Crossing the Credit Channel: Credit Spreads and Firm Heterogeneity

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Firms with high leverage experience a more pronounced increase in credit spreads than firms with low leverage in response to a monetary policy tightening. A large fraction of this increase is due to a component of credit spreads that is in excess of firms' expected default risk. A stylized heterogeneous firm model with default risk, financially constrained intermediaries, and segmented financial markets is able to account for these facts. Our findings imply that financial intermediaries play an important role in shaping the transmission of monetary policy to firm-level outcomes.
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What do firm-level funding costs and firms' balance sheets tell us about the transmission mechanism of monetary policy? Combining a bond-level data set on credit spreads with firm-level balance sheet information, we document that monetary policy has heterogeneous effects on firms, depending on their level of leverage. A surprise monetary policy tightening leads to an increase in credit spreads that is larger for firms with high leverage. A decomposition of credit spreads into an expected default component and a residual risk premium component shows that the latter accounts for most of the relative increase in spreads for highly leveraged firms.

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The empirical approach we employ is inspired by recent studies that investigate the role of financial frictions in the transmission of monetary policy to firms. The vast majority of these studies estimate the response of firm-level quantities, such as investment or employment, to high-frequency surprises in federal funds futures around policy announcements by the Federal Reserve's Federal Open Market Committee (FOMC), as pioneered by Gürkaynak, Sack and Swanson (2005).[1] This paper's empirical innovation is to focus on credit spreads as an outcome variable, and to exploit their decomposition into expected default and risk premium components to tease out the relative importance of different transmission mechanisms. Credit spreads can be precisely measured at a much higher frequency than firm-level quantities, which are (at best) available at a quarterly frequency. As FOMC decisions happen at irregular times during the year, any empirical analysis that focuses on quantities requires aggregating interest rate surprises over quarters or years—therefore potentially giving rise to an aggregation bias.[2] 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 cleaner identification of the impact of monetary policy on firm-level outcomes, as well as a more precise estimation of its effects. Despite all these advantages, credit spreads have been widely overlooked in the literature.

In our empirical analysis, we proceed as follows. First, we construct a new bond-level data set of 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. Second, we construct a measure of exogenous monetary policy surprises exploiting high-frequency variation in the price of federal funds futures contracts around policy announcements, as in Jarociński and Karadi (2020). Third, we estimate the heterogeneous effect of monetary policy on credit spreads in a 1-week window around FOMC announcements using a panel event-study regression approach. We then employ Gilchrist and Zakrajsek (2012)'s methodology to decompose the overall effect of monetary policy on credit spreads into a component capturing the transmission via firms' expected default and a residual component capturing the transmission via financial intermediaries' effective risk bearing capacity (the Excess Bond Premium (EBP) in Gilchrist and Zakrajsek (2012)'s parlance).

The analysis delivers the following empirical results. A monetary policy surprise that raises the policy rate by 25 basis points leads to an average increase in credit spreads of 27 basis points. This average effect is heterogeneous across firms and varies considerably with firm leverage. For example, the response of credit spreads for firms that lie above the median of the leverage distribution is around 18 basis points larger than the response of credit spreads for firms below the median.

[1]See, for example, Ottonello and Winberry (2020).

[2]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, which may yield inconsistent estimates of the aggregated impulse responses (Ramey, 2016).

Our baseline results hold when controlling for other firm characteristics that are typically used to proxy for financial constraints (such as age, size, credit ratings, distance to default, and liquid assets).[3]

Armed with Gilchrist and Zakrajsek (2012)'s decomposition of credit spreads, we then ask whether monetary policy transmits to credit costs via a change in a firm's default risk, a change in the EBP, or both. This is informative because the EBP, which is purged of firms' default premia and orthogonal to firms' fundamentals, can be interpreted as a measure of firms' borrowing costs that is due to the effective risk bearing capacity of financial intermediaries. The results show that, when monetary policy tightens, the EBP increases, and does so more for firms with high leverage. Moreover, the EBP accounts for most of the conditional response of credit spreads to monetary policy, suggesting an important role for intermediaries' (rather than firms') financial constraints in the transmission of monetary policy.

Existing models for the interpretation of firm-level empirical analysis of the type we consider in this paper feature heterogeneity and credit market constraints on non-financial borrowers, but assume representative and frictionless lenders. As such, these models do not have a notion of a *firm-specific* EBP, and thus cannot explain our main findings. Motivated by this, we develop a stylized framework that combines firm heterogeneity and credit market frictions on financial intermediaries.

A form of market segmentation creates a link between high-leverage firms and the tightness of intermediaries' financial constraints, which gives rise to firm-specific EBPs. We calibrate the model to match some key features of firms' leverage and credit spreads in the micro data. We are interested in the transmission of monetary policy via intermediaries' balance sheets. We thus consider an exogenous fall in intermediaries' equity, which tightens their financial constraints and generates an inward shift in the credit supply schedule. In the calibrated model, the shock increases the EBP for all firms, but the increase is larger for high-leverage firms, as we observe in the data. Note, however, this relative response is theoretically ambiguous—reminiscent of what Ottonello and Winberry (2020) document in models with credit market frictions on non-financial borrowers. In our set up, whether high-leverage firms are more or less responsive than low-leverage firms depends crucially on the capital demand elasticity. Intuitively, when the capital demand elasticity is high, the low-leverage firm lies on a flatter portion of the capital demand schedule, which dampens the response of credit spreads to any shift in supply.

The rest of the paper is structured as follows: the remainder of this section places our paper and its contribution in the context of the relevant literature;

[3] We complement our event study analysis by estimating the response of firm-level quantities (debt and investment) to monetary policy at a business cycle frequency, using a panel local projections approach. Our results on credit spreads are consistent with the findings from the local projections exercise, which shows that a surprise monetary policy tightening leads to a persistent contraction in debt and investment that is larger for firms with high leverage.

section I describes the data used in the empirical analysis; section II presents the main empirical results obtained from the high-frequency panel regressions and an extensive set of robustness tests; section III provides further results using the decomposition of credit spreads into expected default and Excess Bond Premium components; section IV provides an interpretation of the empirical results through the lens of our theoretical model; section V concludes.

Literature. — Not surprisingly, there is a voluminous and long-standing literature on the role of financial frictions in the transmission of monetary policy.[4] The vast majority of recent studies focus on the heterogeneous effects of monetary policy on firm-level quantities at quarterly or annual frequency. Importantly, all these studies interpret their empirical findings through the lens of models in which firms are heterogeneous and subject to financial frictions, but obtain funds from a representative frictionless lender. In this class of models, the response of investment for firms that face relatively tighter financial constraints is ex ante ambiguous. Once estimated, such relative responses can be informative about the magnitude of the shift in the capital supply schedule in response to a monetary policy shock—and, therefore, about the quantitative relevance of financial frictions. Our paper contributes to this literature in two ways. First, by considering the response of credit costs rather than just quantities to monetary policy, our empirical evidence helps to disentangle the relative shifts in the capital supply and demand schedules—i.e. the main focus of the analysis in recent studies. Second, the decomposition of credit spreads into expected default and risk premium components motivates us to consider a theoretical framework where the financial intermediation sector is also characterized by heterogeneity and financial frictions. This enables us to highlight the role of an additional mechanism that can drive shifts in the capital supply schedule—something that has been overlooked in previous studies and, importantly, can change the interpretation of the results therein.

Ottonello and Winberry (2020) use US firm-level data on 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.[5] Using a representative sample of US manufacturing firms, Crouzet and Mehrotra (2020) show that small firms' higher volatility over the business cycle does not seem to be explained by financial factors, such as leverage or liquid asset holdings. 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

[4]See, among many others, Bernanke and Gertler (1989), Bernanke and Blinder (1992), Kashyap, Lamont and Stein (1994), Gertler and Gilchrist (1994), Kashyap and Stein (1995), Kashyap and Stein (2000).

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

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.[6] All these papers interpret their empirical findings as supportive of an important role played by firms' financial frictions. Differently, and in a similar spirit to our paper, recent work by Ferreira, Ostry and Rogers (2023) study firms' heterogeneous response to monetary policy using firm-level excess bond premia as a state variable (rather than as an outcome variable), and interpret their findings with a model of constrained financial intermediaries that builds on the one we develop in section IV.

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, Ozdagli and Perez-Orive (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 of firms subject to greater information frictions have a weaker reaction to monetary policy. Gurkaynak, Karasoy Can and Lee (2019) show that the response of firm-level stock prices to monetary policy depends on the firm cash flow exposure. As we do, these three papers find an important role for financial frictions in explaining the firm-level response to monetary policy.[7]

I. 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 A. 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

[6] 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 the housing values of firms' directors.

