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Stock Market's Assessment of Monetary Policy Transmission: The Cash Flow Effect

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ABSTRACT

We show that firm liability structure and associated cash flows matter for firm behavior and that financial market participants price stocks accordingly. Stock price reactions to monetary policy announcements depend on the type and maturity of debt issued by the firms and the forward guidance provided by the Fed, both at and away from the zero lower bound. Further, the marginal stock market participant knows the current liability structures of firms and does not rely on rules of thumb. The cash flow exposure at the time of monetary policy actions predicts future investment, assets, and net worth, clearly violating the Modigliani-Miller theorem.

AN INFLUENTIAL BRANCH OF THE MACROFINANCE literature focuses on financial conditions to amend standard macroeconomic models to better fit the observed effects of monetary policy on real activity and helps explain why financial markets are so important and financial crises so destructive. These models, in which the Modigliani-Miller theorem fails, collectively require cash in the firm to be more valuable than cash outside it. While the financial accelerator models are compelling, the literature remains thin on empirical evidence due to the difficulty of establishing identified effects. Similarly, our understanding of the effects of monetary policy on stock prices is also

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incomplete, due in part to the heterogeneity of firms in many dimensions and the interaction between monetary policy and this heterogeneity of firm level stock prices not yet being well understood. Monetary policy effects on stock prices are more often studied at the aggregate or industry level, as in the influential work of Bernanke and Kuttner (2005).

In this paper, we study stock market reactions to monetary policy at the level of individual firms' equity prices, which reflect the stock market participants' beliefs about the effect of monetary policy on firms' performances. To do so, we focus on the liability difference caused by fixed versus floating rate obligations of otherwise similar firms. While fixed rate liabilities are reduced in a net present value sense and their future cash flows are *unchanged* by higher interest rates, floating rate liabilities' net present values are either unchanged or mildly lowered, but their future cash flow obligations *increase*.

Given this difference, an increase in the policy rate, apart from its standard macroeconomic and discount rate impacts, has two effects. First, it mechanically leads to a cash transfer from equity holders to bond (or loan) holders if debt is floating rate and unhedged, with the effect more pronounced the longer the maturity of the debt and the stronger the forward guidance. This lowers the firm value. Whether this effect is priced in at high frequency in response to monetary policy surprises is an interesting question. We study this.

The second effect arises from firms' cash flow exposures. Current and expected future cash flows change in response to monetary policy surprises based on the amount and maturity of floating rate liabilities on firms' balance sheets and whether these liabilities are hedged. If financial accelerator channels are present in the data, firms with more cash flow exposure should be more adversely affected by cash outflows induced by higher interest rates. This should again lower firm values for firms with high cash flow exposures and, importantly, also lead to changes in real outcomes for these firms. We study this as well.

The first effect, if present in the data, is a balance sheet effect that leads to a redistribution. But if the Modigliani-Miller theorem holds, it will not have direct effects on firm behavior—a reshuffling of liabilities between loan and bond holders on the one hand and residual claimants (equity holders) on the other hand will have no real effects. In contrast, the second possible effect involves changes in real outcomes at the firm level due to cash flow exposure, and hence, is a direct channel of monetary policy transmission, which provides a test of the Modigliani-Miller theorem. We find strong evidence for both effects.

Although we discuss these two effects in detail below, the mechanism that underlies our econometric tests boils down to comparing two firms that are identical except that one has fixed rate debt while the other has floating rate debt of the same maturity. We assume that this difference in debt type is due to lender specific reasons or to the CFOs of the two firms having different beliefs about the path of short rates. Supporting this interpretation, Kirti (2020) finds that banks that have more floating rate liabilities choose to lend more in floating rates and hold more floating rate securities and Barbosa and Özdağlı (2021) show that lender effects are present in the bond market as well. The key here is the independence of this aspect of a firm's liability structure from the policy surprise and the policy surprise not differentially affecting the firms through other channels.[1]

A key contribution of this paper is to show that the maturity dimension is important. One period fixed rate debt and floating rate (after the last reset date) debt are not different as they both will mature and either will be paid off or rolled over at the new (post policy) interest rate. But with longer maturities, fixed and floating rate debt of the same maturity have different properties. Loosely, one can think of long maturity floating rate debt as being rolled over every period at the new short rates, with rollover guaranteed until maturity. Expected cash flow in the periods before maturity depends on expected short rates. In contrast, fixed rate debt gets rolled over only infrequently, at maturity, and its cash flow is fixed until maturity irrespective of the short rates. The longer the maturity of debt (our exposure measure) and larger the change in expected short rates (monetary policy path surprise), the more pronounced the difference between the two liability structures. Thus, the difference in cash flows between fixed versus floating rate debt as a function of debt maturity and forward guidance surprises is the object of our analysis.

If financial market participants price this information, firm-level stock price responses to monetary policy will depend on the balance sheet structure and monetary policy path surprises in a testable way, with more exposed firms' stock prices falling more in response to positive (contractionary) policy path surprises. Further, if financial market frictions are present for the S&P500 firms we study, that is, if Modigliani-Miller fails, we should see real effects of monetary policy at the firm level, with more exposed firms' real outcomes declining more in response to positive policy path surprises.

To establish this mechanism, we proceed in two steps. We first examine whether firms that have more cash flow exposure due to more and longer maturity floating rate debt see a larger stock price reaction to monetary policy surprises regarding forward guidance at high frequency. This is indeed the case. We show that the relevant measure of monetary policy is not the surprise about the current setting of interest rates but rather the surprise about future path of rates, and that it is the interaction between this surprise and cash flow exposure, which depends on not only the amount but also the maturity of floating rate obligations, which predicts stock price reactions. We further show that when measured this way, stock market reactions to monetary policy surprises as a function of firms' cash flow exposures have not changed during the zero lower bound (ZLB) period; forward guidance has been as effective during the ZLB as it had been before it.

Before proceeding to real effects, we take a detour and ask what we find to be an interesting question: whether the marginal stock market investor

[1] Our identification clearly rests on the exogeneity of the fixed versus floating rate debt and maturity structure with respect to the monetary policy surprise. To ensure this, we control for an extensive list of covariates and conduct various robustness checks, including instrumental variables analysis.

actually knows firms' balance sheets, in particular, their cash flow exposures, and prices in the interaction between cash flow exposure and monetary policy at high frequency, or whether persistence in cash flow exposure for most firms allows stock market participants to learn rules of thumb such as certain firms fare worse in, say, tightening cycles. We devise tests that differentiate between the two alternatives and find that what drives the stock price effects at high frequency is indeed knowledge of firms' balance sheets and understanding of their interactions with monetary policy, rather than rules of thumb. The marginal stock market investor is quite sophisticated.

Turning next to real effects, we show that firms that have more cash flow exposure fare worse in terms of real outcomes in the quarters following surprise policy path increases. In particular, we show that following a monetary policy tightening these firms' capital investment expenditures, total assets, and net worth decline more. These effects are based on balance sheet changes due to monetary policy actions external to the firm and constitute strong empirical evidence for real effects of cash flows. It is notable that these effects are present for the S&P500 firms, which are often thought of as the least financially constrained corporations.[2]

Articulating our arguments and coming up with our econometric approach requires drawing on methods and ideas from the monetary policy event study literature, the firm valuation and stock pricing strands of the corporate finance and asset pricing literatures, and the literature on the role of financial frictions in monetary policy transmission.

An extensive literature studies the relationship between asset prices and monetary policy. Some examples include Thorbecke (1997) and Ehrmann and Fratzscher (2004), who study the relationship between monetary policy and stock returns, and Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005), who introduce high-frequency identification of monetary policy surprises and examine their impact on stock prices and bond yields, which Campbell et al. (2012) and Swanson (2021) extend to consider the effectiveness of unconventional monetary policy in recent years. In related work, Gorodnichenko and Weber (2016) provide evidence that stock market participants are aware of different sectors' price stickinesses and show how such information is priced following monetary policy announcements. We study a similar question in the context of firms' liability structures.

The literature on the interaction between monetary policy and financial frictions is rich, especially in theoretical work. Some examples in this vein include Gertler and Gilchrist (1994), Kiyotaki and Moore (1997, 2019), Bernanke, Gertler, and Gilchrist (1999), Gertler and Kiyotaki (2010), Adrian, Colla, and Shin (2012), Ciccarelli, Maddaloni, and Peydró (2013), and Gertler and Karadi

[2] S&P500 firms are by definition large and, with few exceptions, older firms. Hadlock and Pierce (2010) find large, old firms do not face tight financial constraints. Looking at the S&P500 directly, Brisker, Çolak, and Peterson (2013) show that inclusion in the index relaxes financial constraints of firms and note that S&P500 firms should not be thought of being financially constrained. We show instead that cash flow matters even for these firms.

(2015). These studies focus mainly on the credit channel of monetary policy. As Boivin, Kiley, and Mishkin (2010) argue, the literature on unconventional or nonneoclassical transmission mechanisms is still thin, mainly due to the lack of supporting empirical evidence.

With respect to the effects of monetary policy on firm liabilities, Kashyap, Stein, and Wilcox (1993) and Becker and Ivashina (2014), among others, show that firms try to substitute other forms of borrowing when bank loans decline, which suggests the existence of a bank lending channel. Three recent papers in this literature relevant for our work are English, Van den Heuvel, and Zakrajšek (2018), who demonstrate that interest rate shocks transmit to bank equity valuations through interactions with the maturity mismatch between bank assets and liabilities, Greenwald (2019), who find that changes in interest rates also push firms closer to interest coverage covenants, which have real effects and Ippolito, Özdağlı, and Perez-Orive (2018), who show that bank loan leverage, which is mostly floating rate, affects the stock price response to monetary policy surprises but that this relationship broke down during the ZLB episode. We build on the conceptual framework of the latter paper and document the importance of accounting for the maturity dimension for both stock pricing and real effects, offering empirical evidence of its salience. Doing so shows that the effect in question persisted during the ZLB as well.

Turning to the household finance side of this question, Di Maggio et al. (2017) show that households with adjustable rate mortgages observe greater effects of low interest rates and have larger real reactions. More closely related to our paper, Garriga, Kydland, and Šustek (2017) find that the combination of long-duration adjustable rate mortgages and persistent monetary policy shocks have large effects on household balance sheets and housing investment. We complement their work by considering firm balance sheet analog of this mechanism, introducing controls so that firm liability structure can be treated as exogenous to policy, similar to mortgages in that literature.

On the real side of monetary policy transmission, we inform the debate on cash flow sensitivity of investment, which goes back to Fazzari et al. (1988) and Kaplan and Zingales (1997). Our proposed measure of a firm's exposure to interest rate risk allows for a structured and better identified analysis of the cash flow effect of monetary policy, which propagates through the firm's liability structure and ultimately affects its investment behavior. Investment is sensitive to cash flow.

Finally, we contribute to the literature on stock price determination. This literature is large, with important contributions along various dimensions including responses of stock prices to monetary policy, such as Bernanke and Kuttner (2005), Ippolito, Özdağlı, and Perez-Orive (2018), and Gorodnichenko and Weber (2016). We interpret our findings as evidence of investor sophistication, which is intimately tied to the issue of stock market efficiency. Some examples from this literature are Maloney and Mulherin (2003), who provide evidence in support of stock market sophistication in a study of price discovery in the aftermath of the Challenger crash, and Chen, Kelly, and Wu (2020), who document that hedge funds' information acquisition activities mitigate the impairment to information flows following exogenous reductions in analyst coverage due to the closures of brokerage firms. We contribute to this body of work by showing that market participants know the current liability structure of S&P500 firms and quickly price in interactions between firm liabilities and monetary policy forward guidance after Federal Open Market Committee (FOMC) announcements.

We present the main results, discussion, and brief robustness analysis in this paper and relegate details and a battery of tests that further establish robustness of results to an extensive Internet Appendix.[3]

I. Data and Summary Statistics

This section describes the data and provides summary statistics relevant for our analysis. We discuss data sources and variable construction below and provide additional details in the Appendix. Our sample begins in 2004, when detailed information on debt type and maturity becomes available, and ends in 2018. There were 127 FOMC announcements between January 2004 and December 2018. We will examine changes in expected cash outlays of firms on days of monetary policy surprises due to unhedged floating rate obligations on their balance sheets, controlling for other firm characteristics. In particular, we will employ our preferred measures of floating rate exposure while controlling for bank debt leverage to ensure that our results are not proxying for leverage, which matters as shown by Ippolito, Özdağlı, and Perez-Orive (2018).

Before going into specifics, it is useful to elaborate on the frequencies at which various variables are measured and how these work together in our analysis. The policy setting (target) and forward guidance (path) components of monetary policy surprises are the main impulses in our analysis and are available on an intraday basis. The interest rate implications of monetary policy are immediately priced in fixed income markets, and our intraday measures minimize the measurement error in this key independent variable.

We employ equity prices of individual firms at a daily frequency, the highest frequency at which the data are available to us. We study the equity price changes over one- and two-day windows. Finding equity pricing responses to monetary policy in these windows indicates that the effects are not simply jumps that reverse within the day, but rather are persistent. If the effects we focus on are present at an intraday frequency, our daily data would add noise to the system, reducing statistical significance. The results are nonetheless highly statistically significant. Whether these cash flow effects are present in the intraday data, the highest frequency at which these effects can be found, how fast the interaction between policy guidance and cash flow exposure is priced in are important questions that we leave for future work. Our focus here is on daily frequency stock price reactions to monetary policy surprises.

[3] The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

The remainder of the data are based on firms' quarterly financial statements, some of which are filed annually but in different quarters for different firms. Controls such as firm size, leverage, and a long list of others including whether the firm hedges interest rate risk are quarterly observations. The hand-verified hedging indicator that we construct in the spirit of Ippolito, Özdağlı, and Perez-Orive (2018) is the cleanest quarterly binary hedging indicator in the literature and is available to other researchers.

