Falling Rates and Rising Superstars *

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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 near the zero lower bound leads to a stronger rise in market value for industry leaders, and a stronger decline in the borrowing rate. Industry leaders also borrow more, invest more aggressively, and acquire assets at a faster pace. This advantage from falling rates enjoyed by industry leaders diminishes in a higher rate environment. We estimate a "competition-neutral" nominal federal funds rate of about five percentage points, a level at which industry leaders and followers are impacted equally from an interest rate change.

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1 Introduction

There are two trends in the U.S. economy over the last 30 years that have been the focus of a large body of research: the decline in interest rates and the rise in measures of firm market power. Why have these two patterns emerged? Are they linked? One fruitful approach to these questions has been to build macroeconomic models that can explain the long-run co-movement of interest rates and market power (e.g., Farhi and Gourio (2019), Eggertsson et al. (2021), Liu et al. (2022)).

This study takes a complementary empirical approach by attempting to provide well-identified micro-economic estimates of the differential effects of interest rate shocks on industry leaders versus followers. The key finding is that falling rates in the very low interest rate environment of recent times have consistently favored industry leaders. In other words, falling rates tend to promote rising superstars. This result is robust and consistent across a wide range of firm outcomes. The estimates provided here can inform the broader literature on the link between interest rates and market power.

We empirically analyze the impact of falling rates on firms using high frequency interest rate shocks at FOMC announcements as exogenous shifters to the interest rate. Our identification strategy follows the important work of Gürkaynak et al. (2005), Nakamura and Steinsson (2018), and Bauer and Swanson (2021). We estimate a firm's high frequency stock market 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[1].

The high frequency analysis shows that the magnitude of the effect of interest rate change on firm value *rises* with firm size, *especially* in the low interest rate environment of post-2008. In other words, industry leaders have significantly higher duration than industry followers in a low rate environment. This result is particularly striking given that duration 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 duration for industry leaders implies that the dollar value gain for industry leaders should be even more extreme. We define industry leaders as the top 5% of firms by market value within an industry. Industry leaders have a dominant presence in the market and collectively represent about two-third of total value in our sample. We find that a typical industry leader gains about an additional billion dollars in market value (in real 2019 dollars) for every 10 basis points reduction in the one

[1]See Section 2 for details.

year treasury rate in the low interest rate environment of 2013-2019 relative to the high interest rate environment of 1994-2000.

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 to the quarterly level, as in Ottonello and Winberry (2020) and Gertler and Karadi (2015), and merge them to 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, 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.

We find that industry leaders benefit significantly more from lower rates in a low interest rate environment, 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 28 basis points relative to industry followers. If the initial Federal Funds rate is 2%, the effect is 15 basis points.

The leader advantage of falling rates translates into real outcomes as well, with industry leaders investing 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, Plants, 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. In terms of magnitudes, a 10 basis point reduction in the interest rate when the economy is close to the zero lower bound leads to an 15% larger increase in issuance of debt and a 1.2 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.

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. In fact, we can estimate a "competition-neutral" nominal federal funds rate at which the effect of a change in the interest rate is equal for both industry leaders and followers. The competition-neutral nominal federal funds rate is estimated to be about 5%.

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 becomes larger and 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 the borrowing costs faced by firms, and the differential borrowing costs faced by industry leaders versus followers. Finally, as shown in Hillenbrand (2023), a substantial portion of the overall decline in interest rates since the 1980s has occurred around FOMC meetings. While we emphasize from the outset that 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, we believe the estimates capture more than short-term business cycle effects that quickly revert.

The nominal Federal Funds rate has been below 5% for almost the entire period from July 2001 to 2019, (with an exception between 2006 and 2007). It was well below this range from the Great Recession until 2022. In this persistently low interest rate environment, 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 particular rise in concentration since 2000.

The high-frequency difference-in-differences identification strategy used in this paper offers important advantages, but we also conduct a number of robustness tests. The difference-in-differences methodology naturally differences out any macro-level news effects that may be spuriously correlated with high frequency FOMC shocks. For example, Bauer and Swanson (2021) and Bauer and Swanson (2022) 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 changes in 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"—for reasons as yet unknown—that has 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.

How can a falling interest rate, r, influence market competition? We outline two theoretical mechanisms. First, as in Liu et al. (2022), 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.

The 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. (2016), Berlingieri et al. (2017), Olmstead-Rumsey (2019), Autor et al. (2020)). 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 constraints in the transmission of monetary policy to firm investment (e.g., Gertler and Gilchrist (1994), Ippolito et al. (2018), Ottonello and Winberry (2020), Vats (2020)). Another related study is Morlacco and Zeke (2021), who show that in response to a decline in the interest rate, large firms increase their spending on customer capital significantly more than small firms. 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

This section presents evidence from the stock market's response to unanticipated interest rate news shocks in order to understand how firm value depends on interest rate in high versus low interest rate environments, and how this dependence varies by firm size. We begin by developing a simple framework to illustrate the factors that determine the effect of interest rate shocks on firm value.

2.1 Basic Framework

Let V represent the market value of a representative firm. The effect of an unanticipated change in interest rate r on firm value in percentage change terms can be defined as $\frac{\mathrm{d}\ln V}{\mathrm{d}r}$, which is also referred to as duration, D, in asset pricing literature. The same effect in dollar terms is $\frac{\mathrm{d}V}{\mathrm{d}r}$, and is referred to as dollar duration, $D^{\$}$. A simple Gordon growth model of valuation is useful for understanding how V responds to changes in r. Valuation according to the Gordon growth formula is given by $V = \frac{E}{r-g}$, where E is current net earning and g is expected growth rate of earnings going forward. This simple valuation model implies that duration is given by:[2]

[2]Dollar duration is analogously given by: $D^{\$} = \frac{\mathrm{d}V}{\mathrm{d}r} = -\frac{E(1-\frac{\mathrm{d}g}{\mathrm{d}r})}{(r-g)^2}$

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

The Gordon growth valuation framework is obviously highly stylized, but there are three important takeaways from this simple framework that should also hold more broadly. First, the response of firm value to change in interest rate depends on the level of interest rate, with the firm value rising faster in a low rate environment. This is the well known "convexity" result in asset pricing. Second, the effect of interest rate change 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 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. More generally, how interest rate affects larger versus smaller firms is an empirical question that we turn to next.

2.2 High Frequency Approach To Identifying Duration

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 (2022)).

Our specific measure follows Nakamura and Steinsson (2018) and Bauer and Swanson (2022), who calculate the first principal component of changes in the Federal Funds rate and Eurodollar futures contracts around FOMC announcements between 1994 and 2019.[3] 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.[4] The unit of measure of the first principal component does not have an underlying economic meaning. We therefore

[3]FOMC announcements started being communicated directly through a press release in 1994. Hence post-1994 FOMC announcements provide the cleanest opportunity for high-frequency analysis.

[4]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.

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 estimate a firm's stock market value response to the high frequency interest rate shock analogously, using the New York Stock Exchange Trade and Quote (TAQ) high frequency trading data. We construct the 30-minute stock market return around FOMC announcements by computing the return from 10 minutes prior to 20 minutes after the FOMC announcement[5]. The high frequency firm level market value response to the interest rate shock allows us to estimate D in equation (1). Formally, let ω_t be the high frequency interest rate news shock described above for an FOMC announcement on day t, and R_{it} be the corresponding stock market return for firm i. Define duration, or the sensitivity of firm value to the interest rate shock, over a given time period T as D_i^T. T can be the entire sample period 1994-2019, or a sub-period like 1994-2008. We can estimate D_i^T by running the following regression restricting to sample period T:[6]

$$R_{it} = \alpha_i + D_i^T * \omega_t + \epsilon_{it} \tag{2}$$

There are two key advantages of using the high-frequency shock ω_t to identify D_i^T in equation (2). 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 (2022) 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 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 (2023) shows that the long-run secular decline in U.S. Treasury yields since 1980

[5]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.

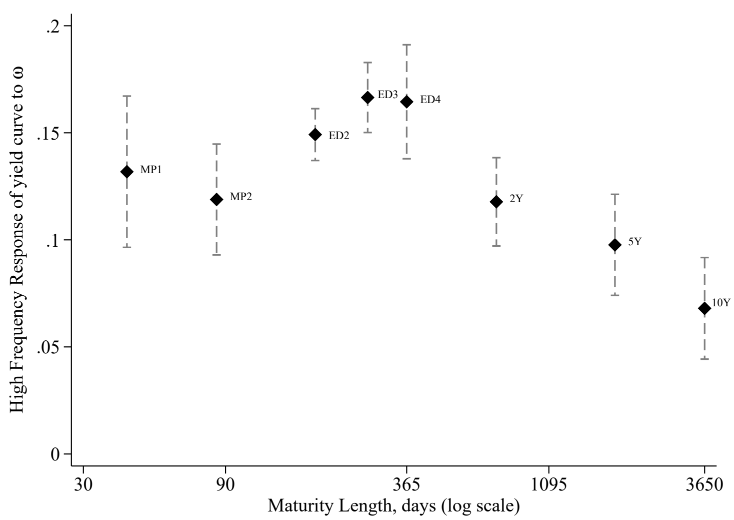
[6]The estimation sample is restricted to firms that experience at least 50 FOMC shocks over period T in order to ensure that there is reasonably sufficient data for estimating each D_i^T.

is captured almost entirely by changes in interest rates around Federal Reserve meetings. Thus, FOMC shocks contribute significantly toward the long-term trends in U.S. interest rates.

We further provide direct evidence here that our shock ω_t shifts long-maturity interest rates as well. 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 maturity of interest rates range from around thirty days (for federal funds rate futures) to ten years. The first five interest rates are the same rates (described above) used to construct the first principal component ω_t. So the first 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 and 10-year, respond strongly to the ω_t shock as well. In particular, 2-year, 5-year and 10-year interest rates move by 12, 10 and 7 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.

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



MP1 is the expectation of Fed Funds Rate for the remainder of the month. MP2 is the expectation of 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) .

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 4.8 percentage points from the high interest rate environment of 1994-2000, to the very low interest rate environment of 2013-2019. The magnitude of the decline in the very short rate is remarkably similar to the decline in 5-year rate of 4.3 percentage points between the same periods.

2.3 Empirical Results

We use the high frequency method in equation (2) to estimate $\widehat{D_i^T}$ - the sensitivity of firm value to interest rate shocks. We then use second stage regressions to test how $\widehat{D_i^T}$ changes over time and for different types of firms. Since second stage regressions use an estimated coefficient as the dependent variable, we need to make appropriate adjustments in computing standard errors to deal with the "generated regressor" issue.

How powerful are interest rate shocks for firm value on average?

We begin by estimating the average firm value sensitivity to interest rate shocks over the entire 1994-2019 period. We estimate (2) for each firm over the 1994-2019 period, and then take the average. Average firm-level duration is estimated to be -0.71, which means that a one unit increase in ω_t (which is equivalent to 10 basis point increase in the one-year treasury), leads to a decline in firm value of 0.71 percentage points.

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 rate equals 7.1 percentage points. Our estimate of -0.71 is close to the estimate of -0.65 in Nakamura and Steinsson (2018). The difference in estimates is driven by Nakamura and Steinsson (2018) estimating the impact on the S&P index, while we estimate it separately for each firm and for different sample periods.

As mentioned, the standard error in our second stage regression needs to account for the fact that our firm-level duration measure is an estimate itself. We therefore adopt the following bootstrap procedure to estimate standard errors. Each iteration of the bootstrap samples with replacement while clustering at the FOMC level. Each iteration then estimates D_i^T for all firms separately and takes their average. The distribution of coefficients coming from this procedure gives us the standard error. The bootstrapped standard error for average duration is 0.14, reflecting a high level of precision in the estimate[7].

[7]The appendix section A.1 runs a placebo experiment, where we estimate average duration by picking randomly from non-FOMC days to compute high frequency stock returns. The analysis shows that our estimate of -0.71 is far away from the placebo distribution of estimated durations, that center around zero.