[7] Our paper is also related to a recent literature arguing firms' borrowing capacity is tightly linked to the firms' earnings flows, as current earnings are subject to scrutiny by lenders. Drechsel (2018) and Lian and Ma (2019) 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.

156 FOMC announcements over the 1999-2017 period, has information on $9,115$ unique bonds and $1,123$ unique firms, and a total of $285,794$ observations.

A. 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, Sack and Swanson, 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 between the central bank and financial market participants are present, interest rate surprises can also capture (i) a difference in expectations about the state of the economy (e.g. the size of the output gap) or (ii) a difference in the actual central bank reaction function relative to the expectation of market participants.[8] To address this issue, in this paper we follow the methodology developed by Jarociński and Karadi (2020) to decompose monetary policy news from other contemporaneous non-monetary news embedded in the interest rate surprises.

The decomposition (reported in Figure 1) 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] As in Jarociński and Karadi (2020), 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 (FF4) contract (s_t^{FF4}), from which we obtain the orthogonal monetary (ϵ^m) and

[8] See Melosi (2017) and Nakamura and Steinsson (2018) for examples where central bank announcements can simultaneously convey information about monetary policy and the central bank's assessment of the economic outlook. Bauer and Swanson (2020) argue that the empirical evidence supporting this channel is not robust, and favor an alternative interpretation where market participants learn about the central bank's reaction function.

[9] Alternatively one could project the high frequency interest rate surprises on the difference between private forecasts and the Federal Reserve's Greenbook forecast (Barakchian and Crowe (2013) and Gertler and Karadi (2015) or Greenbook forecast revisions (Miranda-Agrippino and Ricco (2021)).

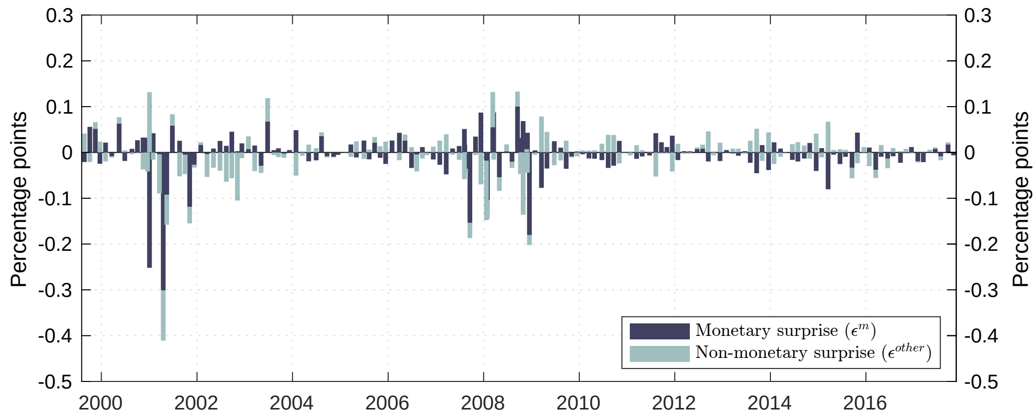

FIGURE 1. HIGH FREQUENCY INTEREST RATE SURPRISES DECOMPOSITION

Note: The 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 Jarociński and Karadi (2020) applied on data on Fed funds futures and equity price surprises around 156 FOMC announcements from February 1990 to November 2017. The monetary and non-monetary news series are obtained as the median across $5,000$ admissible models. See Online Appendix C for additional details. Sample period: August 1999 to November 2017.

non-monetary (ϵ^{other}) surprises plotted in Figure 1. In our sample, the monetary surprise explains 70 percent of the total variance of s_t^{FF4}, while the remaining 30 percent is explained by the non-monetary surprise.

B. 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 period August 1999–August 2018 for 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.[10]

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

[10]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.

by Gilchrist, Yankov and Zakrajsek (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 and their response to shocks. 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.

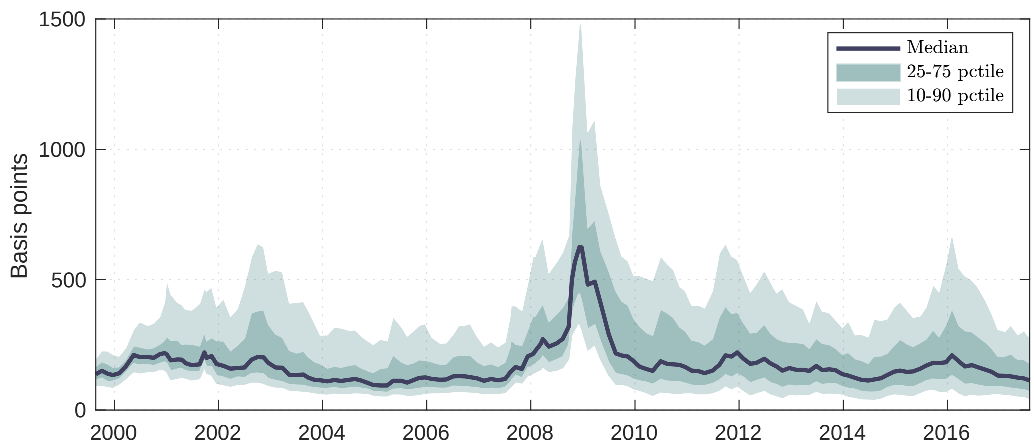

Figure 2. The Cross-section of Corporate Bond Spreads

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 areas display the 25-75 percentile range. The light shaded areas display the 10-90 percentile range. Sample period: August 1999 to November 2017.

When combined with the monetary policy surprises data, the sample period we focus on runs from August 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 issuance in our data set in 2014 was 495 billion US dollars, which is about 70 percent of the total market issuance in that year.[11] 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 2 plots the median OAS in our data

[11]Data from the Federal Reserve. See item *New Security Issues (1.46), U.S. Corporations, non-financial*.

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 crucial in identifying the heterogeneous effects of monetary policy on firms' borrowing costs.

C. 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. Table 1 reports the summary statistics for firms that have leverage below and above the median leverage ratio in our sample, where leverage is defined as the ratio of total debt over total assets. We focus on leverage because it is the key state variable that affects the tightness of financial constraints in models of financial frictions (as in the one we develop in section IV) and that governs the cost of external finance.

TABLE 1—FIRM-LEVEL SUMMARY STATISTICS: HIGH VS. LOW LEVERAGE

	Total Assets	Time since IPO	Credit Rating	Credit Spread	Amount Issued
			Low Leverage (below median)		
Mean	57800	38	–	183	663
Standard Dev.	72277	14	–	183	536
25th Percentile	11446	26	BBB2	88	300
Median	31151	42	BBB1	136	500
75th Percentile	69314	50	A2	212	788
N	152182				
			High Leverage (above median)		
Mean	37107	34	–	274	630
Standard Dev.	59074	17	–	286	595
25th Percentile	7570	18	BB2	112	300
Median	19238	35	BBB2	189	500
75th Percentile	44317	49	BBB1	337	750
N	152179				

Note: Summary statistics for firms below/above the median leverage in the sample. *Total Assets* and *Amount Issued* are in million \$; *Time since IPO* is in years; *Credit Spread* is in basis points; N is the number of total observations. The sample of bonds in this table covers the period between August 1999 and August 2018. The sample consists of $1,093$ unique firms and $9,427$ unique bonds.

As in our model, the data are consistent with a positive relation between leverage and the tightness of financial constraints.[12] In our data set, firms with high

[12]Note that in principle the relationship between leverage and financial constraints is ex ante ambigu-

leverage are smaller (as measured by total assets), younger (as measured by the number of years since IPO), and have lower credit ratings. Importantly, high leverage firms also have high credit spreads. For example, the average credit spread among high-leverage firms is 274 basis points, compared to an average spread of 183 for low-leverage firms. If low-leverage firms were more financially constrained than high-leverage firms, we should observe a negative relation between credit spreads and leverage. These unconditional correlations are in line with the predictions from our simple theoretical model.[13]

Two additional features of our sample are worth highlighting. Firstly, our sample consists of large, well-established firms (as in Gilchrist and Zakrajsek (2012)). While certainly non-representative of the universe of US non-financial firms, the fact that these firms have publicly-traded debt and equity is crucial for the questions we seek to answer in this paper, as it allows an empirical decomposition of credit spreads into a default risk and risk premium components. In addition, recent studies have highlighted the dominant role large firms play in US economic activity and the macroeconomic significance of shocks which affect them (Gabaix, 2011; Crouzet and Mehrotra, 2020). Secondly, while large firms tend to be the most credit-worthy by traditional measures, what is crucial for the question in this paper 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.

II. The Heterogeneous Effects of Monetary Policy on Credit Spreads

In this section we present our main empirical results. First, we estimate the heterogeneous effects of monetary policy on credit spreads using an event-study panel regression approach. Second, we report an extensive set of robustness tests, where we control for alternative proxies of financial constraints and employ alternative measures of monetary surprises.