The cash flow exposure variable, which incorporates debt type and maturity information, is observed as a clean measure annually and as a noisier and less available measure quarterly. We use the annual measure as baseline and show that the results are robust to using the quarterly measure when available.

To the extent that our quarterly observations of balance sheet variables overlap with market participants' information sets (we lag the balance sheet variables, as explained below, to ensure that the information we condition on was available to market participants on the policy date), the regressions we run will correspond exactly to the mechanism we have in mind. If market participants have access to more frequent updates to balance sheet variables, including exposure, our variables will contain classical measurement error, attenuating the coefficients. We find that our coefficients of interest are statistically and economically significant despite this possible downward bias.

The variables we employ to assess real effects (assets, net worth, etc.) are also based on firm balance sheets and are observed quarterly. For these variables, the changes that we study also take place at a quarterly frequency—unlike stock price changes, which are daily—and thus, we aggregate the monetary policy surprises within a quarter to construct a quarterly policy surprise measure.

A. Monetary Policy Data

Establishing causal links between stock prices and monetary policy is difficult at low frequencies, and thus, the literature has moved toward high-frequency event studies. This literature uses daily or higher frequency changes in prices of short-dated money market instruments or derivatives to capture monetary policy surprises on policy dates and the reactions of stock prices to these surprises. The standard approach is to use the scaled changes in spot-month Federal Funds Futures contracts, as pioneered by Kuttner (2001). Figure 1 shows the aggregate S&P500 reaction to these monetary policy surprises.

It is clear that there were few policy surprises as captured by the Kuttner measure between 2004, when our data begin, and 2008, when the Global Financial Crisis hit and monetary policy in the United States reached the ZLB, and there were no such policy surprises for several years thereafter. This is not because there were no monetary policy surprises in this period per se, but rather because policy surprises that did arise corresponded to changing expectations about the future course of policy rates induced by FOMC statements, not to changes in the immediate policy. Indeed, because the FOMC

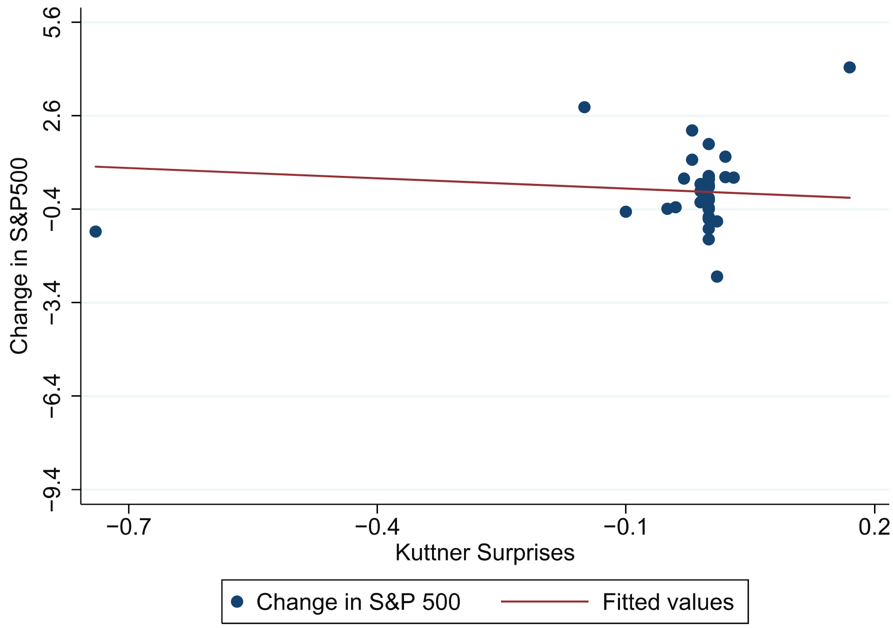


Figure 1. Daily aggregate stock price changes in response to Kuttner surprises. The figure plots daily changes in the S&P500 Index against Kuttner surprises on the FOMC announcement dates between January 2004 and December 2008. The line plots OLS fitted values. (Color figure can be viewed at wileyonlinelibrary.com)

signaled its policy decisions fairly transparently before its meetings, monetary policy surprises in the 21st century, during and before the ZLB period, have come mainly from what are now referred to as forward guidance surprises.

To capture forward guidance surprises, we use the Gürkaynak, Sack, and Swanson (2005) measures, GSS surprises henceforth, in our analysis. GSS surprises are constructed under the identifying assumption that FOMC announcements drive changes in asset prices in a 30-minute window around the announcement. Asset price changes during this window can therefore be attributed to a genuine monetary policy surprise that could not have been anticipated on the basis of information available up until the announcement. The use of high-frequency data makes this identifying assumption credible, which is also the identifying assumption underlying the Kuttner surprises that are daily.

GSS surprises, unlike the Kuttner monetary policy surprises employed by Ippolito, Özdağlı, and Perez-Orive (2018), are two-dimensional. The first dimension is related to the change in current policy setting and the second to the change in market perceptions of future policy rates, that is, forward guidance. Following Gürkaynak, Sack, and Swanson (2005), we refer to these factors as the "target factor" and the "path factor," respectively. These factors are given as the first two principal components of the change in the yield curve up to one year maturity in a 30-minute window around an FOMC announcement, rotated such that one factor (path) is orthogonal to the Kuttner surprise.

Hence, the path factor captures only those revisions to expectations of interest rates up to one year ahead that are not driven by the surprise in the current policy action (target), and the two rotated factors remain orthogonal to each other by construction. Campbell et al. (2016) and Swanson (2021) discuss the mechanics of GSS surprises and how they can be used to address other questions. The temporal separation afforded by GSS surprises is particularly useful here given that floating rate debt maturity, which relates firm liabilities to future expected interest rates, plays an important role in our analysis.

Figure 2 shows the S&P500 response to monetary policy, this time separately for target and path surprises. The target factor is essentially the Kuttner surprise and hence the top panel is similar to Figure 1, over a longer sample. The bottom panel is striking as it shows that path surprise variation has been high in the sample period and aggregate stock prices have responded strongly to such variation.[4]

While introducing path surprises allows us to capture much more of the variation in monetary policy surprises and the resulting changes in aggregate stock returns, aggregate stock price responses alone are not useful for understanding the transmission of monetary policy. We therefore turn to the stock prices of individual firms and exploit cross-sectional variation in firms' cash flow exposure to study a particular type of financial accelerator as well as test market participants' understanding of firm balance sheets and the effect of monetary policy on these.

B. Firm-Level Data

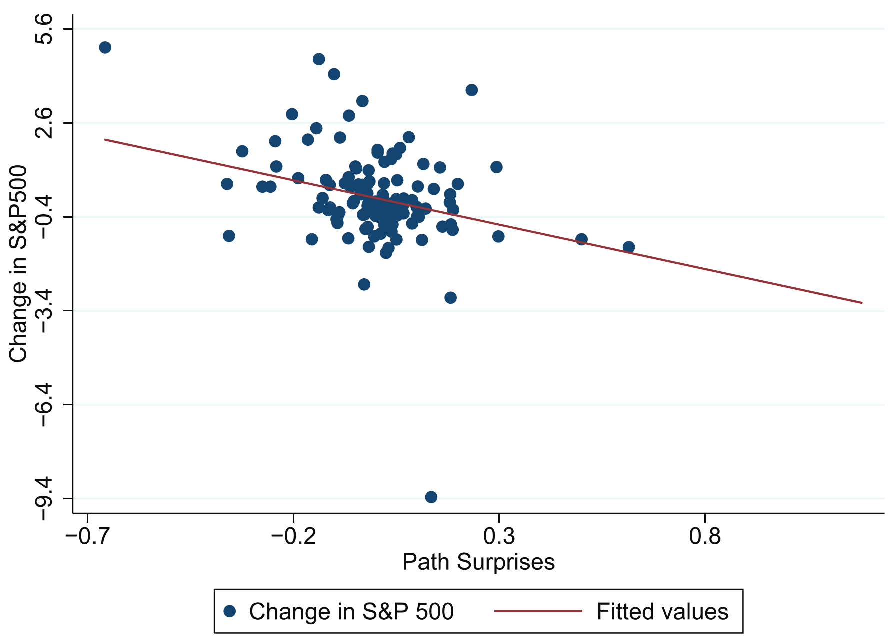
To provide evidence on how FOMC announcements affect financial market assessments of individual firms' exposures to floating rate debt and stock prices, we construct a panel data set for which the cross-sectional dimension corresponds to firms in the S&P500 index and the time (event) dimension to the FOMC announcement dates. The Appendix summarizes variable definitions, frequencies, and data sources.

Our sample comprises firms that were part of the S&P500 at any point between 1957 (creation of the index) and 2018 (end of our sample) whose balance sheet data are also available in the Capital IQ (CIQ) database. This gives us 975 firms.[5] The stock return we focus on is computed using the percentage change of the closing quotes of stock prices between the day before and the

[4] GSS do not find a significant effect of the path factor on stock prices in the 1990 to 2004 sample, when path surprises and hence identifying variation were rarer. Monetary policy effects on stock index aggregates are also confounded by possible time-varying information effects, where surprises may also signal central banks' private information and exert different influences on aggregate indices based on the information perceived by market participants. Our identification, based on cross-sectional differences in firm liability structures, is independent of these effects.

[5] Our results are robust to using the much smaller sample of firms that have never left the index.

Panel (A) Target Surprises.



Panel (B) Path Surprises.

Figure 2. Daily aggregate stock price changes in response to GSS surprises. Panel A plots daily changes in the S&P500 Index against the target surprises on the FOMC announcement dates between January 2004 and December 2018, and the Panel B plots the same time series against the path surprises. The lines plot OLS-fitted values. (Color figure can be viewed at wileyonlinelibrary.com)

day after an FOMC announcement, obtained from the Center for Research in Security Prices (CRSP) database.[6]

We relate the stock return to a measure of a firm's cash flow exposure stemming from floating rate liabilities. These are financial obligations whose interest rates vary with benchmark rates, most often the London Interbank Offered Rate (LIBOR), over the course of their contract periods. To calculate cash flow exposure, we require detailed information about firms' debt structures beyond face values, such as debt categories (e.g., bank loans, bonds), interest rate types (fixed versus floating rate), and maturity per category and type. These data are available at an annual frequency in 10-K forms that are filed at the end of each firm's fiscal year, which we obtain from the CIQ database.[7] In robustness tests, we also use information from mostly unaudited quarterly 10-Qs.

Floating rate exposure of each firm in our sample is constructed as follows. First, we omit floating rate debt items that are convertible, issued in currencies other than U.S. dollars, or are nonrecourse, as well as debt items that have already defaulted as these behave differently from other debt. Together, these items represent a small fraction of all debt issuance. Second, for each item, we set maturity to either the final payment date as specified in the contract or the simple average of the lower and upper bounds of the designated payment interval, depending on which case is applicable. The maturity of a perpetuity (very rare in the sample) is set to 100 years. Finally, we multiply the maturity of each item from the previous step by the corresponding leverage ratio (i.e., the outstanding value of the debt item divided by total assets of the firm) and sum across items to obtain the firm's floating rate exposure as

$$Exposure_i = \sum_j \frac{FRDA_{ij}}{TA_i} FRDM_{ij}, \tag{1}$$

where subscript i indexes firms and j debt items. The time subscript is omitted for simplicity. On the right-hand side, *FRDA* and *FRDM* denote the amount and maturity of the floating rate debt item, and *TA* denotes total assets. By construction, this measure of exposure captures both the maturity and the leverage of a firm's floating rate obligations, and thus, is a measure of future cash flow exposure. We therefore use the expressions "floating rate exposure" and "cash flow exposure" interchangeably when referring to this measure. Note that some of these debt items are callable. As the firm will exercise its option only when doing so will benefit shareholders, callability biases the results against finding the mechanism we are testing.

The standard balance sheet items, explained in detail in the Appendix, come from the Compustat database. Using these items, we compute size, profitability, book leverage, market-to-book ratio, asset maturity, and other firm characteristics that we employ as control variables in our analysis. These

[6] Similarly, our results are robust to using a one-day window, from the close of the day before the FOMC meeting to the close of the announcement day.

[7] The Internet Appendix provides details and descriptive statistics.

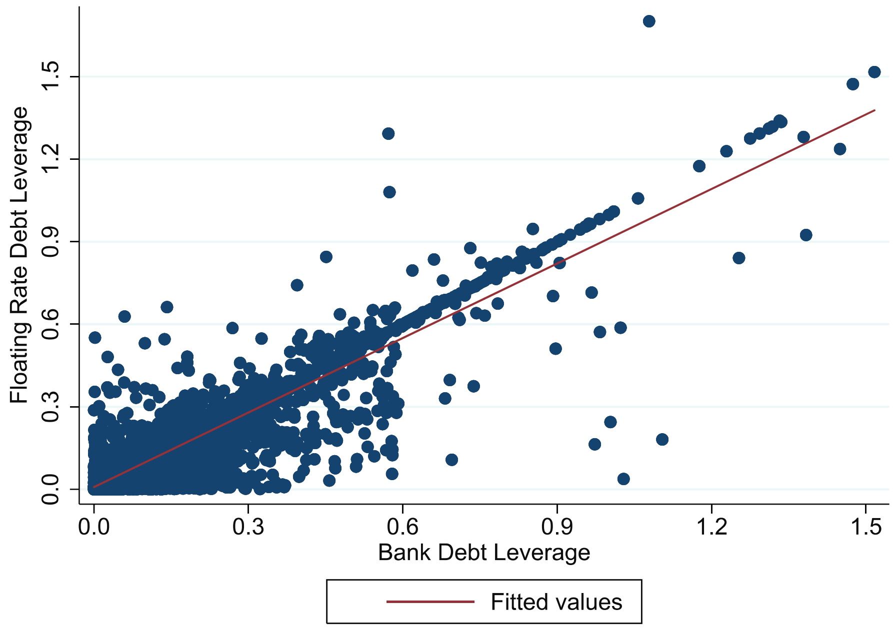


Figure 3. Floating rate debt leverage, and bank debt leverage. Floating rate debt is all obligations whose interest rates are variable. Bank debt is the sum of term loans and (drawn) credit lines. They are expressed as fractions of total assets to give Floating Rate Debt Leverage and Bank Debt Leverage, respectively. The line plots OLS-fitted values. (Color figure can be viewed at wileyonlinelibrary.com)

variables are available at a quarterly frequency. Our empirical work also employs financial slack, retained earnings, dividend per share, and short-term debt as control variables. Size is deflated by the consumer price index (CPI) and recast in real terms. Floating rate exposure and leverage, profitability, market-to-book ratio, financial slack, retained earnings, and short-term debt, which are scaled by total assets, do not need to be deflated.

