Crossing the Credit Channel: Credit Spreads and Firm Heterogeneity[☆]

Gareth Anderson[†] Ambrogio Cesa-Bianchi[‡]

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Abstract

We show that credit spreads rise after a monetary policy tightening, yet spread reactions are heterogeneous across firms. Exploiting information from a unique panel of corporate bonds matched with balance sheet data for US non-financial firms, we document that firms with high leverage experience a more pronounced increase in credit spreads than firms with low leverage. A large fraction of this increase is due to a component of credit spreads that is in excess of firms' expected default—the excess bond premium. Consistent with the spreads response, we also document that high-leverage firms experience a sharper contraction in debt and investment than low-leverage firms. Our results provide evidence that balance sheet effects are crucial for understanding the transmission mechanism of monetary policy.

Keywords: Monetary Policy, Heterogeneity, Credit Spreads, Excess Bond Premium, Credit Channel, Financial Accelerator, Event Study, Identification.
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[†]IMF and University of Oxford. Email: ganderson2@imf.org.
[‡]Bank of England, CFM, and CEPR. Email: ambrogio.cesa-bianchi@bankofengland.co.uk.

1 Introduction

What do firm-level funding costs and firm balance sheets tell us about the transmission mechanism of monetary policy? In this paper we combine a unique bond-level data set on credit spreads with firm-level balance sheet information to show that monetary policy has heterogeneous effects on firms, depending on their level of leverage. Following an interest rate hike, highly leveraged firms experience a more pronounced increase in borrowing costs and a sharper contraction in debt and investment. Our results point to a strong role for financial frictions in shaping the transmission mechanism of monetary policy.

Economic theory suggests that the effect of monetary policy on financially constrained firms relative to unconstrained firms is ambiguous. Financial frictions imply that firms face an upward sloping marginal cost of investment, with more constrained firms facing a steeper marginal cost curve. Absent any offsetting channels, the borrowing and investment of more constrained firms will generally be less responsive to monetary policy shocks that change the demand for capital. But more constrained firms may be also more sensitive to the financial accelerator (Bernanke and Gertler, 1995), whereby a monetary policy shock affects cash flows and collateral values, shifting the marginal cost of investment curve. This channel operates in the opposite direction, making the borrowing and investment of financially constrained firms relatively more responsive to monetary policy shocks.[1] Following the seminal contribution of Gertler and Gilchrist (1994), recent studies have investigated the relative strength of these two channels by looking at the response of constrained versus unconstrained firms to monetary policy, and reached contrasting conclusions (e.g. Ottonello and Winberry, 2018, Jeenas, 2018, Cloyne et al., 2018).

The vast majority of recent studies in this area estimate the response of firm-level quantities (such as output, investment, or employment) to high-frequency surprises in federal funds futures around policy announcements (Gürkaynak et al., 2005). This approach, however, poses two challenges. First, firm-level quantities are, at best, available at a quarterly frequency. As monetary policy decisions happen at a higher frequency and at irregular

[1] In the Appendix we derive a simple theoretical framework that formalizes the two mechanisms described in this paragraph.

times during the year, interest rate surprises have to be aggregated over quarters or years—therefore potentially giving rise to an aggregation bias.[2] Second, recent advances in the monetary policy literature have shown that the commonly used interest rate surprises are polluted by 'non-monetary' news capturing a signalling channel of central banks' actions (Nakamura and Steinsson, 2018). As this signalling component is related to the systematic response of monetary policy to developments in the economy, interest rate surprises (which reflect both monetary and non-monetary news) exert two opposing forces on the variables of interest—therefore potentially introducing a confounding factor.

The approach proposed in this paper addresses both of these issues. First, we construct a new, high-frequency, bond-level data set and we use it to study the effects of monetary policy on firms' corporate bond spreads. Credit spreads are available at a daily frequency and are measured directly from the prices of senior unsecured corporate debt traded in the secondary market. Economic theory has stark predictions on both the aggregate and the cross-sectional response of credit spreads to changes in monetary policy, which we are able to test with this data set. Specifically, if the financial accelerator is quantitatively strong, a tightening in monetary policy should lead to an average increase in credit spreads, which is larger for firms that are relatively more financially constrained.[3] Moreover, the forward-looking nature of credit spreads makes them respond to news more quickly than quantities. The high-frequency nature of our analysis delivers a clean identification of the impact of monetary policy on firm-level outcomes. Despite all these advantages, credit spreads have been widely overlooked in the literature.[4]

Second, we construct a measure of monetary policy surprises that explicitly takes into account the non-monetary component embedded in raw interest rate surprises. To do

[2]Recent studies have shown that this aggregation is far from innocuous: commonly used methods of aggregating shocks to match the frequency at which the variable of interest is observed can induce serial correlation in the series of aggregated shocks (Ramey, 2016) and yield inconsistent estimates of the aggregated impulse responses (Gazzani and Vicondoa, 2019, Chudik and Georgiadis, 2019).

[3]The opposite (i.e. a fall in average credit spreads that is larger for financially constrained firms) should be observed if the financial accelerator is quantitatively weak. See the theoretical model in Appendix A.

[4]Previous studies have largely focused on the effects of monetary policy on firm-level quantities. Where borrowing costs have been considered, they have typically been calculated using proxies for firms' interest expenses. These, however, do not fully capture the marginal cost of new borrowing, which is what economic theory has predictions about. Credit spreads, in contrast, are constructed from the market price of corporate bonds, and are therefore conceptually closer to the notion of theoretical models.

that, we first measure the change in the implied federal funds rate from a futures contract computed over 30-minute windows around FOMC announcements, as in most recent papers in the literature. We then decompose these raw interest rate surprises into a monetary component and non-monetary component using the methodology developed by Jarocinski and Karadi (2018).[5]

Third, and finally, we estimate the effects of monetary policy surprises on credit spreads at the bond level in a 1-week window around FOMC announcements using a panel event-study regression approach. For comparison with the literature, we complement our analysis by looking at the response of firm-level debt and investment at a business cycle frequency, using a panel local projections approach. In contrast with the previous literature, however, we use our measure of monetary policy surprises—which strips out the non-monetary component of interest rate surprises—and we investigate the joint response of firm-level prices and quantities, which is crucial to interpret the results.

Our results are as follows. A monetary policy shock that raises the policy rate by 25 basis points leads to an average increase in credit spreads of 28 basis points. This average effect is heterogeneous across firms and varies widely with firm leverage. For example, the response of credit spreads for firms that lie below the median of the leverage distribution is around 20 basis points and is much smaller than the response of credit spreads for firms above the median, which is around 33 basis points. While we focus on leverage as our main source of firm-level heterogeneity—since it has a direct mapping into the tightness of financial constraints in the theoretical model that we use to interpret the results—our results hold when controlling for other firm characteristics that are typically used to proxy for financial constraints, such as age, size, and liquid assets.

We also consider a decomposition of credit spreads that allows us to sharpen our understanding of how monetary policy transmits to credit costs. Specifically, we employ Gilchrist and Zakrajsek (2012)'s framework to decompose credit spreads into two orthogonal components: a component capturing fluctuations in firms' expected default and a residual compo-

[5]This methodology exploits the different sign of the conditional correlation between interest rates and equity prices in response to monetary and non-monetary shocks in a short 30-minute window around FOMC announcements. More details are provided in Appendix C.

nent capturing fluctuations of credit spreads in excess of firms' default compensation (i.e. the excess bond premium (EBP) in Gilchrist and Zakrajsek (2012)'s parlance).[6] Armed with this decomposition we can ask whether monetary policy transmits to credit costs via a change in a firm's probability of default, a change in the EBP, or both. This is informative because the excess bond premium, which is purged of default premia and orthogonal to firms' fundamentals, can be interpreted as a measure of firms' borrowing costs that is more directly linked to financial market frictions. The results show that virtually all of the conditional response of credit spreads to monetary policy is accounted for by the EBP.

Controlling for the presence of non-monetary news in high-frequency interest rate surprises is of crucial importance, both in the time series and in the cross section. To show this, we compare the response of credit spreads conditional on the raw interest rate surprises, as well as their monetary and non-monetary components. The average response of credit spreads to the raw interest rate surprises is estimated at around 10 basis points, almost three times smaller than the credit spread response to the monetary policy surprises. This is because an increase in the raw interest rate surprises, in general, combines two mechanisms that have opposing effects on credit spreads: (i) a monetary policy contraction that acts to increase credit spreads; and (ii) the systematic response of monetary policy to a positive news shock originating in the economy, that acts to compress credit spreads.[7] Consistent with this interpretation, the response of credit spreads to the non-monetary surprises is negative, at around -25 basis points. Intuitively, and as we discuss in more detail below, the presence of non-monetary news gives rise to a large and significant downward bias not only in the average response of credit spreads, but also in the relative response of high-leverage *versus* low-leverage firms.

Finally, because of the high-frequency nature of the analysis, one might worry that the estimated impact of monetary policy on credit spreads simply reflects a transitory

[6]Specifically, we regress corporate bond spreads on a firm-specific estimate of the distance to default using a Merton-KMV framework and on a vector of bond-specific controls. The fitted value from this regression isolates the variation in credit spreads that is due to fluctuations in the creditworthiness of firms. More details are provided in Appendix E.

[7]Jarocinski and Karadi (2018) argue their results are consistent with the central bank tightening its policy to respond to improved (current and future) *demand* conditions, which should act to compress credit spreads.

adjustment in prices (e.g. due to liquidity or trading frictions), with no persistent effects on firm-level quantities. With this in mind, we construct a version of our data set to estimate the dynamic effects of monetary policy at business cycle frequency, using a local projections approach (Jorda, 2005). Not only does this allow us to investigate the persistence of the effects of monetary policy on credit spreads and compare our results with aggregate macro studies, but it also enables us to consider the response of firm-level debt and investment, which we construct from balance sheet data. Our results from this alternative approach are consistent with the high-frequency analysis. We find that a policy hike driven by a monetary policy surprise leads to a persistent contraction in average debt and investment, and a persistent increase in average credit spreads. We also find that the effects of the monetary policy surprises are larger for firms with high leverage: their debt and investment contract by more and their credit spreads increase by more.

The rest of the paper is structured as follows: section 2 describes the data used in the empirical analysis; section 3 presents the main empirical results obtained from the high-frequency panel regressions, and an extensive set of robustness tests; section 4 reports the results from the panel local projections at business cycle frequency; section 5 reviews the recent literature and how our paper relates to it; section 6 concludes. In the Appendix we describe a simple theoretical framework that we use to interpret our results, the data sources, the construction of the monetary policy surprises, and an extensive set of additional results, both for the high-frequency panel regressions and the lower frequency local projections.

2 Data

We compile our bond-level data set by combining the following sources: intra-day surprises in interest rates and equity prices around FOMC announcements; daily bond-level information from ICE Bank of America Merrill Lynch (ICE BofAML) and Thomson Reuters Datastream; daily equity prices from the Center for Research in Security Prices (CRSP); and quarterly firm-level balance sheet data from Compustat. Below, we briefly describe each data source. Additional details on the sources and data treatment are provided in Appendix B.

Our final data set merges all bond- and firm-level information into an 'event study' data set around FOMC announcement days. Specifically, we collect all available bond data on a monetary policy announcement day (t), and keep all bonds for which we can match equity price and balance sheet data. Our final data set covers 156 FOMC announcements over the 1999-2017 period, has information on $9,413$ bonds and 975 firms, and a total of $281,330$ observations.

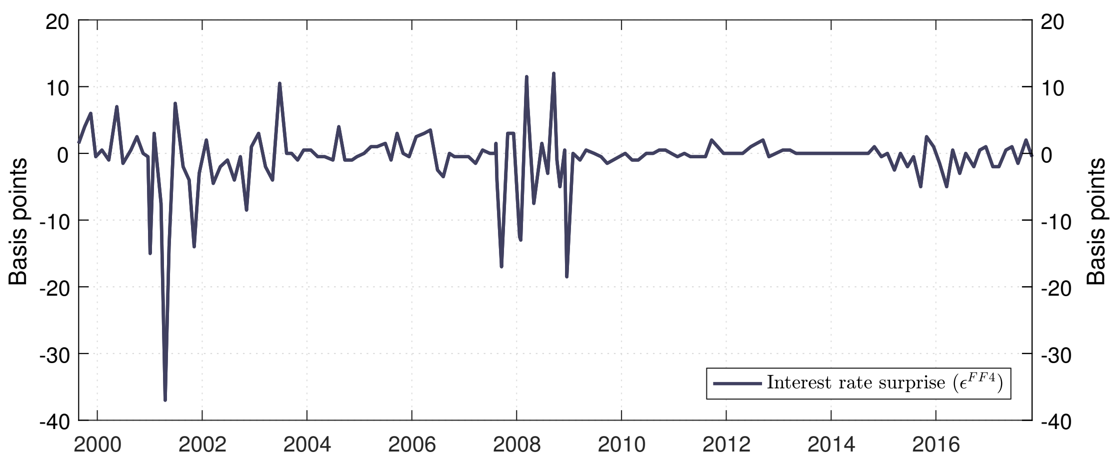
2.1 Identification of Monetary Policy Surprises

A key challenge in measuring changes in monetary policy is that most of the variation in the federal funds rate is driven by the Federal Reserve's endogenous response to aggregate economic conditions. To address this issue, the common practice in the recent literature is to use the change in the federal funds rate implied from a federal funds futures contract, computed using a narrow 30-minute window of time around a monetary policy announcement by the FOMC (see Kuttner, 2001, Gürkaynak et al., 2005). As futures contracts provide a measure of market participants' expectation for the evolution of interest rates, these 30-minute surprises can be thought of as a noisy proxy for an exogenous monetary policy shock. The identifying assumption is that, given the short time horizon over which they are measured, the interest rate surprises cannot be 'contaminated' by other non-monetary news.

But it is still possible that the unexpected component of policy decisions (as measured by the interest rate surprises) contains news about the determinants of monetary policy, therefore introducing a confounding factor. When information frictions are present, a 'signalling channel' of monetary policy can arise: central bank announcements can simultaneously convey information about monetary policy and the central bank's assessment of the economic outlook (Romer and Romer, 2000, Melosi, 2017, Nakamura and Steinsson, 2018). Recent studies have shown that such a signalling component can be sizable in high-frequency market-based surprises around policy announcements by the Federal Reserve.[8]

To address this issue, in this paper we follow the methodology developed by Jarocinski and Karadi (2018) to disentangle monetary policy news from other contemporaneous non-monetary news embedded in the interest rate surprises. This is achieved by a simple rotation of the covariance matrix of high-frequency movements in interest rates and stock market prices in a narrow window around the policy announcement. The identifying restrictions are simple and intuitive: shocks that lead to a negative comovement of interest rates and equity prices are interpreted as driven by monetary news, while shocks that lead to a positive comovement of interest rates and equity prices are interpreted as driven by non-monetary news.[9]

Figure 1 High Frequency Interest Rate Surprises



Note. This figure plots the raw 30-minute surprise in the 3-month ahead federal funds futures (FF4) contract (s_t^{FF4}) for each FOMC meeting in our sample.

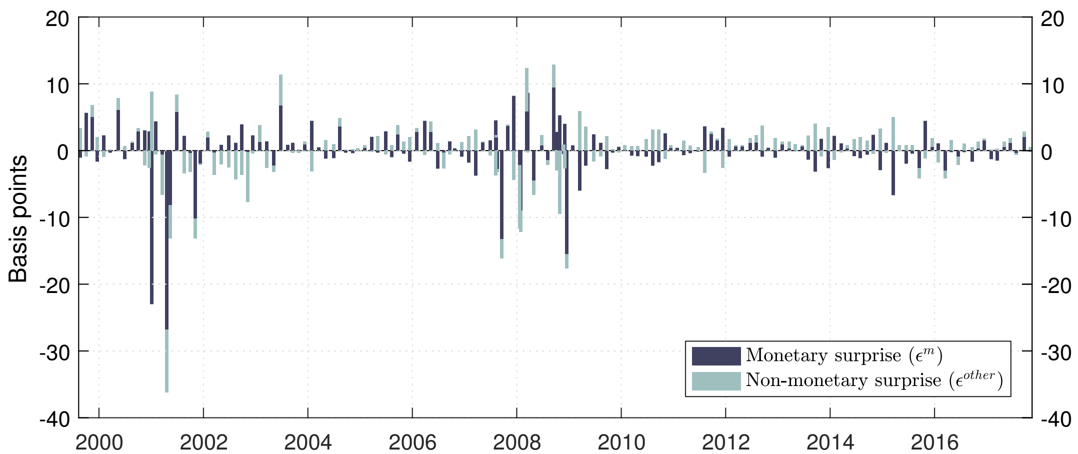
As in Jarocinski and Karadi (2018), we perform the decomposition using 30-minute surprises in the S&P 500 stock market index (s_t^{eq}) and the 3-month ahead federal funds futures

[8]See Barakchian and Crowe (2013), Ramey (2016), Miranda-Agrippino and Ricco (2017), Jarocinski and Karadi (2018), Lunsford (2018). Note, however, that the presence and strength of such a signalling component is an empirical question and depends, among other things, on the sample period and the futures contracts used. For example, Cesa-Bianchi et al. (2020) develop a test of overidentifying restrictions to assess the potential information content of high frequency interest rates surprises. Using UK data, they find no evidence of a statistically significant bias due to the presence of information effects.

[9]Alternatively one could project the high frequency interest rate surprises on the difference between private forecasts and Greenbook forecasts (Gertler and Karadi (2015)) or the Greenbook forecasts and forecats revision (Miranda-Agrippino and Ricco (2017)).

(FF4) contract (s_t^{FF4}). Figure 1 displays the behavior of s_t^{FF4} over time, while Figure 2 displays the underlying orthogonal monetary (ϵ^m) and non-monetary (ϵ^{other}) surprises that drive s_t^{FF4}. In our sample, the monetary surprise explains 75 percent of the total variance of s_t^{FF4}, while the remaining 25 percent is explained by ϵ^{other}.

Figure 2 Interest Rate Surprises Decomposition: Monetary vs. Non-monetary Shocks



Note. This figure plots the monetary (ϵ^m, dark bars) and non-monetary (ϵ^{other}, light bars) components that drive the raw interest rate surprise s_t^{FF4}. The decomposition is obtained with the methodology of Jarocinski and Karadi (2018). See Appendix C for details.

In Appendix C we also show that we get a very similar series of monetary surprises (ϵ^m) when, instead of using s_t^{FF4}, we use a 'synthetic' interest rate obtained by extracting a principal component from a panel of (standardized) interest rates on different futures contracts—namely federal funds futures (FF1 to FF6, i.e. the current-month contract rate and the contract rates for each of the next five months) and eurodollar futures (ED1 to ED8, i.e. the current quarter contract rate and the contract rates for each of the next seven quarters). This shows that the Jarocinski and Karadi (2018) monetary policy surprise (i) is not affected by the noise that is inherent in a single futures contract and (ii) is robust to using information from interest rates at longer tenors—a particularly nice feature given that a large part of our sample covers the zero lower bound.[10]

[10]For example, Gürkaynak et al. (2005) argue that eurodollar futures were more liquid over our sample period than Fed Funds futures for maturities longer than two quarters. See also Swanson (2017).