A. Event Study Firm-level Panel Regressions

Exploiting the cross-sectional dimension of our data set using an event study approach, we ask: 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 choose leverage to be able to directly compare to prominent studies in the existing literature (e.g.

ous. A firm that has no access to credit markets will have zero leverage, which implies that leverage can be higher for financially unconstrained firms. As explained below, our data are not consistent with such a negative relation between leverage and the tightness of financial constraints—maybe not surprisingly as our sample is composed of large firms that have relatively unimpeded access to external financing (see Farre-Mensa and Ljungqvist, 2016).

[13]See the discussion in section IV. For additional evidence on the positive relation between leverage and credit spreads in our data, see Figure D.1 in Online Appendix D.

Ottonello and Winberry, 2020), but also because in many models of financial frictions leverage is tightly linked to the cost of external finance and firms' borrowing and investment decisions.

Choosing leverage as a conditioning variable, however, also poses some challenges. First, leverage might not be the only relevant dimension capturing financial constraints. In robustness analysis, however, we condition on alternative proxies that are typically used in the literature (e.g. age, size, distance to default, liquid assets) and we find essentially the same results. Second, leverage is itself an endogenous choice. In response to shocks that shift the demand and/or supply of capital, firms may find it optimal to adjust their leverage, which in turn can feed back into their borrowing costs. The distribution of leverage may not, therefore, be rank invariant to monetary policy shocks, and so interpreting whether ex-post heterogeneity in firm outcomes is driven by ex-ante differences in leverage becomes more difficult. This issue, which naturally applies to every paper in the literature, is particularly severe for empirical studies that focus on firm-level quantities and, therefore, consider the response of firm-level outcomes at a lower frequency over a horizon of many quarters/years. Our high-frequency event study approach allows us to make some progress in addressing this concern, as it is less likely that firms adjust their leverage in the period immediately following a monetary policy shock.

We define leverage as the ratio of total debt over total assets and, with a slight abuse of notation, we denote by $L_{j,t-1}$ the leverage of firm j in the quarter preceding the monetary policy announcement at time t. 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: $\ell_{j,t-1}$, 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). We then consider how the response of spreads to monetary policy surprises varies across the two groups by estimating the following baseline specification:

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

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; $\beta_{sct,t}$ is a dummy variable taking a value of 1 for all firms belonging to the same sector (sct) in a given time period t, to account for heterogeneity in the effects of monetary policy across industrial sectors;[14] and ϵ_t^m is our measure of monetary policy surprises on FOMC announcement days. The size of the surprise is normalized so that it corresponds to a 25 basis point increase in the 1-year T-bill, a common

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

convention in the literature. 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.[15]

In this baseline specification we consider a 1-week change in the spread, from the day before the announcement to five trading 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) and Gilchrist et al. (2020) use a two-week window to analyze how corporate bond spreads respond to monetary policy surprises.[16]

Table 2 reports the estimation results. Standard errors, reported in parentheses, are clustered two-way at the firm and time (i.e. event) level. In column (1) of Table 2 we start with a more simple specification than specification (1), which excludes time-sector fixed effects, abstracts from the role of leverage, and considers just the average response of credit spreads in the cross-section of firms to monetary policy. The results show that a 25 basis point surprise tightening leads to an increase in credit spreads of about 27 basis points. The estimated coefficient, which is significant at the 5 percent significance level, 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, for example, by Gertler and Karadi (2015) in VAR analysis).[17]

In column (2) of Table (2) we report the results from our baseline specification (1), where we interact the monetary policy surprise with firms' leverage and include time-sector fixed effects. The estimated γ coefficient is positive and statistically significant and suggests that the response of credit spreads to monetary policy surprises for high-leverage firms is around 18 basis points larger *relative* to low-leverage firms. In column (3) of Table 2 we report the results obtained from a specification that is identical to (1) but where we control for additional firm-specific covariates, namely firm (log) size, sales growth, and the net working capital ratio. The estimated coefficient is virtually identical to the one in col-

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

[16]In contrast, papers focusing on Treasury bonds or equity prices (for example, Gürkaynak, Sack and Swanson (2005) or Ozdagli (2018)) typically use 1-day or 2-day windows.

[17]Note that the magnitude of the response is also in line with the aggregate VAR results in Gertler and Karadi (2015), despite the different sample period and methodology. In contrast to our approach, Gertler and Karadi (2015) look at the response of the EBP (averaged across firms) to the raw monetary surprises s_t^{FF4}. They find that the EBP increases by about 13 basis points in response to a monetary surprise that raises the 1-year rate by 25 basis points. We show in Appendix that we get a similar coefficient when estimating (1) using the raw interest rate surprises and decomposing credit spreads into an expected default component and the EBP.

Table 2—Heterogeneous Response of Credit Spreads

	(1)	(2)	(3)	(4)	(5)	(6)
	Average	Time-Sector FE	Controls	Within	IV	Pre-crisis
MP surp. (ϵ^m)	26.94**					
	(10.44)					
MP surp.× High Lev. ($\epsilon^m \times \ell_j$)		18.34**	18.60**			18.52**
		(9.09)	(9.37)			(7.20)
MP surp.× High Lev. ($\epsilon^m \times \tilde{\ell}$)				12.98*		
				(7.44)		
1yr Rate.× High Lev. ($\epsilon^m \times \ell_j$)					17.57***	
					(1.37)	
Observations	285794	279603	267306	279603	279603	52056
R squared	0.034	0.308	0.303	0.308	-0.014	0.341
Double Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Time x Sector FE	No	Yes	Yes	Yes	Yes	Yes

Note: Results from estimating specification (1), namely $\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma(\epsilon_t^m \ell_{j,t-1}) + \delta \ell_{j,t-1} + e_{ij,t}$ 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; $\ell_{j,t-1} = 1$ 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; $\tilde{\ell}_{j,t-1} = 1$ when within-firm leverage of firm 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, and the net working capital ratio. 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 $p < 0.1$).

umn (2). Ottonello and Winberry (2020) 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 column (2) may be driven by permanent differences in firm leverage. In column (4) we report the results obtained from a specification that is identical to (1) but where the high-leverage dummy is based on within-firm variation in leverage ($L_{j,t-1} - \mathbb{E}_j[L_{j,t-1}]$). The estimated coefficient is smaller than in column (2) but is still positive and statistically significant. In column (5) 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 (1) on a sample that excludes the global financial crisis and the subsequent period, i.e. that excludes all observations after December 2007. The results are reported in column (6) and are broadly similar to those in column (2).

How do our results compare to those in the existing literature? As noted in the introduction, previous studies mainly focused on the heterogeneous (and ex-ante ambiguous) response of firm-level investment to monetary policy.[18] As discussed extensively in these studies (most notably in Ottonello and Winberry, 2020) the relative response of firms that face tighter financial constraints can be informative about the magnitude of the shift in the capital supply schedule—and, thus, on the quantitative importance of financial frictions. Needless to say, information on how the cost of external finance responds to monetary policy shocks greatly helps in discerning the relative importance of capital demand and capital supply shifts. For this reason, existing studies attempt to proxy for the cost of external finance with interest payments, as reported in the firm's balance sheet (e.g. `xint` in Compustat) and investigate how they respond to monetary policy. Cloyne et al. (2018) show that younger, non-dividend paying firms experience a larger increase in average interest payments relative to older dividend paying firms. In contrast, Ottonello and Winberry (2020) show that average interest payments increase by less for high-leverage firms relative to low-leverage firms following a monetary policy tightening.

While our evidence aligns better with the findings in Cloyne et al. (2018), relying on balance sheet data has two 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 (i.e. what theory has predictions about). Second, economic theory has predictions about the cost of borrowing net of the risk-free interest rate. The relative response of interest expenses across firms ignores the possibility that the relevant risk free rate can vary across firms depending on the maturity of their outstanding debt. Focusing on credit spreads allows us to make some progress in addressing these issues. While still an imperfect proxy, the yield implied by the price of traded corporate bonds is conceptually closer to the marginal cost of new borrowing than the backward-looking interest expense measure used in other studies. Furthermore, by calculating the spread (through the subtraction of a same-maturity risk free interest rate) at the bond level we are able to compare the cost of borrowing net of movements in risk free rates and across different maturities.

B. Robustness of the Baseline Results

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

Additional firm characteristics. — While the results in Table 2 show the robustness of our findings to a comprehensive set of alternative specifications, one

[18] For a more direct comparison with the existing literature, Appendix B complements our event study analysis by also reporting the response of firm-level quantities (debt and investment) to monetary policy at a business cycle frequency, using a panel local projections approach. The results show that a surprise monetary policy tightening leads to a persistent contraction in debt and investment that is larger for firms with high leverage.