Are interest rate shocks more powerful in a low rate environment?

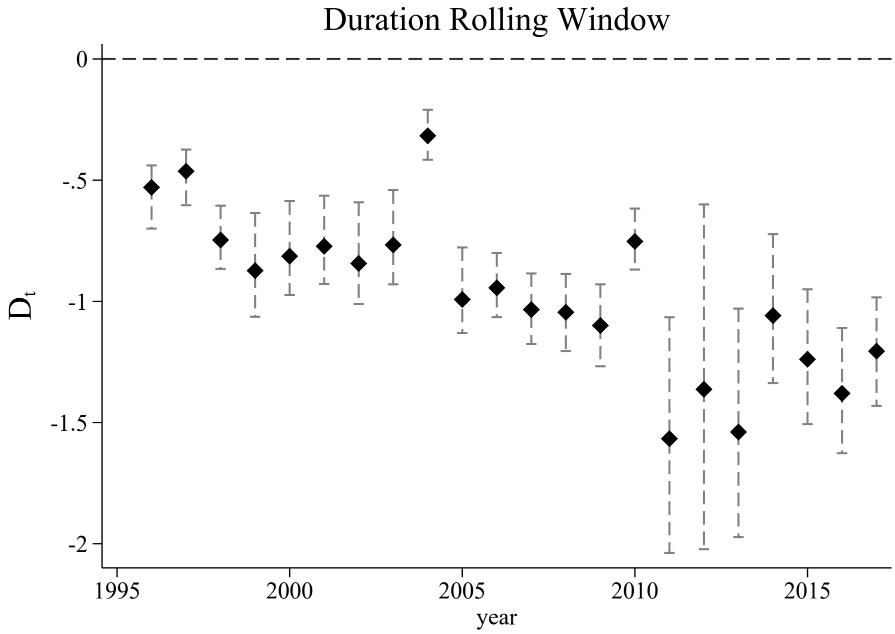
We estimate the impact of interest rate shocks on firm valuation separately in high and low interest rate environments. We first define the 1994-2008 period as high interest rate environment with an average federal funds rate of 4.2 percentage points, and 2009-2019 as low interest rate environment with an average federal funds rate of 0.6 percentage points. We also use an alternative definition that defines 1994-2000 as high interest rate environment with an average federal funds rate of 5.6 percentage points, and 2013-2019 as low interest rate environment with an average federal funds rate of 0.8 percentage points.

The first row of Panel A of table 1 estimates duration separately for high and low rate environments. There is a significant increase in the magnitude of duration by 0.55 and 0.65 respectively across the two definitions of high/low interest rate environments. We also report bootstrapped p-values for the increase in duration using the same procedure described above. The rise in duration in the low rate environment is significant in terms of magnitude. For example, an increase of 0.55 implies that the equivalent of a one percentage point decline in the one-year rate leads to an additional 5.5 percentage point increase in firm valuation on average. Section 2.1 mentioned that the effect of interest rate shocks in a low rate environment may be larger due to convexity. But a second reason is that FOMC interest rate shocks are more impactful at the longer end of the yield curve due to "forward guidance", thus making these shocks more powerful.

The second row of Panel A reports the average dollar duration, $D^{\$}$, for low versus high interest rate periods. Dollar duration is measured in units of real 2019 dollars. As with simple duration, dollar duration also rises in the low interest rate environment. The magnitude of the increase is large once again. For example, a 10 basis point decline in the one-year rate in the high rate environment of 1994-2000 increased market value of the average firm by 54.9 million dollars in real terms. The same decline increased market value by 162 millions dollars in the low interest rate environment of 2013-2019, or an additional 107 million dollars.

Figure 2 plots duration estimates for more disaggregated time periods between 1994 and 2019. Since the duration estimates use variation in FOMC shocks over time, we need the time window to be sufficiently wide in order to estimate duration separately over a sub-period. Nonetheless, the evidence shows that the magnitude of duration progressively rises as the level of the interest rate continues to fall over our sample period.

Figure 2: Rolling Duration



This figures represents the estimate of mean $D^{\$}$ over the years. To avoid small-sample issues, we estimate the coefficient using a rolling window of five years. For instance, the coefficient of 1996 was calculated running the regression of Equation 2 between 1994 and 1998 for each company, and then taking the mean coefficient across all companies.

Does a fall in interest rate benefit larger firms more?

Section 2.1 showed that a priori it is not clear whether larger firms (by market value) necessarily benefit more from an interest rate decline. The net impact depends on two factors. First, whether larger firms are also high growth firms, and second whether larger firms benefit disproportionately from falling rates in terms of future cash flow growth. We can empirically test the dependence of firm-level duration on firm value by regressing firm-level duration on the percentile rank of firms by value. In particular, we estimate:

$$\widehat{D_i^T} = \alpha + m^T * X_i + \epsilon_i \tag{3}$$

where T denotes high/low interest rate time periods, X_i is percentile rank from zero to one by firm value, and m^T estimates the relationship between firm duration and firm size. The first row of Panel B of table 1 estimates (3) and shows a significant dependence of firm size on duration, with larger firms responding more strongly to a decline in interest rate. Moreover, the dependence on firm size gets stronger in low interest rate environment.

The second row of Panel B puts an additional control of mean window length (in minutes) used to construct a firm's stock market price reaction to 30-minute FOMC window. Since

Table 1: The Effect Of Interest Rate Shocks On Firm Value

	High Rate Period 1994-2008	**Low Rate Period** 2009-2019	**Difference**	**High Rate Period** 1994-2000	**Low Rate Period** 2013-2019	**Difference**
			Panel A: Average Firm Duration			
$\widehat{D}$	-0.67***	-1.22***	-0.55*	-0.58***	-1.23***	-0.65**
	(0.17)	(0.30)	[0.054]	(0.15)	(0.32)	[0.033]
$\widehat{D}^{\$}$	-37.89***	-110.41***	-72.51***	-54.91***	-161.86***	-106.94***
	(9.86)	(20.61)	[0.000]	(19.76)	(32.84)	[0.002]
N	3,597	2,184	1,412	1,465	1,599	517
			Panel B: Duration By Firm Size			
$\widehat{m}$	-0.55***	-0.77***	-0.21	-0.24**	-0.60***	-0.36*
	(0.12)	(0.17)	[0.156]	(0.14)	(0.23)	[0.073]
$\widehat{m}$ w/	-0.03	-0.50	-0.47	0.07	-0.46*	-0.52*
window control	(0.20)	(0.29)	[0.101]	(0.17)	(0.34)	[0.080]
			Panel C: Leader-Follower Dollar Duration Difference			
Overall Leader	-482.9***	-1,296.9***	-813.9***	-719.3***	-1,835.1***	-1,115.8**
	(117.3)	(245.9)	[0.001]	(288.1)	(374.7)	[0.013]
Within-Industry	-476.0***	-1,110.3***	-634.3***	-610.9***	-1,602.2***	-991.2**
Leader	(124.0)	(213.2)	[0.004]	(246.9)	(338.9)	[0.014]

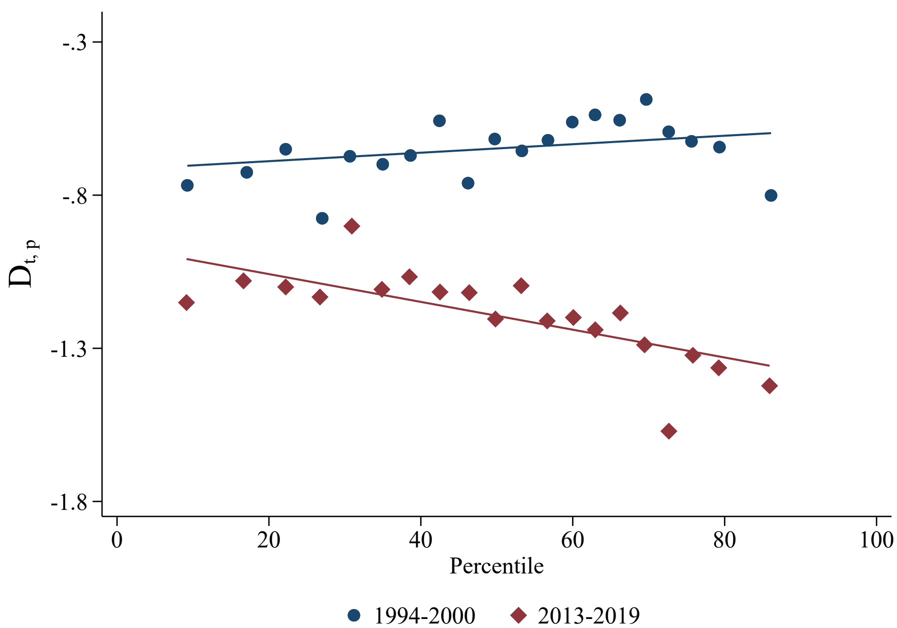
Standard errors in parentheses; P-values in square brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

larger firms are more liquid and trade more often, the exact length of trading window corresponding to the 30-minute FOMC window tends to be smaller than smaller firms. Thus there might be a spurious, e.g. liquidity spread related, reaction to FOMC shock that is included in the firm size percentile coefficient m^T. The second row of panel B shows that inclusion of window length removes the correlation of firm size with duration in high interest rate environment, but the correlation remains significant in the low interest rate environment.

More importantly, the increase in sensitivity to firm size in the low rate environment becomes even stronger. Moving from the lowest to the highest percentile of firm value increases a firm's value sensitivity to interest rate by 0.52 in the low interest rate environment of 2013-2019 relative to the high interest rate environment of 1994-2000. This is a large increase in sensitivity in terms of magnitude. For example, it implies that largest firms benefit by 5.2 percentage points more relative to smallest firms in response to a one percentage point interest rate decline.

Figure 3 plots the average firm duration against twenty 5-percentile bins by firm value for high and low interest rate environments respectively. The figure thus provides a graphical representation of the results summarized in second row of panel B of Table 1.[8] The figure further shows that the relationship between firm duration and size-percentile is linear as posited in the estimating equation earlier, and the slope of this relationship becomes steeper in the low interest rate period of 2013-2019. The key takeaway is the flat relationship between duration and firm size percentiles in the high interest rate environment, and the steep negative relationship in the low interest rate environment.

Figure 3: Duration for Percentiles



Note: results of mean $D_{t,p}$ for each percentile/period. Both the outcome and duration variables are residualized by the window size and then recentered using their unconditional mean for visualization purposes. What we refer by "window size" is the average time length between the last trade that happened 10 minutes before the FOMC and the first trade that happened 20 minutes after the FOMC.

The concentration of dollar-duration effect on top 5 percent

Figure 3 and Panel B of Table 1 show that duration, or the semi-elasticity of firm value with respect to the interest rate, rises with firm size. Since the firm size distribution is highly

[8]This is done after residualizing on mean window length of high frequency stock return, and then adding back the overall mean.

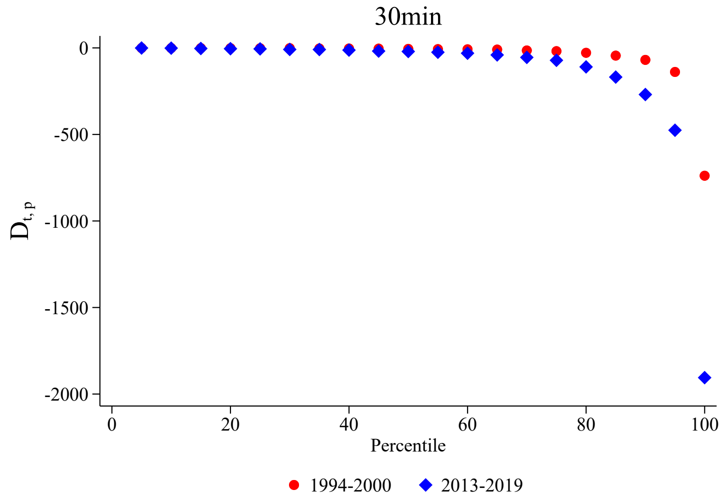
skewed, the increasing sensitivity of firm value in *proportional* terms means that in absolute terms large firms must be building a huge advantage with falling interest rates. For example, the top 5 and top 10 percent of firms represent 67% and 78% of total firm value respectively. The top 5 percent of firms are incredibly dominant in terms of value, and since these firms benefit even more in proportional terms from an interest rate decline, the dollar-weighted impact of an interest rate decline must be incredibly skewed toward these top firms.