2.2 Bond-level Credit Spreads

We consider credit spreads constructed from daily data on the prices of senior unsecured corporate debt traded in the secondary market over the 1999–2017 period, issued by 975 US listed non-financial corporations. We collect the data from ICE Bank of America Merrill Lynch (ICE BofAML) Global Index System. Specifically we use the constituents of the Global Corporate Index (`G0BC`) and the Global High Yield Index (`HW00`). Using bond identification numbers (the ISIN code), we complement the ICE BofAML data with additional bond level data from Thomson Reuters Datastream, as detailed in the Appendix.[11]

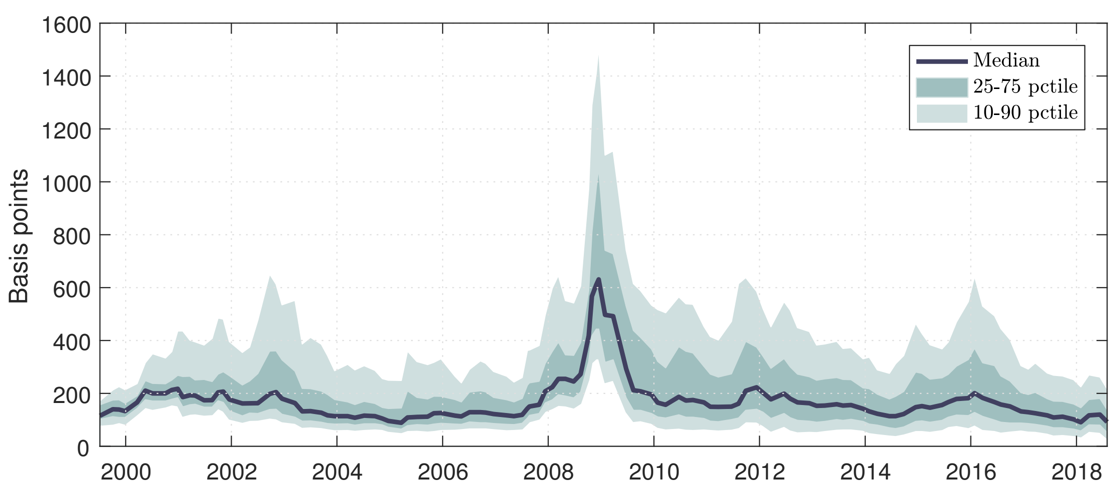
The main variable of interest for our study is the Option Adjusted Spread (OAS), which we denote by cs_t. The OAS is defined as the number of basis points that the government spot curve is shifted in order to match the present value of discounted cash flows to the corporate bond's price. The OAS has two key features that make it a useful measure of credit spreads for this study. The first one is a maturity adjustment: spreads are computed relative to a risk-free security that replicates the cash-flows of the corporate debt instrument. As noted by Gilchrist et al. (2009), this adjustment is important, as a maturity mismatch between the risky bond and the risk-less bond can lead to a mechanical bias in the measurement of credit spreads. The second one is an option adjustment. It is well known that the vast majority of corporate bonds issued by non-financial corporations embed a call option that allows the issuer to redeem the security prior to its maturity. If a bond is callable, policy-induced movements in Treasury yields will, by changing the value of the embedded call option, have an independent effect on the bond price, complicating the interpretation of the response of bond yields and the associated credit spreads (see Duffee, 1998). The OAS adjusts for this by removing the price of embedded options from the overall price of the bond.

Moreover, since they are constructed from the market price of corporate bonds, Option Adjusted Spreads are conceptually closer to the notion of the cost of external finance in models of financial frictions (namely, the marginal cost on new borrowing) than other prox-

[11] This is the same source as the one used in the latest part of the data set of Gilchrist and Zakrajsek (2012). We outline in the appendix a list of differences between our data and theirs.

ies used in the literature. For example, Ottonello and Winberry (2018) and Cloyne et al. (2018) measure firm-level borrowing costs with interest payments, as reported in the firm's balance sheet. However, relying on balance sheet data has three notable drawbacks. First, interest expenses reflect past lending decisions and are therefore a 'backward' measure of borrowing costs, which can diverge substantially from the marginal cost on new borrowing. Second, interest expenses will partly reflect risk-free interest rates, while economic theory has predictions on the cost of borrowing *net* of the risk free interest rate. Third, interest expenses ignore the widely heterogeneous maturity of debt across firms. In our sample, for example, the average maturity of outstanding bonds is 10 years with a standard deviation of 8 years. Focusing on credit spreads allows us to address these issues. The yield implied by the price of corporate bonds can be thought of as a better proxy for the marginal cost of new borrowing . Furthermore, by calculating the spread (through the subtraction of a same-maturity risk free interest rate) we are able to compare the marginal cost of borrowing at a given maturity across firms.

Figure 3 The Cross-Section of Corporate Bond Spreads



Note. The figure plots the panel of corporate bond spreads in our data set around FOMC dates. The dark solid line displays the cross-sectional median of credit spreads. The dark shaded area displays the 25-75 percentile range. The light shaded areas displays the 10-90 percentile range.

The sample period we focus on runs from July 1999 to November 2017. The data set has information on an extensive share of the full universe of US corporate bonds. For example, the flow of new issuances in our data set in 2014 was 495 billion US dollars, which is about 70 percent of the total market in that year.[12] We clean the data by following standard data treatment as, for example, in Gilchrist and Zakrajsek (2012). Specifically, we drop bonds with an issued amount lower than 1 Million US dollars, if the maturity is smaller than 1 year or greater than 30 years, and if the spread is above $3,500$ basis points. We focus on non-financial, senior, unsecured bonds issued in domestic currency. Figure 3 plots the median OAS in our data set for each date t, together with the $25-75$ and $10-90$ percentiles. The data displays significant variation both in the time series and in the cross-sectional dimension, which is going to be crucial to identify the heterogeneous effects of monetary policy on firms borrowing costs.

2.3 Additional Firm-level Information

As the bond-level data described above includes a firm identifier, it can be matched to other firm-level information. For listed firms within our bond panel we match daily equity data (share price and number of shares outstanding) from the Center for Research in Security Prices (CRSP); as well as quarterly balance sheet information (including total assets, total debt, sales, age) from Compustat.[13]

As noted in Figure 3, the behavior of spreads is very heterogeneous in the cross-section. As a preliminary, unconditional exploration, we check whether this heterogeneity is linked to firms' characteristics and, in particular, to the leverage of the firm. We focus on leverage because it is the key state variable that affects the cost of external finance in models of financial frictions and is the variable which we use to interpret our findings in Appendix A.

Table 1 reports the summary statistics for firms that have leverage below and above the median leverage ratio in our sample, respectively. In our data set, firms with high leverage

[12] Data from the Federal Reserve. See item *New Security Issues (1.46), U.S. Corporations, nonfinancial*.

[13] Our sample consists of relatively large firms with publicly-traded debt and equity. As large firms tend to be the most credit-worthy by traditional measures (see Farre-Mensa and Ljungqvist, 2016), previous empirical research in this area typically assumes that such firms have relatively unimpeded access to external financing. What is crucial for the question in this paper, however, is to be able to identify a group of firms that is *relatively* more constrained than other firms. The large degree of heterogeneity in our sample allows us to do so. If we were to consider smaller, bank dependent firms it is likely that the heterogeneity in financial constraints would be even stronger (Levin et al., 2004).

Table 1 Summary Statistics: High vs. Low Leverage

	Low Leverage (below median)				
	Mean	SD	P25	Median	P75
Firm Total Assets ($M)	56,427	70,788	11,208	30,277	67,243
Firm Age (years)	38	14	26	42	50
Firm Credit Rating			BBB2	BBB1	A2
Firm Hadlock-Pierce Constraint	-4.2	0.4	-4.5	-4.4	-4.0
Bond Spread (basis points)	177	159	88	136	207
Bond Amount Issued ($M)	648	523	300	500	750
Total Observations	134,379				
	High Leverage (above median)				
	Mean	SD	P25	Median	P75
Firm Total Assets ($M)	36,432	57,452	7,570	19,136	44,033
Firm Age (years)	33	16	18	34	49
Firm Credit Rating			BB2	BBB2	BBB1
Firm Hadlock-Pierce Constraint	-4.2	0.4	-4.5	-4.3	-3.8
Bond Spread (basis points)	267	249	113	190	336
Bond Amount Issued ($M)	619	584	300	500	750
Total Observations	131,176				

Note. Summary statistics for firms below/above the median leverage in the sample. The sample period covers the period between August 1999 and September 2018. The sample consists of 975 firms and 9,413 bonds. *Hadlock-Pierce Constraint* refers to the index developed by Hadlock and Pierce (2010).

also have high credit spreads, a fact that is in line with the predictions from our simple theoretical model (see Figure A.2). For example, the average credit spread among high-leverage firms is 267 basis points, compared to an average spread of 177 for low-leverage firms.

But Table 1 shows that (i) high-leverage firms are also smaller (as measured by total assets), younger, and have lower credit ratings; and (ii) that the relation between leverage and credit spreads is non-monotonic, as some firms in the high-leverage group have lower credit spreads than firms in the low-leverage group. For example, the 25^{th} percentile of spreads in the high-leverage group (at 113 basis points) is smaller than the 75^{th} percentile of spreads in the low-leverage group (at 207 basis points). These two facts show that heterogeneity is multi-dimensional and that there are potentially other relevant empirical proxies for financial constraints—such as age, size, liquid assets, etc., which are frequently considered in the literature. While in the following sections we will focus on leverage as our main proxy for financial constraints, in robustness exercises we will also control for these alternative proxies.

3 Event Study Firm-level Panel Regressions

In this section we report the results from event-study, firm-level panel regressions. We first present the results from a simple specification which regresses credit spreads on monetary policy surprises, where we allow the coefficient to vary with firm-level leverage. Second, we consider an exhaustive set of robustness checks, as well as alternative proxies for financial constraints, and show that the results are largely unchanged. Third, we show that our results also hold when considering the component of spreads that is 'purged' of default premia and, therefore, can be thought of as being more closely associated to financial frictions. Finally, we show that it is important to use our purged series of monetary surprises, since the non-monetary news embedded in the raw interest rate surprises can lead to a substantial bias in the estimated effects of monetary policy on credit spreads, both in the time series and in the cross-section.

3.1 The Heterogeneous Effects of Monetary Policy on Credit Spreads

We consider the following event study specification:

$$\Delta cs_{ij,t} = \alpha_i + \beta \epsilon_t^m + e_{ij,t}, \tag{1}$$

where $\Delta cs_{ij,t}$ is the change in spread of bond i belonging to firm j around an FOMC announcement day t; α_i is a bond fixed effect, which should account for unobserved heterogeneity resulting from time-invariant bond characteristics; and ϵ_t^m is our measure of monetary policy surprises on FOMC announcement days. The coefficient β captures the average effect of monetary policy on firms' credit spreads. The size of the surprise is normalized so that it corresponds to a 25 basis point increase in the 1-year T-bill.

In our baseline specification we consider a 1-week change in the spread, from the day before the announcement to five working days after the announcement. We do this because corporate bond markets might take time to incorporate the effects of the monetary policy surprise. Corporate bonds, and particularly high yield bonds, tend to be less liquid than other assets, such as equities and treasuries. Therefore, a slightly longer window is warranted to allow them to react. This choice is somewhat conservative relative to comparable event studies in the literature. For example, Gertler and Karadi (2015) use a two-week window to analyze of how the aggregate Baa spread responds to monetary policy surprises.[14] In addition, in section 4 we also estimate the dynamic response of credit spreads to monetary policy with local projections at a business cycle frequency, thereby considering a range of different horizons.

Table 2 reports the estimation results. Standard errors, reported in parentheses, are clustered two-way at the firm and time (i.e. event) level. Column (1) of Table 2 shows that a 25 basis point surprise tightening leads to an increase in credit spreads of about 28 basis points. The estimated coefficient, which is significant at the 1 percent significance level, captures the average response of credit spreads in the cross-section of firms to monetary policy. It provides strong support to the notion that the cost of external finance increases by more than the risk free rate in response to a monetary tightening (as shown by Gertler and Karadi (2015) and Caldara and Herbst (2016) in VAR analysis). Interestingly, we get a similar coefficient when we only exploit the time series variation in our data (i.e., by taking a cross-sectional average of credit spreads for each FOMC meeting and running a simple time series OLS regression), which provides evidence that our results are not driven by outliers.[15] Finally, note that both the sign and the magnitude of the response is in line with the aggregate VAR results in Gertler and Karadi (2015), despite the different sample period

[14] In contrast, papers focusing on Treasury bonds or equity (as Gürkaynak et al. (2005) or Ozdagli (2018)) typically use 1-day or 2-day windows.

[15] See Table F.7 in Appendix.

Table 2 Heterogeneous Response of Credit Spreads to Monetary Policy

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)
	Baseline	Low/High Leverage	Leverage Interaction
MP surp. (ϵ^m)	28.17***		27.46**
	(10.72)		(10.65)
MP surp.×Low Lev. ($\epsilon^m \times \ell_j^{Low}$)		21.35***	
		(7.41)	
MP surp.×High Lev. ($\epsilon^m \times \ell_j^{High}$)		32.52**	
		(13.77)	
MP surp.×Lev. ($\epsilon^m \times L_j$)			11.34*
			(6.79)
Double clustering	Yes	Yes	Yes
Time-sector FE	No	No	No
R-squared	0.034	0.032	0.029
Observations	281,330	275,676	275,676

Note. Results from estimating specifications (1), (2), and (3), where ϵ_t^m is the monetary policy surprise; $\Delta cs_{ij,t}$ is the change in spreads of bond i belonging to firm j between the day before the FOMC announcement and five days after the announcement; α_i is a bond fixed-effect; $\ell_{j,t-1}^{High} = 1$ when the leverage of firm j lies above the median of the leverage distribution (and zero otherwise), while $\ell_{j,t-1}^{Low} = 1$ when the leverage of firm j lies below the median of the leverage distribution (and zero otherwise); L_j is the standardized leverage of firm j. Standard errors (reported in parentheses) are clustered two way, at the firm level and time level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis point increase in the 1-year T-bill. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

and methodology. In their monthly VAR, the excess bond premium increases by about 13 basis points in response to a 25 basis point surprise in the 1-year rate instrumented with the raw interest rate surprises (i.e. s_t^{FF4} instead of our baseline measure ϵ_t^m). We show below that we get a similar coefficient when estimating (1) using the raw interest rate surprises, and decomposing the effect into default compensation and the excess bond premium.

We now explore the cross-sectional dimension of our data set in greater detail. In particular, we ask the following question: does monetary policy transmit in a heterogeneous fashion across firms, depending on their balance sheet characteristics? We focus on leverage as our main measure of firms' balance sheet positions. We make this choice because in many models of financial frictions (including the one we derive in Appendix A) leverage is tightly linked to the cost of external finance and firms' borrowing/investment decisions. But we are not implying that leverage is the only proxy for financial constraints. In robustness analysis, we condition on alternative proxies that are typically used in the literature (e.g. age, size, liquid assets) and we find essentially the same results.[16]

We denote by $L_{j,t-1}$ the leverage of firm j in the quarter preceding the monetary policy announcement at time t. Leverage is defined as the ratio of total debt over total assets, as is common in the literature. We start with a simple specification where we split our sample of bond observations into two groups, based on where each firm lies in the leverage distribution. Specifically, we define two dummy variables: $\ell_{j,t-1}^{High}$, which equals 1 when the leverage of firm j lies above the median of the leverage distribution in the quarter preceding the monetary policy surprise (and zero otherwise), and $\ell_{j,t-1}^{Low}$, which equals 1 when the leverage of firm j lies below the median of the leverage distribution (and zero otherwise). We then consider how the response of spreads to monetary policy surprises varies across the two groups by estimating the following specification:

$$\Delta cs_{ij,t} = \alpha_i + \beta_1 \left(\epsilon_t^m \ell_{j,t-1}^{Low}\right) + \beta_2 \left(\epsilon_t^m \ell_{j,t-1}^{High}\right) + e_{ij,t}. \tag{2}$$

Coefficients β_1 and β_2 capture the impact of monetary policy on credit spreads for low- and high-leverage firms, respectively. The results are reported in column (2) of Table 2. They show that the response of credit spreads for low-leverage firms is smaller than the average effect, at around 21 basis points. The response of credit spreads for firms in the high-leverage group is much larger, at around 33 basis points.

Next, we consider a continuous measure of leverage and estimate a specification where we interact the monetary policy surprise with firms' leverage in the quarter that precedes the monetary policy surprise:

$$\Delta cs_{ij,t} = \alpha_i + \beta \epsilon_t^m + \gamma \left(\epsilon_t^m L_{j,t-1}\right) + \delta L_{j,t-1} + e_{ij,t}. \tag{3}$$

[16] Depending on which sub-sample of the overall universe of firms is considered, however, there might be other firm characteristics that better capture financial constraints—e.g. age (as in Cloyne et al., 2018, Bahaj et al., 2018) or liquid assets (as in Jeenas, 2018).

We standardize $L_{j,t-1}$ over the sample so that the coefficient γ captures the marginal impact of ϵ_t^m on $\Delta cs_{ij,t}$ for a firm whose leverage is 1 standard deviation above the average leverage in the sample. Results from this specification are reported in column (3) of Table 2. They show that firms with higher-than-average leverage experience a larger-than-average increase in credit spreads. The effect is statistically significant and economically sizeable. A firm whose leverage ratio is 1 standard deviation above the average, experiences a credit spread increase that is around 11 basis points larger than for the average firm.

What do our results tell us about the transmission mechanism of monetary policy? In Appendix A we develop a simple model that allows us to interpret the empirical results reported in Table 2. The model shows that (i) the response of corporate bond spreads to monetary policy surprises may differ in sign depending on the strength of the financial accelerator mechanism; and (ii) the magnitude of the response across firms depends on firms' leverage. In particular, if the financial accelerator is quantitatively strong, a tightening in monetary policy should lead to an average *increase* in credit spreads, which is larger for firms that have (relatively) high leverage. The opposite (i.e. a *fall* in average credit spreads that is larger for low-leverage firms) should be observed if the financial accelerator is quantitatively weak. Our results can therefore be interpreted as evidence of a strong role for the financial accelerator mechanism.

How do our results compare to those in the existing literature? Ottonello and Winberry (2018) show that borrowing costs are persistently lower for high-leverage firms relative to low-leverage firms following a monetary policy tightening.[17] In contrast, Cloyne et al. (2018) show that younger non-dividend paying firms experience a persistent increase in borrowing costs relative to older dividend paying firms. While our evidence aligns better with the findings in Cloyne et al. (2018), both approaches have the drawback of measuring borrowing costs with interest related expenses. Interest payments can differ substantially from the marginal borrowing cost on new borrowing, which is what economic theory has predictions about. Moreover, this measure of borrowing costs does not take into account the wide heterogeneity in the average maturity of a firm's debt, therefore leading to potentially

[17] See their Appendix A.3. Note that they consider a monetary policy easing, but as model they employ is linear, the sign of the estimates can be flipped to consider a monetary policy tightening (as in this paper).

misleading results. Our approach addresses both of these issues: the yield implied by the price of corporate bonds provides a better proxy for the marginal cost of new borrowing; and the granularity of our data set allows us to control for each bond's maturity.

In the following sections we show that (i) our baseline results are virtually unchanged when considering an exhaustive set of robustness checks; (ii) the results are driven by changes in the excess bond premium, i.e. the component of spreads that is purged of default premia and can be interpreted as a measure of firms' borrowing costs that is more closely related to financial market frictions; (iii) the non-monetary news embedded in raw interest rate surprise can lead to misleading results.

3.2 Robustness of the Baseline Results

In this section we report the results from an extensive set of additional empirical exercises showing the robustness of our main results.

Ozdagli and Weber (2017) document substantial heterogeneity in the effects of monetary policy across industrial sectors. This raises the question of whether our baseline results are simply driven by a systematic correlation between leverage and industrial sectors. To address this concern we add to our specification time-sector fixed effects, namely:

$$\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma \left(\epsilon_t^m \ell_{j,t-1}^{High} \right) + \delta \ell_{j,t-1}^{High} + e_{ij,t}, \tag{4}$$

where $\beta_{sct,t}$ is a dummy variable taking value of 1 for all firms belonging to the same sector (sct) in a given time period t.[18] Note that, since the linear effect of ϵ_t^m is absorbed by the time-sector fixed effect, the term γ captures the response of high-leverage firms *relative* to low-leverage firms.[19] The results from this specification are reported in Table 3, column (1). The estimated γ coefficient is still positive and highly statistically significant.

[18] We use the finest available sector classification provided by BofAML, which includes information on 59 sectors. See Appendix B for more details.

[19] In Appendix F we report the results from this specification (and all other specifications described in this section) using the continuous leverage interaction ($L_{j,t-1}$) rather than the high leverage dummy ($\ell_{j,t-1}^{High}$), namely $\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma \left(\epsilon_t^m L_{j,t-1} \right) + \delta L_{j,t-1} + e_{ij,t}$. The results are unchanged.

In column (2) of Table 3 we report the results obtained from a specification that is identical to (4) but where we control for additional firm-specific covariates, namely firm (log) size, time since IPO (in years), the firm credit rating, and sales growth. The estimated coefficient is virtually identical to the one in column (1).