We employ two measures of floating rate leverage (as opposed to exposure), which are also used by Ippolito, Özdağlı, and Perez-Orive (2018). The first is bank debt leverage as a fraction of total assets. This measure assumes that bank debt is the floating component of firm liabilities. The second measure is floating rate debt leverage, which is total floating rate debt (all obligations, including bank debt, indicated to have a variable interest rate) as a fraction of total assets. Both measures are calculated using CIQ and Compustat data and are included in our analysis to distinguish leverage from exposure.

Figure 3 plots floating rate debt leverage against bank debt leverage and shows that the two measures are closely related. Figure 4, however, reveals that our preferred measure of cash flow exposure contains variation that is informative over and above the information in the leverage measures. These figures suggest that maturity matters, independent of leverage. Our econometric work below formalizes this argument. Figure 5 provides the simple average of the exposure measure in each decile of bank debt leverage and confirms the

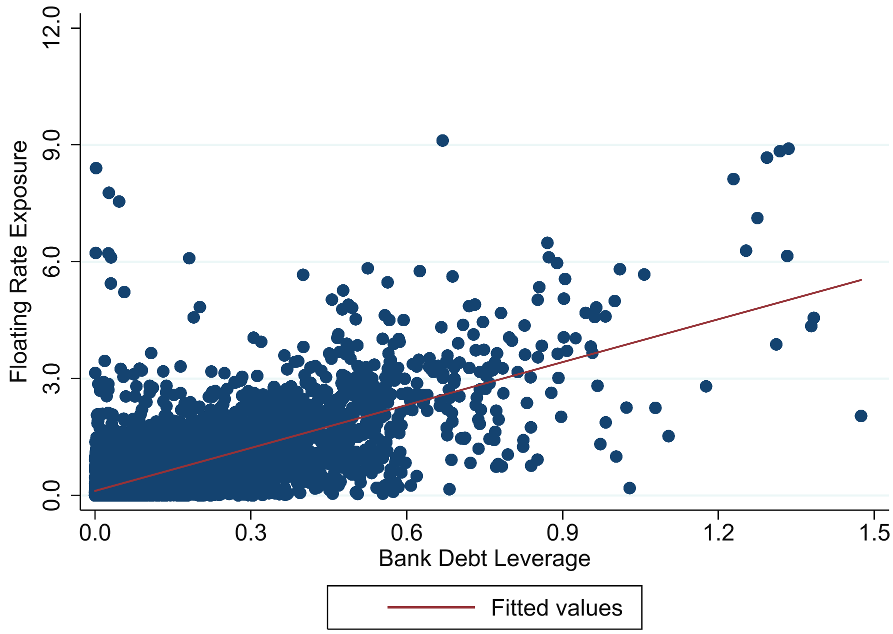


Figure 4. Floating rate exposure and bank debt leverage. Bank Debt Leverage is the ratio of bank debts (term loans + drawn credit lines) to total assets. Floating Rate Exposure is constructed by multiplying each floating rate debt item by its maturity and expressing the resulting sum as a fraction of total assets. The line plots OLS-fitted values. (Color figure can be viewed at wileyonlinelibrary.com)

positive relationship between the two, as in Figure 4, but further shows that the relationship is neither linear nor monotonic.

We address firms' interest rate risk hedging behavior in a way that is close in spirit to that of Ippolito, Özdağlı, and Perez-Orive (2018), but we increase the frequency from annual to quarterly. We first construct a hedging dummy variable by using 10-K reports from the Securities and Exchange Commission (SEC) database (the original source of 10-K forms in CIQ). The reports, which each firm regulated by the SEC is required to file at the end of its fiscal year, provide textual information about the firm's hedging activity related to interest rate risk. We set the hedging dummy to one if the following phrases are found in the report: "hedge interest rate," "hedge against interest rate," "interest rate swap," or their variants.[8] As we show below, the positive interaction effect among the path surprise, cash flow exposure, and the hedging dummy provides further evidence for the cash flow channel of monetary policy.

[8] We also check for false positives such as "not hedge interest rate," "not use interest rate swap," etc. This hedging indicator, which we checked by hand, improves the state of the art in binary hedging measures. Bretscher, Schmid, and Vedolin (2018) propose a continuous hedging measure that we do not use in the paper because the data required to construct it are available for only a fraction of our sample. As an aside, hedging is a persistent variable with a median hedging autocorrelation of 0.6 in the quarterly data that we compiled.

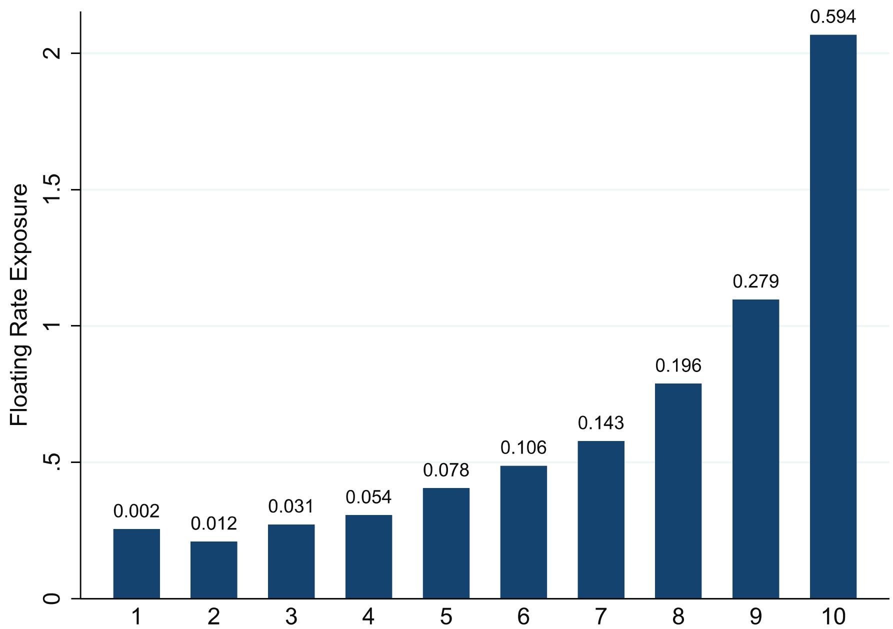


Figure 5. Floating rate exposure over deciles of bank debt leverage. The figure plots the simple average of the floating rate exposure in each decile of the bank debt leverage. "1" along the horizontal axis means between the bottom and the 1st decile, "2" means between the 1st and the 2nd decile, and so on. The simple average of the bank debt leverage within each decile is reported above the corresponding bar. (Color figure can be viewed at wileyonlinelibrary.com)

To control for the possibility that interest rate derivatives are purchased for speculative rather than hedging purposes, we omit firms that invest in interest rate derivatives but have a floating rate leverage ratio (i.e., total floating rate debt over total assets) that is below 1%. This decreases the number of firms to 873 in the baseline sample (January 2004 to December 2008) and 935 in the extended sample (January 2004 to December 2018). Lastly, we drop financial firms, as these firms are very different from other firms along many dimensions. This step yields the final sample sizes of 720 and 773, respectively.[9] We conduct our empirical analysis on these samples, for which summary statistics are presented in Table I.

We merge event window stock returns and the GSS factors with the firm-level variables described above, taking into account the fact that end of the fiscal year differs across firms. This allows us to match the latest available balance sheet information in CIQ (available at an annual frequency in our baseline) to FOMC announcements at a quarterly frequency rather than use calendar years, which would sacrifice resolution. Because the SEC requires that 10-K forms be released to public within 90 days following the end of a

[9] Although we drop financial firms for comparability to earlier literature, our results are insensitive to whether financial and/or utility firms are in the sample.

Table I

Summary Statistics for Balance Sheet Variables

This table is based on the full sample used for the regressions in Table III. The dummy variable Hedge = 1 corresponds to firms that engage in hedging activities against interest rate risks of their floating rate obligations. Exposure is the sum of maturity weighted floating rate debts as a fraction of total assets. Bank Debt Leverage is the ratio of total bank debts to total assets. Floating Rate Debt Leverage is the ratio of total floating rate debts to total assets. Size is the logarithm of the book value of total assets (deflated by CPI), Profitability is the ratio of operating income before depreciation to total assets, Book Leverage is the ratio of total debts to the sum of total debts and the book value of equity, Market-to-Book Ratio is the ratio of the sum of the market value of equity and total debts to total assets, Asset Maturity is the weighted average of imputed short-term and long-term asset maturities with the weights being the ratios of the asset values to total assets, and Short-Term Debt is the ratio of short-term debt to total assets. Summary statistics based on different samples (for instance, the full sample before controlling for speculative investment in interest rate derivatives and dropping financial firms; see Section I.B) are similar to these.

	Hedge=0		Hedge=1		Entire Sample	
	Mean	*SD*	Mean	*SD*	Mean	*SD*
Exposure	0.61	0.63	0.75	0.71	0.68	0.67
Bank Debt Leverage	0.14	0.12	0.16	0.14	0.15	0.13
Floating Rate Debt Leverage	0.14	0.12	0.16	0.14	0.15	0.13
Size	4.42	1.18	4.63	1.15	4.52	1.17
Profitability	0.04	0.02	0.03	0.02	0.04	0.02
Book Leverage	0.42	0.27	0.51	0.26	0.46	0.27
Market-to-Book Ratio	1.57	1.04	1.42	0.87	1.50	0.96
Asset Maturity	0.52	0.52	0.54	0.48	0.53	0.50
Short-Term Debt	0.03	0.04	0.03	0.05	0.03	0.05
Observations	23,465					

firm's fiscal year, we assume that both Compustat and CIQ variables are observed with one quarter delay.[10]

II. Cash Flow Channel of Monetary Policy

In this section, we test the joint hypothesis that monetary policy affects cash flows of firms based on their unhedged floating rate debt exposures and that this is reflected in stock prices at high frequency. We find strong evidence supporting this conjecture. Based on our event study of FOMC announcements, we further find that floating rate exposure, rather than floating rate leverage, is an important determinant of stock market reactions to monetary policy surprises, and that the cash flow channel of monetary policy operates through the innovation to the expected path of future policy rates, rather than through the innovation to the current policy rate target. The cash flow channel manifests in the negative interaction effect between cash flow exposure and

[10] In our sample, 98% of firms file their 10-K within 90 days. Our results continue to hold with more noise under a more conservative data matching scheme that assumes firm balance sheet variables are observed with a 180-day delay, as in Fama and French (1992), or with a one year delay as in Ippolito, Özdağlı, and Perez-Orive (2018).

the monetary policy path (forward guidance) surprise. The interaction of hedging and these variables has a positive effect, which indicates that interest rate hedging is indeed perceived by stock market participants as protecting against floating rate debt exposure.

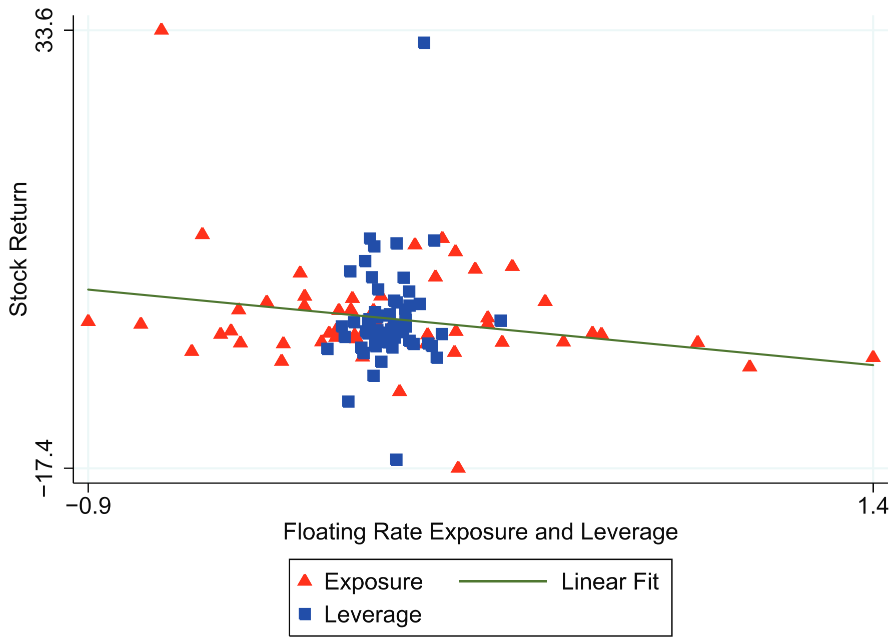
We also find that the monetary policy channel presented above did not change at the ZLB, consistent with the view that forward guidance was a dominant source of monetary policy surprises, operating symmetrically in and out of the ZLB. This result supports the recent work of Debortoli, Galí, and Gambetti (2020) and Swanson (2018), who employ different metrics of policy effectiveness and argue that monetary policy transmission was not different at the ZLB.