Figure 4 plots the dollar duration estimates for the twenty five-percentile groups separately for the high rate environment (1994-2000) and the low rate environment (2013-2019). Dollar duration is measured in 2019 real dollars, and the y-axis represents the response to a one-unit change in ω_t which is normalized to 10 basis points change in the one-year treasury. The result shows how the dollar impact of interest rate change (in 2019 real dollar terms) is concentrated at the top end of the firm size distribution, *especially* in the low interest rate environment.

For example, during the high interest rate environment of 1994-2000, the average firm-value rise in dollar terms is only about a million dollars for firms in the lowest decile in response to a one unit increase in ω_t. The response to an interest rate decline rises gradually and gets to about 69 million dollars for firms between the 85th and 90th percentile. However, the dollar impact really balloons for the largest firms, reaching around 138 million dollars for firms in the 90th to 95th percentile, and a much larger 738 millions dollars for firms in the top 5 percent.

Similarly, we know from earlier results that the effect of interest rates on firms value is significantly stronger in the low rate environment. However, the rise in interest rate effect in dollar terms is also highly concentrated for top 5 percent of firms. For example, the effect of a one unit decline in ω_t rise from 738 million dollars during 1994-2000, to over 1.9 billion dollars for firms in the top 5 percent during the low interest rate environment of 2013-2019. The same increase in dollar terms is much more muted for smaller firms as is evident from figure 4.

Figure 4: Dollar Duration for Percentiles



Note: results of mean $D^{\$}_{t,p}$ for each percentile/period. $D^{\$}_{t,p}$ is measured in millions of 2019 dollars.

The very skewed nature of the dollar-weighted impact of interest rate decline on firm-value motivates the specification in Panel C of Table 1 that estimates dollar duration difference for top 5 percent firms in the market overall, and also within-industry separately. We shall refer to the top 5 percent of firms as either market or industry leaders. The results show that market leaders gain value by an additional 719 million dollars for a one unit decline in ω_t, relative to rest of the firms in the high interest rate environment of 1994-2000. This difference rises to an incredible 1.83 billion dollars in the low interest rate environment of 2013-2019, and the rise in difference is highly significant.

The important takeaways from the high frequency analysis of the stock market response to interest rate shocks are that, (a) larger firms are more strongly impacted in proportional terms, especially in a low interest rate environment, and (b) these effects are massively concentrated in the top 5 percent of firms in dollar terms. Since the absolute dollar size of the effect matters in terms of competition across firms in an industry, we focus on the top 5 percent, or industry leaders, versus the rest of firms in the analysis that follows. For example, gaining an additional billion dollars of firm value that a firm can potentially borrow against, is likely to be a lot more consequential for industry competition, than differences of a few million dollars.

3 Longer-run effect 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 motivation and empirical methodology for answering this question.

3.1 Falling interest rate and rising firm concentration

A natural implication of the high frequency analysis is that if larger firms benefit disproportionately from lower rates in a low interest rate environment, then these firms should become more dominant in the low interest rate environment. Table 2 shows that the aggregate evidence is consistent with this implication[9]. The table uses data on market share of top 4 and top 20 firms in an industry based on sales and employment from Autor et al. (2020)[10]. We also construct analogous market share by stock market value using data from Compustat.

Table 2 shows that the average federal funds rate decline from 5.6pp in 1994-2000 to only 0.8pp in 2013-2019, a decline of 4.8pp. The decline in interest rates was not limited to the short rate either, as 5-year treasury rate also declined from 6.1pp to 1.8pp, a decline of 4.3pp. Consistent with the high frequency empirical results, the shift downward in the yield curve is associated with a rise in market share held by the top 4 and top 20 firms. Market shares of the top 4 firms increased by 5.5, 3.9 and 9.0 percentage points for sales, employment and stock market value respectively across these two time periods. The results are similar for top 20 firms. Thus, the shift to the very low interest rate environment in the post-2008 era is associated with a significant rise in the market share of the largest firms - consistent with the high frequency results that falling rates disproportionately favor large firms in the low interest rate environment.

[9] It is important to note that this study does not seek to establish a causal relationship between the long-run decline in interest rates and the long-run rise in market power. Given the single times series of these two variables, establishing such a relationship in the long-run likely requires a model-based approach.

[10] The data is available in 5-year periods, and the first year that is also included in our sample is 1997. For the year windows that include more than one data point from Autor et al. (2020), we take the mean value across data points in that window. For instance, in 1994-2008, we take the mean of the data points in 1997, 2002, and 2007.

Table 2: Falling Interest Rates And Rising Firm Concentration

	High Rate Period 1994-2008	**Low Rate Period** 2009-2019	**Difference**	**High Rate Period** 1994-2000	**Low Rate Period** 2013-2019	**Difference**
Interest Rates:						
Fed Funds Rate	4.2	0.6	-3.6	5.6	0.8	-4.8
5Y Treasury Yield	4.9	1.7	-3.2	6.1	1.8	-4.3
Top 4 Share by:						
Sales	26.9	29.9	2.9	24.4	29.9	5.5
Employment	21.5	23.7	2.2	19.7	23.7	3.9
Market Value	53.7	59.3	5.6	50.2	59.3	9.0
Top 20 Share by:						
Sales	48.0	52.2	4.2	44.8	52.2	7.4
Employment	38.9	42.2	3.2	36.8	42.4	5.6
Market Value	83.8	87.6	3.8	81.5	87.9	6.3

Note: Data for interest rates comes from FRED, and data for concentration comes from Autor et al. (2020)

3.2 Constructing firm-level outcomes

In order to analyze the longer-term effects of interest rate changes on firms, we build a firm-level quarterly data set using the merged CRSP-Compustat data from 1994 to 2019 to coincide with the high frequency interest rate shocks ω_t. Starting from the full quarterly data set of US-incorporated public firms, we apply the following filters that are standard in the literature (e.g. Gutiérrez and Philippon (2017b) and Ottonello and Winberry (2020)).

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 .5 and 99.5 percentile and we linearly interpolate missing values of assets.

We measure a firm's cost of borrowing at the quarterly level by dividing interest expenses by the level of interest-bearing debt. In the analysis, a critical distinction will be between industry "leaders" and "followers". The baseline definition of industry leaders is according to size as measured by market value. A firm is classified as an industry leader if it is in the top 5 percent of firms in its respective Fama-French industry based on market value at the beginning of the period when outcomes are computed. 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.

3.3 Constructing interest rate shocks at quarterly frequency

Since firm outcomes are available at quarterly frequency, we need to translate the high frequency interest rate shocks ω_t to quarterly frequency as well. We follow the literature on this (see Ottonello and Winberry (2020) and Gertler and Karadi (2015)), and aggregate FOMC shocks (ω_t) over a quarter. This can be done in one of two ways. First, we can sum up the FOMC 30-minute high frequency shocks over a quarter. However, a second conceptually preferable approach is introduced by Gertler and Karadi (2015) who take the appropriate weighted average of FOMC shocks in a quarter since firms will be more exposed to FOMC shocks that happen earlier in the quarter. We follow the Gertler and Karadi (2015) procedure, and adjust firm-level outcomes accordingly as well. Nonetheless, all of our results are materially unaffected if we take the unadjusted approach and simply sum FOMC shocks over a quarter. We continue to refer to the quarterly interest rate shock as ω_t, with t referencing the quarter of the shock constructed.

We first test if the FOMC news-based quarterly ω_t shock impacts firms borrowing cost. A priori there is good reason to believe this would be the case, since almost all 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. Our firm-level borrowing cost measure correlates very well with measures of firm financial strength as shown in Table 3. For example, industry leaders pay 171 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 earning, and higher rating pay lower rates (columns (4) - (8)).[11]

Figure 5 estimates the impulse response function for the average (debt-weighted) 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 33 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.

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 are due to a “news” effect as in Nakamura and Steinsson (2018) or an updating of the Fed reaction function

[11] 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.

Table 3: Borrowing Cost

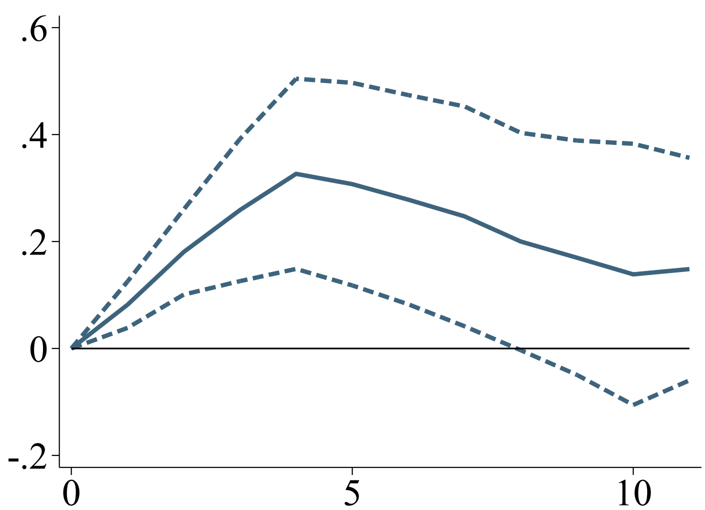
	(1) Leader	(2) Market Value	(3) Leverage	(4) P/E	(5) ICR	(6) Distance to Default	(7) Earnings / Assets	(8) S&P Ratings
X	-1.71***	-0.40***	1.37***	-0.72***	-0.13***	-0.17***	-8.09***	1.02***
	(0.082)	(0.013)	(0.12)	(0.074)	(0.0032)	(0.012)	(0.63)	(0.031)
N	231,859	238,736	240,341	179,772	176,426	109,084	225,731	76,177
R-sq	0.138	0.183	0.125	0.158	0.253	0.127	0.144	0.360

Standard errors in parentheses

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

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 indicate quarter fixed effects and $x_{i,t}$ is the variable we want to check the relation with borrowing cost. P/E estimates are multiplied by 100 for visualization purposes.

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



The figure shows the impulse response function of borrowing cost to 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 create biases due to firms entering/leaving the sample. Standard Errors are clustered at quarter level.

as in Bauer and Swanson (2022). The goal of the analysis here is to exploit the change in interest rates around Fed meetings no matter what 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 was not a concern for section 2 since it used high frequency stock return outcomes on the left hand side as well, but when running quarterly impulse responses, we want to make sure that some prior news is not differentially impacting outcomes for leaders versus followers. We conduct a number of tests in Section 6.1 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 borrowers versus leaders is due to changes in interest rates around the Fed meetings, and not due to differences in macroeconomic news that occur before the meetings.

Table 4 provides summary statistics for the firm-level panel data. We report summary statistics for a firm's borrowing cost, quarterly stock returns, assets, revenue, capital expenditures, acquisitions, debt, and leverage. Variable construction for each of these variables in Compustat sample is described in Table 4'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 4.6 basis point change in the 1-year zero coupon T-bill.