Table 3 HETEROGENEOUS RESPONSE OF CREDIT SPREADS TO MONETARY POLICY: ROBUSTNESS

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)	(4)	(5)
	Time-sector FE	Controls	Within Leverage	IV	Pre-crisis
MP surp.×High Lev. ($\epsilon^m \times \ell_j^{High}$)	20.54**	20.61**			18.73**
	(9.31)	(9.58)			(7.29)
MP surp.×High Lev. ($\epsilon^m \times \mathcal{L}_j^{High}$)			13.68*		
			(8.07)		
1yr Rate x High Lev. ($\epsilon^m \times \ell_j^{High}$)				19.67***	
				(1.41)	
Double clustering	Yes	Yes	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.312	0.307	0.312	-0.030	0.346
Observations	275,311	263,417	275,311	275,311	52,016

NOTE. Results from estimating specification (4), namely $\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma \left(\epsilon_t^m \ell_{j,t-1}^{High} \right) + \delta \ell_{j,t-1}^{High} + e_{ij,t}$ and its variants described in the text, where ϵ_t^m is the monetary policy surprise; Δcs_{it} is the change in spreads between the day before the FOMC announcement and five days after the announcement; $\ell_{j,t-1}^{High} = 1$ when the leverage of firm j lies above the median of the leverage distribution (and zero otherwise); α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $\mathcal{L}_{j,t-1}^{High} = 1$ when within-firm leverage of form j lies above the median of the leverage distribution (and zero otherwise); *1yr Rate* is the interest rate on the 1-year T-bill. Standard errors (reported in parentheses) are clustered two way, at the firm level and time level. Additional controls include firm (log) size, sales growth, credit rating, and time since IPO. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

Ottonello and Winberry (2018) show that using *within-firm* variation in leverage (i.e. $L_{j,t-1} - \mathbb{E}_j[L_{j,t-1}]$), rather than the level of a firm's leverage as in our baseline, can make a substantial difference for the estimated sensitivity of a firm's investment to monetary policy. The intuition is that the baseline results in Table 2 may be driven by permanent differences in firm leverage. In column (3) we report the results obtained from a specification that is identical to (4) but where the high-leverage dummy is based on within-firm variation in leverage $(L_{j,t-1} - \mathbb{E}_j[L_{j,t-1}])$, which we denote by $\mathcal{L}_{j,t-1}$. The estimated coefficient is smaller than in column (1) but is still positive and statistically significant.

In column (4) we report the results from an instrumental variable (IV) specification, where we use our monetary policy surprises as an instrument for the change in the 1-year government bond yield around FOMC announcements. Again, the results are largely unchanged.

Finally, we run our time-sector fixed effects specification (4) on a sample that excludes the global financial crisis, i.e. that excludes all observations after December 2007. The results are reported in column (5). A comparison with the results in column (1) shows that the sensitivity of credit spreads to monetary policy surprises has not materially changed since the pre-crisis period.

While the results in Table 3 show the robustness of our results to a comprehensive set of alternative specifications, one additional concern is that leverage might be correlated with other firm characteristics. Indeed, the stylized facts in Table 1 show that, in our sample, firms with high leverage tend to be smaller, younger, and have lower credit ratings. It could therefore be the case that our regressions are capturing the heterogeneous effects of these other characteristics, rather than leverage. To address this concern, we run a series of 'double-interaction' regressions. That is, we estimate the following specification:

$$\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma \left(\epsilon_t^m \ell_{j,t-1}^{High}\right) + \delta \left(\epsilon_t^m X_{j,t-1}^{High}\right) + \mathbf{\Gamma W}_{j,t-1} + e_{ij,t}, \tag{5}$$

where $X_{j,t-1}^{High}$ is a dummy variable that is defined in an identical way to $\ell_{j,t-1}^{High}$ but is based on other firm characteristics (such as age, size, credit rating, etc.); and $\mathbf{W}_{j,t-1}$ includes both $\ell_{j,t-1}^{High}$ and $X_{j,t-1}^{High}$. The γ coefficient now has a slightly different interpretation. Consider the case of $X_{j,t-1}^{High}$ being firms' size. Then γ captures the relative impact of monetary policy on high-leverage firms among the group of large firms. Effectively, we are double sorting firms by their position in the leverage distribution and in the size distribution. As in previous specifications, in this section we also include time-sector fixed effects. The results are reported in Table 4.

Table 4 HETEROGENEOUS RESPONSE OF CREDIT SPREADS TO MONETARY POLICY: DOUBLE SORTING

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	Size	Sales Growth	Credit Rating	Time IPO	DD	Debt-Ebitda	Liquid Assets
MP surp.×High Lev. $(\epsilon^m \times \ell_j^{High})$	20.54**	20.60**	21.39**	18.50**	20.36**	20.50**	19.02**	20.87**
	(9.31)	(9.38)	(9.54)	(8.34)	(9.12)	(9.02)	(9.05)	(9.51)
MP surp.×Size $(\epsilon^m \times X_j^{High})$		0.38						
		(7.84)						
MP surp.×Sales growth $(\epsilon^m \times X_j^{High})$			-4.68					
			(6.52)					
MP surp.×Credit rating $(\epsilon^m \times X_j^{High})$				-11.56				
				(8.17)				
MP surp.×Time IPO $(\epsilon^m \times X_j^{High})$					-2.36			
					(5.02)			
MP surp.×DD $(\epsilon^m \times x_j^{High})$						-3.27		
						(8.35)		
MP surp.×Debt-Ebitda $(\epsilon^m \times X_j^{High})$							16.44**	
							(7.33)	
MP surp.×Liquid Assets $(\epsilon^m \times X_j^{High})$								3.77
								(4.37)
Double clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.312	0.312	0.312	0.313	0.312	0.313	0.315	0.312
Observations	275,311	275,311	274,933	273,422	275,311	273,416	247,265	275,305

NOTE. Results from estimating specification (5), namely $\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma\left(\epsilon_t^m \ell_{j,t-1}^{High}\right) + \delta\left(\epsilon_t^m X_{j,t-1}^{High}\right) + \mathbf{\Gamma W}_{j,t-1} + e_{ij,t}$, where ϵ_t^m is the monetary policy surprise; Δcs_{it} is the change in spreads between the day before the FOMC announcement and five days after the announcement; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $\ell_{j,t-1}^{High} = 1$ when firm j leverage lies above the median of the leverage distribution (and zero otherwise); $X_{j,t-1}^{High} = 1$ when a given characteristic (X) of firm j, namely size, sales growth, credit rating, time since IPO, distance to default (DD), debt-to-EBITDA ratio, and liquid assets lies above the median of its distribution (and zero otherwise). $\mathbf{\Gamma W}_{j,t-1}$ includes both $\ell_{j,t-1}^{High}$ and $X_{j,t-1}^{High}$. Standard errors (reported in parentheses) are clustered two way, at the firm level and time level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill.

For comparison with our baseline, column (1) of Table 4 reports the results from specification (4), i.e. the specification including time-sector fixed effects and a single interaction based on firm leverage. Columns (2) to (8) report the results from specification (5), where $X^{High}_{j,t-1}$ is based on firm-level proxies for firms' financial constraints typically used in the literature. In particular, we consider firm (log) size, sales growth, credit ratings, time since IPO, a measure of the firm's distance to default (calculated using the Merton-KMV framework, detailed in Appendix E), the ratio between total debt and EBITDA, and the measure of a firm's liquid assets used in Jeenas (2018), respectively.

First, note that the estimated γ coefficient—which captures the relative response of firms with leverage above the median of the leverage distribution—is very similar (and, in fact, not statistically different) in all columns.[20] This result suggests that leverage is not simply capturing the effect of other firm-level characteristics. Second, the interaction coefficients based on the other firm characteristics generally have the expected sign but are often not statistically significant. This does not mean, however, that when considered alone they do not matter. In Appendix F we show that, when considered alone, they generally are statistically significant and with the expected sign (see Table F.5). For example, we find that older firms are less responsive to monetary policy shocks, as in Cloyne et al. (2018) and Bahaj et al. (2018). We also find that firms with high liquid assets are less responsive to monetary policy shocks, as in Jeenas (2018). Differently from the results in Ottonello and Winberry (2018), however, we find that the credit spreads of firms with higher distance to default respond by less to monetary policy surprises.

3.3 Expected Default and the Excess Bond Premium

In this section, we consider a decomposition of credit spreads that allows us to sharpen our understanding of how monetary policy transmits to credit costs. Specifically, we merge our data set with additional information on firms' balance sheets and stock prices and employ Gilchrist and Zakrajsek (2012)'s framework to decompose credit spreads into two orthogonal

[20] This is also true when estimating 'double-interaction' regressions using the continuous leverage interaction $L_{j,t-1}$ instead of the high leverage dummy $\ell^{High}_{j,t-1}$. See Table F.3 in the Appendix.

components: (i) a component capturing fluctuations in firms' expected default and (ii) a residual component that captures fluctuations in credit spreads in excess of firms' default compensation (i.e., the excess bond premium, EBP, in Gilchrist and Zakrajsek (2012)'s parlance). This residual component can be interpreted as a measure of firms' borrowing costs that is due to financial market frictions.[21] Armed with this decomposition we can ask whether monetary policy transmits to credit costs via firms' likelihood of default or via the excess bond premium.

To obtain the credit spreads decomposition we proceed as follows. We regress corporate bond spreads on a firm-specific estimate of the distance to default, calculated using the Merton-KMV framework, and on a vector of bond-specific controls. The fitted value from this regression—which isolates the variation in credit spreads that is due to fluctuations in the creditworthiness of firms—is our empirical proxy for firms' expected default risk. In Appendix E we report all the details of this procedure and a comparison of our results with the original Gilchrist and Zakrajsek (2012) decomposition. Using this decomposition of credit spreads into a fitted component reflecting the creditworthiness of firms ($\hat{cs}_{ij,t}$) and a residual component reflecting the price of default risk ($\hat{\nu}_{ij,t}$), we estimate how these components respond to monetary policy surprises.

We start by estimating the simple baseline specification (1) that captures the average effect of monetary policy on $\hat{cs}_{ij,t}$ and $\hat{\nu}_{ij,t}$. For comparison, column (1) of Table 5 also reports the estimated response of overall credit spreads ($cs_{ij,t}$) to monetary policy—which is therefore identical to our baseline estimate reported in Table 2. Columns (2) and (3), which decompose the average effect in column (1) into an expected default component and an excess bond premium component, show that virtually all of the effect of monetary policy on credit spreads is due to the excess bond premium. The coefficient on $\hat{\nu}_{ij,t}$, at 25 basis points, is in fact highly statistically significant and about eight times larger than the coefficient on $\hat{cs}_{ij,t}$ (which instead is not statistically different from zero).

[21] These frictions could operate both at the firm level (as in Bernanke et al. (1999)), at the intermediary level (as in He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), Gertler and Kiyotaki (2010) and Gertler and Karadi (2011)), or both. Understanding the relative importance of firm-level vs. intermediary-level frictions goes beyond the scope of this paper and represents a fruitful area for future research.

Table 5 Expected Default and Excess Bond Premium

	(1)	(2)	(3)
Dep. Variable:	Spread (Δcs)	Default Risk ($\Delta \hat{cs}$)	Exc. Bond Premium ($\Delta \hat{\nu}$)
MP surp. (ϵ^m)	28.17***	3.07	25.10**
	(10.72)	(1.86)	(10.39)
Double clustering	Yes	Yes	Yes
Time-sector FE	No	No	No
R-squared	0.034	0.030	0.032
Observations	281,330	281,330	281,330

Note. Results from estimating specification (1), namely $y_{ij,t} = \alpha_i + \beta \epsilon_t^m + e_{ij,t}$, where $y_{it} = (\Delta cs_{ij,t}, \Delta \hat{cs}_{ij,t}, \Delta \hat{\nu}_{ij,t})$; ϵ_t^m is the monetary policy surprise, $\Delta cs_{ij,t}$, $\Delta \hat{cs}_{ij,t}$, and $\Delta \hat{\nu}_{ij,t}$ are the change in spreads, fitted spreads and the excess bond premium between the day before the FOMC announcement and five days after the announcement, respectively; α_i is a bond fixed-effect. Standard errors (reported in parentheses) are clustered two way, at the firm level and time level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

Our results are comparable to existing macro studies, notably to the VAR analysis of Gertler and Karadi (2015). As we explain in more detail in the next section, Gertler and Karadi (2015) estimate a smaller impact response of the excess bond premium to monetary policy surprises, but this difference can be explained by the different series of monetary surprises we use. When, as in Gertler and Karadi (2015), we use the raw interest rate surprises (s_t^{FF4}) we get a quantitative response of the excess bond premium that is very similar to theirs, despite the different sample period and methodology.

While the fitted spreads $\hat{cs}_{ij,t}$ can explain almost 75 percent of the variation in overall credit spreads, the excess bond premium $\hat{\nu}_{ij,t}$ inherits much of the volatility of credit spreads (see Table E.1 and Figure E.1 in the Appendix). Therefore, the result in Table 5—that monetary policy transmits to credit spreads mainly *via* the excess bond premium—could simply reflect the higher variance of $\hat{\nu}_{ij,t}$ relative to $\hat{cs}_{ij,t}$. To check whether this is the case, we re-estimate specification (1) after standardizing both series, which we label $\widetilde{\Delta \hat{cs}}_{ij,t}$ and $\widetilde{\Delta \hat{\nu}}_{ij,t}$. The results (reported in Table F.6 in the Appendix) show that the response of $\widetilde{\Delta \hat{\nu}}_{ij,t}$ is still larger than $\widetilde{\Delta \hat{cs}}_{ij,t}$. This implies that the larger coefficient in Table 5 is not only due to the higher variance of $\hat{\nu}_{ij,t}$ (relative the to $\hat{cs}_{ij,t}$), but also to a stronger transmission via the excess bond premium.

We next turn to the cross-sectional response of the expected default and the excess bond premium components to monetary policy. We estimate a specification with time-sector fixed effects, as in equation (4). The estimated γ coefficient captures the impact of monetary policy on the credit spread of high-leverage firms relative to low-leverage firms. The estimated coefficients on $cs_{ij,t}$, $\hat{cs}_{ij,t}$, and $\hat{\nu}_{ij,t}$ are reported in Table 6, in columns (1), (2), and (3), respectively. The results show that the excess bond premium accounts for virtually all the relative response of credit spreads to a monetary policy surprise, with an estimated coefficient of 20.10. The expected default component also has a positive coefficient even though it is quantitatively small and statistically insignificant.

Table 6 Expected Default and Excess Bond Premium: Heterogeneity

	(1)	(2)	(3)
Dep. Variable:	Spread (Δcs)	Default Risk ($\Delta\hat{cs}$)	Exc. Bond Premium ($\Delta\hat{\nu}$)
MP surp.×Lev. ($\epsilon^m \times \ell_j^{High}$)	20.54**	0.44	20.10**
	(9.31)	(0.60)	(9.39)
Double clustering	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes
R-squared	0.312	0.381	0.303
Observations	275,311	275,311	275,311

Note. Results from estimating specification (4), namely $\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma\left(\epsilon_t^m \ell_{j,t-1}^{High}\right) + \delta\ell_{j,t-1}^{High} + e_{ij,t}$, where ϵ_t^m is the monetary policy surprise; Δcs_{it} is the change in spreads between the day before the FOMC announcement and five days after the announcement; $\ell_{j,t-1}^{High} = 1$ when firm j leverage lies above the median of the leverage distribution (and zero otherwise); α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect. Standard errors (reported in parentheses) are clustered two way, at the firm level and time level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

In sum, the results in this section show that a large proportion of the overall movement in credit spreads is accounted for by a component that is orthogonal to firm fundamentals, and that can be interpreted as a measure of firms' borrowing costs that is due to financial market frictions. As such, the results reinforce the evidence that financial frictions play a quantitatively important role for the transmission of monetary policy to credit spreads.

3.4 The Role of Non-monetary News

Standard interest rate surprises can contain significant non-monetary news due to a signalling channel of monetary policy decisions (see, for example, Nakamura and Steinsson, 2018). We show in this section that the presence of this non-monetary news can introduce a significant downward bias in the estimated effect of monetary policy on credit spreads. To do that, we compare the response of credit spreads to the raw interest rate surprises (s_t^{FF4}), and their monetary (ϵ_t^m) and non-monetary (ϵ_t^{other}) components.

We start with the simple specification (1). Table 7 reports the estimation results, where note that the estimates obtained with the monetary surprises (ϵ^m) are identical to those in Table 2 and are reported here to facilitate the comparison. The average response of credit spreads to the raw interest rate surprises (s_t^{FF4}) is estimated at 10.29 basis points, as shown in column (1). This estimate is almost three times smaller than the credit spread response to monetary surprises (ϵ^m), reported in column (2). The estimate in column (1) not only is smaller, but also is less statistically significant, with a p-value of 0.08 relative to a p-value of less than 0.01 in our baseline. These differences are due to the fact that an increase in s_t^{FF4} is, in general, due to a linear combination of two forces that have opposing effects on credit spreads: (i) a monetary policy contraction (ϵ^m) that acts to increase credit spreads; and (ii) a systematic monetary policy tightening by the central bank to respond to improved demand conditions (ϵ_t^{other}), which acts to compress credit spreads (see Jarocinski and Karadi, 2018). Consistent with this interpretation, the response of credit spreads to non-monetary news (ϵ_t^{other}) is strongly negative at -24.73 basis points (as shown in column (3) of Table 7), even though is not statistically significant.

Controlling for non-monetary news in high-frequency interest rate surprises is therefore important to explain economy-wide (i.e. average) responses, as extensively documented by Jarocinski and Karadi (2018). But, as we show next, it is also important to explain

Table 7 Response of Credit Spreads to Raw Interest Rate Surprises And Their Monetary and Non-Monetary Components

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)
Indep. Variable:	Interest rate surp. (s^{FF4})	Monetary surp. (ϵ^{m})	Non-monetary surp. (ϵ^{other})
Monetary surp. (ϵ^{m})	10.29*	28.17***	-24.73
	(5.86)	(10.72)	(16.35)
Time-Sector FE	No	No	No
Double clustering	Yes	Yes	Yes
R-squared	0.034	0.030	0.032
Observations	281,330	281,330	281,330

Note. Results from estimating specification (1), namely $y_{ij,t} = \alpha_i + \beta\epsilon_t^m + e_{ij,t}$, with different high frequency surprises. In column (1) the independent variable is the raw FF4 surprise (s_t^{FF4}); in column (2) is our baseline monetary surprise (ϵ_t^m); and in column (3) is the non-monetary surprise (ϵ_t^{other}); Δcs_{it} is the change in spreads between the day before the FOMC announcement and five days after the announcement. Standard errors (reported in parentheses) are clustered two way, at the firm level and time level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

the cross-sectional response of firm-level outcomes. Table 8 reports the results from estimating specification (4), where we consider how firms with different leverage respond to the raw interest rate surprises (s_t^{FF4}), and their monetary (ϵ_t^m) and non-monetary (ϵ_t^{other}) components.

Columns (1), (2), and (3) report the coefficient estimates from specification (4), where we include time-sector fixed effects and we interact the surprises s_t^{FF4}, ϵ_t^m, and ϵ_t^{other} with the high-leverage dummy. The estimates in column (1) show that, in response to a policy hike driven by s_t^{FF4}, high-leverage firms experience an increase in credit spreads that is only 9.45 basis points larger than low-leverage firms. As already documented in Table 2 (and reported here in column (2) for ease of comparison), a much stronger pattern holds when considering the monetary policy surprises ϵ^m. The elasticity of credit spreads to ϵ^m is twice as big as the elasticity to s_t^{FF4}, and is also more more precisely estimated. This is because, as documented in Table 7 for the average response of credit spreads, s_t^{FF4} masks two opposite forces at work, i.e. a monetary policy hike (ϵ^m) and the systematic response

Table 8 Response of Credit Spreads to Raw Interest Rate Surprises And Their Monetary and Non-Monetary Components: Cross-section

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)
Indep. Variable:	Interest rate surp. (s^{FF4})	Monetary surp. (ϵ^m)	Non-monetary surp. (ϵ^{other})
MP surp.×High Lev. ($\epsilon \times \ell_j^{High}$)	9.45*	20.54**	-12.27
	(5.52)	(9.31)	(11.35)
Double clustering	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes
R-squared	0.311	0.311	0.311
Observations	275,311	275,311	275,311

Note. Results from estimating specification (4), with different high frequency surprises. In column (1) the independent variable is the raw FF4 surprise (s_t^{FF4}); in column (2) is our baseline monetary surprise (ϵ_t^m); and in column (3) is the non-monetary surprise (ϵ_t^{other}); Δcs_{it} is the change in spreads between the day before the FOMC announcement and five days after the announcement; $\ell_{j,t-1}^{High} = 1$ when firm j leverage lies above the median of the leverage distribution (and zero otherwise); $\beta_{sct,t}$ is a time-sector fixed effect. Standard errors (reported in parentheses) are clustered two way, at the firm level and time level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

of the central bank to positive news in the economy (ϵ_t^{other}). Consistent with this view, when considering an increase in interest rates driven by non-monetary surprises (ϵ_t^{other}) we find that credit spreads fall, and do so more for firms that are highly leveraged.