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.

Table 3—Leverage & Additional Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	Size	Sales Growth	Credit Rating	Time IPO	DD	Debt-Ebitda	Liquid Assets
Leverage	18.34**	18.28**	19.01**	16.09**	18.19**	18.28**	16.73*	18.61**
	(9.09)	(9.02)	(9.28)	(8.02)	(8.92)	(8.77)	(8.63)	(9.30)
Size		-0.23						
		(7.19)						
Sales Growth			-4.85					
			(4.94)					
Credit Rating				-11.38				
				(7.94)				
Time IPO					-2.33			
					(5.02)			
DD						-2.97		
						(8.20)		
Debt-Ebitda							14.52**	
							(6.98)	
Liquid Assets								2.82
								(4.01)
Observations	279603	279603	279075	277288	279603	277281	251257	279597
R squared	0.308	0.308	0.309	0.310	0.308	0.310	0.311	0.308
Double Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time x Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Results from estimating specification (2), namely $\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma(\epsilon_t^m \ell_{j,t-1}) + \delta(\epsilon_t^m x_{j,t-1}) + \Gamma W_{j,t-1} + e_{ij,t}$, 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; $\ell_{j,t-1} = 1$ when firm j's leverage lies above the median of the leverage distribution (and zero otherwise); $x_{j,t-1} = 1$ 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). $\Gamma W_{j,t-1}$ includes both $\ell_{j,t-1}$ and $x_{j,t-1}$. 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.

To address this concern, we run a series of regressions in which we control for the interaction of other firm characteristics with the monetary policy shock. That is, we estimate the following specification:

$$\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma\left(\epsilon_t^m \ell_{j,t-1}\right) + \delta\left(\epsilon_t^m x_{j,t-1}\right) + \Gamma W_{j,t-1} + e_{ij,t}, \tag{2}$$

where $x_{j,t-1}$ is a dummy variable that is defined in an identical way to $\ell_{j,t-1}$ but is based on other firm characteristics (such as age, size, credit rating, etc.);

and $W_{j,t-1}$ includes both $\ell_{j,t-1}$ and $x_{j,t-1}$. The results are reported in Table 3. The γ coefficient now has a slightly different interpretation. Consider the case of $x_{j,t-1}$ being firms' size. Then γ captures the relative impact of monetary policy on high-leverage firms controlling for the interaction of monetary policy with firm size. As in previous specifications, in this section we also include time-sector fixed effects.

For comparison with our baseline, column (1) of Table 3 reports the results from specification (1), 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 (2), where $x_{j,t-1}$ 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 Online 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.[19] This 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.

Alternative interest rate surprises. — We consider using the raw high-frequency interest rate surprises (s_t^{FF4}) instead of our preferred measure of monetary surprises (ϵ_t^m), based on Jarociński and Karadi (2020)'s approach. Column (1) of Table 4 reports the coefficient estimates from specification (1), where we include time-sector fixed effects and we interact the raw interest rate surprises s_t^{FF4} with the high-leverage dummy. The interaction coefficient (measuring the response of high-leverage firms relative to low-leverage firms) is still positive, but halves in size and is not statistically significant, in contrast to our baseline estimate, which we report here in column (2) for ease of comparison.

This pattern is consistent with s_t^{FF4} potentially being driven by a linear combination of true monetary policy shocks (of which ϵ_t^m is a noisy proxy) and a component working in opposite direction, which could reflect a Federal Reserve information effect or market participants learning about the Federal Reserve's reaction function (as discussed in section I.A). Consistent with this view, we find that an increase in interest rates that is driven by the non-monetary surprises (ϵ_t^{other}) leads to an average *fall* in credit spreads.[20] Importantly, and in a way that mirrors our baseline results for ϵ_t^m, column (3) of Table 4 shows that ϵ_t^{other}

[19] This is also true when estimating 'double-interaction' regressions using the continuous leverage interaction $L_{j,t-1}$ instead of the high leverage dummy $\ell_{j,t-1}$. See Table F.2 in Online Appendix F.

[20] The results for the average response of credit spreads (i.e. based on specification (1)) are not reported here for brevity, and relegated to Table F.8 in Online Appendix F.

Table 4—Monetary Vs. Non-Monetary Surprises

	(1)	(2)	(3)
	Int. Rate Surp. (s^{FF4})	Monetary Surp. (ϵ^m)	Non-monetary Surp. (ϵ^{other})
MP surp.× High Lev. ($\epsilon^m \times \ell_j$)	8.95	18.34**	-11.57
	(5.49)	(9.09)	(11.61)
Observations	279603	279603	279603
R squared	0.308	0.308	0.308
Double Clustering	Yes	Yes	Yes
Time x Sector FE	Yes	Yes	Yes

Note: Results from estimating specification (1), namely $\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma(\epsilon_t \ell_{j,t-1}) + \delta \ell_{j,t-1} + e_{ij,t}$, with different high frequency surprises (ϵ). 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; $\ell_{j,t-1} = 1$ 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. 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 $p < 0.1$).

leads to a fall in credit spreads which is larger for high-leverage firms (even though the effect is not statistically significant). In sum, the results from this robustness exercise show how the non-monetary news embedded in raw interest rate surprises can lead to a large downward bias in the estimated effect of monetary policy on credit spreads, both in the time series and in the cross-section.

Option adjustment. — Bonds that are either callable or convertible carry an embedded option, whose value might vary with economic conditions. The data provided by ICE BofAML adjust for this by netting out the value of the embedded option from the price of the bond before computing the spread to Treasuries. It is possible, though, that the short interest rate model used by the data provider to adjust for the value of options does not fully capture potential changes in the volatility of short rates around FOMC announcements, potentially leading to a bias in our estimates. To address this possibility, we have estimated our specification using a smaller sample of bonds that do not embed any options. The results are reported in Tables F.10 and F.11 in Online Appendix F (for the average and the heterogeneous effects, respectively) and show that we can recover our main result—namely that in response to monetary policy tightening, spreads increase, and do so more for highly leveraged firms.

III. Inspecting the Mechanism: Expected Default & Excess Bond Premium

We now consider an empirical 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 the framework of Gilchrist and Zakrajsek (2012) to decompose credit spreads into two orthogonal components: (i) a component capturing fluctuations in firms' expected default risk and (ii) a residual component that captures fluctuations in credit spreads above and beyond the compensation that investors require for expected defaults. Gilchrist and Zakrajsek (2012) define the average of this residual component (across bonds/firms at time t) as the Excess Bond Premium (EBP).

The spread decomposition is motivated by the empirical finding that not all of the variation in corporate bond credit spreads can be attributed to the financial health of the issuer.[21] Gilchrist and Zakrajsek (2012) show empirically that the EBP is tightly linked to the financial position of financial intermediaries, and an increase in the EBP can be interpreted as a reduction in the effective risk-bearing capacity of the financial sector, which leads to a contraction in the supply of credit. The intuition, which we formalize in the theoretical model in the next section, comes from the fact that a fall in intermediaries' equity implies a higher credit spread for any given level of a firm's leverage.[22] While the EBP has been used extensively in the empirical monetary policy literature, the novelty of our approach lies in exploiting cross-sectional variation in *bond-specific* EBPs. As we show in the theoretical framework we develop in the next section, by focusing on the component of spreads which is not associated with firms' default risk, bond-specific EBPs can give us a sense of the role that financial intermediaries play in the transmission of monetary policy.

To obtain the decomposition of credit spreads, we proceed as follows. We regress corporate bond spreads on a firm-specific 'distance to default' measure, calculated using the Merton-KMV framework, and on a vector of bond-specific controls.[23] The fitted value from this regression ($\hat{cs}_{ij,t}$) isolates the variation in credit spreads due to fluctuations in the creditworthiness of firms. Note that the regression has an R^2 of about 75%, showing that default risk and bond-specific controls capture the vast majority of the unconditional variation in credit spreads. The residual ($\hat{\nu}_{ij,t}$) reflects the variation in credit spreads that is in excess of firms' expected default risk.

Armed with this decomposition, we estimate how the two components of credit spreads 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

[21]See Collin-Dufresne, Goldstein and Martin (2001), Elton et al. (2001), and Driessen (2005).

[22]This is true in the short-run as capital is fixed. After the shock hits, firms find it optimal to adjust their leverage taking into account the new capital supply schedule.

[23]In Online Appendix E we report all the details of this procedure and a comparison of our results with the original decomposition of Gilchrist and Zakrajsek (2012).