3.4 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,

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

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 $t+h-1$, $L_{i,j,t-1}$ is an indicator variable equal to 1 if firm i is an industry leader in the top 5% of market capitalization in its industry j at date $t-1$, 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 3.3, $z_{i,j,t} = \{L_{i,j,t-1}, L_{i,j,t-1} * FFR_{t-1}\}$ is a vector of market leadership controls while $\theta_{i,j,t-l} = \{\Delta y_{i,t-l}, \omega_{t-l} * L_{i,t-l-1}, \omega_{t-l} * L_{i,t-l-1} * FFR_{t-l}, z_{i,t-l}\}$ is a vector containing lagged values of all variables in the system. We also control for industry-time fixed effects $\alpha^h_{j,t}$, which removes

Table 4: Summary Statistics of Main Variables

	N	Mean	SD	p25	p50	p75
Borrowing Cost	239,918	7.24	3.35	5.05	6.89	8.91
Assets	379,739	2,974.39	16,221.91	52.49	236.41	1,179.48
Property Plant and Equipment	378,791	1,026.90	5,537.62	5.95	40.19	287.98
Revenue	378,545	601.80	3,017.20	10.81	56.76	269.87
Capital Expenditure	310,242	6.62	14.85	1.83	3.86	7.64
Acquisitions Expenditure	296,026	3.75	14.07	0.00	0.00	1.61
Debt	362,764	932.50	6,702.77	1.19	25.27	313.02
Leverage	362,717	23.32	23.26	2.43	19.08	36.10
MP shock	104	-0.00	0.46	-0.12	0.09	0.23

Notes: This table reports summary statistics for our main variables. Borrowing Costs 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 Acquisition Expenditure is the sum of Capital Expenditure (capxy) over 4 quarters divided by its lagged assets (atq). Acquisition Expenditure is the sum of funds destined to companies acquisitions (acqy) over 4 quarters 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 Costs, Leverage, Acquisition Expenditure, and Capital Acquisition 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 GSS, and was rescaled to have an instatenous unit impact of 10 bps on the 1-year zero-coupon treasury. We follow the procedure of Gertler and Karadi (2015) to aggregate ω at quarterly level.

all cross-industry variation.

Regarding standard errors, Olea and Plagborg-Møller (2020) 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). 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. (2022).

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^h_{ZLB} and β^h_{Δ}. This can be seen by comparing estimated equation (4) for industry leaders (with $L_{i,j,t-1} = 1$) versus industry followers (with $L_{i,j,t-1} = 0$). The differential response to interest rate shock ω_t for leaders versus followers can be written as:

$$\beta^h_{ZLB} * \omega_t + \beta^h_{\Delta} * \omega_t * FFR_{t-1} \tag{5}$$

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}.

The empirical model in (5) has an interesting implication. Let us fix the outcome variable to be investment as an example, and suppose there is a negative shock to interest rates (ω_t) starting from a very low level of interest rates, approximated by $FFR_{t-1} = 0$. The model postulates that β^h_{ZLB} will be negative, and therefore a negative shock to interest rates close to the zero lower bound will lead to a positive relative increase in investment for leaders relative to followers.

However, suppose instead there is a negative shock to interest rates starting from a high level of the lagged interest rate FFR_{t-1}. In this case, the effect of the negative shock is captured by both β^h_{ZLB} and β^h_{Δ}. The model postulates that if β^h_{Δ} is positive, which our high frequency results suggest is the case, then the relative increase in investment for a leader versus a follower after a negative interest rate shock will be mitigated when the initial interest rate is high. At a high enough initial interest rate, the total effect of a negative shock to interest rates on leader versus follower investment may reverse, with the follower seeing a larger increase in investment after a negative interest rate shock.

In general, equation (5) implies that when the level of interest rate is r, the relative impact of interest rate change on lender versus follower is $(\beta_{ZLB} + r * \beta_{\Delta})$. We can hence define the level of interest rate that is "competition-neutral" by setting this expression equal to zero. The competition-neutral rate is the interest rate at which a change in interest rate has the same effect for both industry leaders and followers. We estimate this neutral level of interest rate in Section 5.

4 Empirical Results

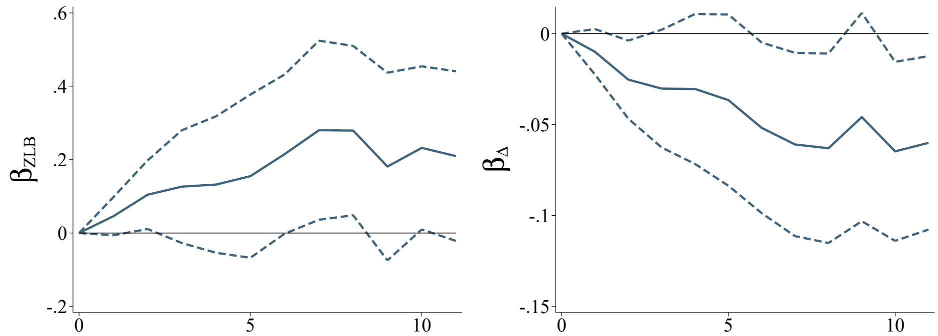
This section reports results from estimating Equation (4) for a range of firm-level outcome variables. We estimate local projections at horizon of up to 11 quarters after a shock and plot the main coefficients of interest, β^h_{ZLB} and β^h_{Δ} with their 95 % confidence bands.

4.1 Firm Cost of Capital

How does a decline in interest rates affect the cost of capital for industry leaders versus followers? Figure 6 reports coefficients β^h_{ZLB} and β^h_{Δ} from estimating 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[12], a decline in the interest rate favors industry leaders more by lowering their borrowing cost more than industry followers. A 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 patter to be consistently repeated for all firm outcomes.

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

Figure 6: Response of Borrowing Cost to interest rate shocks



Note: estimation of Equation 4 for borrowing costs from h = 1 to h = 12. Outcome variables are defined in Table 4. Standard Errors are clustered at quarter level.

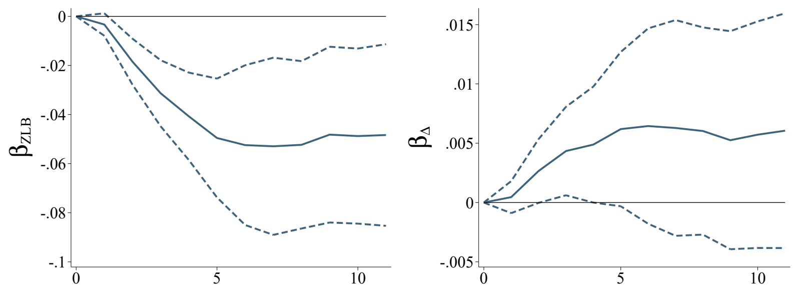
In terms of magnitude, a decline in the interest rate by 10 basis points near ZLB leads to a 28 basis point relative decline in the borrowing cost faced by leaders versus followers two years later. The point estimate for β_Δ eight quarters out is about -0.06. This implies that the differential decline in the leaders' borrowing cost advantage for a 10 basis points negative interest rate shock at the zero lower bound shrinks by about forty percent when the level of the interest rate 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 Section 5.

4.2 Firm Growth

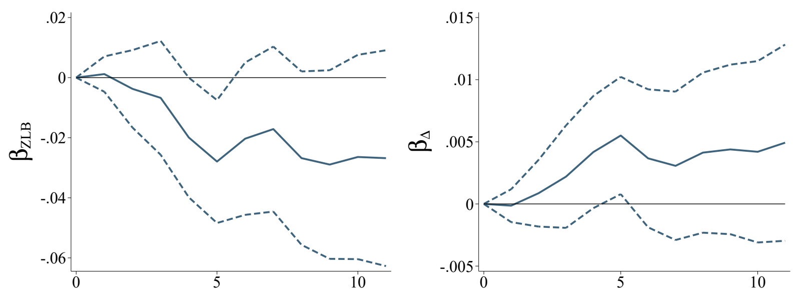
Figure 7 plots β^h_{ZLB} and β^h_Δ from equation (4) with measures of firm growth - assets size and sales revenue - as outcome variables. The results show that a decline in interest rates leads to a relative increase in firm size and firm revenue for leaders versus followers when the initial Federal Funds rate is near zero, and this relative increase gets diminished in higher interest rate environments.

Figure 7: Response of firm growth to interest rate shocks

(a) Assets



(b) Revenue



Note: estimation of Equation 4 for assets and revenue from h = 1 to h = 12. Outcome variables are defined in Table 4. Standard Errors are clustered at quarter level.

In terms of magnitude, a 10 basis point decline in interest rates near ZLB leads to about 3 to 5 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 when the federal funds rate is 2% instead of 0%.

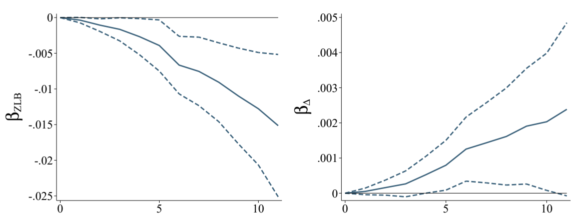
4.3 Firm Investment and Acquisitions

Figure 8 plots β^h_{ZLB} and β^h_Δ from equation (4) with property, plant and equipment (PPE), capital expenditure (CAPX), and acquisitions as outcome variables. The outcomes variable 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.

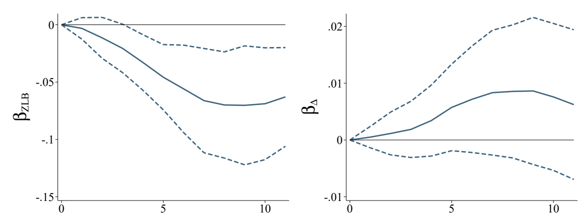
The cumulative Capital and Acquisitions Expenditures for leaders is 0.9pp and 0.7pp larger than for followers at the ZLB after eight quarters. The stronger effect for industry leaders is diminished at higher interest rates, with the relative impact on capital expenditure dropping by about one-third when the level of federal funds rate is 2%, and the relative impact on acquisitions dropping by about one-half.

Figure 8: Response of firm investment and acquisitions to interest rate shocks

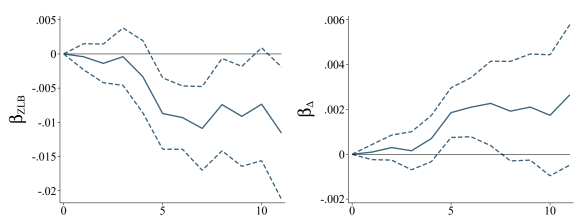
(a) CAPX



(b) PPE



(c) Acquisitions



Note: estimation of Equation 4 for capital expenditures, PPE, and acquisitions from h = 1 to h = 12. Outcome variables are defined in Table 4. Standard Errors are clustered at quarter level.

4.4 Firm Financing

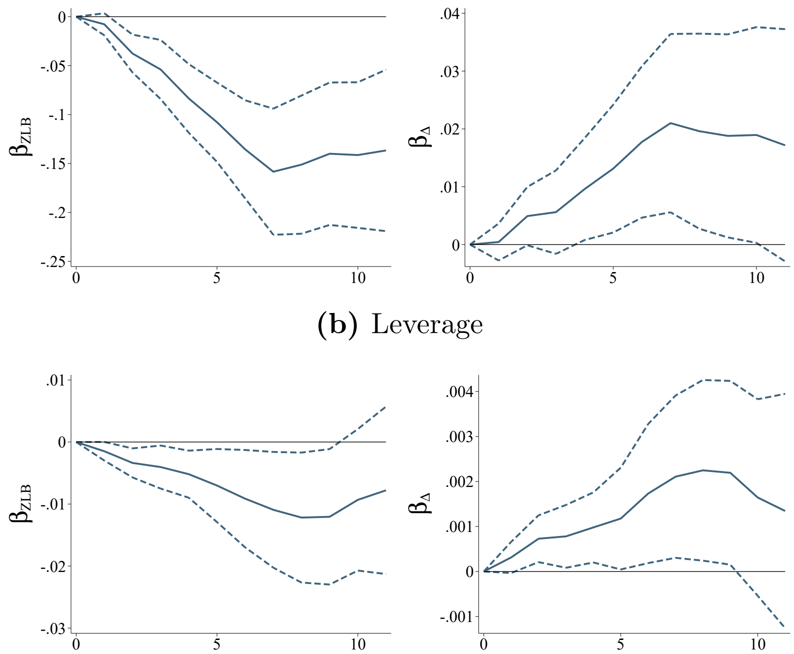
Figure 9 plots β^h_{ZLB} and β^h_Δ from equation (4) with total debt and firm leverage as outcome variables. These variables measure how the interest rate shock affects firms' external financing. We have already seen that a fall in interest rate disproportionately lowers borrowing cost for industry leaders, 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 15pp rise in the stock of debt two years out for industry leaders versus followers at the BLB. 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 roughly when federal

Figure 9: Response of Debt and Leverage to interest rate shocks

(a) Debt

(b) Leverage



Note: estimation of Equation 4 for debt and leverage from h = 1 to h = 12. Outcome variables are defined in Table 4. Standard Errors are clustered at quarter level.

funds rate rises by 2pp. Overall, the results on firm borrowing and leverage are also consistent with the recent work of Chatterjee and Eyigungor (2020), 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.

