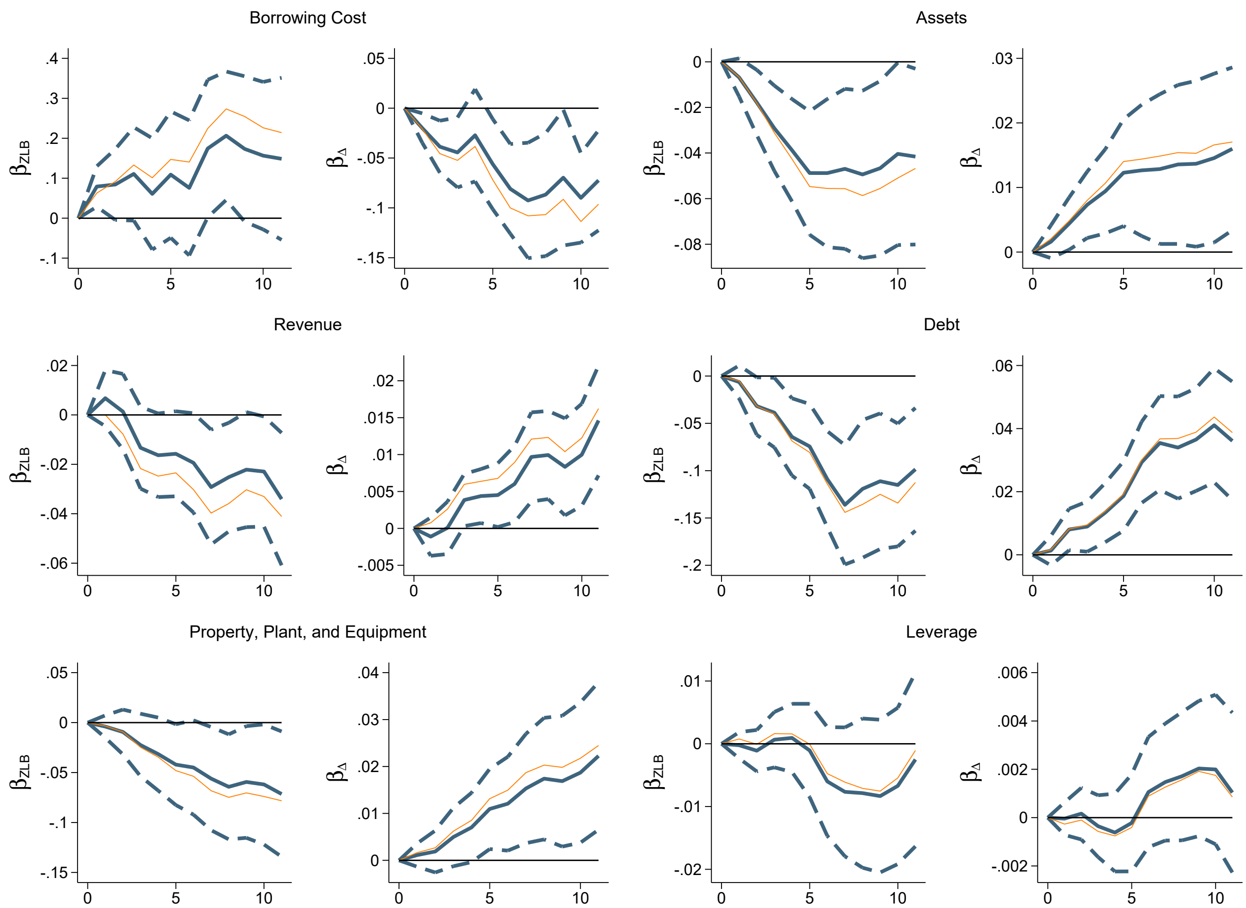
In sum, the snowballing effect of borrowing costs, financing and investment are largely unaffected by the precise definition of industry leaders.

A.3.6 Levels Specification

A further robustness check in Figure A.5 consists of estimating the main specification (equation 4) with the dependent variable in levels and adding firm-fixed effects instead of first differences.

Since capital expenditure and acquisitions are by definition already measuring changes, those are omitted from Figure A.5. We obtain very similar results as in our baseline specification.

Figure A.5: LP robustness to outcomes in levels



Note: The solid blue-gray lines in Figure A.5 display coefficient estimates of β^h_{ZLB} and β^h_Δ from equation (4) for each outcome variable defined in Table 3, $h = 1, ..., 11$, using levels of the dependent variable as the regressand rather than the difference (i.e., using $y_{i,j,t+h-1}$ rather than $\Delta y_{i,j,t+h-1} = y_{i,j,t+h-1} - y_{i,j,t-1}$). The dotted lines depict 95 percent confidence intervals around β_{ZLB} and β_Δ from standard errors clustered at the quarter level. Coefficient estimates from the baseline estimation are plotted in orange.

A.4 Individual Estimates of Competition-Neutral Rate

We use the equation $\eta = \frac{-\beta^h_{ZLB}}{\beta_\Delta}$, derived from equations (3) and (4), to estimate the competition-neutral rate $\hat{\eta}$ for each outcome variable. Asymptotically consistent standard errors for each of these neutral rates are calculated according to the delta method. Defining $\hat{\eta} = g(\hat{\beta}_{ZLB}, \hat{\beta}_\Delta)$, the variance of $\hat{\eta}$ is given by $\nabla g(\hat{\beta}_{ZLB}, \hat{\beta}_\Delta)' \Sigma \nabla g(\hat{\beta}_{ZLB}, \hat{\beta}_\Delta)$, where $\nabla g(\hat{\beta}_{ZLB}, \hat{\beta}_\Delta)$ denotes the gradient of g and Σ denotes the covariance matrix of $[\hat{\beta}_{ZLB}, \hat{\beta}_\Delta]$. We use coefficients corresponding to horizon $h = 8$ to estimate η.

Table A.4 reports the nine individual estimates of the neutral rate. Given our variable definitions, the competition-neutral rate is measured in terms of nominal federal funds rate. The estimates for competition-neutral rate range from 5 percentage points in the case of high-frequency stock market response, to about 3 percentage points for estimates coming from equation (4).

Table A.4: Neutral rate $\hat{\eta}$ estimate for each outcome variable

	Estimates of the Neutral Rate								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	R_{it}	Borrowing Cost	Assets	Revenue	PPE	CAPX	Acquisitions	Debt	Leverage
$\hat{\eta}$	5.01***	3.00***	4.17***	3.54***	4.09***	2.84***	1.71*	3.71***	3.56**
	(0.61)	(0.75)	(1.15)	(0.78)	(0.90)	(0.96)	(0.98)	(0.52)	(1.42)
N	795,059	149,612	275,479	265,457	273,002	244,545	224,704	195,278	255,109

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$. Table A.4 presents estimates of the neutral rate implied from the high-frequency and quarterly estimates. The neutral rate η is an estimate of the nominal federal funds rate such that a monetary policy shock ω has the same impact for both industry leaders and followers. It is given by $\hat{\eta} = -\frac{\beta_{ZLB}}{\beta_{\Delta}}$. Column (1) presents the $\hat{\eta}$ implied by the estimated coefficients from the high-frequency specification in column (2) of Table 2, while columns (2) through (9) present $\hat{\eta}$ from the 7-quarters-ahead (i.e., $h = 8$) local projection estimates from the quarterly data using equation (4). Standard errors of these estimates are calculated according to the delta method.