TABLE 5—EXPECTED DEFAULT AND EXCESS BOND PREMIUM: AVERAGE EFFECT

	(1)	(2)	(3)
	Spread (Δcs)	Default Risk ($\Delta \hat{cs}$)	Exc. Bond Premium ($\Delta\hat{\nu}$)
MP surp. (ϵ^m)	26.94**	2.92	24.02**
	(10.44)	(1.78)	(10.10)
Observations	285794	285794	285794
R squared	0.034	0.030	0.032
Double Clustering	Yes	Yes	Yes
Time x Sector FE	No	No	No

Note: Results from estimating specification (1), namely $y_{ij,t} = \alpha_i + \beta\epsilon^m_t + e_{ij,t}$, where $y_{it} = (\Delta cs_{ij,t}, \Delta\hat{cs}_{ij,t}, \Delta\hat{\nu}_{ij,t})$; ϵ^m_t 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 $p < 0.1$).

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 24 basis points, is highly statistically significant and about eight times larger than the coefficient on $\hat{cs}_{ij,t}$, which instead is not statistically different from zero.[24]

We next turn to the cross-sectional response of the fitted spread and the excess bond premium components to monetary policy. We estimate a specification with time-sector fixed effects, as in equation (1). 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 EBP accounts for virtually all of the relative response of credit spreads to a monetary policy surprise. The expected default component also has a positive coefficient even though it is quantitatively small and statistically insignificant.

In sum, this section shows that a large proportion of the overall movement in credit spreads (both in the time series and in the cross section) is accounted for by a component that is orthogonal to firms' default risk.[25] In the next section, we develop a theoretical framework that allows us to rationalize these results.

[24]Note that our results do not imply that default risk is not moving in response to monetary policy shocks. Table F.9 in Online Appendix F shows that our distance to default measure falls by 0.33 standard deviations in response to a contractionary monetary policy surprise. While the response of the distance to default is statistically significant, its magnitude is very small compared to the unconditional variance of the distance to default. So, it is not surprising that the contribution of default risk to the overall response of credit spreads to monetary policy shocks is not quantitatively important.

[25]As noted above, this does not mean that, conditional on other shocks, default risk does not play a role in driving fluctuations in credit spreads. On the contrary, most of the *unconditional* variance of credit spreads is driven by default risk.

Table 6—Expected Default and Excess Bond Premium: Heterogeneity

	(1)	(2)	(3)
	Spread (Δcs)	Default Risk ($\Delta \hat{cs}$)	Exc. Bond Premium ($\Delta\hat{\nu}$)
MP surp.× High Lev. ($\epsilon^m \times \ell_j$)	18.34**	0.30	18.05*
	(9.09)	(0.57)	(9.16)
Observations	279603	279603	279603
R squared	0.308	0.373	0.300
Double Clustering	Yes	Yes	Yes
Time x Sector FE	Yes	Yes	Yes

Note: Results from estimating specification (1), namely $y_{it} = \alpha_i + \beta_{sct,t} + \gamma(\epsilon_t^m \ell_{j,t-1}) + \delta\ell_{j,t-1} + e_{ij,t}$, 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; $\ell_{j,t-1} = 1$ when firm j's 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 $p < 0.1$).

IV. Interpretation

In this section we develop a simple theoretical framework that sheds light on our finding that firms with high leverage see their firm-specific EBP increase by more than firms with low leverage in response to a monetary policy shock. To do that, we combine two key ingredients: firm heterogeneity and credit market frictions on financial intermediaries. To keep the framework tractable and deliver analytical intuition, we abstract from credit market frictions on firms, which are extensively analyzed in previous work (e.g. Ottonello and Winberry, 2020).

A. Theoretical Framework

There are two islands of mass unity. Each island, denoted by j, is populated with the following agents: (1) a continuum of entrepreneurs of mass unity, each managing firm i; and (2) a financial intermediary. Within an island, entrepreneurs are (ex-ante) identical, but differ across islands in their riskiness (which we formally define below). We label the firms in the low-risk island as 'safe' (S) and those in the high-risk island as 'risky' (R), so that $j = \{S, R\}$. In what follows we describe the problems of entrepreneurs and financial intermediaries on a given island.

Entrepreneurs. — Entrepreneurs have access to the following technology $y = \tilde{\omega}_j K^\alpha$, where $\tilde{\omega}_j$ is an idiosyncratic productivity shock (not known ex ante) whose distribution is heterogeneous across islands. Entrepreneurs have limited net worth

(N_j), which differs across islands. We assume that net worth is larger for entrepreneurs on the safe island, so that $N_S > N_R$. As net worth is limited, entrepreneurs have to finance capital expenditures (K) with a mixture of net worth (N_j) and external funds (B). Entrepreneurial debt is supplied by a financial intermediary (described below) at a gross interest rate rate R^B.

The idiosyncratic productivity shock $\tilde{\omega}_j$ can take two values $\tilde{\omega}_j = \{0, \omega_j\}$ with probability p_j and $1 - p_j$, respectively. The probabilities can be heterogeneous across islands, and so are indexed by j, too. When $\tilde{\omega}_j$ takes the low value (with probability p_j), the entrepreneur loses everything and declares default. We assume that the default probability of the safe firm is smaller than the default probability of the risky firm, namely $p_S < p_R$. As in Christiano and Ikeda (2011), we place the following restriction on the idiosyncratic productivity shocks and their probabilities:

$$\omega_j(1 - p_j) = z, \tag{3}$$

where z is a non-random parameter known to all. Thus, each firm's investment project generates the same expected return, but differs in terms of riskiness.

Entrepreneurs maximize expected profits subject to their balance sheet constraint:

$$\max_K \{zK^\alpha - R^B B\} \tag{4}$$

$$s.t. \quad K = N_j + B. \tag{5}$$

The first order condition associated with the firm's problem implies the following expression for the capital demand schedule (which, since net worth is fixed, can also be thought as a credit demand schedule):

$$CS = \frac{\alpha z K^{\alpha-1}}{R} \tag{6}$$

where CS is the (gross) credit spread, defined as $CS \equiv \frac{R^B}{R}$; and R is the known risk-free interest rate. The demand for capital can be plotted in the $\{K, CS\}$ space as a downward sloping convex curve.

Financial intermediary. — In each island, a financial intermediary supplies funds to entrepreneurs. Financial intermediaries on different islands are endowed with the same amount of net worth, which we refer to as equity E. By combining equity with deposits D raised from households, the intermediary lends funds B to entrepreneurs, which offer a gross return R^B.

We assume that financial intermediaries cannot intermediate across islands. This form of market segmentation is meant to capture a well-known feature of corporate bond markets, namely that investors face heterogeneous restrictions regarding the riskiness of the assets they can buy, reflecting regulatory constraints or voluntary institutional conventions.[26] In addition to market segmentation, we follow Gertler and Kiyotaki (2010) and Gertler and Karadi (2011) in assuming that the financial intermediary can default after receiving the payment from the entrepreneur and abscond with a fraction θ of total assets. The financial intermediary will not default if the profits when not defaulting exceed the profits when defaulting—and this acts as an incentive compatibility constraint.[27]

The financial intermediary takes the return to deposits R and the lending rate R^B as given, and chooses the amount of funds it lends and deposits to maximize expected profits, subject to the incentive compatibility constraint, the balance sheet constraints, and non-negativity constraint on deposits:

$$\max_{D,B} \; (1-p_j)R^B B - R(B-E) \tag{7}$$

$$\begin{aligned} s.t. \quad & (1-p_j)R^B B - R(B-E) \geq \theta(1-p_j)R^B B \\ & B = E + D \\ & D \geq 0. \end{aligned} \tag{8}$$

The difference relative to the standard Gertler-Kiyotaki-Karadi formulation is that financial intermediaries have some risk on their asset side: if an entrepreneur defaults, intermediaries lose some of their assets, but have to repay the promised amount to depositors.

The solution to the intermediary's problem yields their supply schedule for credit to firms. The credit supply schedule differs depending on whether the intermediary's financial constraint binds or not. In particular, credit supply is a piecewise function with a kink where the financial constraint becomes binding:

$$CS = \begin{cases} \frac{1}{1-p_j} & \text{if } \; N_j < K \leq N_j + \frac{E}{\theta} \\ \frac{1}{(1-p_j)}\frac{1}{(1-\theta)}\left(1 - \frac{E}{K-N_j}\right) & \text{if } \; K > N_j + \frac{E}{\theta} \end{cases} \tag{9}$$

When the financial constraint does not bind, the credit supply schedule is flat at $1/(1-p_j)$.[28] In this region, the level of credit spreads depends exclusively on the default probability p_j, and thus is independent of firms' capital expenditures K. When the constraint binds, the credit supply schedule is upward-sloping. In this

[26]For example, while pension funds can only buy investment-grade securities, hedge funds do not usually face such restrictions and typically invest in high-yield assets (see, for example, Chernenko and Sunderam, 2012). Similarly, Manconi, Massa and Yasuda (2012) document how investment funds hold a much higher proportion of their corporate bond portfolios in junk rated bonds than insurance companies, consistent with the greater regulatory constraints faced by the latter.