Figure 6 illustrates the idea behind our event study and highlights the importance of focusing on exposure rather than leverage.[11] The top panel provides partial regression plots between stock returns and both floating rate exposure (triangles) and floating rate leverage (squares) for the FOMC announcement on March 28, 2006. This event was associated with a (contractionary) path surprise of about 18 basis points (bps). On this day, the correlation between firm level stock returns and exposure is −0.25, consistent with a cash flow channel working through exposure. In contrast, the correlation between stock returns and leverage is about 0.14, which does not support a cash flow effect. The figure shows that the range of exposure is much wider than that of leverage, as maturity variance is also present in exposure. Based on the evidence for that day, it is visually clear that the maturity of debt matters for understanding the interaction between monetary policy surprises and stock price reactions.

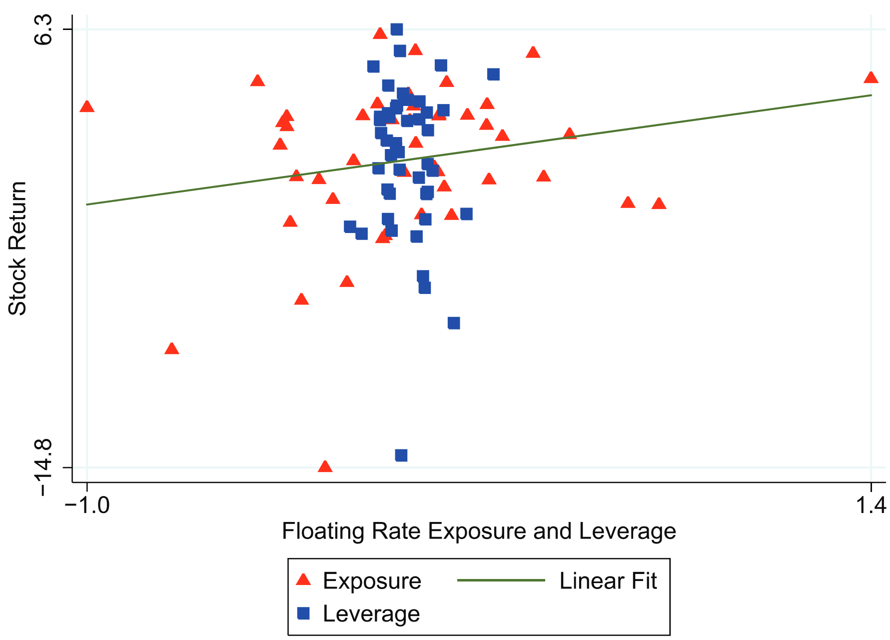
The bottom panel presents similar partial regression plots for the FOMC announcement on August 8, 2006, which was associated with a path surprise of about −3 bps. In contrast to the top panel, the correlation between stock return and the exposure measure is about 0.22, reflecting the expansionary nature of the surprise. This result again supports our proposition regarding the cash flow channel whereby stock prices of firms with higher exposure to floating rates fare better in response to easing surprises in high frequency. The correlation between stock returns and leverage measure, in contrast, is −0.04, which is near zero but whose sign nonetheless runs against the mechanics of a cash flow channel. The figure and the associated correlations on these dates suggest that floating rate exposure, not floating rate leverage, is the appropriate measure for studying the cash flow effect of monetary policy.[12] In what follows, our event study investigates this relationship systematically, taking full advantage of the panel structure of our data set.

[11] To make the figure clear and informative, for both event dates, we plot only those observations whose exposure levels are above the bottom third in the full sample. The figure is harder to decipher but the implications are qualitatively the same without this filter.

[12] Note that these are partial regression plots for exposure conditional on leverage (and other controls) and vice versa, which are consistent with the panel data analysis to be presented below. This pattern of correlations holds for the vast majority of events in our sample irrespective of the size of the monetary policy surprises.



Panel (A) March 28, 2006



Panel (B) August 8, 2006

Figure 6. Partial regression plots with floating-rate exposure and leverage for non-hedgers. The figure presents partial regression plots between stock returns and floating rate exposure (in triangles) and floating rate leverage (in squares) for nonhedgers, as well as the OLS-fitted line for the former. Panel A is for the FOMC announcement on March 28, 2006, which had a path surprise of 18 bps (contractionary). Panel B is for the FOMC announcement on August 8, 2006, which had a path surprise of −3 bps (expansionary). (Color figure can be viewed at wileyonlinelibrary.com)

A. Empirical Design

As discussed by Gürkaynak and Wright (2013), the event study methodology based on high-frequency data allows researchers to circumvent endogeneity issues related to omitted variable bias and reverse causality. This is especially useful in the current context because there is evidence that, at low frequencies, FOMC decisions are influenced by stock market movements (Rigobon and Sack (2004), D'Amico and Farka (2011)).

Identification of the policy surprise is established by conditioning on the timing of FOMC releases and high-frequency responses to the surprise components of these announcements. By definition of the surprise, the target and path factors are independent over time, and thus, analysis can be done via OLS. Given the panel structure of our data, we include firm and/or time fixed effects and cluster standard errors at the event (time) level.

The model we estimate is

$$\begin{aligned}\triangle p_{it} &= \beta_0 + \beta_1 target_t + \beta_2 path_t + \beta_3 exposure_{it-1}\\ &\beta_4 target_t * exposure_{it-1} + \beta_5 hedge_{it-1} * target_t * exposure_{it-1}\\ &+ \beta_6 path_t * exposure_{it-1} + \beta_7 hedge_{it-1} * path_t * exposure_{it-1}\\ &+ \beta_8 leverage_{it-1} + \beta_9 target_t * leverage_{it-1} + \beta_{10} hedge_{it-1} * target_t * leverage_{it-1}\\ &+ \beta_{11} path_t * leverage_{it-1} + \beta_{12} hedge_{it-1} * path_t * leverage_{it-1}\\ &+ \lambda(remaining\ controls\ and\ interaction\ terms) + \varepsilon_{it},\end{aligned} \tag{2}$$

where i indexes firms, t indexes the FOMC announcements, $\triangle p_{it}$ denotes the stock return around an FOMC announcement, $target_t$ is the monetary policy target (Kuttner) surprise, $path_t$ is the monetary policy forward guidance surprise, $hedge_{it-1}$ is the hedging dummy whose value is equal to 1 if firm i hedges against interest rate risk, $leverage_{it-1}$ is the floating rate leverage measure, and $exposure_{it-1}$ is the floating rate exposure measure. Regressions include firm and/or time fixed effects and controls include size, profitability, book leverage, market-to-book ratio, and asset maturity, among other variables and with interactions as listed in table caption. Of these controls, the most consequential ones are size and asset maturity. All variables in the regression other than the monetary policy surprise and the stock price change are lagged by one quarter (or more, in robustness tests) to ensure that the relevant variables are in the market participants' information sets.

The intraday monetary policy surprise measure and the various covariates and interactions as shown in the Appendix and extended in robustness checks (Section II.C) are used to identify the effect of monetary policy surprises on stock prices through cash flow exposure. The covariates and interactions control for other mechanisms (which may be correlated with cash flow exposure) through which monetary policy surprises affect firms. For example, if larger firms have more exposure, and size affects the stock price reaction directly, then controlling for size ensures that this effect does not appear through exposure. Importantly, any firm-specific, time invariant unobservable will be captured by the fixed effects. It is worth noting that lagging the exposure measure to ensure that it is in market participants' information set further helps in identification as the lagged exposure measure will not reflect contemporaneous unobservable firm-level behavior that is correlated with current exposure and may be transmitting policy surprises directly to stock prices (although it is not easy to think of what such behavior may be). We use this insight as the basis of an instrumental variable (IV) robustness exercise in Section II.C.

B. Results

We first focus on the pre-ZLB period in the United States (January 2004 to December 2008) and find that the transmission mechanism works through the interaction between cash flow *exposure* and the monetary policy *path* surprise. We then use this finding to reinterpret the ZLB period (January 2009 to December 2015). The full sample (January 2004 to December 2018) also includes the post-ZLB period, which allows us to verify our argument that the cash flow channel of monetary policy was intact throughout the first two decades of the 21^{st} century.

B.1. Pre-ZLB Results

Table II presents the baseline findings of our paper. The first column is analogous to Ippolito, Özdağlı, and Perez-Orive (2018) with our data and shows that when there is a surprise in the policy action (target), stock prices of firms that have more floating rate leverage are more affected, but hedging against interest rate risk mitigates this effect.[13] Thus, in this regard, our data have the same properties as those used in earlier work.

Our contribution begins with the second column, which shows that when we use our exposure measure and allow for both target and path surprises as well as leverage and exposure, the relevant variable turns out to be exposure's interaction with path. Once again, hedging against interest rate risk reduces the impact of the cash flow exposure on firm' stock prices. Note that the R^2 more than doubles as we move from target and leverage to path and exposure, which highlights the importance of the additional information on maturity embedded in the exposure measure for understanding stock price reactions to monetary policy. One might expect the target and exposure interaction to also matter, to the extent that surprises to current policy also change expectations of the policy stance going forward. While this idea is correct, the target

[13] Here, we use bank debt to measure floating rate leverage rather than debt that is explicitly identified as floating rate. This is different from our exposure measure, which uses all debt that is declared to have a floating rate. Table IA.VI in the Internet Appendix shows that using the analogous floating rate leverage measure rather than bank debt in this and other regressions does not affect our results.

Table II

Pre-ZLB

The dependent variable is the two-day stock return bracketing an FOMC announcement. The sample covers 47 FOMC announcements between January 2004 and December 2008. The dummy variable Hedge = 1 if a firm enters into interest rate swaps to protect against interest rate risks of its floating rate obligations. Firm-level control variables are size, profitability, book leverage, market-to-book ratio, asset maturity, financial slack, retaining earnings, dividend per share, and their interactions with target and path surprises and the hedging indicator. Leverage refers to bank debt leverage. All regressions include firm-level fixed effects unless otherwise noted. Column (1) replicates Ippolito, Özdağlı, and Perez-Orive (2018) using our data. Column (2) replaces their bank debt leverage measure with our floating rate exposure and includes both target and path surprises. Column (3) adds bank debt leverage as a separate regressor. Columns (4) and (5) are versions of (3) with only time fixed effects and both firm and time fixed effects, respectively. Column (6) replaces raw stock return with Fama-French adjusted stock return as the dependent variable. Column (7) adds controls and their interaction terms to (6). Coefficients of control variables are not shown here for brevity. Numbers in parentheses are standard errors clustered at the event level. Only firms whose floating rate debts constitute more than 1% of total assets are included to control for potentially speculative interest rate derivative investments. We also drop financial firms. The sample comprises 720 firms after these filters. All independent variables are trimmed at the bottom and top 1% (the results are robust to using winsorization instead). *, **, and ***indicate statistical significance at 10%, 5%, and 1%, respectively.

Variables	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return	(7) Stock Return
Target	−11.70**	−19.26***	−20.47***			−2.66	−0.83
	(5.03)	(6.68)	(7.26)			(2.71)	(7.64)
Path		−10.14***	−10.19***			1.23	6.52
		(3.41)	(3.79)			(1.16)	(4.29)
Exposure		0.07	0.18	0.27*	0.30	−0.04	0.40*
		(0.20)	(0.25)	(0.14)	(0.22)	(0.22)	(0.21)
Target*Exposure		0.13	−2.16	−3.23*	−2.37	−1.79	−3.01**
		(1.60)	(1.93)	(1.70)	(1.72)	(1.33)	(1.49)
Hedge*Target*Exposure		−1.58	−0.35	1.85	0.08	0.55	3.86
		(2.03)	(3.96)	(3.23)	(3.21)	(1.88)	(2.83)
Path*Exposure		−2.74***	−3.19***	−1.97***	−2.40***	−1.36***	−2.04***
		(0.74)	(0.69)	(0.68)	(0.60)	(0.39)	(0.62)
Hedge*Path*Exposure		2.86***	4.25***	3.09***	3.20***	2.78***	3.20***
		(0.99)	(1.09)	(1.08)	(0.99)	(0.77)	(0.75)

(*Continued*)

Table II—*Continued*

Variables	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return	(7) Stock Return
Leverage	2.35		−0.53	−1.21	−1.01	0.44	−0.50
	(1.79)		(1.46)	(0.82)	(1.34)	(1.58)	(1.43)
Target*Leverage	−18.03**		15.74	17.11	14.37	17.87	14.53
	(8.82)		(13.20)	(11.27)	(13.00)	(10.66)	(14.63)
Hedge*Target*Leverage	27.90***		−5.62	−8.31	−4.68	−23.74	−8.61
	(9.20)		(24.91)	(20.94)	(22.68)	(18.67)	(23.12)
Path*Leverage			3.58	0.56	2.09	3.07	1.25
			(4.43)	(3.40)	(4.06)	(2.53)	(4.59)
Hedge*Path*Leverage			−9.35	−4.94	−5.10	−9.86*	−4.80
			(5.59)	(4.07)	(4.75)	(5.35)	(6.02)
Observations	9,922	7,027	5,877	5,877	5,877	9,712	5,877
R^2	0.06	0.16	0.17	0.33	0.37	0.68	0.81
Firm FE	YES	YES	YES	NO	YES	YES	YES
Time FE	NO	NO	NO	YES	YES	NO	NO
Firm Controls/Contr*Surp*Hedge	YES	YES	YES	YES	YES	NO	YES

surprise does not exert a statistically significant effect on one-year-ahead expected rates (as measured by the change in the fourth euro futures contract) and explains a trivial share of their variance. The path surprise alone captures changes in the expected future path of the short rate, and therefore, triggers the channel through cash flow exposure that we study.

The third column of the table shows that when all covariates are included in the regression, the information in the exposure measure encompasses that of leverage and only the interaction between exposure and path exerts a statistically significant effect on firm-level stock prices. Note that including leverage and its interactions does not help in an R^2 sense either, further suggesting that it is the exposure measure that matters, with leverage operating in regressions that exclude exposure because it proxies in part for the more informative measure. Again, note that hedging against interest rate risk counteracts the negative effect on stock prices.