In sum, the results in this section show how the non-monetary news embedded in raw interest rate surprises can lead to a large and significant downward bias in the estimated effect of monetary policy on credit spreads, both in the time series and in the cross-section. It is therefore important to 'purge' interest rate surprises from this non-monetary component, something that has so far been neglected in the literature on the heterogeneous effects of monetary policy on firms. Indeed, the presence of this non-monetary news can rationalize some of the contrasting results found in the literature on the heterogeneous effects of monetary policy on firm-level investment.

4 Firm-level Panel Local Projections

The focus of the analysis so far has been on the high-frequency response of credit spreads. In our view, the high-frequency approach naturally leads to a more credible identification of the impact of monetary policy on firm-level outcomes, as well as a more precise estimation of its effects. However, the impact of monetary policy on credit spreads documented so far could be driven by transitory adjustments in prices. It might also be the case that our measured policy surprises are short-lived disturbances to market interest rates with no persistent effects on firm-level outcomes. With this in mind, we extend the daily event-study regressions of the previous section to a business cycle frequency analysis.

We proceed in two steps. First, for firms in our data set, we collect quarterly data on total debt and investment from Compustat (details reported in Appendix B) and we revisit the evidence on the heterogeneous effects of monetary policy on firm-level debt and investment, closely following the approach used in recent papers (i.e. by using a simple panel local projection approach as in Jorda, 2005). We then run a similar exercise on credit spreads.[22] Our analysis differs in two dimensions relative to previous studies, namely in (i) the use of credit spreads, whose response provides a crucial additional dimension to interpret the results on firm-level quantities; and (ii) the use of monetary policy surprises that are purged of the non-monetary news component (which can lead to biases in the estimated response of firm-level outcomes).

We start with a simple exercise where we split our sample into two groups based on where each firm lies in the leverage distribution and we estimate the *average* dynamic effect of monetary policy (on a given firm-level outcome $y_{j,t}$) by group:

$$y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta_1^h \left(\epsilon_t^m \ell_{j,t-1}^{Low}\right) + \beta_2^h \left(\epsilon_t^m \ell_{j,t-1}^{High}\right) + \sum_{p=1}^{P_X} \mathbf{\Gamma}_p \mathbf{X}_{j,t-p} + \sum_{p=1}^{P_Z} \mathbf{\Xi}_p \mathbf{Z}_{t-p} + e_{j,t+h}, \quad (6)$$

where y_{t+h} is the independent variable of interest at horizon h; ϵ_t^m is the monetary policy

[22]We use the longest available sample for these exercises. In the case of debt and investment, the sample is constrained by the high-frequency monetary policy surprises, which can only be computed starting from 1990. In the case of credit spreads, the sample is instead constrained by the the BofAML corporate bond data set, which provides data starting from 1999.

surprise, which has been aggregated at quarterly frequency by taking an average of ϵ_t^m within each quarter t;[23] α_j^h is a firm-level fixed effect; $\ell_{j,t-1}^{Low}/\ell_{j,t-1}^{High}$ are dummy variables that equal 1 when the leverage of firm j in the quarter that precedes the monetary policy surprise lies below/above the median of the leverage distribution (and zero otherwise); β_1^h and β_2^h are the coefficients of interest that measure the average effect of ϵ_t^m on y_{t+h} for low- and high-leverage firms, respectively; $\mathbf{X}_{j,t}$ and $\mathbf{Z}_t$ are firm-level and aggregate controls, respectively; and h denotes the horizon, with $h = 0, 1, 2, ..., H$. In the experiments we report below, $\mathbf{X}_{j,t}$ includes firm leverage, (log) size, quarter real sales growth, and current assets share, with $P_X = 1$; and $\mathbf{Z}_{t-p}$ includes quarterly real GDP growth, quarter on quarter inflation, the VIX index, and the interest rate on the 1-year nominal T-bill, with $P_z = 4$.

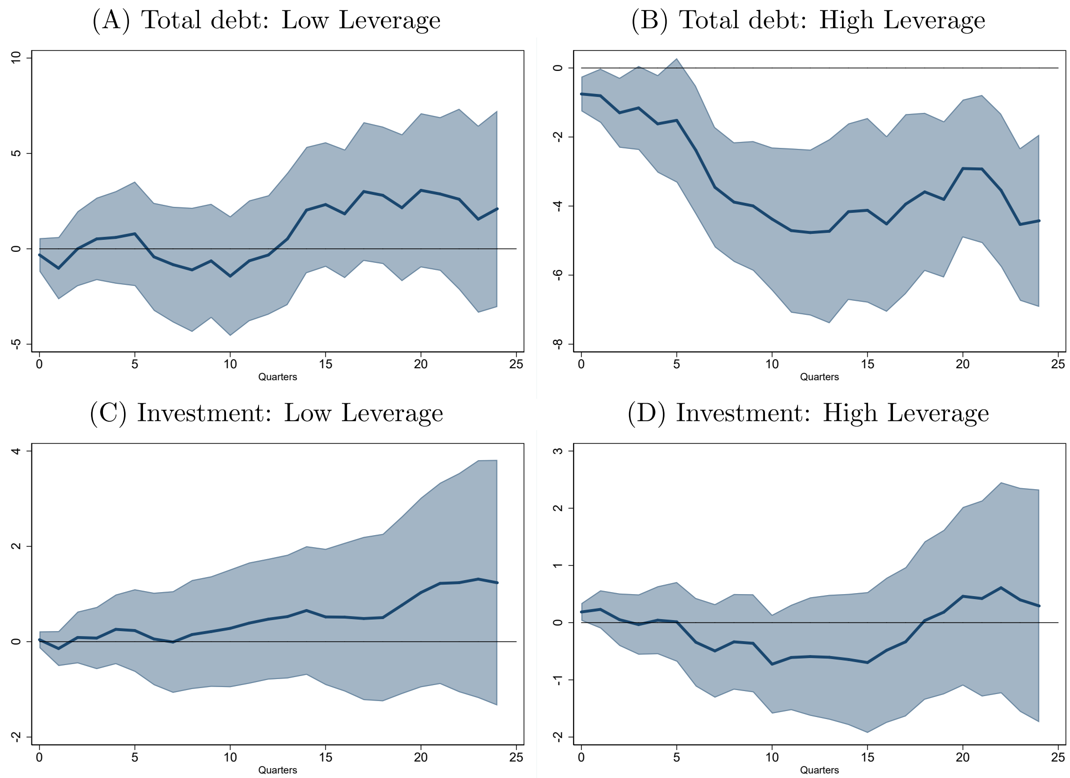
Figure 4 displays the estimated impulse responses (β_1^h and β_2^h) for total debt (top panels) and investment (bottom panels). The shaded areas display the 90 percent confidence intervals based on two-way clustered standard errors, at the firm and time level. Panel (A) shows that the total debt of low-leverage firms (i.e. with leverage below the median) does not respond in a statistically significant fashion to the monetary policy surprise. In contrast, Panel (B) shows that firms with high leverage (i.e. above the median) experience a large and statistically significant contraction in total debt which peaks around 10 quarters after the shock.

A similar picture emerges from the response of investment, reported in the bottom panels of Figure 4. Panel (C) shows that low-leverage firms are not significantly affected by the monetary policy surprise. High leverage firms, instead, experience a contraction in investment that peaks between 10 and 15 quarters and is borderline statistically significant. Note that these effects are less precisely estimated than those on total debt, which may reflect the noisy nature of firm-level investment.

To investigate more formally whether the differential response between high- and low-leverage firms is statistically significant, we estimate the dynamic effect of monetary policy

[23] Equivalent aggregation methods are adopted in Stock and Watson (2012) and Caldara and Herbst (2016), for example.

Figure 4 AVERAGE IMPULSE RESPONSES: QUANTITIES
HIGH VS. LOW LEVERAGE



NOTE. Average impulse response of total debt and investment for low (i.e. below the median) and high (i.e. above the median) leverage firms. The impulse responses (β_1^h and β_2^h) are estimated with the local projection specification in (6), namely $y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta_1^h \left(\epsilon_t^m \ell_{j,t-1}^{Low}\right) + \beta_2^h \left(\epsilon_t^m \ell_{j,t-1}^{High}\right) + \sum_{p=1}^{P} \mathbf{\Gamma}_p \mathbf{X}_{j,t-p} + \sum_{p=1}^{P} \mathbf{\Xi}_p \mathbf{Z}_{t-p} + e_{j,t+h}$, where $h = 0, 1, 2, ..., 24$; j; ϵ_t^m is the monetary policy surprise; α_i is a bond fixed-effect; $\ell_{j,t-1}^{High} = 1$ when firm j leverage lies above the median of the leverage distribution (and zero otherwise), while $\ell_{j,t-1}^{Low} = 1$ when firm j leverage lies below the median of the leverage distribution (and zero otherwise). The shaded areas display 90 percent confidence intervals based on two-way clustered (time and firm) standard errors.

on $y_{j,t}$ for the group of high-leverage firms *relative* to low-leverage firms:

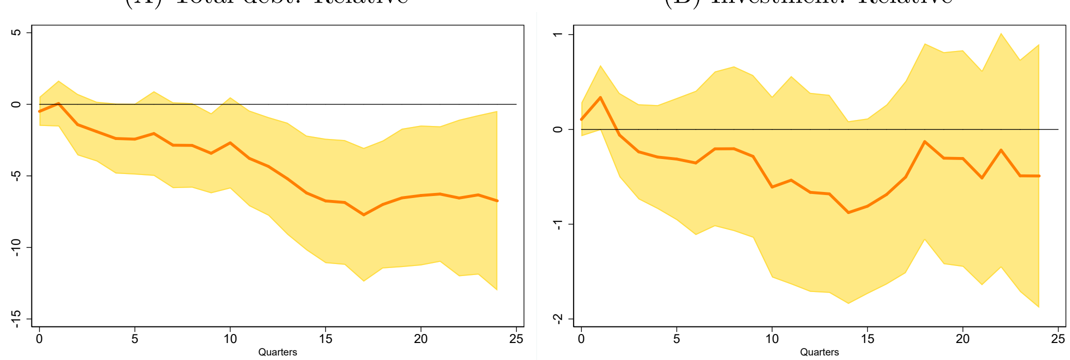
$$y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta_{sct,t} + \gamma^h \epsilon_t^m \ell_{j,t-1}^{High} + \sum_{p=1}^{P_X} \mathbf{\Gamma}_p \mathbf{X}_{j,t-p} + \sum_{p=1}^{P_Z} \mathbf{\Xi}_p \mathbf{Z}_{t-p} + e_{j,t+h}, \qquad (7)$$

where $\beta_{sct,t}$ is a sector-time fixed effect; $\ell_{j,t-1}^{High}$ is a dummy variable that equals 1 when the leverage of firm j in the quarter that precedes the monetary policy surprise lies above the median of the leverage distribution (and zero otherwise); and γ^h is the coefficient of interest that measures the effect of ϵ_t^m on y_{t+h} for high-leverage firms relative to low-leverage firms; and h denotes the horizon, with $h = 0, 1, 2, ..., H$.

The resulting relative impulse responses for total debt and investment, captured by the coefficient γ^h, are reported in Figure 5, in Panel (A) and Panel (B), respectively. Panel (A) shows that the relative response of total debt for high-leverage firms becomes negative and statistically significant shortly after the shock hits. That is: firms with high leverage decrease their stock of debt by more than firms with low leverage. Panel (B) shows that a similar picture emerges for firm-level investment. The differential impulse response is zero on impact, and becomes negative in the quarters following the shock, with a profile that resembles closely the one of total debt—even though the effects are less precisely estimated. Note that the results are virtually unchanged (if anything slightly stronger) if we estimate specification (7) on pre-crisis data as in Jeenas (2018), Ottonello and Winberry (2018), and Cloyne et al. (2018); as well as if we compute our high-leverage dummy based on within-firm variation in leverage, namely $L_{j,t-1} - E_j[L_{j,t-1}]$, as in Ottonello and Winberry (2018) (results reported in Appendix G).

Figure 5 RELATIVE IMPULSE RESPONSES: QUANTITIES

(A) Total debt: Relative (B) Investment: Relative



NOTE. Relative impulse response of total debt and investment. The impulse responses (γ^h) are estimated with the local projection specification in (7), namely $y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta_{sct,t} + \gamma^h \epsilon_t^m \ell_{j,t-1}^{High} + \sum_{p=1}^{P_X} \mathbf{\Gamma}_p \mathbf{X}_{j,t-p} + \sum_{p=1}^{P_Z} \mathbf{\Xi}_p \mathbf{Z}_{t-p} + e_{j,t+h}$, where $h = 0, 1, 2, ..., 24$; j; ϵ_t^m is the monetary policy surprise; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $\ell_{j,t-1}^{High} = 1$ when firm j leverage lies above the median of the leverage distribution (and zero otherwise). The shaded areas display 90 percent confidence intervals based on two-way clustered (time and firm) standard errors.

If interpreted through the lens of the theoretical model we derive in Appendix A, the results on firm-level debt and investment reported in this section are consistent with the event study results on credit spreads, and therefore suggestive of a strong role for the financial accelerator mechanism. We now provide further evidence in support of this finding by looking at the response of credit spreads to monetary policy within the same panel local projection approach used above for debt and investment.

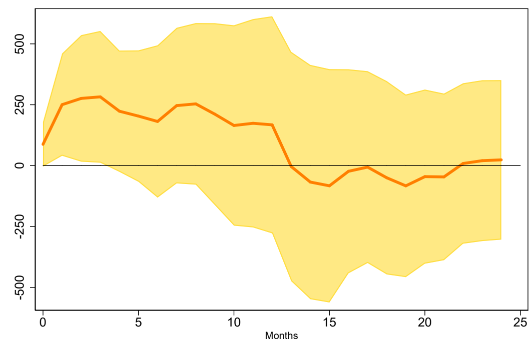
To do that, we first need to construct a data set on credit spreads at business cycle frequency. Recall that, in the data set used in the event study analysis, the time dimension denotes FOMC meetings. As the FOMC holds eight scheduled meetings during the year that are not equally spaced over time, some additional data is needed to construct meaningful time series for credit spreads at business cycle frequency. We proceed as follows. We start by downloading end-of-month observations on credit spreads from ICE-BofAML. We then take an average of credit spreads across all outstanding bonds for each firm in a given month, which gives us a monthly firm-level data set on credit spreads. More details on the construction of this data set are provided in Appendix B.

We can now gauge the relative effects of monetary policy on credit spreads for firms with different levels of leverage by estimating specification (7). Figure 6 reports the relative impulse response, captured by the coefficient γ^h. It shows that, on impact, high-leverage firms experience an increase in credit spreads relative to low-leverage firms of about 50 basis points. The effect is statistically significant only at a short horizons. But the point estimate is high and positive for many periods after the shock hits, before slowly decreasing to zero.

In sum, the results in this section show that the patterns uncovered in the previous section with the high-frequency event study regressions also hold at business cycle frequency.[24] This is true in the time series dimension, with debt and investment falling and credit spreads increasing in response to a contractionary monetary policy surprise; as well as in the cross-sectional dimension, with debt and investment falling by more and credit spreads increasing by more for firms that have high leverage. The analysis in this section also points to the usefulness of high-frequency event study analyses, where the impact of

[24] In Appendix G we report an extensive set of additional results, including the average response of total debt, investment and credit spreads; and the role of monetary vs. non-monetary news.

Figure 6 Relative Impulse Responses: Credit Spreads



Note. Relative impulse response of credit spreads. The impulse responses (γ^h) are estimated with the local projection specification in (7), namely $y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta_{sct,t} + \gamma^h \epsilon_t^m \ell_{j,t-1}^{High} + \sum_{p=1}^{P_X} \mathbf{\Gamma}_p \mathbf{X}_{j,t-p} + \sum_{p=1}^{P_Z} \mathbf{\Xi}_p \mathbf{Z}_{t-p} + e_{j,t+h}$, with $h = 0, 1, 2, ..., 24$. The shaded areas display 90 percent confidence intervals based on two-way clustered (time and firm) standard errors.

monetary policy on firm-level outcomes can be estimated with higher precision than with lower frequency local projections or vector autoregressive models.

5 Relation to the Existing Literature

Before offering some concluding remarks, in this section we provide additional details on how our paper relates to recent studies in the literature. Not surprisingly, there is a voluminous literature on the role of financial frictions for the transmission of monetary policy.[25] Because of the increasing availability of better quality and more granular firm-level data, in recent years there have been a plethora of studies on the heterogeneous effects of monetary policy on firms. This has led to an ongoing debate on the role and the quantitative importance of financial frictions in explaining the cross-sectional response of firms. As a review of the older literature is beyond the scope of this paper, we focus on a few key recent studies in this section.

The vast majority of recent papers focus on firm-level quantities at quarterly or annual

[25]See, among many others, Bernanke and Blinder (1992), Bernanke and Gertler (1989), Bernanke and Gertler (1995), Kashyap et al. (1994), Gertler and Gilchrist (1994), Kashyap and Stein (1995), Bernanke et al. (1999), Kashyap and Stein (2000), Gertler and Kiyotaki (2010), and Gertler and Karadi (2011).

frequency—such as output, investment, employment, for example—and have reached contrasting conclusions. Ottonello and Winberry (2018) use data on firm-level fixed capital investment from Compustat and find that firms with high leverage and a low distance to default respond to a monetary policy tightening by reducing investment less than low-leverage firms.[26] Using a representative sample of US manufacturing firms, Crouzet and Mehrotra (2018) show that small firms' higher volatility over the business cycle does not seem to be explained by financial factors, such as leverage, liquid asset holdings or access to public debt markets. Both papers conclude that the empirical evidence is not consistent with an important role for the financial accelerator mechanism in explaining cross-sectional differences in firm-level behavior.

In contrast, with data from Compustat for US firms, Jeenas (2018) finds that firms with higher leverage and lower liquid asset holdings at the time of a contractionary monetary surprise tend to experience lower fixed capital expenditure, inventories and sales growth. Cloyne et al. (2018) use firm-level investment data—for both US firms (from Compustat) and UK firms (from Thomson Reuters' WorldScope)—and find that younger firms paying no dividends exhibit the largest and most significant change in capital expenditure in response to monetary policy surprises. Bahaj et al. (2018) use a detailed near-representative data set for UK firms and show that a firm's number of employees responds more strongly to monetary policy among young and highly leveraged firms.[27] Using a large firm-bank level data set for European countries, Kalemli-Ozcan et al. (2018) show that firms with higher leverage reduce investment more and this effect strengthens when these firms are linked to weak banks. All these papers interpret their empirical findings as supportive of an important role played by financial frictions.

As in this paper, a smaller set of recent papers focus on firm-level outcomes that are observable at high frequency, namely share prices. Ippolito et al. (2018) show that the stock prices of firms with floating rate debt respond to monetary policy more when these firms are un-hedged against interest rate risk. Ozdagli (2018) shows that the stock prices

[26]Note that they consider a monetary policy easing throughout their paper, but (as model they employ is linear) the sign of the estimates can be flipped to consider a monetary policy tightening as in this paper.

[27]Differently from the above-mentioned papers, Bahaj et al. (2018) focus on a specific type of balance sheet effect, namely the role of changes in housing values of firms' directors.

of firms subject to greater information frictions have a weaker reaction to monetary policy. Gurkaynak et al. (2019) show that the response of firm-level stock prices to monetary policy depends on the firm cash flow exposure, which can be measured as the sum of maturity-weighted floating rate debts as a fraction of total assets. They also show that firms with higher cash flow exposure experience a higher contraction in capital investment and net worth in the quarters following a policy hike. As we do, these three papers find an important role for financial frictions in explaining the firm-level response to monetary policy.[28]

This paper is—to our knowledge—the first one that considers credit spreads for the analysis of the heterogeneous transmission of monetary policy to firm-level outcomes. Indeed, the novelty of our approach lies in (i) the use of high-frequency information on the firm-level cost of external finance; and (ii) the use of monetary policy surprises that are purged of the non-monetary news that plague commonly used high-frequency interest rate surprises. In contrast, to test the quantitative relevance of competing theoretical mechanisms, the existing literature has focused on the heterogeneous response of firm-level quantities to high-frequency surprises in raw federal funds futures.