[27]Note that, in the data, there is a strong correlation between the riskiness of a firm's bonds (as measured by credit ratings) and firm leverage (see Figure D.1 in Online Appendix D), which justifies specifying the market segmentation in terms of leverage rather than credit ratings.

[28]We only consider equilibria where capital expenditures are financed with some positive amount of borrowing, namely $K > N_j$.

region, credit spreads are the sum of a fixed component due to default probability and a component capturing the tightness of intermediaries' financial constraints which is increasing in firms' capital expenditures K (and, thus, in intermediaries' leverage).

Because of heterogeneity in entrepreneurs' net worth N_j and default probability p_j, our model features heterogeneous supply schedules for safe and risky firms. We analyze the role of net worth and the default probability in turn: (i) lower net worth implies, all else equal, higher entrepreneurial borrowing and, thus, higher intermediaries' leverage. As discussed above, this tightens the financial constraint, which becomes binding at lower levels of capital. In the region where the constraint is not binding, credit spreads are unchanged, as they solely depend on p_j. While in the region where the constraint is binding, lower net worth is associated (for a given level of capital) with higher credit spreads; (ii) a higher default probability is associated, for any given level of capital, with higher credit spreads, reflecting the higher default risk. Conversely, the EBP is independent of the firm's default risk, as shown by equation (9). In sum, the model implies patterns of leverage, credit spreads and default risk for the safe and risky firms that are in line with what we observe in the data, as reported in Table 1 and as described in more detail in the next section.

B. *Equilibrium & Curve Shifting*

We compute the equilibrium in the capital market—given by the intersection between the demand and the supply schedules described above—in a numerical example, choosing the parameter values of the model to match some key features of our data. Specifically, for both high-leverage and low-leverage firms, we target the unconditional average of leverage, credit spreads, and their decomposition into default risk and excess bond premium components for firms in the manufacturing sector, which we report in Table 7 (columns *Data*).[29]

After normalizing the risk free rate to $R = 1$, we are left with eight parameters to hit eight targets. We start by setting the default probability for the safe and risky firm, p_S and p_R, to match the average value of the default risk component of credit spreads for both high- and low-leverage firms. This leads to $p_S = 0.0178$ and $p_R = 0.020$. We then jointly calibrate entrepreneurs' net worth, N_S and N_R, intermediaries' equity, E, the capital demand elasticity, α, the technologically determined rate, z, and the fraction of assets the banker can abscond, θ, to match the remaining moments. This delivers $N_S = 0.275$, $N_R = 0.125$, $E = 0.012$, $\alpha = 0.975$, $z = 1.024$, and $\theta = 0.13$. Despite its simplicity, the model matches the unconditional moments of the data well, as shown in Table 7 (columns *Model*).

Next, we use our framework to see how monetary policy affects firms' credit

[29]We use data for high- and low-leverage firms in a specific sector, as opposed to using data across all sectors in our sample, because the substantial amount of firm heterogeneity across sectors could pollute our calibration targets. We pick the manufacturing sector (`2000`$\leq$`sic`$\leq$`3999`) as it is the largest in terms of number of observations.

Table 7—High vs. Low Leverage Firms: Data vs. Model

	Low Leverage		High Leverage	
	Data	*Model*	*Data*	*Model*
Leverage (Debt/Assets)	0.24	0.26	0.48	0.45
Credit spreads (bp)	230	228	351	353
Default risk (bp)	181	181	204	204
Excess bond premium (bp)	49	47	148	149

Note: The columns labelled *Data* report the average values of leverage, credit spreads, and their decomposition into expected default and excess bond premium for high-leverage and low-leverage firms in the 'Manufacturing sector' ($2000 \leq \texttt{sic} \leq 3999$) in our data set. The columns labelled *Model* report the values of the same variables computed from the theoretical model.

spreads. Motivated by the vast empirical literature on the transmission of monetary policy shocks via financial intermediaries' balance sheets, we model a monetary policy tightening as an exogenous fall in intermediaries net worth (see, among many others, Gertler and Karadi (2011)).[30] The resulting tightening in intermediaries' financial constraints creates an inward shift of the supply schedule. Note, however, that unlike the convex supply curves that arise in the firm financial frictions problem of Bernanke, Gertler and Gilchrist (1999), the upward-sloping section of the supply schedule (9) is concave. It is therefore not obvious whether the shock will have a larger effect on high- or low-leverage firms' credit spreads.

We characterize the effect of the shock numerically, by considering an exogenous fall in intermediaries' equity E of 10 percent.[31] Figure 3 reports the results from this experiment, by plotting the capital market equilibrium in the space $\{K, CS\}$ before and after the shock (solid and dashed lines, respectively). Lower intermediaries' equity E implies, all else equal, a higher leverage ratio for financial intermediaries. As discussed above, this tightens the financial constraint. The resulting inward shift of the credit supply schedules (dashed lines) implies an increase in credit spreads for both firms. In our parametrization, the increase is larger for the risky firm ($\Delta CS_R = 11.1$ basis points) than for the safe firm ($\Delta CS_S = 6.4$ basis points). This experiment shows that the implications of the model are qualitatively in line with our empirical findings: a fall in intermediaries' equity leads to an overall increase in the excess bond premium component of credit spreads, with the effect being larger for high-leverage firms.[32]

[30]For simplicity, we abstract here from movements in the capital demand schedule induced by monetary policy. As we discuss in Online Appendix A, the main conclusions of the analysis in this section hold true when considering shifts in the capital demand schedule.

[31]Recent studies show that the size of the drop in intermediaries' net worth in response to monetary policy changes depends upon the maturity of financial intermediaries' assets and liabilities and the degree to which portfolios are marked to market, see Hoffmann et al. (2019) and Di Tella and Kurlat (2021), among others. Di Tella and Kurlat (2021), for example, calibrate a model which produces net worth losses of around 30 percent in response to a 100 basis point interest rate increase.

[32]The analysis in this section is purposefully illustrative and is not meant to deliver quantitative implications that are exactly in line with the empirical evidence. A richer version of our model (featuring, for example, heterogeneity in capital demand) could generate stronger transmission from monetary policy

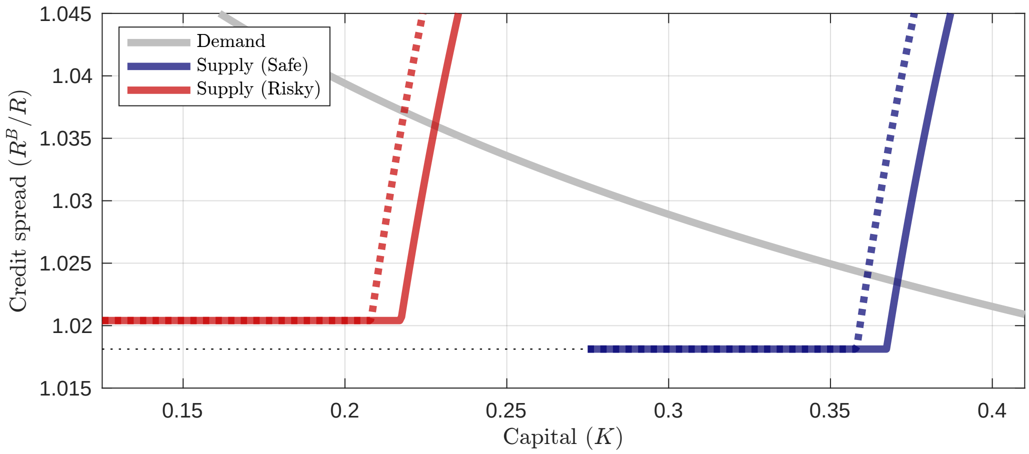

Figure 3. Monetary Policy Tightening: Intermediaries' Equity Shock

Note: Equilibrium in the capital market. On the horizontal axis is capital K and on the vertical axis is the credit spread CS. The gray line is the demand schedule, the red line is the supply schedule for the risky firm, the blue line is the supply schedule for the safe firm.

While the model is calibrated to the average high- and low-leverage firm in our sample, the empirical results show that the relation holds across the full leverage distribution. Moreover, our calibration implies that the safe firm is virtually unconstrained—its equilibrium sits very close to the kink of the supply schedule—casting doubts about the generality of the model's properties. We thus generalize the model experiment by considering a set of different values for the net worth of the safe firm: we start from the same value used in our baseline (0.275), and we gradually decrease it to reach the value of net worth of the risky firm (0.125). In other words, we consider a set of safe firms whose credit supply schedules (blue lines) progressively shift to the left.