Finally, the last two columns of the table employ Fama-French-adjusted stock returns (i.e., difference between the raw stock return and the expected stock return based on the Fama-French three-factor model, Fama and French (1992, 1993, 1995)) over the event window as an alternative dependent variable.[14] The R^2 increases substantially, indicating that our floating rate exposure measure accounts for a substantial proportion of firm-level variation in policy day stock returns that are not attributed to the standard Fama-French factors.

The results above suggest that market participants pay attention to firms' balance sheets, particularly to their liability structures, and factor in the transfer between debt holders and equity holders that arise when expectations of future interest rates change (path surprise) in pricing stocks. This is a high level of sophistication, an issue we return to in Section III. We note that Table II by itself is silent on whether monetary policy's impact through floating rate exposure has real effects. The transfer between debt holders and equity holders alone will qualitatively generate Table II even if the Modigliani-Miller theorem holds, and this balance sheet effect has no real repercussions. We study monetary policy transmission effects in Section IV.

B.2. Did Monetary Policy Work Differently at the ZLB?

A nascent literature argues that monetary policy at the ZLB worked just like unconstrained monetary policy, through the use of forward guidance and quantitative easing (Swanson (2018), Debortoli, Galí, and Gambetti (2020)). An important exception is Ippolito, Özdağlı, and Perez-Orive (2018), who find that the floating rate channel worked only before the ZLB and ceased to exist when the constraint was binding.

[14] The Fama-French adjustment is along the lines of Gorodnichenko and Weber (2016), in which factor loadings are full sample coefficients of the returns on the factors and the predicted returns based on these are deducted from the raw returns to obtain adjusted (abnormal) returns.

Table III shows that the floating rate channel remained intact during the ZLB.[15] We test for a change in the relationship at the ZLB by including a binary variable for this period (January 2009 to December 2015) and interacting it with the cash flow channel variables. None of the interactions are statistically significant, showing that the binding constraint on immediate policy actions did not materially affect the cash flow channel, which depends on the interaction of path and cash flow exposure.[16] Thus, when measured using our exposure measure, the cash flow channel effects at the ZLB are also consistent with the view that the ZLB did not pose a major impediment to monetary policy effectiveness during the Great Recession.[17]

In addition to showing that monetary policy transmission to financial markets was unchanged during the ZLB in this dimension as well, this result implies that fully measuring firms' cash flow exposure—inclusive of debt maturity—and the monetary policy component that this exposure interacts with—forward guidance—are important constituent parts of answers to substantive questions. This point is worth emphasizing: although for simplicity we often model interest debt and interest rate to be of one period, for some questions, fully capturing maturity structures is necessary. The theoretically coherent balance sheet and monetary policy surprise measures that we use demonstrate that factoring these in makes a difference in empirical applications.

C. Robustness

The results presented above are highly robust, with the effect that we find coming across clearly in the data. Below we discuss some of the tests we carry out. Results are reported in the Internet Appendix.

Tables IA.VIII to IA.XIII in the Internet Appendix demonstrate that our findings hold in the period before and including the ZLB. Moreover, the results do not change when we employ an instrumental variable analysis in which the terms involving (already lagged) exposure are instrumented by those involving (further) four-quarter lagged exposure, which controls for current firm-specific information driving floating rate exposure. The results are also robust to using a narrower one-day window for stock returns, alternative measures of floating

[15] Table IA.VII in the Internet Appendix provides regression coefficients for all regressors.

[16] The marginal effects of a 100 bp path surprise for a nonhedged firm at the ZLB are −6.57% at the 90th percentile of exposure distribution, −7.81% at the 95th percentile, and −10.12% at the 99th percentile. All of these results are statistically significant at the 1% or 5% level, indicating statistical and economic significance.

[17] Ippolito, Özdağlı, and Perez-Orive (2018) follow Wright (2012) and use an unconventional monetary policy surprise that is closely related to the change in the 10-year yield as the policy surprise during the ZLB. We verified that the difference between our results stem from our inclusion of maturity information in the exposure measure, not from the using path versus change in a longer term interest rate. Gürkaynak, Sack, and Swanson (2005) show that the change in the 10-year yield around policy announcements is driven by path, hence this is not surprising.

Table III

Full Sample Including ZLB

The dependent variable is the two-day stock return bracketing an FOMC announcement. The sample covers 127 FOMC announcements between January 2004 and December 2018, which includes the ZLB period. This is incorporated into the regression model using a dummy variable (denoted by ZLB in the table, where ZLB = 1 from January 2009 to December 2015). Column (1) augments column (3) in Table II using this dummy variable. Column (2) is a version of (1) with only time fixed effects and column (3) includes both firm and time fixed effects. All other conventions are identical to those in Table II. Leverage refers to bank debt leverage. A total of 773 firms remain in the sample after controlling for potentially speculative derivative investments and dropping financial firms. Regression coefficients of control variables are reported in the Internet Appendix. *, **, and ***indicate statistical significance at 10%, 5%, and 1%, respectively.

Variables	(1) Stock Return	(2) Stock Return	(3) Stock Return
Target	−19.21**		
	(8.31)		
Path	−10.78***		
	(3.52)		
Exposure	−0.01	0.11	0.05
	(0.13)	(0.10)	(0.12)
Target*Exposure	−2.88	−3.27*	−2.83
	(1.78)	(1.89)	(1.89)
Hedge*Target*Exposure	2.29	1.86	0.81
	(3.91)	(3.29)	(3.43)
ZLB*Target*Exposure	3.30	−3.37	−2.70
	(9.51)	(4.67)	(5.19)
Hedge*ZLB*Target*Exposure	−7.30	6.11	7.50
	(12.97)	(8.20)	(8.69)
Path*Exposure	−2.40***	−1.56**	−1.66**
	(0.63)	(0.67)	(0.65)
Hedge*Path*Exposure	3.38***	2.62**	2.73***
	(1.03)	(1.03)	(1.04)
ZLB*Path*Exposure	0.18	−0.10	0.01
	(1.85)	(1.38)	(1.35)
Hedge*ZLB*Path*Exposure	−2.18	−1.48	−1.57
	(2.72)	(2.29)	(2.21)
Leverage	0.00	−0.55	−0.19
	(0.71)	(0.54)	(0.64)
Target*leverage	13.46	15.62	14.10
	(11.97)	(11.65)	(11.56)
Hedge*Target*Leverage	−9.46	−4.31	−2.70
	(22.37)	(21.29)	(20.86)
ZLB*Target*Leverage	−41.97	−1.42	−3.11
	(63.70)	(36.74)	(42.02)
Hedge*ZLB*Target*Leverage	89.12	−2.86	−13.88
	(104.41)	(48.99)	(58.68)
Path*Leverage	1.40	−0.37	0.06
	(3.69)	(3.00)	(3.39)
Hedge*Path*Leverage	−4.81	−3.10	−2.93
	(4.82)	(3.87)	(4.02)
ZLB*Path*Leverage	9.31	7.79	6.81
	(9.67)	(6.54)	(6.90)

(*Continued*)

Table III—*Continued*

Variables	(1) Stock Return	(2) Stock Return	(3) Stock Return
Hedge*ZLB*Path*Leverage	4.05	−1.53	−1.53
	(11.53)	(6.98)	(6.93)
Observations	23,465	23,465	23,465
R^2	0.09	0.30	0.32
Firm FE	YES	NO	YES
Time FE	NO	YES	YES
Firm Controls/Contr*Surp*Hedge*ZLB	YES	YES	YES

rate exposure and leverage,[18] alternative monetary policy surprises,[19] and additional control variables.[20] Including average liability maturity as a separate variable and in interactions similar to those of exposure and leverage does not change our results either. In each of these tests, it is not leverage or maturity alone, but the exposure measure we propose that drives the results.

The results are also robust to considering scheduled FOMC meetings only, which, together with the partial regression evidence above, alleviates the concern that our findings may be driven by a handful of influential events such as unscheduled FOMC meetings during the Great Recession. Our findings also go through using the quarterly exposure and leverage measures when available. These trade off the advantage of being more up to date and the disadvantage of being potentially less accurate because 10-Q forms, which are the source of the additional observations, are mostly unaudited. The results also pass falsification tests in which we look at two-day stock returns one week before FOMC announcements and find no relationship. Thus, it is not the case that high exposure firms always behave differently for some reason that is unrelated to monetary policy. Rather it is the increased variation in forward guidance created by the policy announcement that drives the result. In sum, extensive robustness tests consistently show that monetary policy affects firms' stock prices differentially as a function of their cash flow exposures.

III. Sophistication or Rules of Thumb?

We interpreted the results above as evidence of a good understanding of firm liability structures and their interaction with monetary policy surprises by stock market participants. An interesting question is whether financial market participants indeed study firms' balance sheets and, understanding the

[18] For instance, we consider the cash flow exposure measure based on floating rate debt items with outstanding maturities less than five years or based on bank debt items only.

[19] In particular, we use GSS monetary policy surprises based on the change in the yield curve up to two years in maturity rather than one.

[20] For instance, we control for the S&P credit rating, which proxies for access to credit, and the fixed rate exposure measure, which is obtained by applying the expression in equation (1) to fixed-rate debt items.

effect of monetary policy path surprises, price stocks accordingly, or whether the persistence of exposure leads market participants to learn rules of thumb according to which certain firms fare better or worse as interest rates increase or decrease. In this section, we show that the marginal stock market investor is quite sophisticated in that the repricing of stocks in high frequency is based not on rules of thumb but instead on knowledge of current balance sheet conditions.

We devise three tests of stock market participants' sophistication in studying and interpreting firms' liability structures and the interaction of these liability structures with monetary policy. These tests are designed to differentiate between investors following current firm liability structures and investors using rules of thumb to react to monetary policy surprises. In our weakest test, we separately examine firms that have recently had IPOs. These firms would not have stock market histories that can be used to develop rules of thumb and hence should not show the effect that we find if market participants do not study firms' balance sheets. Specifically, we interact a dummy for firms that have had an IPO in the past eight quarters with our variables of interest.

The first column of Table IV shows that IPO interaction effects are not statistically significant, suggesting that these firms' stock price reactions, as a function of their cash flow exposures and the path surprise, are not different from those of other firms. Since rules of thumb based on past stock price performance under different monetary conditions are by construction not present for these firms, the results suggest that investors are indeed paying attention to firms' current balance sheets.

While verifying our conjecture, this test is relatively weak due to two reasons. First, firms that have an IPO and enter our sample soon after are small in number (even though firms that are in the S&P500 index during any time in its history are in the sample) and hence standard errors of variables interacted with the dummy are quite wide. Second, firms that have had a recent IPO do not have stock price histories but do have balance sheet histories. If market participants follow rules of thumb or look at past profits, it is not clear what the implications for a firm with a recent IPO would be. If they use some type of heuristic (derived from past performance) for all firms that also applies to newly traded firms, we would again find no recent IPO effect.

While these concerns make this test a relatively weak one, they inform our next test, which separates firms that have seen the largest quarterly positive and negative changes in their floating rate exposure. Specifically, we construct separate dummies for the largest 20% of firm-quarters[21] based on the distribution of positive and negative *changes* in exposure between two filings of 10-Ks. Note that the number of observations for which the large positive change (more exposure) and large negative change (less exposure) dummy variables are equal to one constitute 20% of observations each, by construction. If market participants follow current balance sheets and assess their interactions with monetary policy, then these categories are irrelevant

[21] We check robustness using a variety of alternative threshold levels and find similar results.

Table IV

Stock Market Sophistication

The sample period ranges from January 2004 and December 2018. The dependent variable is the two-day stock return bracketing an FOMC announcement. IPO Dummy indicates whether firms are within the first two years of IPO. Positive Dummy corresponds to observations that belong to the top 20% of positive changes in exposure in the sample. Similarly, Negative Dummy corresponds to observations that belong to the top 20% of (absolute values of) negative changes in exposure. In column (1), similar results obtain when we instead use firms within the first quarter of IPO, within the second quarter of IPO, and so on. Column (3) includes both current and lagged exposure and their interaction terms. All regressions include firm and time fixed effects. Other conventions are identical to those in the tables above. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Variables	(1) (Dummy for Initial 8 Quarters after IPO) Stock Return	(2) (Dummy Large Changes) Stock Return	(3) (Current and Lagged Exposure) Stock Return
Exposure	0.05	0.10	−0.04
	(0.12)	(0.12)	(0.12)
Path*Exposure	−1.68**	−1.99***	−2.13***
	(0.65)	(0.63)	(0.70)
Hedge*Path*Exposure	2.68***	3.12***	2.64**
	(0.96)	(1.02)	(1.07)
IPO Dummy	−0.83		
	(0.82)		
IPO Dummy*Path	−4.12		
	(3.24)		
IPO Dummy*Path*Exposure	6.34		
	(4.06)		
IPO Dummy*Hedge*Path*Exposure	−4.25		
	(4.80)		
Positive Dummy		−0.17	
		(0.92)	
Positive dummy*Path		−3.28	
		(3.79)	
Positive Dummy*Exposure		−0.14	
		(0.66)	
Positive dummy*Path*Exposure		2.62	
		(2.11)	
Positive Dummy*Hedge*Path*Exposure		−1.02	
		(2.49)	
Negative Dummy		0.83	
		(0.73)	
Negative Dummy*Path		−0.64	
		(2.16)	
Negative Dummy*Exposure		−0.17	
		(0.50)	
Negative Dummy*Path*Exposure		2.52	
		(1.79)	
Negative Dummy*Hedge*Path*Exposure		−2.66	
		(2.04)	

Continued

Table IV—*Continued*

Variables	(1) (Dummy for Initial 8 Quarters after IPO) Stock Return	(2) (Dummy Large Changes) Stock Return	(3) (Current and Lagged Exposure) Stock Return
Lagged Exposure			−0.05
			(0.10)
Path*Lagged Exposure			0.81
			(0.69)
Hedge*Path*Lagged Exposure			−1.50
			(0.98)
Observations	23,465	23,465	19,255
R^2	0.32	0.32	0.33

and the dummy interactions will be insignificant. If, in contrast, investors employ rules of thumb based on past performance, then firms that have increased (decreased) their exposure will be treated like lower (higher) exposure firms and the dummy interactions will be positive (negative). This test is therefore does not suffer from the possible problems of the first one.