There are three important advantages in using credit spreads. First, since quantities are measured at a relatively low frequency, most studies had to rely on quarterly or annual data. Monetary policy decisions, however, happen at a higher frequency and at irregular times during the year, so these studies tend to aggregate monetary policy surprises over quarters or years. This aggregation is far from innocuous: for example, Ramey (2016) shows that the method used by Gertler and Karadi (2015) to aggregate the FOMC announcement surprises induce serial correlation in the resulting monthly series—an undesirable feature as these surprises can be thought of as exogenous only if they capture unanticipated movements in interest rates. Moreover, Chudik and Georgiadis (2019) and Gazzani and Vicondoa (2019) show that commonly used methods of temporally aggregating shocks to match the frequency at which the outcome variable is observed can yield inconsistent estimates of the

[28]Our paper is also related to a recent literature arguing that firms' borrowing capacity is tightly linked to the firm earnings flows, as current earnings are subject to scrutiny by lenders. Lian and Ma (2019) and Drechsel (2018).emphasize the role of debt-to-earnings or debt-to-EBITDA covenants, while Greenwald (2019) focuses on one additional property of debt covenants, namely interest coverage covenants.

temporally aggregated impulse responses.

Second, firm-level quantities may take time to respond to changes in the stance of monetary policy. Credit spreads, instead, react to monetary policy at a much higher frequency, allowing for a more precise identification of both monetary policy surprises and their effects. In fact, even though firm-level debt and/or investment do not immediately respond to monetary policy, the anticipation of these future changes is captured by the forward looking nature of credit spreads.[29]

Third, focusing on credit spreads rather than quantities provides more clear-cut, testable implications.[30] In response to a contractionary monetary policy surprise, the capital demand curve shifts inward *along a firm's marginal cost of investment curve*. For this channel (which we label a 'demand' channel, as it is driven by a change in the demand for capital), both credit quantities and credit spreads fall. In contrast, balance sheet effects (i.e. the financial accelerator) imply an inward *shift of the marginal cost curve*, which decreases credit quantities further, but increases credit spreads (Figure A.2 in Appendix A shows these two effects with a simple comparative statics exercise). For both channels, a contractionary surprise implies a fall in credit quantities, and so empirical investigations of the strength of the financial accelerator mechanism which focus on quantities need to test for a differential sensitivity of constrained and unconstrained firms to monetary policy. In contrast, credit spreads move in different directions depending on the strength of the financial accelerator mechanism. If the credit channel dominates over the demand channel, spreads increase. The opposite happens if the demand channel dominates. Moreover, these effects are stronger, the tighter are a firm's financial constraints. Focusing on credit spreads therefore gives an additional dimension over which the predictions of theory can be tested, as we have a prediction on the *sign of the aggregate response* of credit spreads in the time series dimension, and a prediction on the *magnitude of the relative response* of credit spreads in the cross-sectional dimension.

[29]This is why Ozdagli and Weber (2017), Ippolito et al. (2018), Ozdagli (2018) and Gurkaynak et al. (2019) use stock market prices at the firm level. This paper is the first that exploits high frequency prices at an even finer level of disaggregation (i.e. at the bond level).

[30]While here we only report the simple intuition for why this is the case, a more formal treatment of this argument is reported in Appendix A.

6 Conclusion

Understanding how monetary policy transmits to firms' borrowing and investment decisions is of crucial importance to policy makers. The increased availability of granular firm-level information has led researchers to look at the cross-sectional response of debt and investment to empirically test competing theoretical mechanisms. This paper contributes to an ongoing debate on the role of financial frictions for the transmission mechanism of monetary policy by adding two crucial dimensions that have been overlooked in previous work.

First, we consider the firm-level response of the cost of external finance—in addition to the firm-level response of debt and investment—to monetary policy. The joint response of prices and quantities is crucial to determine the relative magnitude of shifts in the capital demand and capital supply curves. Moreover, credit spreads react to monetary policy at a much higher frequency than debt or investment, allowing for a more precise identification of both monetary policy surprises and their effects.

Second, we build on existing advances in the monetary policy literature and consider a measure of exogenous monetary policy changes that differs from previous studies on this topic. Specifically, we purge high-frequency interest rate surprises from a non-monetary component due to the presence of a signalling channel of monetary policy. Controlling for such non-monetary component is important, as it can introduce a significant bias in the estimated effects of monetary policy on credit spreads, debt, and investment, not only in the time series but also, importantly, in the cross-section.

Our results show that, following a monetary policy hike, high-leverage firms experience a more pronounced increase in borrowing costs and a sharper contraction in debt and investment than low-leverage firms. We interpret our results as being supportive of a credit channel view of monetary policy transmission, where financial frictions are crucial to understand the transmission of monetary policy both in the aggregate and in the cross-section.

Appendix

A Theoretical Framework

In this section we develop a simple theoretical framework that provides one way of interpreting our empirical results. We follow the popular framework in Bernanke et al. (1999). We consider two sets of agents: risk neutral entrepreneurs who run firms and require funding for risky projects and competitive, risk neutral lenders. The relationship between lenders and borrowers is subject to agency costs and is modelled following the Townsend (1979) costly state verification approach. A comparative statics exercise shows that our results both in the cross section and in the time series dimension are consistent with the credit channel view of monetary policy. Specifically, when interpreted through the lens of our simple theoretical model, our results imply that the financial accelerator is quantitatively strong, and is crucial to understanding the cross-sectional response of firms to monetary policy actions.

A Stylized Model of the Credit Channel. Entrepreneurs have heterogeneous levels of net worth, N. In what follows, we will consider the interaction between an entrepreneur with a specific amount of N with competitive banks. This entrepreneur has access to a project with expected gross return $\mathbb{E}[\omega]R^k$, where $\omega \sim \log\mathcal{N}(1, \sigma^2)$ is an idiosyncratic surprise that is private information to the entrepreneur; and R^k is the aggregate return to capital, which is taken as given by the entrepreneur. As net worth is limited, the entrepreneur has to finance capital expenditures (QK) with a mix of net worth (N) and debt (B):

$$QK = N + B, \tag{A1}$$

where debt is supplied by a risk neutral lender at lending rate, R^L (more on this below). The entrepreneur has limited liability: if revenues cannot cover debt repayments (i.e., for bad realizations of ω), the entrepreneur goes bankrupt and loses everything. The competitive risk neutral lender operates under the participation constraint that the expected return on lending equals the gross funding cost, R. The lender therefore offers a menu of loan contracts (R^L, B). In case of bankruptcy, the lender must pay a monitoring cost, μ, to observe entrepreneur returns and seize them.

The entrepreneur maximizes shareholder value:

$$V = \max_{K,B} \frac{1}{R}\mathbb{E}\left(\omega R^k QK - R^L B\right)^+$$

subject to the lender's zero profit condition and balance sheet constraint:

$$\begin{aligned} RB &= \mathbb{I}_{\{\omega R^k QK \geq R^L B\}} R^L B + \mathbb{I}_{\{\omega R^k QK < R^L B\}} (1-\mu)\omega R^k QK \\ K &= N + B \end{aligned}$$

The solution to this maximization problem is standard (see BGG, Appendix C) and implies the following capital supply schedule (which can be also thought as a credit supply schedule as $K = N + B$):

$$EFP \equiv \frac{R^k}{R} = f\left(\frac{QK}{N}\right) \tag{A2}$$

where EFP is the external finance premium (or the discounted return to capital); and $f(1) = 1, \quad f'(\cdot) > 0, \quad f''(\cdot) > 0$. This well-known equilibrium condition states that the return to capital, R^k, has to be equated to the marginal cost of external finance, which is given by the risk free rate, R, times a wedge that is proportional to the leverage ratio, QK/N.[31] Importantly for the empirical exercise in this paper, the credit spread (i.e., the wedge between the lending rate and the risk free rate) can be shown to be itself an increasing function of the EFP (and, therefore, of leverage):

$$CS \equiv \frac{R^L}{R} = g\left(\frac{R^k}{R}\right)$$

where CS is the credit spread; and $g(1) = 1, \quad g'(\cdot) > 0, \quad g''(\cdot) > 0$.

The equilibrium in the market for external financing is determined by the point where the demand for capital intersects the supply of funds (A2). To derive a capital demand schedule we note that, in general equilibrium (and after aggregate and idiosyncratic shocks are realized), the entrepreneur rents capital in a competitive rental market at rental rate (z_t), and sells undepreciated capital $\omega K(1-\delta)$ at a new price Q' after goods production. So, the aggregate gross return on capital has to satisfy:

$$R^k = z_t + \frac{Q'(1-\delta)}{Q} \tag{A3}$$

This condition pins down the capital demand schedule. To plot it in the same space as the credit supply schedule (A2), we (i) note that the rental rate of capital at equilibrium matches the marginal product of capital; and (ii) rescale (A3) by the risk free rate, R. So,

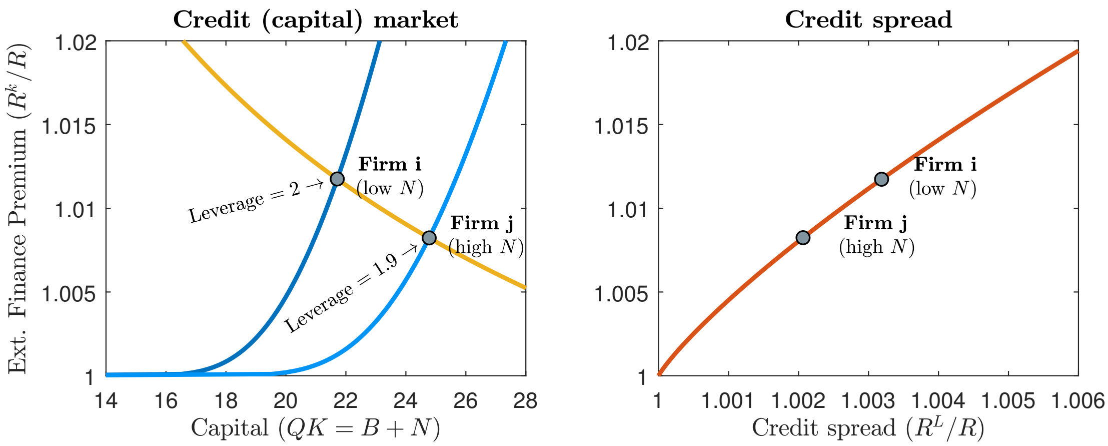
[31]Note that for fully equity financed entrepreneurs the $EFP = 1$.

the capital demand schedule can be expressed as:

$$\frac{R^k}{R} = \frac{1}{R}\left(\alpha K_t^{\alpha-1} + \frac{Q'(1-\delta)}{Q}\right)$$

where we assumed a fixed labor supply for simplicity (so that $z_t = \alpha K_t^{\alpha-1}$).

Figure A.1 EQUILIBRIUM IN THE CREDIT MARKET



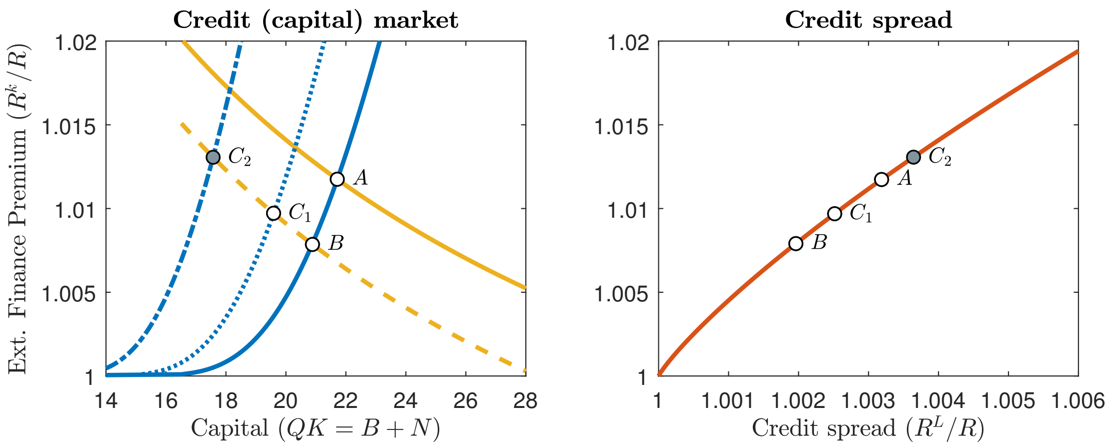
NOTE. The credit supply curves are obtained by setting $\sigma^2 = 0.26$; $\mu = 0.10$; and $N_i = 10$ and $N_j = 15$. Credit demand is obtained by setting $\alpha = 0.35$, $\delta = 0.02$, $R = 4.1\%$ (annualized), and $Q = 1$.

Figure A.1 plots the equilibrium in the credit market for two entrepreneurs with different levels of net worth. Entrepreneur i has low net worth, while entrepreneur j has high net worth. As entrepreneur j can finance a larger amount of capital with net worth, the supply curve she faces is flat over a larger region. That is: relative to entrepreneur i, the supply schedule faced by entrepreneur j is shifted to the right.

The demand schedule and the two supply schedules pin down the equilibrium for the two entrepreneurs, respectively. Relative to firm i, firm j has a larger capital stock, faces a lower external finance premium and a lower credit spread, and has lower leverage. This is intuitive: when net worth is low, firms need to borrow to finance the optimal level of capital expenditure. If the required amount of borrowing creates default risk, then the equilibrium lies where $EFP > 1$, and there is a non-zero credit spread. Entrepreneurs face a trade-off between expanding the firm (higher revenues) and leveraging up (higher borrowing costs).

Curve Shifting: A Monetary Policy Tightening. In Figure A.2 we report a simple curve shifting exercise where we assume that the monetary policy authority increases the risk-free interest rate. We show that monetary policy affects the relative response of more financially constrained firms through two different mechanisms: a dampening mechanism due to the steepness of the supply curve faced by financially constrained firms and an amplifying mechanism due to the financial accelerator. For simplicity, we start by considering the case of firm i in Figure A.1. The initial equilibrium is depicted by point A.

Figure A.2 A Monetary Policy Tightening



Note. The credit supply curves are obtained by setting $\sigma^2 = 0.26$; $\mu = 0.10$; and $N_i = 10$ and $N_j = 15$. Credit demand is obtained by setting $\alpha = 0.35$, $\delta = 0.02$, $R = 4.1\%$ (annualized), and $Q = 1$. The monetary policy tightening corresponds to a 2% increase in the policy rate. The inward shift in the credit supply schedule is obtained by assuming that net worth falls by 8% and 20%, respectively.

A monetary policy tightening, by raising the risk-free interest rate, depresses the demand for capital and its price (Q'). The demand curve shifts downward and the equilibrium moves to point B. As the discounted return on capital is now lower, entrepreneurs find it optimal to decrease borrowing, and, therefore, their leverage. The fall in leverage, reduces the default probability, and as a result the credit spread falls. This is the standard cost channel of monetary policy.

But the unanticipated fall in asset prices also decreases entrepreneurial net worth, because entrepreneurs suffer a capital loss from selling their undepreciated capital at Q'. The fall in net worth relative to the capital stock increases leverage and the expected default probability. This leads to an inward shift in the credit supply schedule. At the old level of capital demand, the premium for external finance increases. As a consequence, the firm size is not optimal anymore and the equilibrium shifts to point C_1. A multiplier effect arises, since the fall in investment decreases asset prices and net worth, further pushing down on investment. This mechanism is the financial accelerator, which is at the heart of the credit channel of monetary policy.

The overall response of credit spreads depends on the strength of the credit channel. The strength of the credit channel is *a priori* ambiguous. Consider, for example, a larger shift in the supply curve that moves the equilibrium to point C_2. It is clear that the equilibrium response of *aggregate* credit spreads to monetary policy crucially depends on the strength of the financial accelerator. This suggests a clear testable implication of the model: credit spreads increase if the financial accelerator is strong, but they fall if the financial accelerator is weak.

A second testable implication of the model comes from the heterogeneous response of firms to monetary policy. Figure A.1 shows that the equilibrium for more constrained entrepreneurs (i.e., those with low levels of net worth and high leverage) lies on a steeper portion of the supply schedule. If in response to a monetary policy tightening credit spreads increase (i.e., if the financial accelerator is strong), the convexity of both $f(\cdot)$ and $g(\cdot)$ implies that credit spreads increase by more for entrepreneurs with lower net worth and higher leverage.

The main implications of the model are consistent with a broader credit channel view in which lenders, rather than firms, are subject to financial constraints. In the simple model described above, the shift in the credit supply curve is due to a change in the borrower's collateral values—i.e. the financially constrained agent—with lenders playing an inconsequential role. However, we would obtain similar predictions (and testable implications) if instead lenders were the financially constrained economic player and firms were not subject to financial frictions. A monetary policy tightening that reduces lenders' net worth would also lower their risk-bearing capacity— see He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), Gertler and Kiyotaki (2010) and Gertler and Karadi (2011). This would result in higher (average) borrowing costs for firms.[32] Highly leveraged firms would experience a larger increase in borrowing costs, as the credit supply curve $f(\cdot)$ would still be increasing and convex—e.g. if lenders were subject to a Value-at-Risk constraints (Adrian and Shin, 2010).

B Data

Corporate bond data. Corporate Bond data for the United States are sourced from the Intercontinental Exchange-Bank of America Merrill Lynch (ICE-BofAML) Global Index System. We focus on bonds in the Global Corporate Index (`G0BC`) and the Global High

[32] For example, Siriwardane (2019) shows that shocks to the capital of financial intermediaries play a significant role in determining CDS spread dynamics.

Yield Index (HW00) over the period 1999-2017.

To measure corporate bond spreads, we use the Merrill Lynch "option adjusted spread" (OAS) on each bond. For bonds without embedded options, the spread reflects the number of basis points that the fair value government spot curve must be shifted so that the present discounted value of cash flows matches the price of the bond. For bonds with embedded options, ICE-BofAML use a log normal short interest rate model to calculate the present value of the bond's cash flows. The OAS is then calculated as the number of basis points that the short interest rate tree must be shifted so that the present discounted value of cash flows matches the price of the bond.[33]

As well as the OAS, we obtain a number of other bond characteristics from the ICE-BofAML Global Index System. Specifically, we obtain data on each bond's age, market value, effective duration, coupon rate, as well as the industry of the issuer. We also use the bond-specific ISIN codes in the data set to obtain additional characteristics on the bonds from Thomson Reuters Datastream. Specifically we merge in information on the seniority of each bond, whether the bond is callable, the issue date of the bond, the redemption date of the bond and the ISO country code of the bond. We also use the Thomson Reuters Datastream to obtain information on the coupon rate and amount issued when it is missing from the ICE BofAML data.

Event study data set. In the event study data set the time dimension denotes FOMC meetings. In Table B.1 we summarize the characteristics of our US corporate bond sample which covers 156 FOMC meetings between August 1999 and November 2017. Our sample consists of 975 firms and $9,413$ bonds. In any given month, each firm has on average around 4 bonds outstanding, although the distribution is positively skewed, with some firms having many bonds outstanding in any given month. The average amount issued is $640 million and the maximum amount issued is $15bn. We consider both high yield and investment grade bonds. The median credit rating is BBB2. Around 60 percent of the bond observations in our sample are callable bonds.

Figure B.1 plots the average credit spread on outstanding bonds in our sample over the period 1999-2017. For comparison, we also plot the average credit spread calculated by Gilchrist and Zakrajsek (2012) (GZ). Our average credit spread closely tracks that of GZ other than for the period 2000-2003, for which the GZ average spread is more elevated. There are a number of reasons for the possible discrepancy between our measure and that of GZ. Firstly, the coverage of bonds in our data set differs from that of GZ. GZ use both Lehman/Warga and Merrill Lynch databases. The proportion of high yield bonds in our

[33] For further details, see ICE Bond Index Methodologies (2017).

Table B.1 Bond Data Set: Summary Statistics

	Mean	Std. Dev.	Min	Median	Max
No. of Bonds per Firm/Month	4.4	5.4	1.0	2.0	59.0
Effective Yield (%)	4.8	2.8	0.1	4.5	38.2
Spread (%)	2.3	2.4	0.1	1.6	35.0
Coupon (%)	5.7	1.9	0.4	5.9	15.0
Amount Issued ($M)	640	563	25	500	15,000
Maturity at Issue (Years)	14.8	9.6	1.5	10.0	50.0
Time to Maturity (Years)	10.7	8.6	1.0	7.4	30.0
Effective Duration	6.8	4.1	0.0	5.8	19.9
Credit Rating (Composite)	-	-	D	BBB2	AAA
Callable (% of Observations)	63.0	-	-	-	-

Note. Summary statistics for all bonds in our data set. The sample period covers 156 FOMC meetings between August 1999 and September 2018. The sample consists of 975 firms and $9,413$ bonds..