4.5 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, but we enumerate the robustness checks here. First, we show robustness to alternative definitions of shock ω, including using just the federal funds rate or the component orthogonal to federal funds. 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. We also show robustness to alternative window length around FOMC, and dropping unscheduled FOMC meetings. Section 6 performs additional tests relating to potential identification concerns with estimating equation (4).

5 The Competition-Neutral Rate

The mitigation of the advantage that leaders receive from a decline in interest rates in a high rate environment across a range of firm outcomes suggests the notion of a "competition-neutral rate", or an economy-wide interest rate level at which the change in the interest rate is neutral from a competition perspective. When the economy is operating at the competition-neutral rate, a change in the interest rate has the same effect for both industry leaders and followers.

The empirical results in this paper suggest the possibility of a neutral rate that balances the level of competition between industry leaders and followers. This opens up interesting questions for future work. For example, if the traditional natural rate of interest does not coincide with the competition-neutral rate of interest, there is a natural trade-off to explore when evaluating monetary, fiscal, and other macroeconomic policies.

Let η be the competition-neutral nominal rate of interest. We can estimate η in our empirical framework as:

$$\eta = -\frac{\beta_{ZLB}}{\beta_{\Delta}}. \tag{6}$$

When the economy-wide interest rate is η, the effect of a change in interest rate is equal for both industry leaders and followers. We next discuss how η can be estimated for each firm-level outcome, and how these different estimates of η can be combined together to give us the implied economy-wide estimate of the competition-neutral rate.

5.1 Individual Estimates of Competition-Neutral Rate

We use equation (6) and the two year out (i.e. at $h = 8$) estimates of β_{ZLB} and β_{Δ} in section 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 $[\hat{\beta}_{ZLB}, \hat{\beta}_{\Delta}]$.

Panel A of Table 5 reports the eight 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 3.85 percentage points in the case of Acquisition Expenditures as the dependent variable, to 8.68 percentage points with Assets as the dependent variable.

While this is a large range, it is important to realize that specifications with smaller point estimates (columns 1, 5, 6 and 8) are much more precisely estimated than remaining specifications that have higher point estimates. We therefore need a formal procedure for appropriately averaging these estimates in order to come up with an efficient estimate of the economy-side competition-neutral rate. The procedure should naturally take into account the standard error of each of the eight estimates, as well as the correlation between each estimate. For example, if two firm-level outcomes are highly correlated, then their respective $\hat{\eta}$ estimates should not treated as independent.

Table 5: Neutral rate $\hat{\eta}$ estimate for each outcome variable

Panel A: Estimates of the Neutral Rate								
	Borrowing Cost	Assets	Revenue	PPE	Capital Exp	Acquisition Exp	Debt	Leverage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{\eta}$	4.43***	8.68**	6.49**	8.17**	5.61***	3.85**	7.71***	5.42***
	(1.03)	(4.31)	(2.57)	(3.71)	(1.64)	(1.75)	(1.91)	(0.74)
N	135,095	252,249	244,239	250,235	232,490	214,512	177,373	234,690

Panel B: Combining estimates of neutral rate			
	(1)	(2)	(3)
	Baseline	Common Sample	Vector Regression
$\bar{\hat{\eta}}$	4.82***	4.95***	5.21***
	(0.47)	(0.45)	(0.40)
N	262,901	120,444	120,444

Standard errors in parentheses

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

This table reports estimates of the neutral interest rate implied from the 8-quarters ahead estimates. The neutral rate η is an estimate of 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 $\hat{\eta} = -\frac{\beta_{ZLB}}{\beta_{\Delta}}$. The combined estimates given in panel B are the weighted average of the estimates in panel A, with weights chosen to minimize the variance of the combined estimator $\bar{\hat{\eta}} = \sum w_k \hat{\eta}_k$. Standard errors of this estimate are calculated according to the delta method.

5.2 Economy-wide Estimate of Competition-Neutral Rate

The efficient estimation of economy-wide competition-neutral rate optimally weighs each individual estimate such that the variance of the economy-wide estimate is minimized. Formally, let R be the $G \times 1$ vector of the individual neutral rate estimates and let Ω be the associated $G \times G$ covariance matrix. Taking these quantities as given for the moment, the variance of the weighted average is given by $w'\Omega w$, where w is the $G \times 1$ vector of weights. Thus, the optimal weights solve the following problem:

$$\min_{w} w'\Omega w \qquad \text{s.t.} \qquad w'\mathbf{1_k} = 1 \tag{7}$$

where $\mathbf{1_k}$ is a $G \times 1$ vector of ones. This problem is identical to a minimum variance portfolio problem with variance-covariance matrix Ω.

The set of weights w^* that minimise the variance of the weighted average and jointly sum to one are given by the solution to the following system:

$$\begin{bmatrix} 2\Omega & 1 \\ \mathbf{1_k}' & 0 \end{bmatrix} \begin{bmatrix} w \\ \lambda \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{8}$$

To carry out this procedure, we first obtain estimates of Ω, the covariance matrix for our estimates of the competition-neutral rate for various firm outcomes. The delta method outlined above gives us estimates of the variance of each estimator, that is, the diagonal entries of Ω. If the samples used to estimate each equation were distinct, we could assume independence and thus that Ω is diagonal. However our eight estimates come from highly correlated variables in the same sample. We must therefore account for this by estimating the covariance between our distinct estimates of the competition neutral rate.

We obtain estimates of the covariance of coefficients across models using the seemingly unrelated regression (SUR) approach introduced by Zellner (1962). We use this method to calculate the covariance matrix of the entire set of regressors across all models and then apply a multivariate version of the delta method to obtain the covariance matrix Ω of the G neutral rate estimates. In turn, we obtain the optimal weights w^* from solving the system of equations in (8) and can construct the joint estimate $\bar{\hat{\eta}} = R'w^*$.

For the SUR model, we proceed as follows. In general terms, one can express the full model for a sample of N observations and G individual models, the seemingly unrelated regressions. Each individual model features K_g regressors and let $K = \sum_g K_g$. Letting $y_{i,g}$ denote the dependent variable and $x_{i,g}$ the vector of independent variables of equation $g \in \{1, ..., G\}$ we can write the full model as the following system of equations:

$$\begin{bmatrix} y_{i,1} \\ \vdots \\ y_{i,G} \end{bmatrix} = \begin{bmatrix} x_{i,1} & 0 & \dots & 0 \\ 0 & x_{i,2} & & \vdots \\ \vdots & & & 0 \\ 0 & \dots & 0 & x_{i,G} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_G \end{bmatrix} + \begin{bmatrix} u_{i,1} \\ \vdots \\ u_{i,G} \end{bmatrix} \tag{9}$$

In our case, $G = 8$. $x_{i,g}$ contains the double and triple interaction terms as well as the lag augmented variables and the time-industry fixed effects. β_g contains $\beta_{ZLB,g}$ and $\beta_{\Delta,g}$ and the coefficients on the other regressors.

More compactly, we can write the system as $Y_i = \beta X_i + U_i$ and after stacking the observations in a matrix, we can in turn express the entire model as:

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{U}$$

where $\boldsymbol{Y} = (Y_1, ..., Y_N)'$ is an $NG \times 1$ vector and $\boldsymbol{X} = (X_1, ..., X_N)'$ is an $NG \times K$ matrix. We can estimate this system by OLS, with the estimate being given by $\hat{\boldsymbol{\beta}} = (\boldsymbol{X'X})^{-1}(\boldsymbol{X'Y})$. These estimates are numerically equivalent to equation by equation OLS estimation of $\hat{\beta}_g$. The covariance matrix of these estimates, $\boldsymbol{\beta}$, can be estimated consistently as $V(\hat{\boldsymbol{\beta}}) = (\boldsymbol{X'X})^{-1}(\sum_i X_i'\hat{U}_i\hat{U_i'}X_i)^{-1}(\boldsymbol{X'X})^{-1}$. The final step consists of applying the multivariate delta-method to obtain the variance-covariance matrix of $\bar{\bar{\eta}}$, $V(\bar{\bar{\eta}})$. Combining everything, we obtain the optimal weights w^* and can use those to construct the single estimate of the neutral rate $\bar{\bar{\eta}}$, which we report in Panel B of Table 5.

We perform three variations of this exercise. First, we use the baseline regressions in equation (4) to obtain a single estimate of the neutral rate (using the two-year out coefficients). These regressions feature overlapping but distinct samples. When an observation is used in model g but is missing in model h, we can just set its weight to zero when calculating the covariance between coefficients in g and h. Hence, if all models were estimated on mutually exclusive samples, the covariance matrix Ω would be diagonal.

Second, we estimate $\bar{\bar{\eta}}$ only from the common sample of observations for which we observe all 8 outcome variables. This ensures that our estimate is not driven by those observations which only enter the estimation for some of the outcome variables. Third, we estimate a version of the SUR where we not only use a common sample but also modify the baseline equation (4) to include the same explanatory variables for all observations. So we include lags of all eight independent variables in each equation when lag-augmenting the regressions. One can interpret the common sample version of the SUR model as a version of the vector regression with zero sign restrictions on the lags of the dependent variable, other than dependent variable of equation g.

Panel B of Table 5 contains our economy-wide estimates of η. The baseline estimate using all available observations in column (1) gives us an economy-wide competition-neutral rate of 4.82 percentage points. This is in the lower range of the individual estimates in Panel A, consistent with the earlier intuition that the lower point estimates in Panel A are more precisely estimated and are therefore more informative.

Columns (2) and (3) use only the common sample and the competition-neutral interest rate is estimated to be 4.95 to 5.21. Overall, these exercises suggest an economy-wide competition-neutral rate of around 5 percentage points over our sample period. Below that rate, a fall in the interest rate benefits leaders more than follower, and the differential benefit grows as the economy-wide nominal interest rate gets closer to zero.

6 Testing for Identification Concerns

This section presents tests to address three identification concerns with the analysis: (1) the predictability of monetary policy shocks shown in Bauer and Swanson (2022), (2) a concern that a spurious time-trend may be responsible for the results, and (3) a concern that the leader indicator variable at the firm level happens to be spuriously correlated with certain firm-level attributes that are the fundamental drivers of the results.

6.1 Macroeconomic News and Predictability

The identification strategy used in the quarterly firm-level analysis compares the differential effect of interest rate shocks on industry borrowers 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.