The second column of Table IV shows that neither of these dummies, in their interactions with our variables of interest, has statistically significant effects on stock price reactions to monetary policy. This is strong evidence that market participants analyze firms' current liability structures, understand the effects of floating rate exposure, and reprice when future expected interest rates change.

Our final test is in similar vein as our second test but employs an even stricter sophistication criterion. If market participants follow rules of thumb based on past performance in terms of our variables of interest, which are related to past exposure that is slow moving, then including past exposure in the analysis will be more helpful than including current exposure. When both past and current exposure are included in the analysis, under the rules of thumb interpretation, past exposure should matter and under the sophistication interpretation, current exposure should matter for stock price reactions.

The last column of Table IV shows that under this test, *only* current exposure matters. This is a very strong test to identify whether stock market investors pay attention to the ebbs and flows of firms' balance sheets. They do.

IV. Real Effects of Cash Flow Exposure

So far we have examined stock price reactions to monetary policy surprises at the firm level, which transmit through firms' cash flow exposures. We find a statistically and economically significant relationship and show that market participants pay attention to firms' current balance sheets.

Floating rate exposure changes firms' cash flows as interest rates change. This is part of a mechanism that underlies all financial accelerator mechanisms, which require cash in the firm to be more valuable than cash outside it. While our results so far are consistent with these models, the stock market reaction in and of itself does not settle the question as the transfer between debt and equity holders of a firm as a result of an interest rate change will produce these findings even if the Modigliani-Miller theorem holds. Accordingly, we directly examine future real outcomes of firms with different cash flow exposures when interest rates change to shed light on whether there is a transmission mechanism to real outcomes that works through cash flows.

Note the clear establishment of causality here. We are not looking at the effect of an interest rate change on firm behavior, as average firm behavior will be cyclical and endogenously related to monetary policy. Rather, our focus is on the effect of changes in interest rates, *through changes in cash flows based on firms' balance sheets*, on firm behavior. Individual firms' balance sheets are exogenous to monetary policy changes (after controlling for the extensive list of covariates and fixed effects that we employ), and hence, our identification comes from the cross-sectional variation in cash flow exposure. Using similar methodology, with leverage as the floating rate measure, Ippolito, Özdağlı, and Perez-Orive (2018) find mixed effects, and that only when studying strongly financially constrained firms, which excludes most of our sample of S&P500 firms. We show that differences in firms' balance sheets lead unambiguously to differences in real outcomes when firms' liability structure and monetary policy surprises are measured as we propose, and that this effect is present even for S&P500 firms.

Our balance sheet regressions take the form

$$\begin{aligned} bsv_{it+x} &= \beta_0 + \beta_1 exposure_{it-1} + \beta_2 path_t * exposure_{it-1} \\ &\quad + \beta_3 hedge_{it-1} * path_t * exposure_{it-1} \\ &\quad + \beta_4 zlb_t * path_t * exposure_{it-1} + \beta_5 hedge_{it-1} * zlb_t * path_t * exposure_{it-1} \\ &\quad + \lambda(remaining\ controls\ and\ interaction\ terms) + \varepsilon_{it+x} \end{aligned} \tag{3}$$

for $x = 1, 2, \ldots, 8$, where t is the reference quarter, bsv_{it+x} is one of the balance sheet variables defined below, and $path_t$ is the aggregated path surprise within the reference quarter. The control variables include the firm balance sheet variables in Table I with appropriate lags, as well as the covariates used in previous regressions.[22] The regressions also feature both year-quarter and firm-level fixed effects.[23]

[22] The results are robust to conditioning on the hedging indicator and the balance sheet variables as of the reference quarter t instead, as well as to also controlling for bank debt or floating rate leverage.

[23] We show abridged versions of regression output for readability. Tables IA.XIV to IA.XXI in the Internet Appendix present more comprehensive tables.

We first look at the cash flow effect on capital investment, which has remained an important debate in the corporate finance literature since the influential work of Fazzari et al. (1988) and Gilchrist and Himmelberg (1995). To measure capital investment, we consider the cumulative change in capital stock in $t+x$ relative to $t-1$ as a fraction of total assets in $t-1$. The first panel in Table V presents the results. A contractionary monetary policy surprise interacts with a firms' cash flow exposure to generate a persistent negative effect on capital investment. However, firms that hedge against the interest rate risk of their floating rate obligations are well protected, as indicated by the positive coefficient on the three-way interaction between the hedging indicator, aggregated path surprises, and floating rate exposure. Overall, these results provide strong evidence for cash flow sensitivity of investment.[24] Furthermore, we find no evidence that this relationship was different at the ZLB, as is indicated by the insignificant coefficient on the interaction between the ZLB indicator, aggregated path surprises, and floating rate exposure. This result verifies our findings based on stock market responses in Section II.B.2 that the ZLB did not disrupt the cash flow channel of monetary policy.

We next turn to net worth, which is a key variable for all financial accelerator mechanisms. As for capital investment, we measure net worth as the cumulative change relative to initial ($t-1$) total assets. The results are reported in the second panel of Table V. Our findings, which are consistent with those for capital investment above, again demonstrate the cash flow channel in action. The effect is persistent and statistically significant, empirically validating a mechanism that exists in a wide class of financial accelerator models whereby having less cash in the firm leads to persistently lower net worth. Moreover, the results indicate that the stock market reactions documented in Section II are also justified by realized future firm outcomes. Again, there is no evidence that the ZLB altered the working of the cash flow channel.

The decline in net worth documented above can occur through a change in total assets, a change in total liabilities, or both. This breakdown of the cash flow effect on net worth, which is interesting in itself as it provides stylized facts that business cycle theories should keep in mind, is what we turn attention to next.[25] Total assets and liabilities are again measured as the cumulative change relative to initial total assets (for total assets, the measure is there-

[24] The marginal effects of a path surprise are negative and highly statistically significant for relatively highly exposed firms, from one quarter ahead to eight quarters ahead. For instance, subject to a 100 bp surprise, a nonhedged firm at the 95$^{\text{th}}$ percentile of the exposure distribution sees its capital investment decline by -16.76% in $t+1$, -20.69% in $t+4$, -20.66% in $t+5$, and -22.32% in $t+8$ relative to initial total assets, with these changes statistically significant at the 1% or 5% level, while a hedged firm sees its capital investment decline by only -11.03%, -8.22%, -4.17%, and -8.35%, respectively, with the latter changes statistically significant at conventional levels only in t+1.

[25] Net worth, studied above, was constructed as total assets less total liabilities. Total assets clearly respond to cash flow. Total liabilities are noisier and due to the practice of accrual accounting and the structure of the data set employed in our study, the cash flow effect we are looking for is better captured by a liability measure constructed by summing "other current liabilities" and "long-term debt."

Table V

Balance Sheet Regressions

This table shows how monetary policy, through interactions with firms' exposure to floating rate liabilities, affects firms' balance sheet conditions and real outcomes. We consider effects on firms' capital stock, net worth, total assets, total liabilities, inventories, and cash holding. We use cumulative changes over initial total assets, $(Y_{i,t+x} - Y_{i,t-1})/Assets_{i,t-1}$, for all variables, which is also the cumulative percentage change with respect to the initial value, $(Y_{i,t+x} - Y_{i,t-1})/Y_{i,t-1}$ for total assets. The variables are multiplied by 100 so that the coefficients are in percentage points. The sample period is January 2004 to December 2018 and the ZLB enters the models using the binary indicator ZLB (ZLB = 1 from January 2009 to December 2015). Path is the aggregated path surprise within reference quarter t. We control for size, profitability, book leverage, market-to-book ratio, asset maturity, financial slack (not included in the cash holding regression because it would in effect include the lagged dependent variable), retained earnings, dividends per share, and short-term debt, which are also interacted with the aggregated monetary policy surprises. We also include firm and year-quarter fixed effects, and cluster standard errors at the quarter level (the results are robust to using quarter-industry clustering instead). Numbers in parentheses are standard errors. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Capital Investment (Cum. Change in Capital Stock over Assets)	$(t+1)$	$(t+2)$	$(t+3)$	$(t+4)$	$(t+5)$	$(t+6)$	$(t+7)$	$(t+8)$
Path*Exposure	−5.32***	−5.61***	−4.55***	−6.37***	−7.31***	−7.40***	−6.90***	−8.98***
	(1.36)	(1.52)	(1.56)	(1.92)	(2.22)	(2.05)	(1.94)	(2.51)
Hedge*Path*Exposure	2.31	1.91	2.62	5.03**	6.65**	5.78**	4.28**	5.63**
	(2.15)	(1.70)	(1.68)	(1.93)	(2.66)	(2.48)	(2.06)	(2.39)
ZLB*Path*Exposure	−0.30	−0.42	0.30	3.24	4.17	9.72*	5.40	8.62
	(1.63)	(2.07)	(2.19)	(2.68)	(4.27)	(5.64)	(5.10)	(6.69)
Hedge*ZLB*Path*Exposure	8.10***	8.88**	7.19*	3.59	1.17	−4.06	1.29	−1.58
	(2.77)	(3.50)	(4.10)	(4.18)	(6.43)	(7.77)	(9.19)	(10.70)
Net Worth (Cum. Change in Net Worth over Assets)								
Path*Exposure	−4.82***	−4.31***	−3.84***	−3.98***	−3.89***	−4.02***	−3.57***	−3.01**
	(1.06)	(1.03)	(1.04)	(1.09)	(1.13)	(1.14)	(1.12)	(1.37)
Hedge*Path*Exposure	−0.73	−0.99	−1.04	−1.45	−0.44	−1.26	−0.44	−2.60
	(1.88)	(1.78)	(1.55)	(1.71)	(1.97)	(2.12)	(2.09)	(2.17)
ZLB*Path*Exposure	2.29	1.08	2.29	2.69	2.33	0.02	1.92	1.94
	(1.70)	(2.80)	(2.57)	(2.55)	(2.18)	(2.70)	(3.63)	(3.80)
Hedge*ZLB*Path*Exposure	7.43***	8.97**	5.61	4.69	0.80	2.40	−3.05	0.75
	(2.73)	(3.63)	(3.56)	(3.70)	(3.20)	(3.20)	(5.24)	(5.52)

(Continued)

Table V—*Continued*

Total Assets (Cum. Perc. Change)								
Path*Exposure	−7.10***	−6.73***	−5.91***	−6.36***	−8.15***	−7.70***	−7.15***	−7.36**
	(1.66)	(1.80)	(1.84)	(1.93)	(2.56)	(2.53)	(2.40)	(2.81)
Hedge*Path*Exposure	−4.06	−4.29	−2.09	−4.22	−2.44	−4.62	−2.59	−6.84*
	(3.80)	(3.30)	(3.35)	(3.50)	(3.78)	(3.79)	(3.86)	(3.99)
ZLB*Path*Exposure	1.36	−0.80	3.59	2.30	0.02	−9.21	−5.78	−6.10
	(2.45)	(5.15)	(5.27)	(5.93)	(5.16)	(6.05)	(9.08)	(9.49)
Hedge*ZLB*Path*Exposure	18.47***	20.74**	12.52	15.46	17.04*	25.13***	18.51	24.77
	(4.93)	(7.92)	(9.04)	(9.57)	(8.97)	(9.05)	(13.68)	(14.91)
Total Liabilities (Cum. Change in Liabilities over Assets)								
Path*Exposure	−2.52***	−2.84***	−2.69***	−2.54***	−3.74***	−3.37**	−3.33**	−4.22**
	(0.84)	(0.78)	(0.89)	(0.90)	(1.34)	(1.41)	(1.56)	(1.68)
Hedge*Path*Exposure	−1.94	−1.47	−0.03	−3.75**	−2.94	−3.26	−0.14	−0.96
	(1.44)	(1.22)	(1.63)	(1.64)	(1.78)	(2.08)	(2.33)	(2.57)
ZLB*Path*Exposure	0.04	−1.62	0.31	−0.88	−1.89	−6.49**	−5.42	−7.62*
	(1.05)	(1.37)	(1.65)	(2.06)	(2.30)	(2.63)	(3.98)	(4.23)
Hedge*ZLB*Path*Exposure	9.62***	11.13**	5.22	10.52**	15.14***	18.95***	15.70**	19.43**
	(3.52)	(4.50)	(4.82)	(4.97)	(5.07)	(5.95)	(7.72)	(8.13)

(*Continued*)