For each pair κ of risky-safe firms, we compute the *relative* change in credit spreads associated with the fall in intermediaries' equity:

$$\Gamma_\kappa = \Delta CS_R - \Delta CS_{S,\kappa}. \tag{10}$$

Figure 4 plots the relative increase in credit spreads Γ_κ as a function of (pre-shock) relative leverage $\mathcal{L}_\kappa$, namely the difference between the leverage of the risky and the safe firm $(L_R - L_S)$. The red diamond denotes our baseline calibration, i.e. the values of Γ_κ and $\mathcal{L}_\kappa$ as implied by Figure 3. The black line with circles shows that the same positive relation between Γ_k and $\mathcal{L}_k$ holds for different values of the net worth of the safe firm, as we find in the data.

As noted above, the concavity of the upward-sloping section of the supply sched-

shocks to credit spreads.

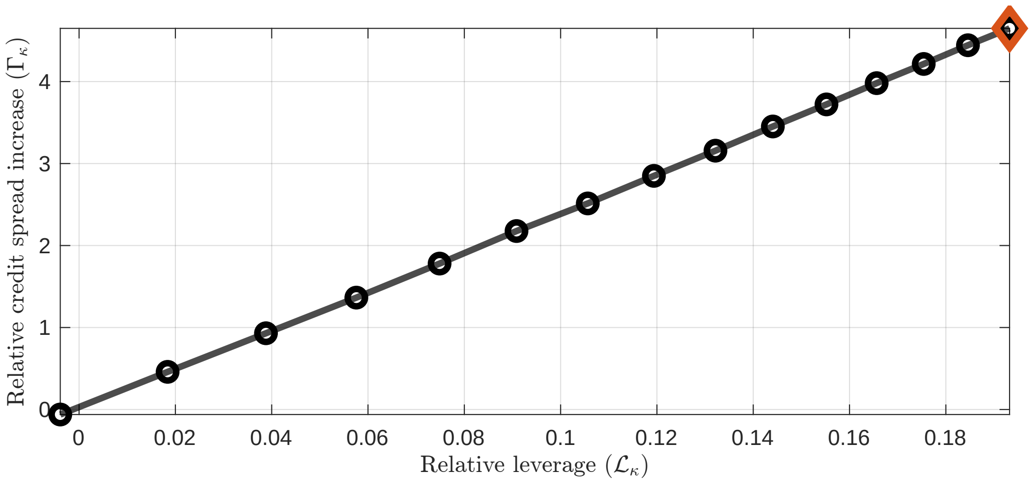

Figure 4. Leverage and Credit Spreads in the Model

Note: On the vertical axis is the relative credit spreads increase ($\Gamma_\kappa = \Delta CS_R - \Delta CS_{S,\kappa}$) conditional on a fall in intermediaries' equity. On the horizontal axis is the (pre-shock) relative leverage ($\mathcal{L}_\kappa = L_R - L_{S,\kappa}$). Each circle corresponds to a different pair of risky-safe firms, obtained by varying the level of net worth (and thus leverage) of the safe firm between 0.125 and 0.297. The red diamond denotes the pair $\{\mathcal{L}_\kappa, \Gamma_\kappa\}$ in our baseline calibration.

ule (9) makes the relative response of credit spreads ex ante ambiguous. Specifically, the heterogeneous responses documented in Figure 3 crucially depend on the elasticity of the capital demand schedule. To see that, consider the limiting case of a perfectly inelastic (i.e. vertical) capital demand schedule. As the high-leverage firm lies on a flatter portion of the supply schedule, an inward shift of the credit supply schedule leads to a smaller increase in credit spreads compared to the low-leverage firm, which instead lies on a steeper portion of the supply schedule. We thus investigate the robustness of our findings to different values of the capital demand elasticity (α). In line with the above intuition, we find that for low-enough values of α we can overturn our result—it is now low-leverage firms that respond more to the shock. Note, however, that such low levels of α would not be consistent with the unconditional properties of the data. Specifically, a relatively elastic capital demand schedule is needed to capture the degree of heterogeneity (in terms of relative size, leverage, and credit spreads) observed in the data.[33]

In sum, the theoretical framework developed in this section delivers two general insights. First, it shows that credit spreads can embed a firm-specific EBP component that, in equilibrium, is larger for high-leverage firms—as we observe unconditionally in our sample of firms. Second, it shows that, when the capital demand schedule is relatively elastic, monetary policy leads to an increase in the

[33] See Online Appendix A for more details on this exercise and further results.

EBP component of credit spreads that is greater for high-leverage firms—as we find in the data conditional on monetary policy shocks.[34]

V. Conclusion

Following a monetary policy tightening, high-leverage firms experience a more pronounced increase in borrowing costs than low-leverage firms. When decomposing the total effect of monetary policy on credit spreads into a component capturing a firm's default risk and a component capturing the compensation required by investors in excess of default risk, virtually all of the conditional response of credit spreads to monetary policy is accounted for by the latter component.

Models that rely on firm heterogeneity alone—like those in the recent literature that analyze the response of firm-level quantities to monetary policy—do not have a notion of firm-specific excess bond premia, and thus have a hard time in interpreting the empirical facts we uncover. To rationalize these facts, we develop a static, partial equilibrium theoretical framework where the net worth of financial intermediaries affects credit spreads heterogeneously and independently of firms' default risk through the combination of financial frictions and a form of market segmentation.

When interpreted through the lens of this framework, our empirical results highlight the role of intermediaries in shaping the transmission of monetary policy to firm-level outcomes. These findings call for a careful modeling of heterogeneity in the financial intermediation sector (as, for example, in Coimbra and Rey (2017) and Jamilov and Monacelli (2020)), as well as its interaction with heterogeneity on the firm side, to understand the investment channel of monetary policy.

REFERENCES

Adrian, Tobias, and Hyun Song Shin. 2010. "Liquidity and Leverage." *Journal of Financial Intermediation*, 19(3): 418–437.

Bahaj, Saleem, Angus Foulis, Gabor Pinter, and Paolo Surico. 2018. "Employment and the Collateral Channel of Monetary Policy." Centre for Macroeconomics (CFM) Discussion Papers 1832.

Barakchian, S. Mahdi, and Christopher Crowe. 2013. "Monetary Policy Matters: Evidence from New Shocks Data." *Journal of Monetary Economics*, 60(8): 950–966.

[34]The model's implications follow from our assumptions of heterogeneity in firms' net worth and market segmentation, which lead the intermediary that matches with the risky firm to operate at a higher leverage than the intermediary that matches with the safe firm. While we think of this as a valid abstraction of the actual mechanisms behind the empirical findings, other non-mutually exclusive mechanisms could be at play. For example, if intermediaries are subject to Value-at-Risk constraints in the spirit of Adrian and Shin (2010), intermediaries lending to riskier firms may exhibit higher and more volatile EBPs because of their assets being riskier, and not only because they operate at higher leverage. Empirically identifying the exact mechanisms (and their relative importance) that lead to a tightening in intermediaries' financial constraints represents an important avenue for future research.

Bauer, Michael D., and Eric T. Swanson. 2020. "The Fed's Response to Economic News Explains the "Fed Information Effect"." National Bureau of Economic Research, Inc NBER Working Papers 27013.

Bernanke, Ben, and Mark Gertler. 1989. "Agency Costs, Net Worth, and Business Fluctuations." *American Economic Review*, 79(1): 14–31.

Bernanke, Ben S, and Alan S Blinder. 1992. "The Federal Funds Rate and the Channels of Monetary Transmission." *American Economic Review*, 82(4): 901–921.

Bernanke, Ben S., Mark Gertler, and Simon Gilchrist. 1999. "The Financial Accelerator in a Quantitative Business Cycle Framework." In *Handbook of Macroeconomics*. Vol. 1, , ed. J. B. Taylor and M. Woodford, Chapter 21, 1341–1393. Elsevier.

Chernenko, Sergey, and Adi Sunderam. 2012. "The Real Consequences of Market Segmentation." *Review of Financial Studies*, 25: 2041–2069.

Christiano, Lawrence, and Daisuke Ikeda. 2011. "Government Policy, Credit Markets and Economic Activity." National Bureau of Economic Research, Inc NBER Working Papers 17142.

Cloyne, James, Clodomiro Ferreira, Maren Froemel, and Paolo Surico. 2018. "Monetary Policy, Corporate Finance and Investment." National Bureau of Economic Research, Inc NBER Working Papers 25366.

Coimbra, Nuno, and Helene Rey. 2017. "Financial Cycles with Heterogeneous Intermediaries." National Bureau of Economic Research, Inc NBER Working Papers 23245.

Collin-Dufresne, Pierre, Robert S. Goldstein, and J. Spencer Martin. 2001. "The Determinants of Credit Spread Changes." *The Journal of Finance*, 56(6): 2177–2207.