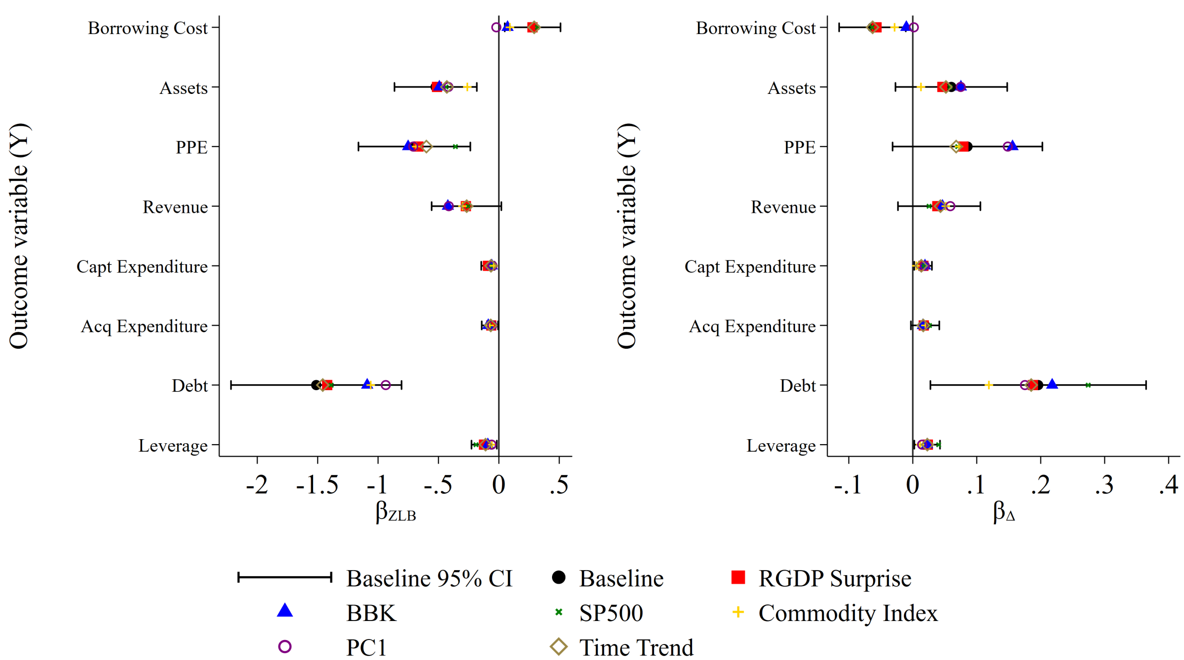
There are two tests that mitigate this concern. First, as Bauer and Swanson (2022) show, the concern regarding spurious news effect goes away if one looks at high frequency stock market response, and we have already done that in section 2.

Second, if the concern is that macroeconomic news has a differential effect on borrowers versus leaders, 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 first replicate the analysis in Bauer and Swanson (2022) that shows that interest rate shocks can be predicted with macroeconomic news that occurs before the Fed meeting. In this replication exercise, we find in univariate tests that there are four macroeconomic news 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.[13] 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 (2022) specification.

The results are shown in Figure 10. 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 almost all of the outcome variables, the estimates from a specification using the control variables lies within the 95% confidence interval of the original estimate.

Figure 10: Robustness to macro news and time trend



The left panel of these figures plots estimates of β^8_{ZLB}, while the right panel plots estimates of β^8_{Δ}, estimated from the local projection $\Delta y_{i,j,t+8-1} = \alpha^8_{j,t} + \beta^8_{ZLB}(\omega_t * L_{i,t-1}) + \beta^8_{\Delta}(\omega_t * L_{i,t-1} * FFR_{t-1}) + \gamma^8_{ZLB}(n_t * L_{i,t-1}) + \gamma^8_{\Delta}(n_t * L_{i,t-1} * FFR_{t-1}) + \delta'_8 z_{i,t} + \sum_{\ell=1}^{3} \Gamma'_8 \theta_{i,t-\ell} + \epsilon_{i,t+h-1}$, where n_t is a news control and y is the outcome.

[13] Please see Bauer and Swanson (2022) for more details on these macroeconomic news variables.

6.2 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 10 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 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.

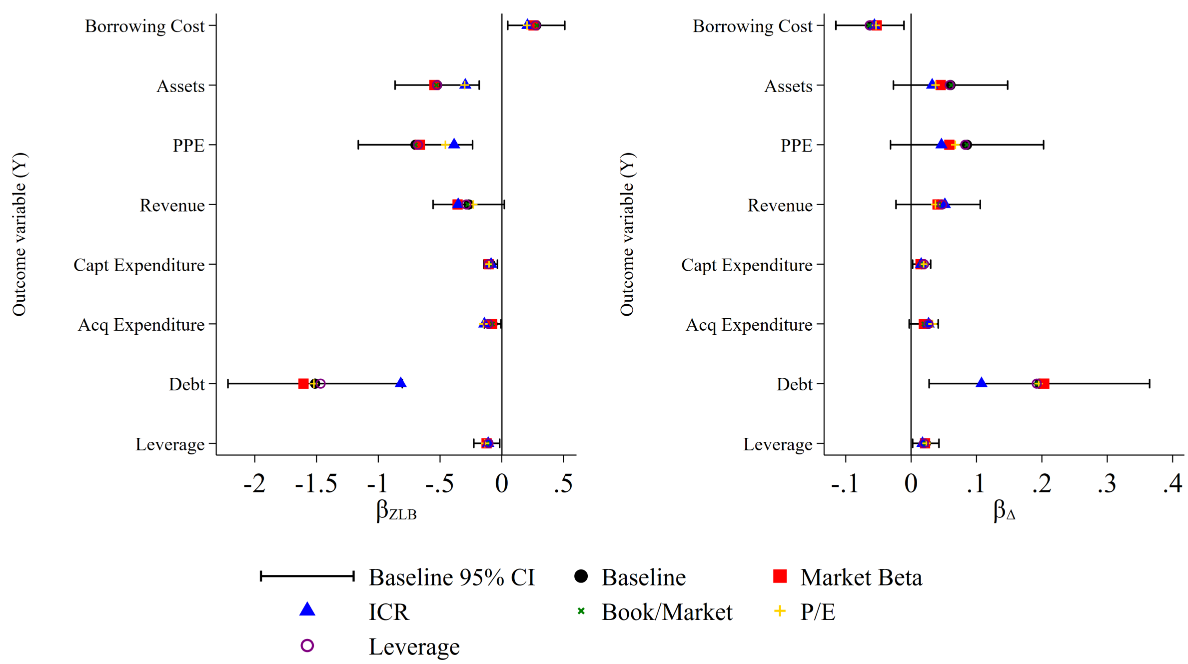
6.3 Firm-level Controls

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 $L_{i,j,t-1}$. The black dot in Figure 11 indicates the baseline estimate for the 8 quarter ahead local projection estimate for β_{ZLB} or β_{Δ} respectively, along with their 95% confidence interval.

Figure 11 then reports how the estimates of β_{ZLB} and β_{Δ} change when adding a specific firm-level controls $x_{i,t-1}$ by a) itself, (b) interacting it with the interest rate shock, (c) with the initial level interest rate, and (d) with 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.

One concern is that leaders and followers differ by their sensitivity to the market. Industry-time fixed effects absorb differences in cross-industry differences in sensitivity to market beta but within-industry differences remain. The first robustness check controls for firms' market beta. 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.

Figure 11: Robustness to various firm-level controls



The left panel of these figures plots estimates of β^8_{ZLB}, while the right panel plots estimates of β^8_{Δ}, estimated from the local projection $\Delta y_{i,j,t+8-1} = \alpha^8_{j,t} + \beta^8_{ZLB}(\omega_t * L_{i,t-1}) + \beta^8_{\Delta}(\omega_t * L_{i,t-1} * FFR_{t-1}) + \gamma^8(x_{i,t-1}) + \gamma^8_{ZLB}(\omega_t * x_{i,t-1}) + \gamma^8_{FFR}(x_{i,t-1} * FFR_{t-1}) + \gamma^8_{\Delta}(\omega_t * x_{i,t-1} * FFR_{t-1}) + \delta_8' z_{i,t} + \sum_{\ell=1}^{3} \Gamma_8' \theta_{i,t-\ell} + \epsilon_{i,t+h-1}$, where $x_{i,t}$ is a firm level control and y is the outcome. Sample sizes vary depending on the control variable x included. The range of sample sizes are given by (144,373-261,756) for Market Beta, (108,191-124,274) for ICR, (144,853-262,396) for Book to market ratio, (112,485-174,047) for price to earnings ratio, and (145,029-250,167) for leverage.

Next, a control for the book-to-market ratio is added (green crosses in Figure 11). 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.

Given that changes in interest rates affect the present value of discounted cash flows, differences in the duration of leaders' and followers' cash flows could partly be driving our results. In particular, if leaders have longer duration cash flows, they would be more sensitive to the same interest change as compared to followers. We use a firm's price-to-earnings ratio as a proxy for the duration of cash flows, with the idea that a higher price-to-earnings ratio implies a longer duration of cash flows. The yellow crosses in Figure 11 indicate that the point estimates when controlling for the price-to-earnings ratio interacted with the interest rate shock do not meaningfully change. Differences in the duration of cash flows are unlikely to be driving the baseline results.

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. All point estimates lie within the baseline 95% confidence band and, except for PPE and assets, there is little difference in the baseline point estimate.

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 11 show that most point estimates are very similar to the baseline estimates. Results are quantitatively slightly smaller for PPE, assets, 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. It should also be kept in mind when considering candidates for firm-level controls that we do not control for firm attributes that are potentially endogenous according to the current theory literature. For example, an interest rate decline in a low rate environment endogenously makes market followers weaker as they cannot compete as well with industry leaders as before. In this sense, one would not want to "over control" with firm level controls in the regression specification.

7 Conclusion

Using high frequency interest rate shocks and stock market response, as well as response of firm outcomes over the longer run from 1994 to 2019, we find that a decline in the interest rate disproportionately benefits industry leaders relative to industry followers. Industry 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.

These results suggest that there is a "competition-neutral" level of interest rate, at which the effect of an interest rate change is the same for both industry leaders and followers. We formally estimate the competition-neutral nominal federal funds rate to be 4.82 percentage points over 1994 to 2019 period when average inflation was 2.2 percentage points. 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 basic empirical facts documented in this paper open some interesting questions for further investigation. What are the deeper factors that make industry leaders benefit from a very low rate environment? We offered some suggestions in the theoretical section, but clearly there may be other useful avenues to explore.

Our results also open up a more fundamental question. What if the competition-neutral rate is significantly different from the natural rate of interest? While it is only natural for monetary policy to move toward the natural rate of interest, one may need to combine monetary policy with other policies such as anti-trust policy to mitigate the potentially negative effects on competition.

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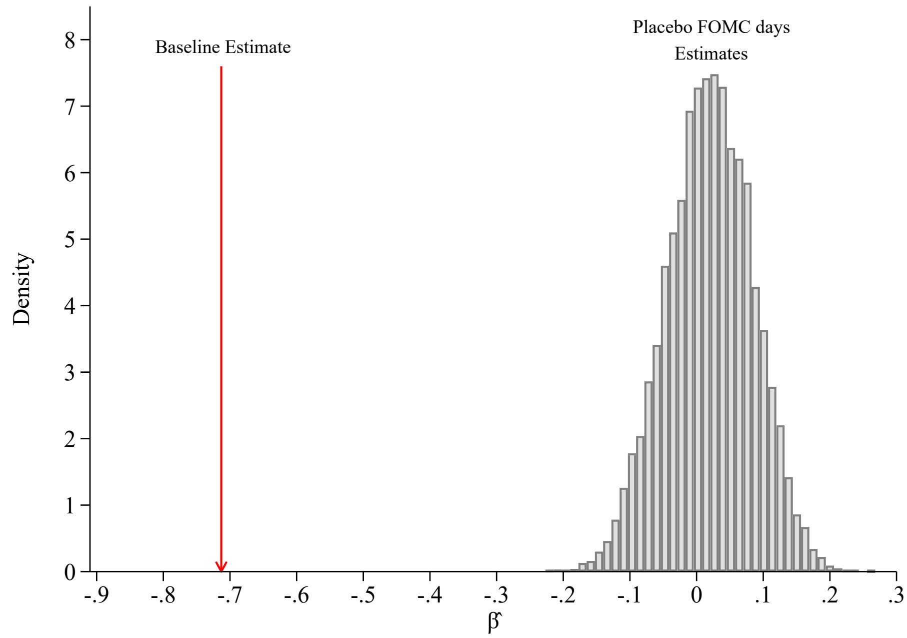
A Online Appendix

A.1 Placebo duration estimates

Figure A.1 shows the average duration effect with a red arrow, and also shows the distribution of results from a run of placebo tests on non-FOMC days to show that our main effect is not driven spuriously. The placebo distribution is constructed as follows. For each FOMC date, 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 compute average duration using the placebo day 30-minute high frequency stock return for each firm. This procedure is bootstrapped many times, with the resulting distribution of average duration shown in figure A.1.