Table V—*Continued*

Inventory Investment (Cum. Change in Inventories over Assets)								
Path*Exposure	−0.38***	−0.40**	−0.31**	−0.22	−0.45***	−0.17	−0.24	−0.32
	(0.11)	(0.16)	(0.14)	(0.14)	(0.16)	(0.24)	(0.22)	(0.24)
Hedge*Path*Exposure	0.07	0.04	−0.09	−0.28*	−0.15	−0.51**	−0.27	−0.33
	(0.11)	(0.11)	(0.12)	(0.16)	(0.17)	(0.24)	(0.22)	(0.24)
ZLB*Path*Exposure	0.17	−0.30	0.01	−0.34	−0.04	−0.41	−0.30	0.10
	(0.21)	(0.30)	(0.45)	(0.49)	(0.44)	(0.53)	(0.80)	(0.97)
Hedge*ZLB*Path*Exposure	0.06	0.63*	0.24	0.77	0.55	1.11	0.78	0.49
	(0.31)	(0.32)	(0.63)	(0.74)	(0.72)	(0.73)	(1.11)	(1.35)
Cash Holding (Cum. Change in Cash Holding over Assets)								
Path*Exposure	−0.06	−0.07	−0.37	−0.81*	−1.00*	−1.03*	−1.22***	−0.41
	(0.25)	(0.36)	(0.39)	(0.44)	(0.53)	(0.51)	(0.44)	(0.49)
Hedge*Path*Exposure	−0.13	0.33	0.61	0.35	0.75	0.71	1.36*	0.96
	(0.47)	(0.81)	(0.68)	(1.01)	(0.72)	(0.85)	(0.77)	(0.59)
ZLB*Path*Exposure	−0.33	−0.30	0.25	0.47	0.70	−2.02**	−0.25	0.03
	(0.36)	(0.60)	(0.82)	(0.69)	(0.88)	(0.99)	(1.24)	(1.91)
Hedge*ZLB*Path*Exposure	1.34	0.24	−0.07	−0.41	−0.03	1.31	−0.02	−2.50
	(0.87)	(1.28)	(1.32)	(1.41)	(1.96)	(1.61)	(1.70)	(2.58)
Firm and Time FEs	YES	YES	YES	YES	YES	YES	YES	YES
Firm controls interacted with surprises	YES	YES	YES	YES	YES	YES	YES	YES

fore also the cumulative percentage change relative to $t-1$). The third and fourth panels of Table V present results for total assets and total liabilities, respectively. We see that both total assets and total liabilities decrease, with the former decreasing to a greater extent. The decline in net worth therefore arises despite the decrease in total liabilities, due to the even larger decrease in total assets, which is consistent with the large decline in capital investment documented above. The coefficients on the interaction term between path surprises and cash flow exposure in these panels line up with the same coefficient in the panel for net worth. In the last two panels of Table V, we report the results for inventory investment and cash holdings, which are also consistent with the working of the cash flow effect. The analysis of cash holdings has ambiguous theoretical underpinnings as firms often liquidate other assets to keep cash in hand, and we have already seen that total assets decrease in response to an adverse policy surprise for firms with high cash flow exposure. The results for cash holding are presented for completeness and show that cash holdings also decline after a few quarters.

Our findings indicate real effects of monetary policy, whose transmission operates through firms' cash flow exposure and the ensuing changes in cash flows due to changes in interest rates. Significantly, we find these effects for S&P500 firms, which are older, larger, and are typically thought of as less financially constrained than other firms (Hadlock and Pierce (2010)). Cash flow sensitivity is thus an important concern for even these firms, with their behavior responding to monetary policy in part through interest rate effects on their balance sheets.

Explicitly testing for the presence of financial frictions driving these real effects requires showing that given a monetary policy shock, more constrained firms' cash flow exposure affects their real outcomes more. To do so, we capture financial constraint by using the weighted average of size, interest coverage, return on assets, and cash holdings (Schauer, Elsas, and Breitkopf (2019) show that this measure outperforms others and can be applied to listed U.S. firms). We include the financial constraint alone, as well as in interactions and report the main results in Table VI, relegating further details to Internet Appendix Tables IA.XX and IA.XXI.

Table VI clearly shows that financial constraints matter, with more constrained firms showing larger sensitivity to cash flows in response to monetary policy shocks.[26] This evidence provides strong support for the relevance of

[26] The marginal effects for capital investment are as follows. At the 95th percentile of exposure distribution and the median of financial constraint distribution, the marginal effects of a 100 bp path surprise for a nonhedged firm are −24.76% in $t+1$, −26.68% in $t+4$, −27.28% in $t+5$, and −17.66% in $t+8$ relative to initial assets, which are statistically significant at the 1% or 5% level. But a hedged firm sees weaker effects of −14.13%, −8.13%, −3.89%, and 4.36%, respectively, which are statistically significant at conventional levels only in $t+1$. At the 10th percentile of financial constraint (less constrained), the effect is weaker and not statistically significant at conventional levels for both hedged and nonhedged firms. However, at the 90th percentile of financial constraint (more constrained), the effect is stronger and statistically significant for the nonhedged firms (−30.30%, −35.05%, −36.63%, and −26.55%, respectively, all at the 1% level) but

Table VI

Balance Sheet Regressions with Financial Constraints

This table shows the effect of financial constraints on balance sheet conditions and real outcomes. We adopt the financial constraint index of Schauer, Elsas, and Breitkopf (2019) that takes the form $FCP_{i,t} = -0.123{*}size_{i,t-1} - 0.024{*}interestcoverage_{i,t-1} - 4.404{*}ROA_{i,t-1} - 1.716{*}cashholdings_{i,t-1}$ (see the Appendix for definitions). The larger (less negative) the value, the more financially constrained the firm is. We use the simple average of this measure in the previous four quarters as an indicator of a firm's financial condition over the past year, reported as Fincon here. It is interacted with monetary policy surprises and the floating rate exposure measure to test the financial accelerator mechanism. Other conventions are identical to those in Table V. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Capital Investment (Cum. Change in Capital Stock over Assets)	(t+1)	(t+2)	(t+3)	(t+4)	(t+5)	(t+6)	(t+7)	(t+8)
Path*Exposure	−19.79***	−20.83***	−16.08***	−27.26***	−30.79***	−31.31***	−24.62***	−30.72**
	(5.30)	(5.80)	(4.03)	(8.42)	(9.73)	(10.42)	(5.86)	(11.75)
Hedge*Path*Exposure	14.20	17.11**	19.95***	32.93***	43.16***	43.60***	32.04***	41.58**
	(8.95)	(7.48)	(5.78)	(11.27)	(12.96)	(14.04)	(10.18)	(17.04)
ZLB*Path*Exposure	2.77	5.15	1.04	13.40	15.53	10.91	0.51	11.45
	(6.64)	(8.27)	(6.55)	(12.35)	(15.46)	(23.47)	(18.02)	(22.74)
Hedge*ZLB*Path*Exposure	34.51	23.94	40.21**	19.94	12.74	20.35	30.67	1.62
	(21.44)	(24.77)	(19.87)	(23.72)	(27.99)	(34.08)	(33.09)	(37.87)
Fincon*Path*Exposure	−7.17**	−7.49**	−4.66**	−11.03**	−12.29**	−13.10**	−8.27**	−11.77*
	(3.19)	(3.45)	(2.05)	(4.80)	(5.47)	(5.95)	(3.13)	(7.01)
Hedge*Fincon*Path*Exposure	6.24	8.51*	9.43**	16.09**	21.86***	22.49**	16.10**	21.99*
	(5.38)	(4.92)	(3.96)	(7.16)	(7.99)	(8.78)	(6.75)	(11.77)
ZLB*Fincon*Path*Exposure	0.84	2.38	−0.52	5.86	6.67	−2.34	−6.27	−1.73
	(4.20)	(5.13)	(3.50)	(7.27)	(8.68)	(12.18)	(8.86)	(11.56)
Hedge*zlb*Fincon*Path*Exposure	17.17	9.74	20.49*	9.92	5.09	16.70	19.23	2.23
	(12.92)	(14.41)	(11.17)	(13.63)	(15.23)	(18.34)	(16.29)	(19.12)
Net Worth (Cum. Change in Net Worth over Assets)								
Path*Exposure	−12.89***	−12.66***	−10.84***	−11.31***	−12.11***	−11.77***	−13.05***	−11.18***
	(3.53)	(3.66)	(3.07)	(3.11)	(2.84)	(2.93)	(3.08)	(3.92)
Hedge*Path*Exposure	4.79	7.87	7.10	7.06	7.51	4.99	15.90**	16.69**
	(7.57)	(6.70)	(5.94)	(6.30)	(6.38)	(6.60)	(6.34)	(6.57)

(Continued)

Table VI—*Continued*

Net Worth (Cum. Change in Net Worth over Assets)								
ZLB*Path*Exposure	−0.98	−2.38	0.93	4.94	−1.21	0.25	7.07	7.41
	(5.38)	(5.67)	(5.55)	(6.06)	(7.25)	(6.49)	(6.25)	(7.22)
Hedge*ZLB*Path*Exposure	28.16*	28.46*	9.32	2.61	0.48	4.86	−13.16	−23.63
	(15.97)	(15.33)	(15.86)	(16.10)	(14.88)	(14.42)	(19.44)	(20.70)
Fincon*Path*Exposure	−3.60	−4.04*	−3.20	−3.70*	−4.35**	−4.58**	−6.13***	−5.55**
	(2.18)	(2.17)	(2.08)	(2.17)	(1.95)	(2.04)	(2.01)	(2.51)
Hedge*Fincon*Path*Exposure	0.94	4.28	2.84	3.24	2.64	1.96	10.50**	12.54**
	(4.07)	(3.91)	(4.20)	(4.18)	(4.26)	(4.86)	(5.16)	(5.29)
ZLB*Fincon*Path*Exposure	−3.16	−3.27	−2.17	0.43	−3.28	−0.23	3.31	3.03
	(3.33)	(3.08)	(3.39)	(3.72)	(4.75)	(4.44)	(3.83)	(4.34)
Hedge*ZLB*Fincon*Path*Exposure	15.04	13.73	5.38	1.76	2.81	3.25	−5.34	−12.95
	(9.59)	(8.71)	(8.79)	(8.92)	(9.40)	(9.32)	(10.33)	(10.70)
Firm and Time FEs	YES	YES	YES	YES	YES	YES	YES	YES
Firm controls interacted with surprises	YES	YES	YES	YES	YES	YES	YES	YES

financial frictions in amplifying and propagating monetary policy transmission, as in financial accelerator models.

V. Central Bank Information Effects

A recent set of papers argues that monetary policy surprises as measured here may be forecastable (Karnaukh (2020), Miranda-Agrippino and Ricco (2021)) and may capture information transmitted from the Fed to the public via monetary policy actions and announcements (Jarociński and Karadi (2020), Andrade and Ferroni (2021)).[27] Bauer and Swanson (2020) nicely show that when the public knows the state of the economy but not the exact monetary policy rule, the surprises we measure will be unforecastable in real time but forecastable ex post. In this case, high-frequency regressions of stock prices on monetary policy surprises and their interpretations are unaffected. The lower frequency analysis presented in Section V has the interpretation we offer under the assumption that the monetary policy surprises are "clean" and may still have the same interpretation under some asymmetric information structures, but may admit other interpretations if policy surprises convey the Fed's private information (perhaps about its preferences) and such information directly affects firm-level real outcomes in a way that is correlated with cash flow exposures.

Model-based analyses of such information effects face serious identification problems (Lee (2020), Gürkaynak et al. (2021)),[28] but empirically asking whether something helps forecast a monetary policy surprise and, if so, whether removing that component makes a difference is possible. In this section, we show that doing so does not affect our findings and hence present the results without taking a stance on whether the analysis is theoretically justified.

This exercise is based on Miranda-Agrippino and Ricco (2021), who run a first-stage regression of the policy surprise on the changes in Fed staff's internal (Greenbook) forecast since the last meeting. We take averages of the variables as in Karnaukh (2020) (although following Miranda-Aggripino and Ricco exactly makes no difference). Running the regression separately for target and path surprises, we find some coefficients that are statistically significant, in line with the papers above. These first-stage regressions are reported in Table VII. Note that the R^2s of these regressions are very low, indicating

weaker and statistically significant at conventional levels only in $t+1$ (−16.58%, −8.03%, −0.31%, and 8.79%, respectively) for hedged firms.

[27] We thank Nina Karnaukh, Silvia Miranda-Agrippino, and Giovanni Ricco for sharing some or all of their data and for answering our questions.

[28] While Lee (2020) focuses on central bank information transmission to the public through a short-term policy rate in a closed economy subject to an occasionally binding ZLB constraint, Gürkaynak et al. (2021) discuss the issue in an open economy context, concentrating on information structure indeterminacy related to exchange rate behavior. Both examine shock identification issues using (otherwise standard) New Keynesian models under asymmetric information.

Table VII
First-Stage Regressions with Greenbook Forecasts

This table provides first-stage regression results where GSS target and path surprises are the dependent variables. The independent variables are average forecast revisions in real GDP, inflation, and unemployment for the current and next three quarters from the Fed's Greenbook data set. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	1994 to 2013				2004 to 2013			
	Baseline Spec.		Extended Spec.		Baseline Spec.		Extended Spec.	
Variables	Target	Path	Target	Path	Target	Path	Target	Path
Real GDP	1.67	7.39**	1.95	6.21	1.36	8.46*	0.81	6.07
	(1.17)	(3.60)	(1.29)	(4.20)	(1.22)	(4.33)	(1.34)	(3.96)
Inflation			0.11	18.36*			4.51	20.58*
			(3.55)	(9.36)			(5.06)	(12.21)
Unemployment			1.51	−8.39			−2.22	−9.51
			(3.17)	(11.08)			(3.28)	(10.69)
Constant	0.00	0.01	0.00	0.01	0.01*	0.02	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Observations	172	172	172	172	87	87	87	87
R^2	0.01	0.04	0.01	0.07	0.02	0.10	0.04	0.15

that any information effects that may be present constitute a small fraction of the surprises.

We next run our core stock price and real effects regressions with the residuals from the first stage, using the extended specification in our sample period.[29] Under the Fed information effect interpretation, these residuals are cleansed and capture the pure monetary policy surprise. (Under the central bank preferences being time varying and unknown to the public interpretation, the first stage captures information about Fed preferences and is still about monetary policy.) Tables VIII and IX show that using this measure of policy surprises, the main results are unchanged—path surprises' interaction with firms' cash flow exposures predicts both stock price responses and future real outcomes for the firms in our sample.