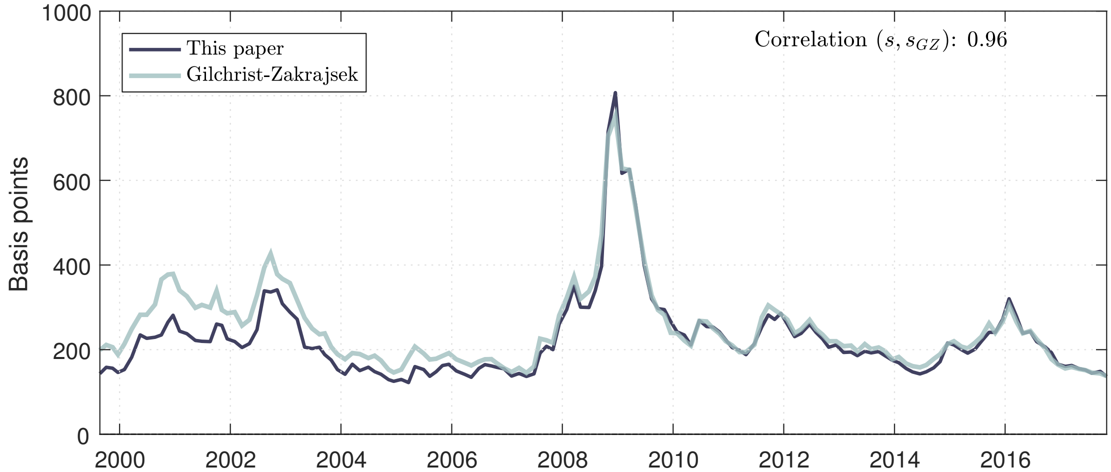
data set is relatively small at the beginning of our sample. If high yield bonds are more prominent in the GZ data set in these years, it may explain the elevated spreads. Secondly, the calculation of spreads is different in GZ. They construct a synthetic risk-free security with the same cash-flows as the corresponding corporate bond and then calculate the spread as the difference between the yield of the corporate bond and the yield of the synthetic security. No adjustment is made at this stage for callable bonds. In contrast, our spread measure is the "option-adjusted spread" calculated by ICE-BofAML.

Construction of monthly data set for local projections. In the event study data set the time dimension denotes FOMC meetings. As the FOMC holds eight (regularly scheduled) meetings during the year that are not equally spaced over time, some additional data is needed to construct a meaningful monthly time series for credit spreads. Therefore, we describe here the simple procedure that we follow to construct a monthly firm-level data for credit spreads. First, we download end of month observations for all bonds in the ICE-BofAML data set. Let $s_{ij,\tau}$ denote the credit spread on bond i issued by firm j at the end of month τ. Second, we construct a monthly series of firm-level credit spreads by taking an average across all bonds (within firm) in each period:

$$s_{j\tau} = \frac{1}{N_{j\tau}} \sum_i s_{ij,\tau}, \tag{A1}$$

where $N_{j\tau}$ is the number of outstanding bonds of firm j in month τ. We then construct a

Figure B.1 Credit Spreads: Comparison with GZ



Note. The Figure plots the series of credit spreads used in this paper (solid dark line) and compares it wit the sereis of credit spreads used in Gilchrist and Zakrajsek (2012) (thick light line).

quarterly firm-level credit spreads panel by taking an average of the firm-month observations (τ) that belong to a given quarter t:

$$s_{jt} = \frac{1}{3} \sum_{\tau \in t} s_{j\tau}. \tag{A2}$$

Share price data. Market capitalization data is required for each firm in order to compute its distance to default using the Merton-KMV approach. For the United States, we use the Center for Research in Security Prices to obtain the daily share price and number of shares outstanding for the listed US firms within our bond price data set.

Balance sheet data for calculation of the excess bond premium. We also require balance sheet information on firm debt in order to compute the distance to default using the Merton-KMV model. The model requires daily data on current liabilities and long-term debt. For listed US firms in our bond price data set, we obtain quarterly balance sheet data from Compustat. We linearly interpolate between balance sheet observations to obtain a daily series for current liabilities and long-term debt.

Monetary policy surprises. We obtain intra-daily data on Federal funds futures contracts and eurodollar futures contracts from Reuters. More details on the surprises are reported in Section C.

Investment. We closely follow the steps in Ottonello and Winberry (2018). In short, we compute investment as the log difference of a measure of the firm capital stock, namely $\Delta \log(k_{j,t+1})$, where $k_{j,t+1}$ denotes the capital stock of firm j at the end of period t. This is done by cumulating the changes of *net plant, property, and equipment* (`ppentq`, item 42) to the first available observations of *gross plant, property, and equipment* (`ppegtq`, item 118). We closely following the cleaning steps used in Ottonello and Winberry (2018). For more details, see their empirical Appendix.

Total debt. Total debt is the sum of Compustat items `dlcq` and `dlttq` (i.e. items 45 and 71).

Other Compustat variables. All other variables from Compustat used in our empirical analysis closely follow the definitions of the empirical Appendix of Ottonello and Winberry (2018).

Sectors in ICE BofAML data set. We use the finest available sector classification provided by ICE BofAML (level 4), which includes information on 59 sectors (reported in Table B.2).

Table B.2 Sectors in BofAML Data Set

Sector name	Sector name
Aerospace/Defense	Air Transportation
Personal & Household Products	Environmental
Diversified Capital Goods	Oil Field Equipment & Services
Support-Services	Auto Parts & Equipment
Packaging	Tobacco
Electric-Generation	Discount Stores
Electric-Integrated	Integrated Energy
Machinery	Trucking & Delivery
Electric-Distr/Trans	RealEstate Dev & Mgt
Gas Distribution	Printing & Publishing
Steel Producers/Products	Non-Electric Utilities
REITs	Gaming
Media Content	Energy - Exploration & Production
Media - Diversified	Tech Hardware & Equipment
Telecom - Wireline Integrated & Services	Food - Wholesale
Telecom - Wireless	Oil Refining & Marketing
Cable & Satellite TV	Metals/Mining Excluding Steel
Building & Construction	Beverage
Pharmaceuticals	Forestry/Paper
Medical Products	Restaurants
Health Facilities	Rail
Software/Services	Recreation & Travel
Theaters & Entertainment	Hotels
Specialty Retail	Advertising
Electronics	Auto Loans
Managed Care	Department Stores
Chemicals	Telecom - Satellite
Food & Drug Retailers	Automakers
Health Services	Transport Infrastructure/Services
Building Materials	

Note. Summary statistics for all bonds in our data set. The sample period covers 163 FOMC meetings between August 1999 and September 2018. The sample consists of 975 firms and $9,413$ bonds.

C Monetary Policy surprises

To construct the monetary policy surprises we closely follow the methodology detailed in Jarocinski and Karadi (2018). Specifically, we identify monetary policy surprises by decomposing 30-minute surprises in the S&P 500 stock market index (s_t^{eq}) and the 3-month federal funds futures (FF4) contract (s_t^{FF4}) using a sign restriction procedure. Specifically, we rotate the covariance matrix of $s = (s_t^{FF4}, s_t^{eq})$ with an orthonormal matrix and keep the draws that satisfy the following sign restrictions.

Table C.1 IDENTIFICATION OF ϵ^m: SIGN RESTRICTIONS

	Monetary shock (ϵ^m)	Non-monetary shock (ϵ^{other})
Equity surprise (s_t^{eq})	$-$	$+$
Interest rate surprise (s_t^{FF4})	$+$	$+$

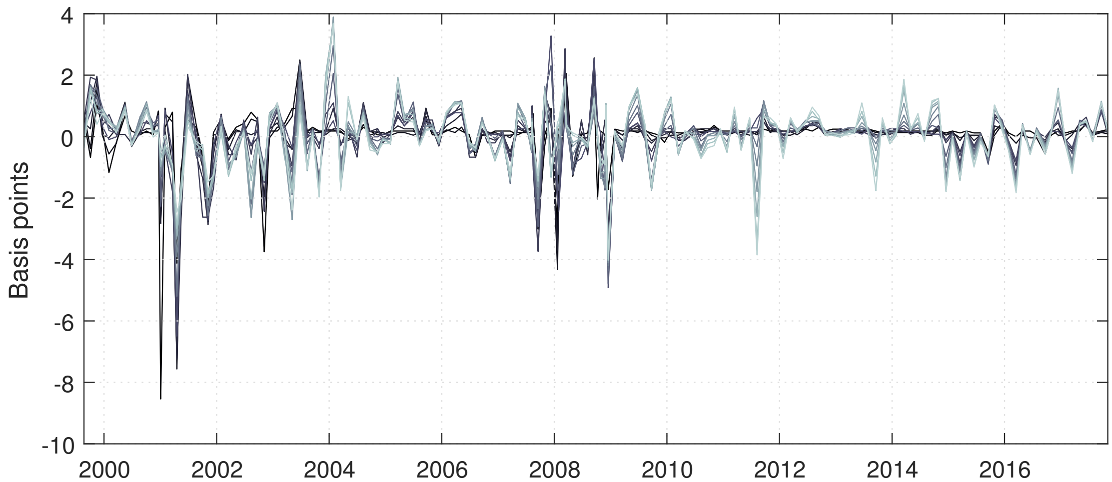
NOTE. Signs imposed to decompose the high frequency surprise s_t^{FF4} into its monetary (ϵ^m) and non-monetary (ϵ^{other}) components.

Figure 1 in the main text displays the behavior of s_t^{FF4} over time, while Figure 2 displays the underlying orthogonal monetary (ϵ^m) and non-monetary (ϵ^{other}) surprises that drive s_t^{FF4}. The monetary surprise explains 75 percent of the total variance of s_t^{FF4}.

We also show here that the Jarocinski and Karadi (2018) series of monetary policy surprises is robust when we use an alternative 'synthetic' interest rate surprise (s_t^{pca}), obtained by extracting a principal component from a panel of (standardized) interest rates on different futures contracts, namely federal funds futures (FF1 to FF6, i.e. the current-month contract rate and the contract rates for each of the next six months) and eurodollar futures (ED1 to ED8, i.e. the current quarter contract rate and the contract rates for each of the next eight quarters). This latter approach shows that the Jarocinski and Karadi (2018) series of monetary policy surprises is robust to (i) the noise that is inherent in a single futures contract and (ii) the information embedded in interest rates with different tenors, therefore capturing surprises in the current and the expected stance of monetary policy—a particularly nice feature given that a large part of our sample covers the zero lower bound.

Figure C.1 plots the panel of (standardized) interest rates on different futures contracts, namely all the FF contracts and all the ED contracts. Not surprisingly, the Figure shows a high degree of comovement across futures contracts. However, the chart also reveals some differences, especially over the zero lower bound period.

Figure C.1 High Frequency Interest Rate Surprises: All Contracts



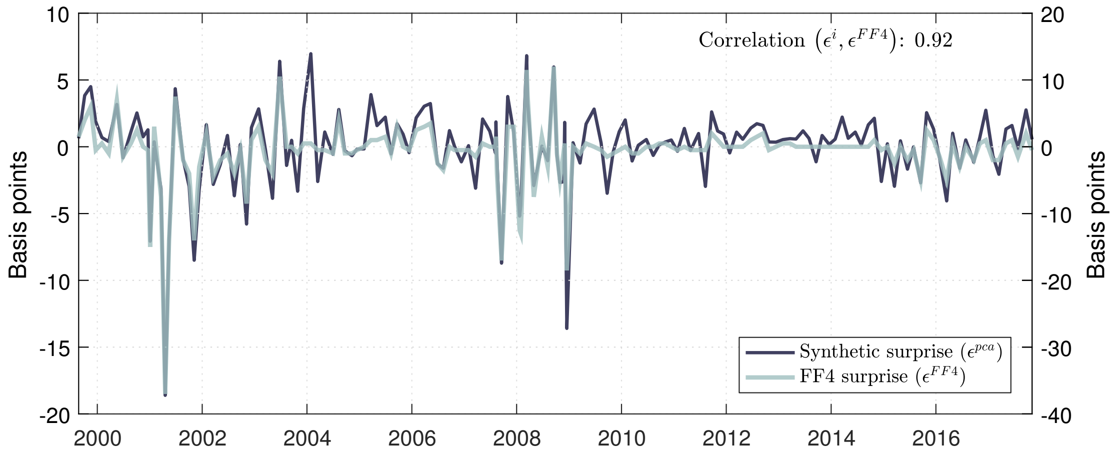
Note. Panel of interest rate surprises based on federal funds futures (FF1 to FF6) and eurodollar Futures (ED1 to ED8).

Figure C.2 reports a comparison between s_t^{pca} (the synthetic interest rate surprise, obtained by taking a principal component of the series in Figure C.1) and s_t^{FF4} (the more commonly used surprises in the 3-month federal funds futures). The correlation between s_t^{pca} and s_t^{FF4} is of 0.92. This difference is mainly due to the zero lower bound period, where the synthetic series of interest rate surprises display more variation than the FF4 surprises.

We than apply the Jarocinski and Karadi (2018) methodology using s_t^{pca} as the series of interest rate surprises. Figure C.3 reports a comparison between our baseline monetary policy surprises (ϵ^m), obtained using s_t^{FF4} , and those obtained with s_t^{pca}, which we label here $\epsilon_t^{m,pca}$. The two series of monetary surprises are highly correlated, at 0.97.

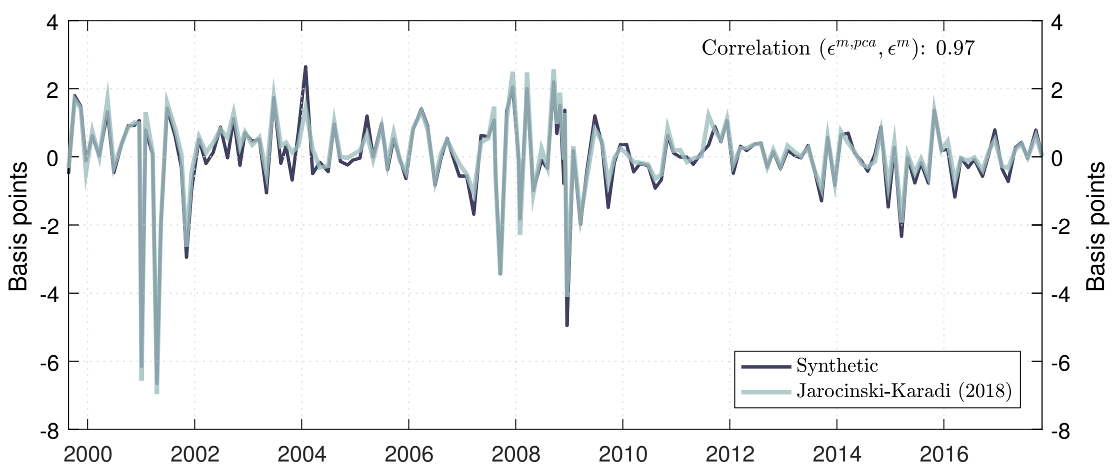
Finally, Table C.2 reports the summary statistics of the FF4 surprises (s_t^{FF4}), the Jarocinski and Karadi (2018) monetary policy surprises (ϵ_t^m, i.e. our baseline measure of monetary surprises), and the monetary surprises based on s_t^{pca} ($\epsilon_t^{m,pca}$).

Figure C.2 High Frequency Surprises: s_t^{FF4} versus s_t^i



Note. The light line is the raw surprise in the 3-month ahead federal funds futures (FF4) contract (s_t^{FF4}. The dark line is a synthetic surprise obtained by extracting a principal component from a panel of (standardized) interest rates on different futures contracts, namely Federal Funds futures (FF1 to FF6) and eurodollar futures (ED1 to ED8). The principal component is computed over the longest available sample common to the interest rates futures series, which spans all FOMC meetings held between 1994 and 2017. The Figure plots the resulting principal component over the sample used in our empirical analysis, namely July 1997 to November 2017.

Figure C.3 High Frequency Monetary Shocks: s_t^{FF4} versus s_t^i



Note. The light line is our baseline monetary surprise (ϵ^m), obtained by applying the Jarocinski and Karadi (2018) methodology using on (s_t^{FF4}, s_t^{eq}). The dark line is the monetary surprise obtained by applying the same methodology on (s_t^{pca}, s_t^{eq}), which we label here $\epsilon_t^{m,pca}$. The two series of monetary surprises are highly correlated, at 0.97.

Table C.2 Interest Rate Surprises and Monetary Policy Shocks: Summary Statistics

	s_t^{FF4}	ϵ_t^m	$\epsilon_t^{m,pca}$
Average	-0.84	0.09	-0.01
St. Deviation	5.08	1.21	1.23
Skewness	-3.00	-2.69	-2.28
Share of tightenings	33%	60%	52%
Share of zeros	22%	0%	0%
Share of loosenings	45%	40%	48%

Note. Summary statistics of raw interest rate surprises, and the monetary policy surprises obtained with the methodology of Jarocinski and Karadi (2018) based on s_t^{FF4} and s_t^{pca}.

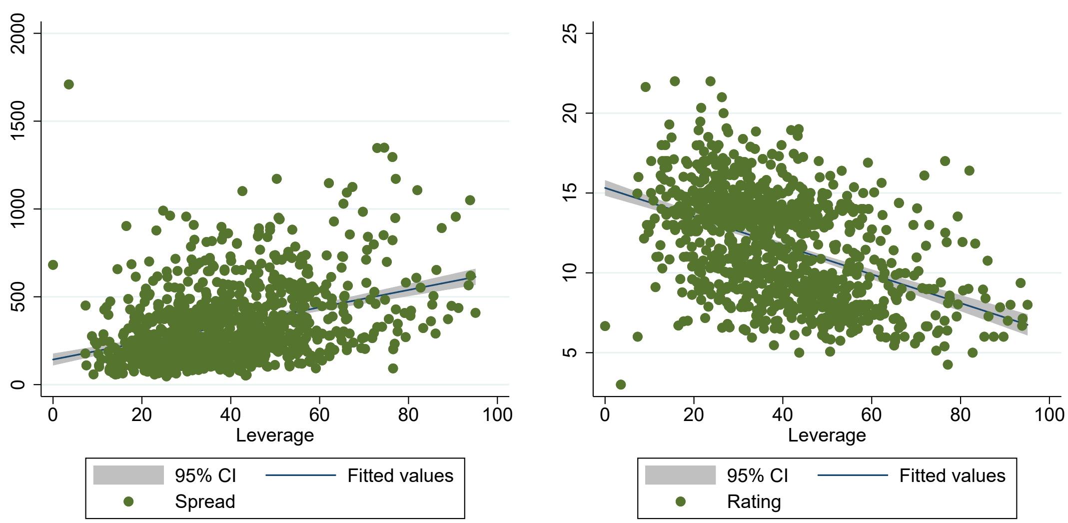
D Leverage, Credit spreads, & Credit ratings

In our data the correlation between credit spreads and leverage is positive. The left panel of Figure D.1 reports a scatter plot of (average) firm level leverage on the horizontal axis against the (average) firm level credit spread. This reduced form correlation is in line with the predictions from the simple model outlined in section A, where firm heterogeneity is driven by differences in net worth. Moreover, it is also supportive of the fact that heterogeneity is not driven by monitoring costs μ or idiosyncratic variance σ.

To see that, first note that, according to the theoretical model in section A, for given net worth, a higher μ or a higher σ would imply a *higher* credit spread and a *lower* leverage. If we assume that all the heterogeneity in the data is driven by differences in the monitoring cost or in the variance of the idiosyncratic surprises, we should observe a negative unconditional relation between credit spreads and leverage, which is clearly not the case in our sample.

The right panel of Figure D.1 also shows that correlation between credit spreads and leverage is positive.

Figure D.1 Leverage, Credit spreads, & Credit ratings



Note. The Figure reports a scatter plot of (average) firm level leverage on the horizontal axis against the (average) firm level credit spread.

E Merton-KMV Model & GZ Credit Spreads Decomposition

In the paper we decompose credit spreads into two orthogonal components: a component capturing fluctuations in firms' expected defaults and a residual component capturing fluctuations of credit spreads in excess of firms' default compensation) that we use in the paper. In this section we explain the procedure we used to obtain this decomposition, which closely follows Gilchrist and Zakrajsek (2012).