Figure A.1: Placebo Baseline



A.2 Further Robustness Checks

In this last subsection, we provide a battery of additional robustness checks. First, we show that our results are robust to alternative definitions of our leader variable. Second, we exclude unscheduled FOMC meetings from our policy news shocks time series. Third, we run a specification with the dependent variable in levels - instead of changes. And finally, we show that our results do not depend on the length of the monetary policy time window used in the high-frequency identification procedure.

A.2.1 Alternative Leader 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 do three alternative sortings and show that they do not materially affect results.

First, 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, the top 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.2 reports results for the top 4 measure. Most point estimates (the solid blue line) are very similar to the baseline point estimates (solid black line). For several variables (Assets, PPE, capital expenditures, acquisitions, stock returns), the point estimates are close to identical. One notable exception are the responses of leverage, which turn statistically insignificant and where the point estimates also become economically smaller.

Second, 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.3 reports results for leaders classified within 2-digit SIC industries. Point estimates in panels c) to h) of Figure A.3 are almost identical to the baseline estimates and retain high statistical significance. Results for borrowing costs and debt (Panels a) and b)) are significant but economically smaller in magnitude.

Third, 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. One exception is β_{Δ} for PPE as the dependent variable, which becomes economically and statistically close to zero. Yet, for capital expenditures, another measure of investment, we still find a large and significant snowballing effect as the level of the interest rate is falling.

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

A.2.2 Excluding Unscheduled Meetings

In our next robustness check, we exclude unscheduled FOMC meetings since those meetings may be in response to other confounding shocks. In our sample period, there are 11 unscheduled meetings.[14]

Figure A.5 reports the results for the policy news shock ω. The point estimates are almost identical in most cases. In particular, all results exhibit a statistically significant snowballing effect. Interestingly, the results for stock returns strengthen once we exclude the unscheduled meetings. Both the zero-lower bound and the the snowballing effect are stronger, highlighting that using only regularly scheduled meetings already contains substantial unanticipated information that affects leaders' returns relative to followers.

A.2.3 Levels Specification

A further robustness check in Figure A.6 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.6.

For borrowing costs, debt and leverage (Panels a-c), we obtain very similar results as in our baseline specification. The evidence for the snowballing effect β_Δ is slightly weaker for assets and PPE. However, panel data regressions in levels, especially in panels with relatively short time dimension, are subject to concerns about the Nickell (1981) bias. The lagged dependent variables that we include as regressors introduce correlation between the error term and the mean dependent variable that is captured by the fixed effect, hence producing inconsistent estimates.

A.2.4 Time Window for Federal Funds Shock

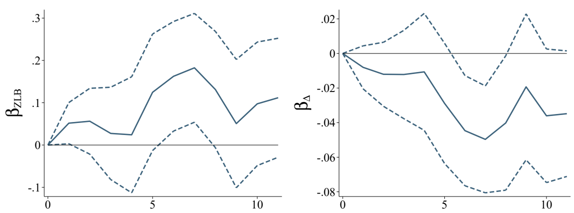
In our last robustness check, we investigate how sensitive our results are with respect to the definition of the time window for shocks to the Federal Funds rate. The identifying assumption for monetary policy shocks identified directly from movements in Fed Funds Futures is that no other macroeconomic 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.

[14] The unscheduled meetings are on 04/18/1994, 10/15/1998, 01/03/2001, 04/18/2001, 09/17/2001, 08/10/2007, 08/17/2007, 01/22/2008, 03/11/2008, 10/08/2008, 10/11/2019

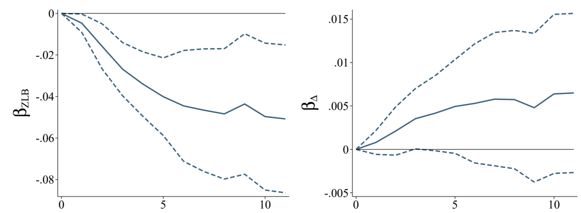
Figure A.7 re-estimates our main specification for our ω shocks but instead of constructing it over a 30-minute time window, the shock in Figure A.7 is identified over a 60 minute time window (-15 minutes to +45 minutes around the FOMC announcement). All our results are fully robust to this alternative definition.

Figure A.2: Robustness: Leader Top 4

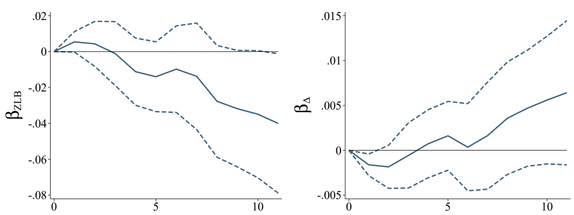
(a) Borrowing Cost



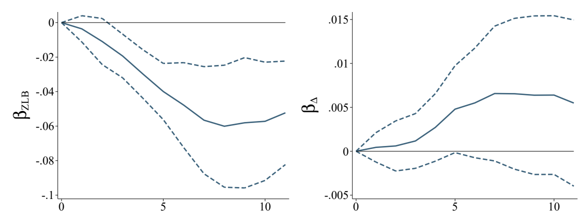
(b) Assets



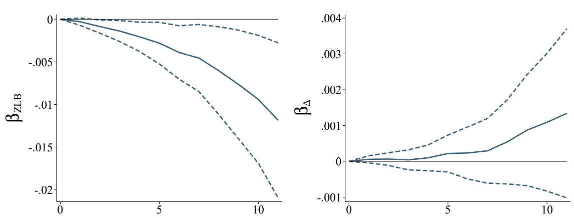
(c) Revenue



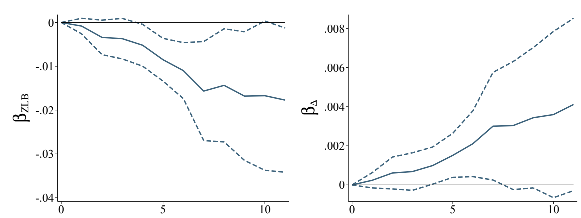
(d) PPE



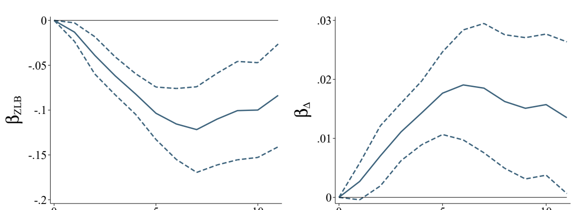
(e) Capital Expenditures



(f) Acquisition Expenditures



(g) Debt



(h) Leverage

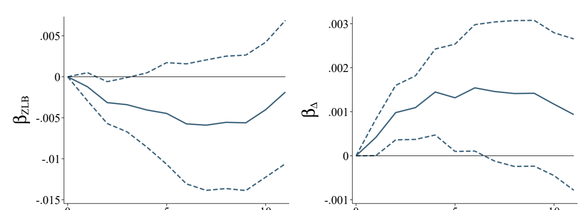
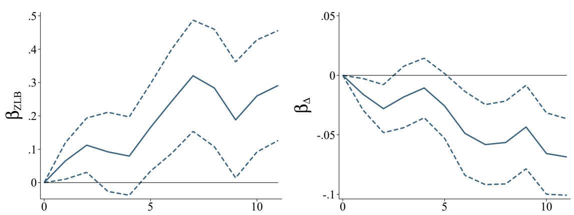
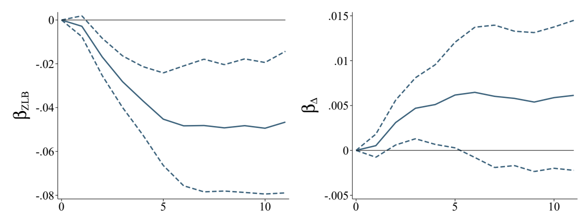


Figure A.3: Robustness: Leader SIC

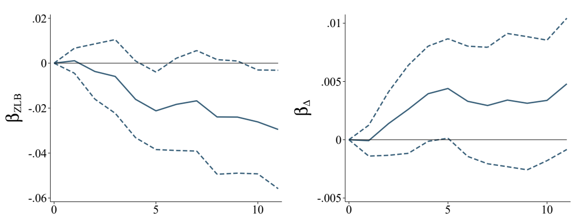
(a) Borrowing Cost



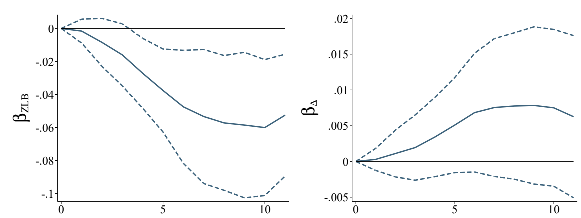
(b) Assets



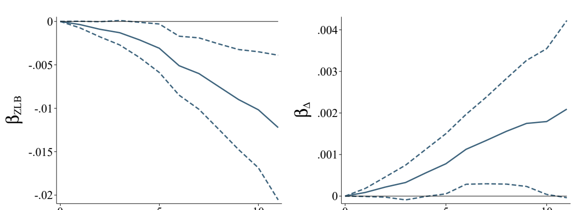
(c) Revenue



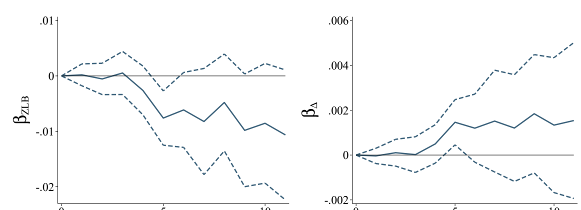
(d) PPE



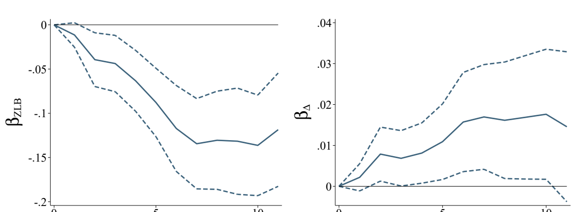
(e) Capital Expenditures



(f) Acquisition Expenditures



(g) Debt



(h) Leverage

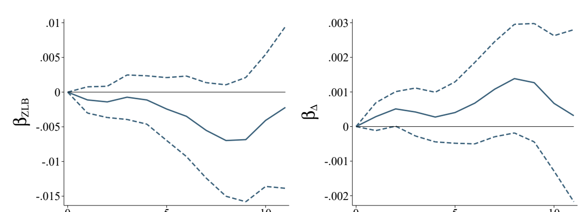
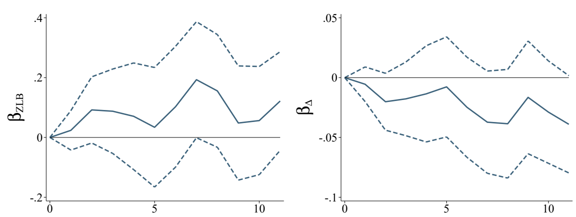
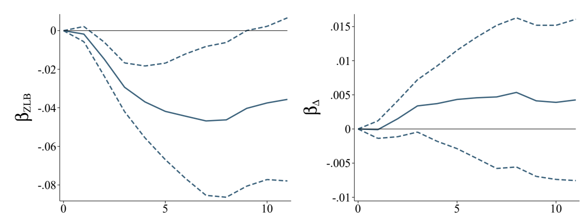