VI. Conclusions

Cash flow matters. Stock market participants know that firms with higher levels of unhedged floating rate obligations will fare worse in an increasing interest rate environment and better in a decreasing one. And they are right, both because higher interest rates mechanically redistribute firm income from dividends to interest payments, and because as future cash flow obligations increase, firm investment and net worth decrease. For these firms, higher interest payments lead to higher cash outflows, and firms cannot costlessly substitute external financing for internal funds. Thus, there is a clear financial

[29] We present the longer sample results for the first stage, going back to 1994, to show that our sample period is not special in this regard.

Table VIII

Stock Market Regressions with Target and Path Residuals

This table runs our stock return regressions in Table III with the residuals obtained from the first-stage regressions in Table VII, using our extended specifications under the last two columns. Targetres is the residual from the first stage regression for target surprises and Pathres is the analogue for path surprises. We consider specifications with only firm fixed effects and both firm and time fixed effects. Other conventions are identical to those in Table III. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Variables	(1) Stock Return	(2) Stock Return
Targetres	−13.46	
	(10.59)	
Pathres	−3.78	
	(4.91)	
Exposure	0.20	0.22
	(0.25)	(0.19)
Targetres*Exposure	−2.88	−2.46
	(2.59)	(2.34)
Hedge*Targetres*Exposure	−0.18	0.22
	(5.44)	(3.88)
ZLB*Targetres*Exposure	−5.11	3.71
	(9.52)	(8.24)
Hedge*ZLB*Targetres*Exposure	21.17	20.00
	(19.75)	(18.32)
Pathres*Exposure	−2.88**	−2.04**
	(1.23)	(1.01)
Hedge*Pathres*Exposure	3.89**	3.00*
	(1.86)	(1.51)
ZLB*Pathres*Exposure	−0.89	−0.66
	(1.75)	(1.73)
Hedge*ZLB*Pathres*Exposure	−0.32	0.35
	(2.59)	(2.18)
Leverage	0.50	−0.26
	(1.01)	(0.95)
Targetres*Leverage	14.79	12.72
	(13.13)	(13.30)
Hedge*Targetres*Leverage	0.72	−0.41
	(24.96)	(21.71)
ZLB*Targetres*Leverage	7.16	−45.82
	(63.70)	(47.98)
Hedge*ZLB*Targetres*Leverage	42.37	61.02
	(63.75)	(52.79)
Pathres*Leverage	0.84	−0.20
	(5.48)	(5.24)
Hedge*Pathres*Leverage	−4.20	−1.14
	(6.24)	(6.09)
ZLB*Pathres*Leverage	17.07**	11.06
	(7.71)	(7.65)
Hedge*ZLB*Pathres*Leverage	1.53	−8.22
	(12.28)	(9.15)
Observations	14,118	14,118

(*Continued*)

Table VIII—*Continued*

Variables	(1) Stock Return	(2) Stock Return
R^2	0.09	0.36
Firm FE	YES	YES
Time FE	NO	YES
Firm controls/Contr*Surp*Hedge*ZLB	YES	YES

accelerator channel that is intimately linked to monetary policy as the rates on firms' new fixed rate debts, as well as the payments of their previously issued floating debts, depend on current interest rates.

We find that looking at the maturity structure of debt obligations is important for understanding the interaction between monetary policy decisions and the cash flow channel. Bank debt and floating rate debt leverage do not sufficiently capture firms' cash flow obligations and how these obligations change in response to monetary policy surprises, as these measures are based on the principal value rather than the commitments for future payments, which depend on maturity as well as the principal value. We empirically see the relevance of debt maturity information.

While studying these questions, we find that the choice of monetary policy surprise measure also matters. The path, or forward guidance, component of monetary policy is the surprise about the future path of interest rates. It is intuitive that this component would have a sizable bearing on future cash flow obligations, and thus is the component that stock market participants pay attention to when updating beliefs about firms' cash flows and reassessing stock prices according to new information. We show that this distinction is important for firms' stock price changes before, during, and after the ZLB.

Studying whether high-frequency stock price responses to monetary policy surprises depend on firms' balance sheets requires jointly testing the existence of such an effect and market participants' ability to incorporate it to prices shortly after a policy announcement. Finding this effect naturally leads to the question of whether market participants actually pay attention to firm balance sheets and understand how they interact with monetary policy, or whether they learn and follow rules of thumb as cash flow exposure is quite persistent. We show that market participants do indeed pay attention to balance sheets and differentiate firms by their current liabilities when repricing stocks in response to monetary policy surprises. This is of independent interest.

Finally, we show that cash flow exposure has real effects. More exposed firms—those that have more unhedged long maturity floating rate obligations—see their investment, assets, and net worth change more in quarters following monetary policy changes. These results provide strong evidence in favor of a financial friction whereby cash in the firm is more valuable than cash outside it. Thus, there is indeed an external finance premium, and unhedged cash flow exposure triggers it. We also find that the ZLB has not

Table IX

Balance Sheet Regressions with Target and Path Residuals

This table reevaluates the balance sheet regressions in Table V with the residuals obtained from the last two columns of Table VII. Other conventions are identical to those in Table V. The results for other variables are also similar to those in Table V. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Capital Investment (Cum. Change in Capital Stock over Assets)	(t+1)	(t+2)	(t+3)	(t+4)	(t+5)	(t+6)	(t+7)	(t+8)
Pathres*Exposure	−5.59**	−5.95***	−3.61*	−5.01**	−5.47*	−5.36*	−5.35**	−7.31**
	(2.08)	(2.19)	(2.07)	(2.25)	(2.75)	(2.79)	(2.41)	(2.96)
Hedge*Pathres*Exposure	2.36	−0.17	0.13	2.87	5.04	3.80	1.71	2.80
	(2.69)	(3.39)	(3.31)	(3.11)	(3.81)	(3.54)	(3.55)	(2.91)
ZLB*Pathres*Exposure	−0.70	−0.97	−1.16	−1.31	−2.14	1.43	3.98	4.37
	(1.70)	(1.83)	(2.21)	(2.26)	(2.60)	(4.02)	(3.39)	(4.24)
Hedge*ZLB*Pathres*Exposure	10.45**	12.04**	10.77**	7.84*	5.77	5.46	5.30	4.87
	(4.23)	(4.97)	(5.25)	(4.46)	(5.00)	(5.42)	(6.45)	(6.23)
Net Worth (Cum. Change in Net Worth over Assets)								
Pathres*Exposure	−5.49***	−4.56***	−3.59**	−3.09**	−3.53***	−3.20***	−3.05**	−2.88**
	(1.59)	(1.48)	(1.46)	(1.31)	(1.23)	(1.13)	(1.13)	(1.22)
Hedge*Pathres*Exposure	−1.63	−2.66	−3.43	−4.37	−1.43	−3.16	−2.84	−3.69
	(2.77)	(3.55)	(3.65)	(3.88)	(4.34)	(4.53)	(4.24)	(4.65)
ZLB*Pathres*Exposure	0.42	−4.19**	−2.17	−1.87	0.27	−0.22	2.82	1.83
	(1.79)	(1.69)	(2.12)	(1.96)	(1.11)	(1.87)	(4.21)	(4.48)
Hedge*ZLB*Pathres*Exposure	12.37***	17.61***	12.42**	12.33**	5.06	7.19	3.44	4.94
	(4.34)	(4.61)	(4.84)	(5.04)	(5.16)	(5.50)	(7.65)	(8.29)
Firm and Time FEs	YES	YES	YES	YES	YES	YES	YES	YES
Firm controls interacted with surprises	YES	YES	YES	YES	YES	YES	YES	YES

changed this relationship, which further suggests that the transmission of monetary policy was unhindered by this constraint.

We leave for future work the study of aggregate effects of this channel and questions related to further differences in balance sheets, such as callability of debt or existence of untapped lines of credit, as well as the effects of quantitative easing and possible asymmetries of positive and negative surprises or surprises that take place in high and low interest rate environments. We also leave for future work the question of how monetary policy should be carried out in light of this mechanism that changes our understanding of real effects of forward guidance.

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Appendix: Variable Definitions

Variable (Frequency)	Type	Definition	Data Source
Stock return (daily)	Regressand	Percentage change of stock price between the day before and the day after an FOMC announcement.	CRSP database
Monetary policy target and path surprises (FOMC meetings)	Regressor	Market-based (i.e., futures contracts) monetary policy innovations. Target factor: a surprise to the current policy target; Path factor: a surprise to the future policy rates.	Authors' calculation following Gürkaynak, Sack, and Swanson (2005)
Floating rate exposure (annual and quarterly)	Regressor	The sum of maturity-weighted floating rate debts, expressed as a fraction of total assets (ATQ).	CIQ and Compustat database
Bank debt leverage (annual and quarterly)	Regressor	Bank debts (= term loans + (drawn) credit lines), expressed as a fraction of total assets (ATQ).	CIQ and Compustat database
Floating rate debt leverage (annual and quarterly)	Regressor	Total floating rate debts, expressed as a fraction of total assets (ATQ).	CIQ and Compustat database
Hedge (quarterly)	Regressor	A dummy variable equal to 1 if a firm hedges against interest rate risks of its floating rate obligations by entering into interest rate derivative contracts.	10-Q and 10-K reports in SEC database

Variable (Frequency)	Type	Definition	Data Source
ZLB (FOMC meetings)	Regressor	A dummy variable equal to 1 from January 2009 to December 2015.	The Federal Reserve website
Size (quarterly)	Regressor	Book value of total assets (ATQ) deflated by CPI, in logarithm.	Compustat database
Profitability (quarterly)	Regressor	Operating income before depreciation (OIBDPQ), expressed as a fraction of total assets (ATQ).	Compustat database
Book leverage (quarterly)	Regressor	The ratio of total debts (DLCQ + DLTTQ) to the sum of total debts and the book value of equity (DLCQ + DLTTQ + CEQQ).	Compustat database
Market-to-book ratio (quarterly)	Regressor	The sum of the market value of equity and total debts (PRCCQ*CSHOQ + DLCQ + DLTTQ), expressed as a fraction of total assets (ATQ).	Compustat database
Asset maturity (quarterly)	Regressor	The sum of (i) the product of gross property, plant, and equipment as a fraction of total assets and as a fraction of depreciation and amortization, respectively, and (ii) the product of current assets as a fraction of total assets and as a fraction of cost of goods sold, respectively, ((PPEGTQ/ATQ)*(PPEGTQ/DPQ)) +((ACTQ/ATQ)*(ACTQ/COGSQ)).	Compustat database
Financial slack (quarterly)	Regressor	Cash holding (CHEQ), expressed as a fraction of total assets (ATQ).	Compustat database
Retained earnings (quarterly)	Regressor	Retained earnings (REQ), expressed as a fraction of total assets (ATQ).	Compustat database
Dividend per share (quarterly)	Regressor	Dividend per share (DVPSPQ).	Compustat database
Short-term debt (quarterly)	Regressor	Short-term debt (DLCQ), expressed as a fraction of total assets (ATQ).	Compustat database
Credit rating (quarterly)	Regressor	S&P Quality Ranking (SPCRSC).	Compustat database
Capital investment (quarterly)	Regressand	Cumulative change in total fixed capital (PPEGTQ), expressed as a fraction of initial total assets (ATQ).	Compustat database

Variable (Frequency)	Type	Definition	Data Source
Net worth (quarterly)	Regressand	Cumulative change in net worth (ATQ - LTQ), expressed as a fraction of initial total assets (ATQ).	Compustat database
Total assets (quarterly)	Regressand	Cumulative percentage change in total assets (ATQ) relative to the initial quarter.	Compustat database
Total liabilities (quarterly)	Regressand	Cumulative change in long-term debt and other current liabilities (DLTTQ+LCOQ), expressed as a fraction of initial total assets (ATQ).	Compustat database
Inventory investment (quarterly)	Regressand	Cumulative change in inventory (INVTQ), expressed as a fraction of initial total assets (ATQ).	Compustat database
Cash holding (quarterly)	Regressand	Cumulative change in cash holding (CHEQ), expressed as a fraction of initial total assets (ATQ).	Compustat database
Financial constraints	Regressor	Adopted from Schauer, Elsas, and Breitkopf (2019), a simple average over the past four quarters of $FCP_{i,t} = -0.123{*}size_{i,t-1} - 0.024{*}interestcoverage_{i,t-1} - 4.404{*}ROA_{i,t-1} - 1.716{*}cashholdings_{i,t-1}$, where $size =$ log(ATQ), $interestcoverage =$ (SALEQ-XSGAQ-COGSQ-DPQ)/XINTQ, $ROA =$ NIQ/ATQ, and $cashholdings =$ CHEQ/ATQ.	Compustat database
Maturity (annual)	Regressor	Three different measures are used: (i) the sum of leverage (debt amount as a fraction of total assets) weighted maturity when interest rate types are known to be floating or fixed, (ii) the sum of leverage weighted maturity for all debt types (including those with unknown interest rate types), and (iii) the simple arithmetic average of all debt types.	CIQ and Compustat database
Real GDP revision	Regressor	Average forecast revisions in quarter-to-quarter real GDP growth for the current and next three quarters.	Miranda-Agrippino and Ricco (2021)

Variable (Frequency)	Type	Definition	Data Source
Inflation revision	Regressor	Average forecast revisions in quarter-to-quarter price index growth for the current and next three quarters.	Miranda-Agrippino and Ricco (2021)
Unemployment revision	Regressor	Average forecast revisions in unemployment rate for the current and next three quarters.	Miranda-Agrippino and Ricco (2021)
Target residuals	Regressor	Estimated residuals from the first stage regression of target surprises on average revisions in real GDP, inflation, and unemployment rate, to control for central bank information effects.	Miranda-Agrippino and Ricco (2021) and own calculations
Path residuals	Regressor	Estimated residuals from the first stage regression of path surprises on average revisions in real GDP, inflation, and unemployment rate, to control for central bank information effects.	Miranda-Agrippino and Ricco (2021) and own calculations

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.