Specifically, we use the Merton-KMV framework to estimate the market value of firms and calculate their distance to default for firms in our data-set. We follow the "iterative procedure" described in detail in Bharath and Shumway (2008). We assume that total firm value, V, follows a geometric Brownian motion:

$$dV = \mu V dt + \sigma_V V dW \tag{A1}$$

where μ is the return on V, σ_V is the volatility of V and dW is a standard Wiener process. Assuming that firm debt can be represented by a discount bond which matures at time T, the firm's equity value is given by the Black-Scholes-Merton equation:

$$E = V\mathcal{N}(d_1) - e^{-rT}F\mathcal{N}(d_2) \tag{A2}$$

where E is the market value of equity, F is the face value of debt, r is the risk-free rate and $\mathcal{N}(.)$ is the cumulative standard normal distribution function. d_1 and d_2 are given by:

$$d_1 = \frac{ln(V/F) + (r + 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}} \tag{A3}$$

$$d_2 = d_1 - \sigma_V \tag{A4}$$

The standard Merton model supplements (A2) with a second equation obtained from Ito's Lemma, giving two equations in two unknowns (V and σ_V) which can be solved simultaneously. But as discussed in Bharath and Shumway (2008), the volatility of market leverage means that simultaneously solving the two equations rarely provides meaningful results. Instead we use the "iterative procedure". We begin by guessing the value of asset volatility, given by $\sigma_V = \sigma_E[E/(E + F)]$, where σ_E is the volatility of the market value of equity. Using this guess, we use (A2) to solve for the market value of the firm, V, for each day in the previous year. Using these estimates of the market value, we update our guess of σ_V by calculating the volatility of returns over the previous year. We continue this process until our guess of σ_V converges. Once the process has converged, we calculate the annual return on assets, μ, using our estimates of the market value of the firm. The distance to default for the firm is given by:

$$DD = \frac{ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}} \tag{A5}$$

In estimating the distance to default for each firm, we follow the literature in considering a one year horizon for debt maturity ($T = 1$). We assume the face value of debt, F, is given by a firm's short-term debt plus half of its long-term debt. The volatility of equity, σ_E, is estimated using daily returns over the previous year.

Armed with a measure of firm default, we then use GZ's empirical corporate bond pricing framework to decompose credit spreads into two orthogonal components: a component capturing fluctuations in firms' expected defaults, and a residual component associated with the price of default risk (i.e., the excess bond premium, EBP, in GZ's parlance). Using our firm-specific measure of distance to default, we regress the (log) spread of bond i for firm j on the distance to default of firm j and a vector of bond-specific controls:

$$ln(cs_{ij,t}) = \lambda DD_{j,t} + \gamma X_{ij,t} + e_{ij,t} \tag{A6}$$

where $cs_{ij,t}$ is the credit spread for firm j on bond i at time t, $DD_{j,t}$ is the firm-specific distance to default and $X_{ij,t}$ is a vector of bond-specific controls. The residuals obtained from estimating A6 form our estimate of the bond-specific EBP.[34]

For comparability with GZ, we focus on senior unsecured bonds issued by domestic companies in the domestic currency. We exclude from our sample observations for which the spread is greater than 3500 basis points or below 5 basis points, bonds which have less than one year or more than thirty years to maturity and bonds which have a face value of less than \$150 million. Our vector of controls $X_{ij,t}$ includes the face value of the bond, its duration, the coupon rate, and the age of the bond. Similar to GZ, we also consider a correction for the bonds that are callable.[35]

[34] Gilchrist and Zakrajsek (2012) define the Excess Bond Premium at the aggregate level as the mean of the bond-specific excess bond premia.

[35] Gilchrist and Zakrajsek (2012) interact a dummy indicator of whether the bond is callable with the controls and the three 'yield curve factors' representing the level, slope and curvature of the yield curve. In contrast, we rely on an option adjustment that is calculated by our data provider.

Table E.1 Credit Spreads Decomposition: OLS Regression

	(log)Spread ($ln(cs_{ij,t})$)
Distance to default	-0.0550***
	(0.0002)
log(Age)	0.0089***
	(0.0004)
Log(Issuance)	-0.0190***
	(0.0008)
log(Duration)	0.2758***
	(0.0008)
log(Coupon)	0.4137***
	(0.0014)
R-squared	0.7491
Observations	897,892

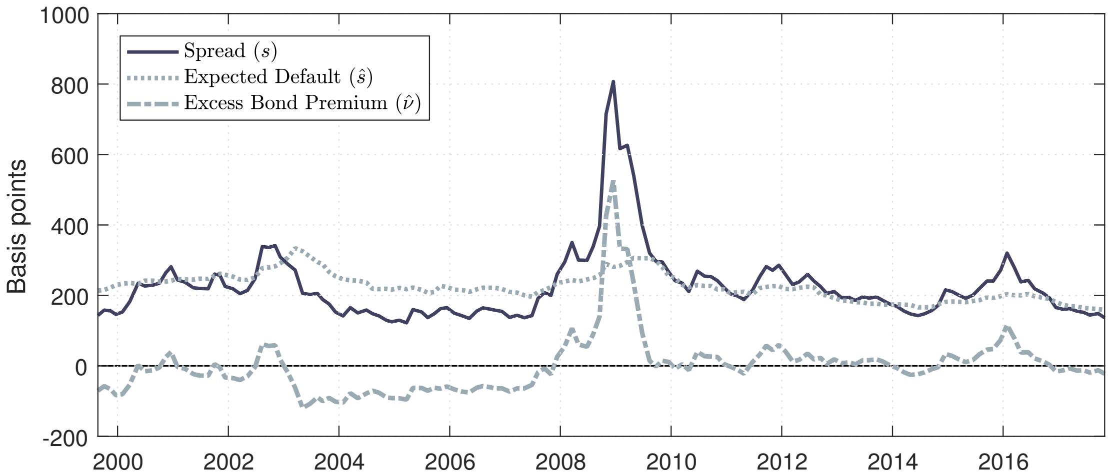
Note. This Table reports the OLS estimation of Gilchrist and Zakrajsek (2012)'s regression. Corporate bond spreads are regressed on our proxy for the distance to default and a number of bond controls, namely age, issuance, duration, and coupon, as well as industry and rating fixed effects. The results from this regression allow us to decompose spreads into a component associated with the probability of default (the fitted value) and the excess bond premium (the residual). The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

In Table E.1 we present the results from the regression of corporate bond spreads on the distance to default and a number of bond controls (shown in Equation (A6)), which we use to decompose spreads into a component associated with the probability of default and the 'excess bond premium'.

Figure E.1 plots the decomposition of average spreads into the average fitted component and the average excess bond premium using the regression results reported in Table E.1. In the five years prior to the financial crisis, the average excess bond premium was low (and largely negative). The average excess bond premium increased sharply during the financial crisis in 2008, peaking at 420 basis points in December 2008. Since the financial crisis, the average excess bond premium has fallen back, although remains at a slightly more elevated level than prior to the crisis.

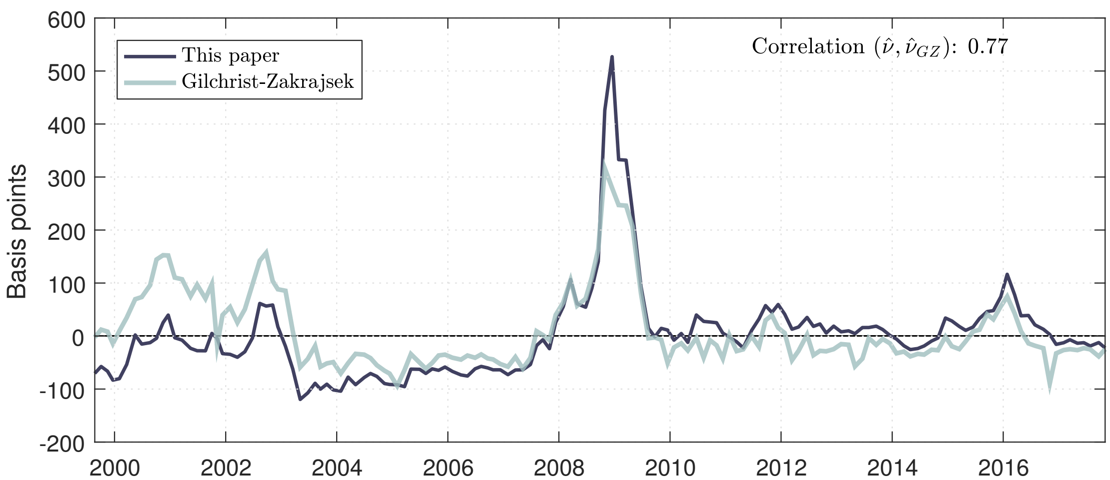
Our average excess bond premium follows a similar profile to the excess bond premium calculated by GZ. The correlation over the whole sample period, from July 1999 to November 2017, is 0.77. Similar to the profiles of average spreads, shown in Figure E.2, the GZ

Figure E.1 CREDIT SPREADS DECOMPOSITION: EXPECTED DEFAULT AND THE EXCESS BOND PREMIUM



NOTE. The Figure plots the decomposition of (average) credit spreads into the (average) fitted component and the (average) excess bond premium, computed according the regression results reported in Table E.1.

Figure E.2 EXCESS BOND PREMIUM: COMPARISON WITH GZ



NOTE. The Figure reports a comparison of the (average) excess bond premium computed in this paper with the excess bond premium calculated by Gilchrist and Zakrajsek (2012). The correlation over the whole sample period, from July 1999 to November 2017, is 0.77.

excess bond premium is elevated relative to our measure for the period 2000-2003. Comparing our measure to the GZ excess bond premium over the period January 2003-November 2017, the correlation coefficient is 0.96.

Note that, in any case, some differences in the profile of the EBP are to be expected. Our sample period is different from the original sample used by GZ. Moreover, we use credit spreads data bracketing FOMC announcements for the estimation of specification (A6), while GZ use end of month observations. The high correlation between our EBP series and GZ's original one is reassuringly suggesting that the EBP is robust to different specifications, data, and potential time variation in the estimated coefficients.

F High Frequency Event Study: Additional results

In this section we describe additional results and robustness checks that are complementary to the findings reported in Section 3.

Table F.1 reports an extended version of Table 2. Specifically, while specification (3) is parsimonious and allows us to empirically test for the relative response of high *versus* low-leverage firms, it is also quite restrictive in that it imposes a linear relation between the sensitivity of credit spreads to monetary policy shocks and leverage. We relax this by splitting our sample of bond observations into quartiles based on where each firm lies in the leverage distribution. We then consider how the response of spreads to monetary policy shocks varies by leverage quartile. That is, we run the following more flexible specification:

$$\Delta s_{ij,t} = \alpha_i + \beta_1 \left(\epsilon_t^m \ell_{j,t-1}^1\right) + \beta_2 \left(\epsilon_t^m \ell_{j,t-1}^2\right) + \beta_3 \left(\epsilon_t^m \ell_{j,t-1}^3\right) + \beta_4 \left(\epsilon_t^m \ell_{j,t-1}^4\right) + e_{ij,t} \tag{A1}$$

where $\ell_j^k = 1$ when the leverage of firm j falls in the k^{th} quartile of the leverage distribution (and zero otherwise). Coefficients β_1 to β_4 capture the impact of monetary policy on credit spreads by leverage quartile. The results are reported in column (3) of Table F.1. They show that the response of credit spreads is increasing with the leverage quartiles, from 19.76 basis points for firms in the first leverage quartile to 40.02 basis points for firms in the fourth leverage quartile.

As mentioned in the main text, we report here the same specifications of section 3.2 with the linear leverage interaction, i.e. $L_{j,t-1}$. Specifically, Table F.2 reports the same robustness exercises shown in Table 3 in the main body of the paper, where instead of using the high-leverage dummy ℓ_j^{High} (which is equal to 1 when the leverage of firm j lies above the median leverage in the distribution), we use the continuous leverage interaction $L_{j,t-1}$.

In order to address the concern that leverage might be correlated with other firm characteristics, in the main text we run a series of 'double-interaction' regressions—see equation (5) Similarly, Table F.3 reports the estimation results from estimation of equation (5) using the continuous leverage interaction $L_{j,t-1}$. The results are unchanged.

Tables F.4 and F.5 report the results from an exercise where we the interaction between monetary policy surprises and alternative firm characteristics (as proxies for financial constraints) instead of leverage. Specifically, we consider firm (log) size, sales growth, credit ratings, time since IPO, a measure of the firm's distance to default (calculated using the Merton-KMV framework, detailed in Appendix E, the ratio between total debt and EBITDA, and the measure of a firm's liquid assets used in Jeenas (2018), respectively. In Table F.6 we report the results from estimating specification (1) after standardizing the fitted spreads $\hat{cs}_{ij,t}$ and the excess bond premium $\hat{\nu}_{ij,t}$, which we label $\widetilde{\Delta \hat{cs}}_{ij,t}$ and $\widetilde{\Delta \hat{\nu}}_{ij,t}$. We do this to check that the result in Table 5—that monetary policy transmits to credit spreads mainly via the excess bond premium—does not simply reflect the higher variance of $\hat{\nu}_{ij,t}$ relative to $\hat{cs}_{ij,t}$. The results show that the response of $\widetilde{\Delta \hat{\nu}}_{ij,t}$ is still larger than $\widetilde{\Delta \hat{cs}}_{ij,t}$. Table F.7 reports the results from a simple time series regression of credit spreads (and their decomposition into fitted spreads and excess bond premium) on the monetary policy surprises. we do this by taking an average of the credit spread of all outstanding bonds at each time period t (using the amount issued with each bond as a weight).

Table F.1 HETEROGENEOUS RESPONSE OF CREDIT SPREADS TO MONETARY POLICY: BASELINE (DIFFERENT SPECIFICATIONS)

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)	(4)
	Baseline	Low/High Leverage	Leverage Interaction	Leverage quartile
MP surp. (ϵ^m)	28.17***		27.46**	
	(10.72)		(10.65)	
MP surp.×Lev. ($\epsilon^m \times L_j$)			11.34*	
			(6.79)	
MP surp.×Lev. Q1 ($\epsilon^m \times \ell_j^1$)				19.76***
				(6.49)
MP surp.×Lev. Q2 ($\epsilon^m \times \ell_j^2$)				22.97**
				(9.10)
MP surp.×Lev. Q3 ($\epsilon^m \times \ell_j^3$)				26.07**
				(10.02)
MP surp.×Lev. Q4 ($\epsilon^m \times \ell_j^4$)				40.02**
				(18.66)
MP surp.×Low Lev. ($\epsilon^m \times \ell_j^{Low}$)		21.35***		
		(7.41)		
MP surp.×High Lev. ($\epsilon^m \times \ell_j^{High}$)		32.52**		
		(13.77)		
Double clustering	Yes	Yes	Yes	Yes
Time-sector FE	No	No	No	No
R-squared	0.034	0.029	0.030	0.031
Observations	281,330	275,676	281,330	275,676

NOTE. Results from estimating specifications (1), (2), (3), and (A1), where ϵ_t^m is the monetary policy surprise; Δcs_{it} is the change in spreads between the day before the FOMC announcement and five days after the announcement; α_i is a bond fixed-effect; L_j is the (standardized) leverage of firm j; $\ell_{j,t-1}^{High} = 1$ when firm j leverage lies above the median of the leverage distribution (and zero otherwise), while $\ell_{j,t-1}^{Low} = 1$ when firm j leverage lies below the median of the leverage distribution (and zero otherwise). Standard errors (reported in parentheses) are clustered two way, at the firm level and time level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill.

Table F.2 HETEROGENEOUS RESPONSE OF CREDIT SPREADS TO MONETARY POLICY: ROBUSTNESS

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)	(4)	(5)
	Time-sector FE	Controls	Within Leverage	Instrumental Var.	Pre-crisis
MP surp.×Lev. ($\epsilon^m \times L_j$)	14.07*	13.60*			16.91***
	(7.47)	(7.73)			(5.14)
MP surp.×Lev. ($\epsilon^m \times \tilde{L}_j$)			12.08**		
			(5.74)		
1yr Rate x Lev. ($\epsilon^m \times L_j$)				12.93***	
				(0.68)	
Double clustering	Yes	Yes	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.311	0.306	0.311	-0.016	0.342
Observations	275,311	263,417	275,311	275,311	52,016

NOTE. Results from estimating specification (4), namely $\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma\,(\epsilon_t^m L_{j,t-1}) + \delta L_{j,t-1} + e_{ij,t}$ and its variants described in the text, where ϵ_t^m is the monetary policy surprise; Δcs_{it} is the change in spreads between the day before the FOMC announcement and five days after the announcement; L_j is the (standardized) leverage of firm j; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $\tilde{L}_j$ is the within-firm ($L_{j,t-1} - \mathbb{E}_j[L_{j,t-1}]$) standardized leverage; *1yr Rate* is the 1-year T-bill. Standard errors (reported in parentheses) are clustered two way, at the firm level and time level. Additional controls include firm (log) size, sales growth, credit rating, and time since IPO. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill.

Table F.3 HETEROGENEOUS RESPONSE OF CREDIT SPREADS TO MONETARY POLICY: DOUBLE SORTING

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	Size	Sales Growth	Credit Rating	Time IPO	DD	Debt-Ebitda	Liquid Assets
MP surp.×High Lev. ($\epsilon^m \times \ell_j^{High}$)	20.54***	20.60***	21.39***	18.33***	20.36***	20.50***	19.02***	20.87***
	(5.72)	(5.44)	(5.82)	(5.01)	(5.69)	(5.80)	(6.88)	(5.81)
MP surp.×Size ($\epsilon^m \times x_j^{High}$)		0.38						
		(5.08)						
MP surp.×Sales growth ($\epsilon^m \times x_j^{High}$)			-4.68					
			(3.94)					
MP surp.×Credit rating ($\epsilon^m \times x_j^{High}$)				-12.39***				
				(4.49)				
MP surp.×Time IPO ($\epsilon^m \times x_j^{High}$)					-2.36			
					(4.61)			
MP surp.×DD ($\epsilon^m \times x_j^{High}$)						-3.27		
						(4.88)		
MP surp.×Debt-Ebitda ($\epsilon^m \times x_j^{High}$)							16.44***	
							(5.49)	
MP surp.×Liquid Assets ($\epsilon^m \times x_j^{High}$)								3.77
								(5.58)
Double clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.311	0.311	0.311	0.312	0.311	0.312	0.314	0.311
Observations	275,311	275,311	274,933	273,422	275,311	273,416	247,265	275,305

NOTE. Results from estimating specification (5), namely $\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma\,(\epsilon_t^m L_{j,t-1}) + \delta\,(\epsilon_t^m X_{j,t-1}) + \mathbf{\Gamma W}_{j,t-1} + e_{ij,t}$, where ϵ_t^m is the monetary policy surprise; Δcs_{it} is the change in spreads between the day before the FOMC announcement and five days after the announcement; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; L_j is the (standardized) leverage of firm j; X_j is a (standardized) generic characteristic of firm j, namely size, sales growth, credit rating, time since IPO, distance to default (DD), debt-to-EBITDA ratio, and liquid assets lies above the median of its distribution (and zero otherwise). Standard errors (reported in parentheses) are clustered two way, at the firm level and time level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill.

Table F.4 Heterogeneous Response of Credit Spreads to Monetary Policy: Other Interactions

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Size	Sales Growth	Credit Rating	Time IPO	DD	Debt-Ebitda	Liquid Assets
MP surp.×Size ($\epsilon^m \times X_j^{High}$)	-2.95						
	(7.76)						
MP surp.×Sales growth ($\epsilon^m \times X_j^{High}$)		-5.82					
		(8.05)					
MP surp.×Credit rating ($\epsilon^m \times X_j^{High}$)			-14.09				
			(9.10)				
MP surp.×Time IPO ($\epsilon^m \times X_j^{High}$)				-3.60			
				(5.62)			
MP surp.×Time DD ($\epsilon^m \times X_j^{High}$)					-7.79		
					(9.15)		
MP surp.×Time Debt-Ebitda ($\epsilon^m \times X_j^{High}$)						24.75**	
						(10.61)	
MP surp.×Liquid Assets ($\epsilon^m \times X_j^{High}$)							2.15
							(4.32)
Double clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.323	0.323	0.325	0.322	0.324	0.314	0.322
Observations	280,917	280,531	279,058	280,992	279,052	247,265	280,898

Note. Results from estimating equation (4), where ϵ_t^m is the monetary policy surprise; Δcs_{it} is the change in spreads between the day before the FOMC announcement and five days after the announcement; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $X_{j,t-1}^{High} = 1$ when a given characteristic (X) of firm j, namely size, sales growth, credit rating, time since IPO, distance to default (DD), debt-to-EBITDA ratio, and liquid assets lies above the median of its distribution (and zero otherwise). Standard errors (reported in parenthesis) are clustered at the firm level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill.