Figure A.4: Robustness: Leader Sales

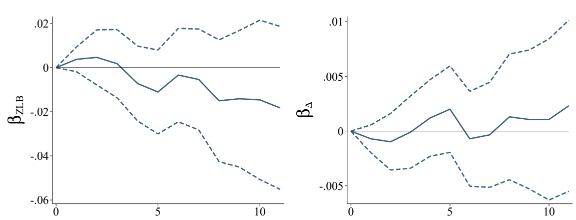
(a) Borrowing Cost



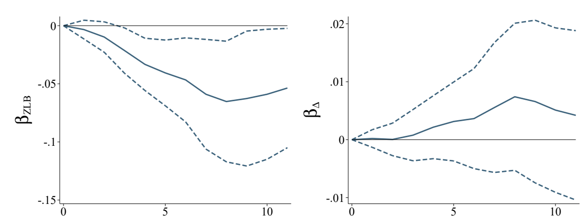
(b) Assets



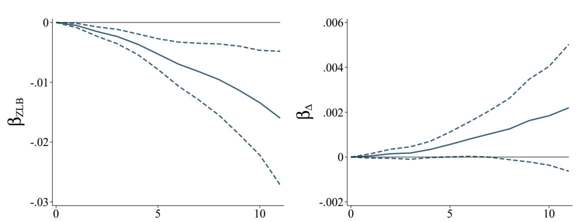
(c) Revenue



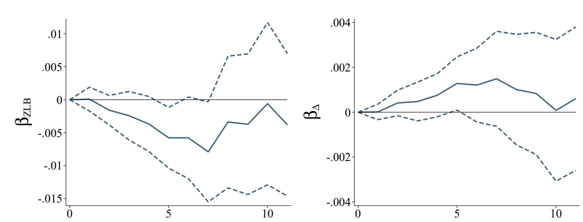
(d) PPE



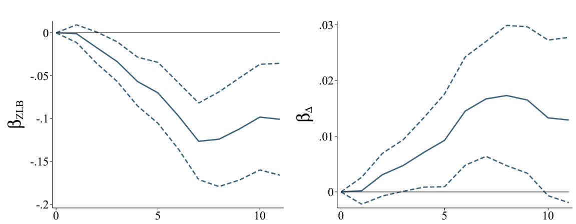
(e) Capital Expenditures



(f) Acquisition Expenditures



(g) Debt



(h) Leverage

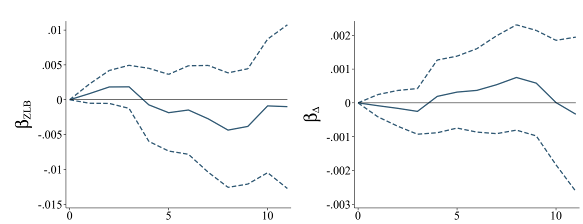
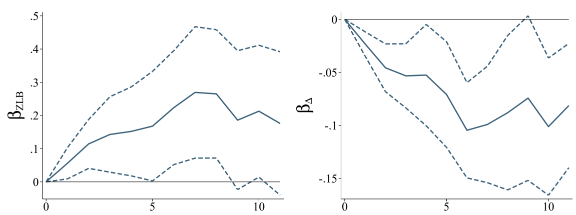
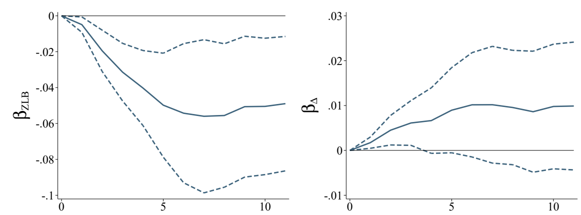


Figure A.5: Robustness: Only Scheduled

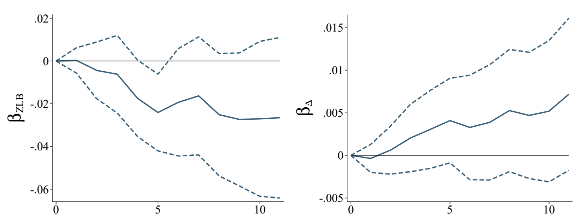
(a) Borrowing Cost



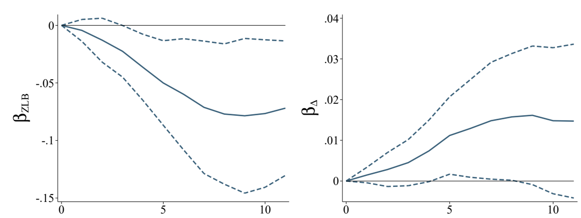
(b) Assets



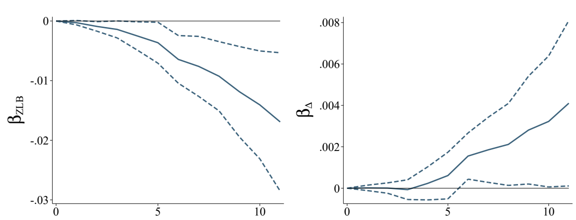
(c) Revenue



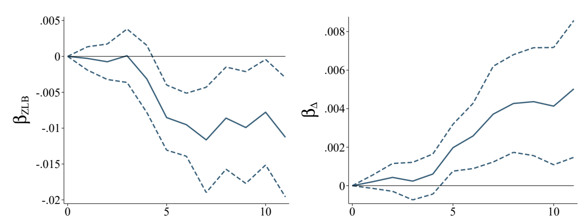
(d) PPE



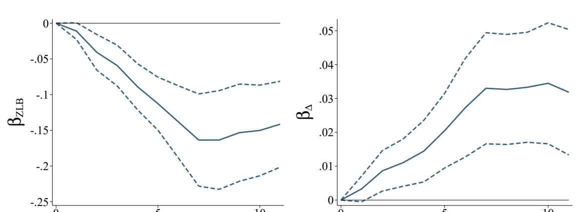
(e) Capital Expenditures



(f) Acquisition Expenditures



(g) Debt



(h) Leverage

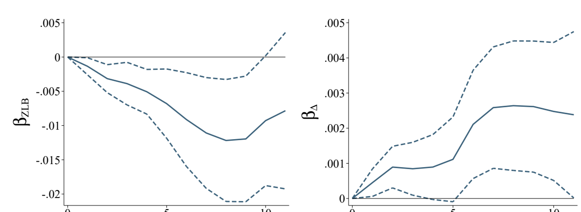


Figure A.6: Robustness: Levels

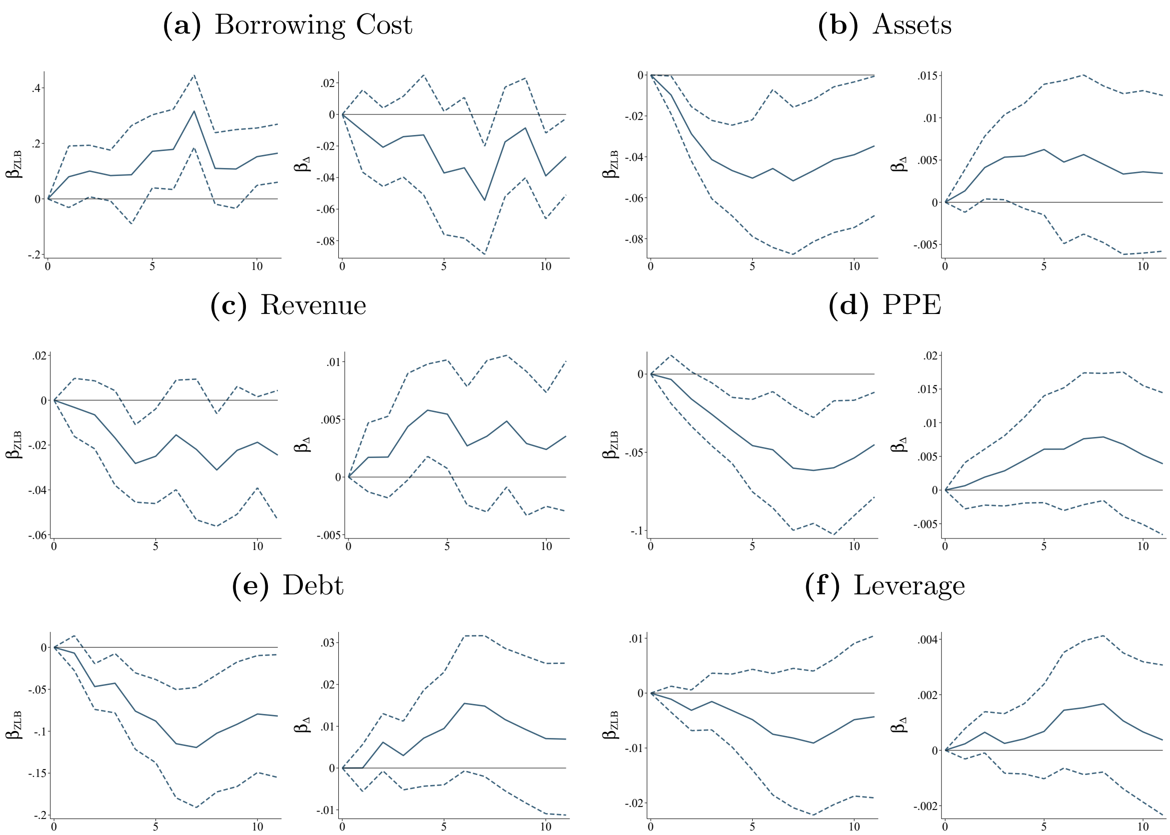
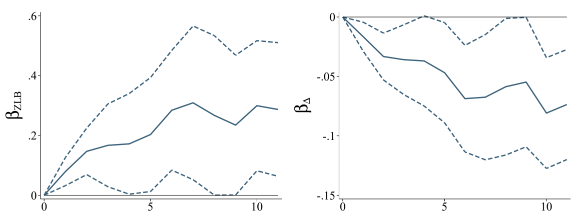
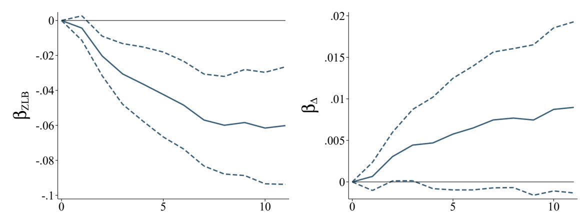


Figure A.7: Robustness: Wide Window

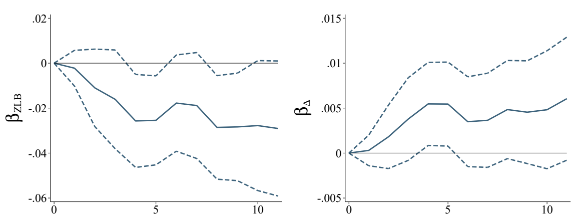
(a) Borrowing Cost



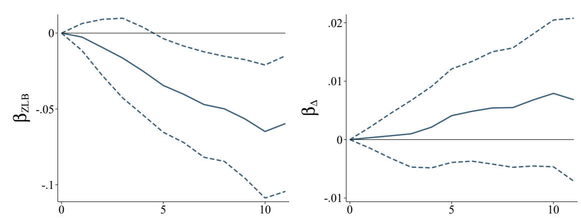
(b) Assets



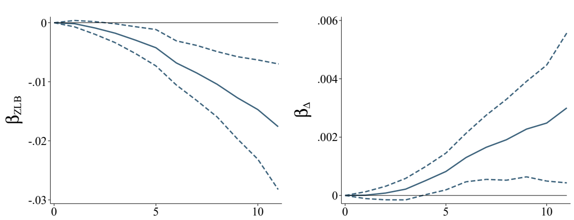
(c) Revenue



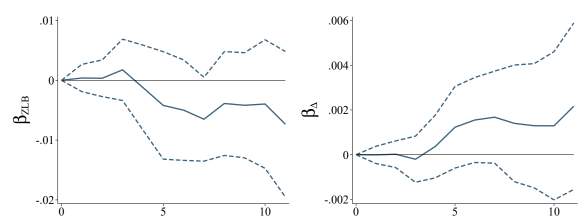
(d) PPE



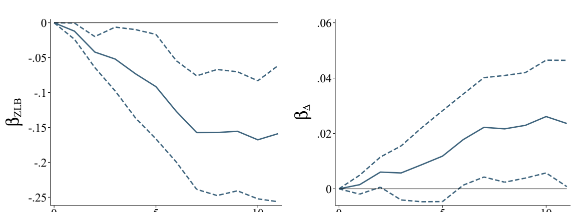
(e) Capital Expenditures



(f) Acquisition Expenditures



(g) Debt



(h) Leverage