Table F.5 HETEROGENEOUS RESPONSE OF CREDIT SPREADS TO MONETARY POLICY: OTHER INTERACTIONS

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Size	Sales Growth	Credit Rating	Time IPO	DD	Debt-Ebitda	Liquid Assets
MP surp.×Size ($\epsilon^m \times X_j$)	-2.16						
	(5.28)						
MP surp.×Sales growth ($\epsilon^m \times X_j$)		0.32					
		(2.66)					
MP surp.×Credit rating ($\epsilon^m \times X_j$)			-13.81				
			(8.77)				
MP surp.×Time IPO ($\epsilon^m \times X_j$)				-3.92			
				(4.09)			
MP surp.×DD($\epsilon^m \times X_j$)					-13.91*		
					(7.41)		
MP surp.×Debt-Ebitda ($\epsilon^m \times X_j$)						5.96**	
						(2.40)	
MP surp.×Liquid Assets ($\epsilon^m \times X_j$)							-0.69
							(1.52)
Double clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.323	0.323	0.324	0.322	0.323	0.314	0.322
Observations	280,917	280,531	279,058	280,992	279,052	247,265	280,898

NOTE. Results from estimating equation (4), where ϵ_t^m is the monetary policy surprise; Δcs_{it} is the change in spreads between the day before the FOMC announcement and five days after the announcement; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $X_{j,t-1}$ is a (standardized) generic characteristic of firm j, namely size, sales growth, credit rating, time since IPO, distance to default (DD), debt-to-EBITDA ratio, and liquid assets lies above the median of its distribution (and zero otherwise). Standard errors (reported in parenthesis) are clustered at the firm level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill.

Table F.6 EXPECTED DEFAULT AND EXCESS BOND PREMIUM: STANDARDIZED SERIES

	(1)	(2)
Dep. Variable:	Default Risk, Standardized ($\Delta\hat{cs}$)	Exc. Bond Premium, Standardized ($\Delta\hat{\nu}$)
MP surp. (ϵ^m)	0.50	0.73**
	(0.30)	(0.30)
Double clustering	Yes	Yes
Time-sector FE	No	No
R-squared	0.030	0.032
Observations	281,330	281,330

NOTE. Results from estimating specification (1), namely $y_{ij,t} = \alpha_i + \beta\epsilon_t^m + e_{ij,t}$, where $y_{ij,t} = \widetilde{\Delta\hat{c}s}_{ij,t}, \widetilde{\Delta\hat{\nu}}_{ij,t}$; ϵ_t^m is the monetary policy surprise, $\widetilde{\Delta\hat{c}s}_{ij,t}$, and $\widetilde{\Delta\hat{\nu}}_{ij,t}$ are the standardized change in fitted spreads and the excess bond premium between the day before the FOMC announcement and five days after the announcement, respectively; α_i is a bond fixed-effect. Standard errors (reported in parentheses) are clustered two way, at the firm level and time level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill.

Table F.7 EXPECTED DEFAULT AND EXCESS BOND PREMIUM: TIME SERIES

	(1)	(2)	(3)
Dep. Variable:	Spread (Δs)	Default Risk ($\Delta\hat{s}$)	Exc. Bond Premium ($\Delta\hat{\nu}$)
MP surp. (ϵ^m)	24.17***	2.00	22.17***
	(7.12)	(1.43)	(6.59)
Double clustering	No	No	No
Time-sector FE	No	No	No
R-squared	0.070	0.013	0.068
Observations	156	156	156

NOTE. Results from estimating a simple time series regression of credit spreads (and their decomposition into fitted spreads and excess bond premium) on the monetary policy surprises, namely $y_t = \alpha_i + \beta\epsilon_t^m + e_t$, where $y_{it} = \Delta cs_t, \Delta\hat{c}s_t, \Delta\hat{\nu}_t$; ϵ_t^m is the monetary policy surprise, Δcs_t, $\Delta\hat{c}s_t$, and $\Delta\hat{\nu}_t$ are the change in spreads, fitted spreads and the excess bond premium between the day before the FOMC announcement and five days after the announcement, respectively, on average across all outstanding bonds at each time t (using the amount issued with each bond as a weight); α_i is a constant. Standard errors are reported in parentheses. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill.

G Local Projections: Additional results

In this section we report a few additional exercises that show the robustness of our main results and allow us to compare our findings to those of recent studies in the literature.

Firm-level quantities. First, we compare our results on debt and investment to Jeenas (2018), Ottonello and Winberry (2018), and Cloyne et al. (2018) by running our estimation on pre-crisis data. Relative to these studies, our sample of firms is smaller (as we keep only firms for which we can match credit spread data) and the series of monetary surprises is different. Figure G.1 reports the relative impulse responses based on specification (7) for total debt (Panel (A)) and investment (Panel (B)). As in our full sample results, the impulse responses in Figure G.1 show that high-leverage firms contract their debt and investment by more than low-leverage firms. Again, as in our baseline, the relative response on debt is more precisely estimated than the relative response of investment.

Second, as discussed in the previous section, Ottonello and Winberry (2018) argue that it is important to use *within-firm* variation in leverage—rather than the firm's leverage in the previous quarter—as an interaction variable, to control for permanent differences in firm leverage. We therefore estimate specification (7) for debt and investment using a dummy variable that is based on *within-firm* variation in leverage, namely $\mathcal{L}_{j,t-1} = L_{j,t-1} - \mathbb{E}_j[L_{j,t-1}]$, as an interaction variable. Figure G.2 shows that our results are not materially affected by the definition of the interaction variable. On the contrary, the negative estimates of the γ^h coefficient become more precisely estimated and significant at the 5 percent confidence level.

Third, we show that it is important to control for the non-monetary component embedded in raw high-frequency interest rate surprises. Figure G.3 reports the average response of total debt (Panel (A)) and investment (Panel (B)) to the two components that drive the raw interest rate surprises, namely the monetary (ϵ^m) and non-monetary (ϵ^{other}) surprises, obtained by estimating specification (6). Panel (A) shows that while the monetary surprise (ϵ^m) leads to a significant reduction in average debt, the non-monetary surprise (ϵ^{other}) leads to an increase in debt. The same is true for investment, reported in panel (B), even though the effects are less precisely estimated. It follows that the *average* response of debt and investment to the raw interest rate surprise (s_t^{FF4}) will, in general, depend on the relative strength of its underlying components, as well as their relative persistence on the variables of interest. Clearly, the relative strength of ϵ^m and ϵ^{other} will also matter for the *relative* response of firm-level outcomes in the cross-section of firms, as shown for credit spreads in the event study analysis.

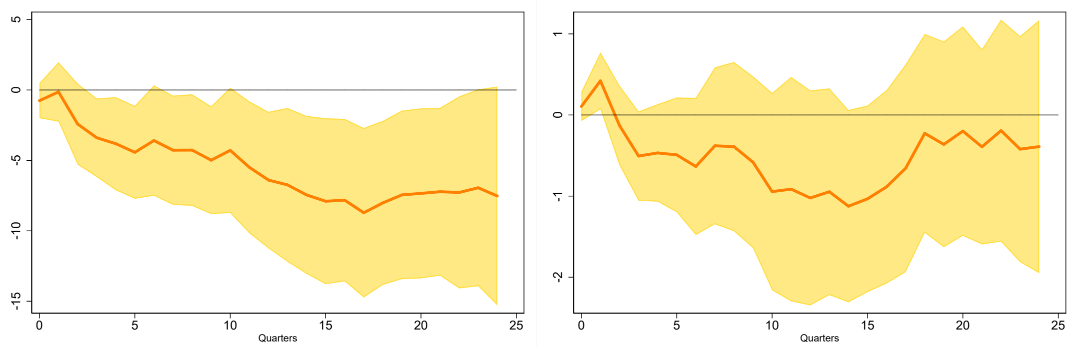
Firm-level credit spreads. Figure G.4 compares the average response of high-leverage and low-leverage firms by estimating specification (6). The shaded areas display the 90 percent confidence intervals based on two-way clustered standard errors (at the firm and time level). The two panels show that credit spreads increase significantly and in a persistent fashion for both high and low-leverage firms. This evidence is consistent with the aggregate evidence provided by Gertler and Karadi (2015). But a comparison of Panel (A) and Panel (B) also shows that firms with high leverage (i.e. with leverage above the median) experience a slightly larger and more persistent increase in credit spreads. Together with the results in the main text (showing that the relative response of high-leverage firms is positive and significant) the impulse responses in Figure G.4 suggests that it is very important to account for sectorial heterogeneity by adding to the specification time-sector fixed effects.

Figure G.5 shows that 6 are robust when using a dummy variable that is based on *within-firm* variation in leverage (namely $\mathcal{L}_{j,t-1} = L_{j,t-1} - \mathbb{E}_j[L_{j,t-1}]$) as an interaction variable, as in Ottonello and Winberry (2018).

Finally, Figure G.6 shows that also for credit spreads it is important to control for the non-monetary component embedded in raw high-frequency interest rate surprises. Figure G.6 reports the average response of credit spreads to the two components that drive the raw interest rate surprises, namely the monetary (ϵ^m) and non-monetary (ϵ^{other}) surprises, obtained by estimating specification (6). It shows that while the monetary surprise (ϵ^m) leads to a significant increase in credit spreads, the non-monetary surprise (ϵ^{other}) leads to an contraction in credit spreads. It follows that the *average* response of credit spreads to the raw interest rate surprise (s_t^{FF4}) will, in general, depend on the relative strength of its underlying components, as well as their relative persistence on the variables of interest. Clearly, the relative strength of ϵ^m and ϵ^{other} will also matter for the *relative* response of firm-level outcomes in the cross-section of firms.

Figure G.1 Relative Impulse Responses: Quantities
Pre-Crisis Sample

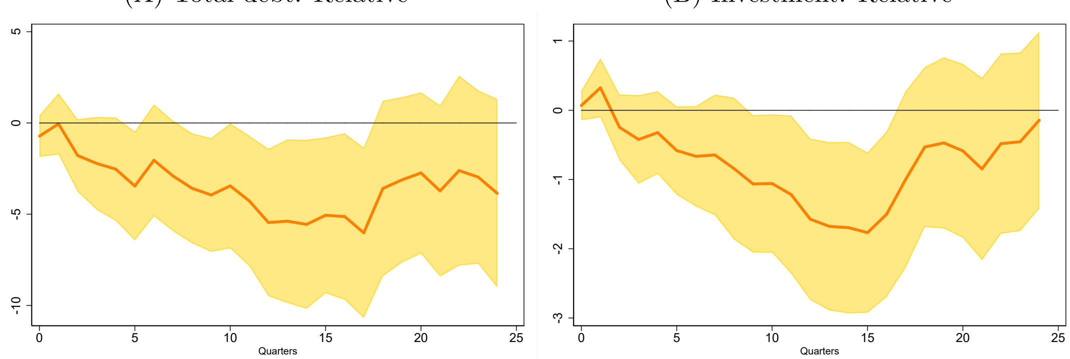
(A) Total debt: Relative　　　(B) Investment: Relative



Note. Relative impulse response of total debt and investment with data up to 2007:Q4. The impulse responses (γ^h) are estimated with the local projection specification in (7), namely $y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta_{sct,t} + \gamma^h \epsilon_t^m \ell_{j,t-1}^{High} + \sum_{p=1}^{P_X} \mathbf{\Gamma}_p \mathbf{X}_{j,t-p} + \sum_{p=1}^{P_Z} \mathbf{\Xi}_p \mathbf{Z}_{t-p} + e_{j,t+h}$, where $h = 0, 1, 2, ..., 24$; j; ϵ_t^m is the monetary policy surprise; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $\ell_{j,t-1}^{High} = 1$ when firm j leverage lies above the median of the leverage distribution (and zero otherwise). The shaded areas display 90 percent confidence intervals based on two-way clustered (time and firm) standard errors.

Figure G.2 Relative Impulse Responses: Quantities
Within-Firm Leverage

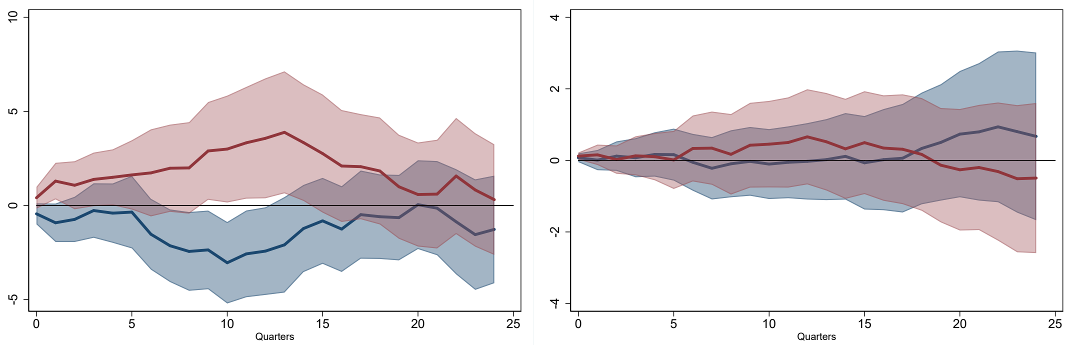
(A) Total debt: Relative　　　(B) Investment: Relative



Note. Relative impulse response of total debt and investment. The impulse responses (γ^h) are estimated with the local projection specification in (7), namely $y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta_{sct,t} + \gamma^h (\epsilon_t^m \mathcal{L}_{j,t-1}^{High}) + \sum_{p=1}^{P_X} \mathbf{\Gamma}_p \mathbf{X}_{j,t-p} + \sum_{p=1}^{P_Z} \mathbf{\Xi}_p \mathbf{Z}_{t-p} + e_{j,t+h}$, where $h = 0, 1, 2, ..., 24$; j; ϵ_t^m is the monetary policy surprise; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $\mathcal{L}_{j,t-1}^{High} = 1$ when the within leverage of firm j (i.e. based on $L_{j,t-1} - \mathbb{E}_j[L_{j,t-1}]$) lies above the median of the leverage distribution (and zero otherwise). The shaded areas display 90 percent confidence intervals based on two-way clustered (time and firm) standard errors.

Figure G.3 Average Impulse Responses:
Monetary vs. Non-monetary Surprises

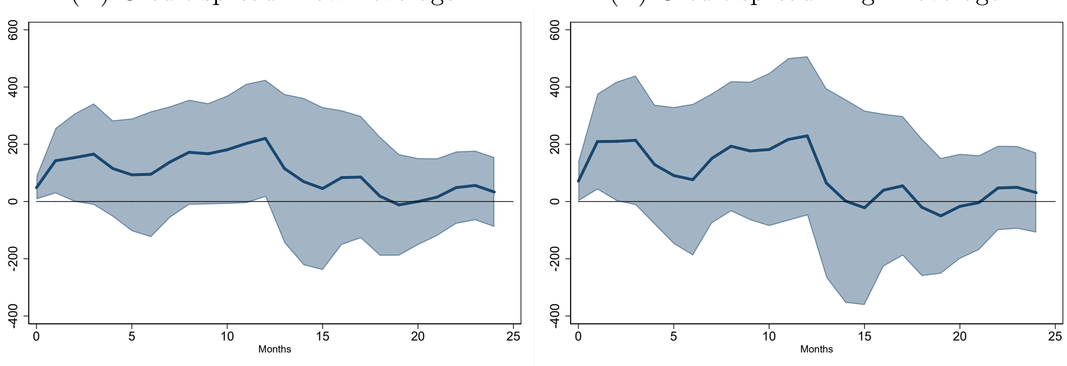
(A) Total debt: ϵ^m vs. ϵ^{other} (B) Investment: ϵ^m vs. ϵ^{other}



Note. Average impulse response of total debt and investment for monetary (ϵ^m, blue) and non-monetary (ϵ^{other}, red) surprises. The impulse responses (β^h) are estimated with a simple local projection specification estimated using $\epsilon = \left\{\epsilon^m, \epsilon^{other}\right\}$ as independent variables respectively, namely $y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta^h\left(\epsilon_t\right) + \sum_{p=1}^{P}\mathbf{\Gamma}_p\mathbf{X}_{j,t-p} + \sum_{p=1}^{P}\mathbf{\Xi}_p\mathbf{Z}_{t-p} + e_{j,t+h}$, where $h = 0, 1, 2, ..., 24$; α_i is a bond fixed-effect. The shaded areas display 90 percent confidence intervals based on two-way clustered (time and firm) standard errors.

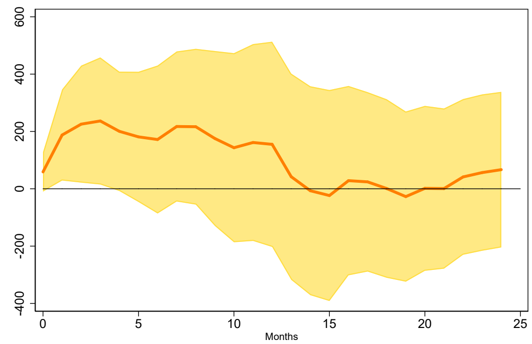
Figure G.4 Average Impulse Responses: Credit Spreads
High vs. Low Leverage

(A) Credit spread: Low Leverage (B) Credit spread: High Leverage



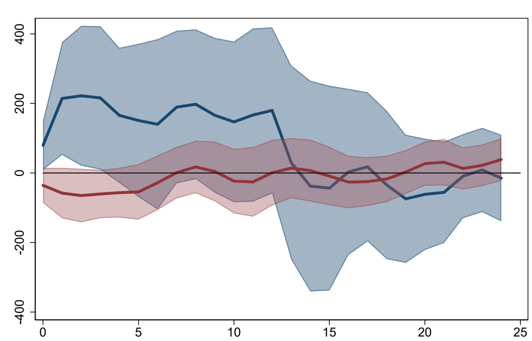
Note. Average impulse response of credit spreads for low (i.e. below the median) and high (i.e. above the median) leverage firms. The impulse responses (β_1^h and β_2^h) are estimated with the local projection specification in (6), namely $y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta_1^h\left(\epsilon_t^m \ell_{j,t-1}^{Low}\right) + \beta_2^h\left(\epsilon_t^m \ell_{j,t-1}^{High}\right) + \sum_{p=1}^{P}\mathbf{\Gamma}_p\mathbf{X}_{j,t-p} + \sum_{p=1}^{P}\mathbf{\Xi}_p\mathbf{Z}_{t-p} + e_{j,t+h}$, with $h = 0, 1, 2, ..., 24$. The shaded areas display 90 percent confidence intervals based on two-way clustered (time and firm) standard errors.

Figure G.5 RELATIVE IMPULSE RESPONSE: CREDIT SPREADS WITHIN-FIRM LEVERAGE



NOTE. Relative impulse response of credit spreads. The impulse responses (γ^h) are estimated with the local projection specification in (7), namely $y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta_{sct,t} + \gamma^h(\epsilon_t^m \mathcal{L}_{j,t-1}^{High}) + \sum_{p=1}^{P_X} \mathbf{\Gamma}_p \mathbf{X}_{j,t-p} + \sum_{p=1}^{P_Z} \mathbf{\Xi}_p \mathbf{Z}_{t-p} + e_{j,t+h}$, where $h = 0, 1, 2, ..., 24$; j; ϵ_t^m is the monetary policy surprise; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $\mathcal{L}_{j,t-1}^{High} = 1$ when the within leverage of firm j (i.e. based on $L_{j,t-1} - \mathbb{E}_j[L_{j,t-1}]$) lies above the median of the leverage distribution (and zero otherwise). The shaded areas display 90 percent confidence intervals based on two-way clustered (time and firm) standard errors.

Figure G.6 AVERAGE IMPULSE RESPONSES: CREDIT SPREADS MONETARY VS. NON-MONETARY NEWS



NOTE. Average impulse response of total debt and investment for monetary (ϵ^m, blue) and non-monetary (ϵ^{other}, red) surprises. The impulse responses (β^h) are estimated with a simple local projection specification estimated using $\epsilon = \left\{\epsilon^m, \epsilon^{other}\right\}$ as independent variables respectively, namely $y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta^h(\epsilon_t) + \sum_{p=1}^{P} \mathbf{\Gamma}_p \mathbf{X}_{j,t-p} + \sum_{p=1}^{P} \mathbf{\Xi}_p \mathbf{Z}_{t-p} + e_{j,t+h}$, where $h = 0, 1, 2, ..., 24$; α_i is a bond fixed-effect. The shaded areas display 90 percent confidence intervals based on two-way clustered (time and firm) standard errors.

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