Crouzet, Nicolas, and Neil R. Mehrotra. 2020. "Small and Large Firms over the Business Cycle." *American Economic Review*, 110(11): 3549–3601.

Di Tella, Sebastian, and Pablo Kurlat. 2021. "Why Are Banks Exposed to Monetary Policy?" *American Economic Journal: Macroeconomics*, 13(4): 295–340.

Drechsel, Thomas. 2018. "Earnings-Based Borrowing Constraints and Macroeconomic Fluctuations." Unpublished manuscript.

Driessen, Joost. 2005. "Is Default Event Risk Priced in Corporate Bonds?" *Review of Financial Studies*, 18(1): 165–195.

Duffee, Gregory R. 1998. "The Relation Between Treasury Yields and Corporate Bond Yield Spreads." *Journal of Finance*, 53(6): 2225–2241.

Elton, Edwin J., Martin J. Gruber, Deepak Agrawal, and Christopher Mann. 2001. "Explaining the Rate Spread on Corporate Bonds." *The Journal of Finance*, 56(1): 247–277.

Farre-Mensa, Joan, and Alexander Ljungqvist. 2016. "Do Measures of Financial Constraints Measure Financial Constraints?" *Review of Financial Studies*, 29(2): 271–308.

Ferreira, Thiago R.T., Daniel A. Ostry, and John Rogers. 2023. "Firm Financial Conditions and the Transmission of Monetary Policy." Cambridge Working Papers Cambridge Working Papers in Economics CWPE2316 2316.

Gabaix, Xavier. 2011. "The Granular Origins of Aggregate Fluctuations." *Econometrica*, 79(3): 733–772.

Gertler, Mark, and Nobuhiro Kiyotaki. 2010. "Financial Intermediation and Credit Policy in Business Cycle Analysis." In *Handbook of Monetary Economics*. Vol. 3 of *Handbook of Monetary Economics*, , ed. Benjamin M. Friedman and Michael Woodford, Chapter 11, 547–599. Elsevier.

Gertler, Mark, and Peter Karadi. 2011. "A Model of Unconventional Monetary Policy." *Journal of Monetary Economics*, 58(1): 17–34.

Gertler, Mark, and Peter Karadi. 2015. "Monetary Policy Surprises, Credit Costs, and Economic Activity." *American Economic Journal: Macroeconomics*, 7(1): 44–76.

Gertler, Mark, and Simon Gilchrist. 1994. "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms." *The Quarterly Journal of Economics*, 109(2): 309–340.

Gilchrist, Simon, and Egon Zakrajsek. 2012. "Credit Spreads and Business Cycle Fluctuations." *American Economic Review*, 102(4): 1692–1720.

Gilchrist, Simon, Bin Wei, Vivian Yue, and Egon Zakrajsek. 2020. "The Fed Takes on Corporate Credit Risk: An Analysis of the Efficacy of the SMCCF." C.E.P.R. Discussion Papers CEPR Discussion Papers 15258.

Gilchrist, Simon, Vladimir Yankov, and Egon Zakrajsek. 2009. "Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets." *Journal of Monetary Economics*, 56(4): 471–493.

Greenwald, Daniel. 2019. "Firm Debt Covenants and the Macroeconomy: The Interest Coverage Channel." Society for Economic Dynamics 2019 Meeting Papers 520.

Gürkaynak, Refet S, Brian Sack, and Eric Swanson. 2005. "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements." *International Journal of Central Banking*, 1(1).

Gurkaynak, Refet S., Gokce Karasoy Can, and Sang Seok Lee. 2019. "Stock Market's Assessment of Monetary Policy Transmission: The Cash Flow Effect." C.E.P.R. Discussion Papers CEPR Discussion Papers 14017.

Hoffmann, Peter, Sam Langfield, Federico Pierobon, and Guillaume Vuillemey. 2019. "Who Bears Interest Rate Risk?" *Review of Financial Studies*, 32(8): 2921–2954.

ICE. 2022. "Bond Index Methodologies." *www.ice.com/publicdocs/data/Bond_Index_Methodologies.pdf*.

Ippolito, Filippo, Ali K. Ozdagli, and Ander Perez-Orive. 2018. "The Transmission of Monetary Policy through Bank Lending: The Floating Rate Channel." *Journal of Monetary Economics*, 95(C): 49–71.

Jamilov, Rustam, and Tommaso Monacelli. 2020. "Bewley Banks." C.E.P.R. Discussion Papers CEPR Discussion Papers 15428.

Jarociński, Marek, and Peter Karadi. 2020. "Deconstructing Monetary Policy Surprises—The Role of Information Shocks." *American Economic Journal: Macroeconomics*, 12(2): 1–43.

Jeenas, P. 2018. "Monetary Policy Shocks, Financial Structure, and Firm Activity: A Panel Approach." Unpublished manuscript.

Jorda, Oscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review*, 95(1): 161–182.

Kashyap, Anil K., and Jeremy C. Stein. 1995. "The Impact of Monetary Policy on Bank Balance Sheets." *Carnegie-Rochester Conference Series on Public Policy*, 42(1): 151–195.

Kashyap, Anil K., and Jeremy C. Stein. 2000. "What Do a Million Observations on Banks Say about the Transmission of Monetary Policy?" *American Economic Review*, 90(3): 407–428.

Kashyap, Anil K., Owen A. Lamont, and Jeremy C. Stein. 1994. "Credit Conditions and the Cyclical Behavior of Inventories." *The Quarterly Journal of Economics*, 109(3): 565–592.

Kuttner, Kenneth. 2001. "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market." *Journal of Monetary Economics*, 47(3): 523–544.

Lian, Chen, and Yueran Ma. 2019. "Anatomy of Corporate Borrowing Constraints." Unpublished manuscript.

Manconi, Alberto, Massimo Massa, and Ayako Yasuda. 2012. "The Role of Institutional Investors in Propagating the Crisis of 2007–2008." *Journal of Financial Economics*, 104(3): 491–518.

Melosi, Leonardo. 2017. "Signalling Effects of Monetary Policy." *Review of Economic Studies*, 84(2): 853–884.

Miranda-Agrippino, Silvia, and Giovanni Ricco. 2021. "The Transmission of Monetary Policy Shocks." *American Economic Journal: Macroeconomics*, 13(3): 74–107.

Nakamura, Emi, and Jon Steinsson. 2018. "High Frequency Identification of Monetary Non-Neutrality: The Information Effect." *Quarterly Journal of Economics*, 133(3): 1283–1330.

Ottonello, Pablo, and Thomas Winberry. 2020. "Financial Heterogeneity and the Investment Channel of Monetary Policy." *Econometrica*, 88(6): 2473–2502.

Ozdagli, Ali K. 2018. "Financial Frictions and the Stock Price Reaction to Monetary Policy." *Review of Financial Studies*, 31(10): 3895–3936.

Ramey, V.A. 2016. "Macroeconomic Shocks and Their Propagation." Vol. 2 of *Handbook of Macroeconomics*, Chapter 0, 71–162. Elsevier.

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 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.[35]

As well as the OAS, we obtain a number of other bond characteristics from the ICE-BofAML Global Index System. We obtain data on each bond's age, market value, effective duration, coupon rate, as well as the industry of the issuer.

[35]For further details, see Bond Index Methodologies by ICE (2022).

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.

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 S&P500 returns from Eikon Refinitiv. More details on the surprises are reported in Online Appendix C.

Investment. We closely follow the steps in Ottonello and Winberry (2020). 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 (2020). 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 (2020).

Firm-level Panel Local Projections

In the paper we claim that our 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 in the main body of the paper 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 to a business cycle frequency analysis.

For the firms in our data set, we collect quarterly data on total debt and investment from Compustat and we aggregate monetary policy surprises at a quarterly frequency over the period 1990Q1 to 2017Q4. With this data set, we use a panel local projection approach, as in Jorda (2005), to examine the heterogeneous effects of monetary policy on firm-level debt and investment. Specifically, we estimate the following specification:

$$y_{j,\tau+h} - y_{j,\tau-1} = \alpha_j^h + \beta_{sct,\tau} + \gamma^h \epsilon_\tau^m \ell_{j,\tau-1} + \sum_{p=1}^{P} \Gamma_p W_{j,\tau-p} + e_{j,\tau+h}, \tag{B1}$$

where $y_{j,\tau}$ is debt or investment of firm j in quarter τ; $\beta_{sct,\tau}$ is a quarter-sector fixed effect; $\ell_{j,\tau-1}$ is a dummy variable that equals 1 when the leverage of firm j in $\tau - 1$ 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_τ^m on $y_{\tau+h}$ for high-leverage firms relative to low-leverage firms; h denotes the horizon, with $h = 0, 1, 2, ..., H$; and $W_{j,\tau}$ is a vector of (lagged) firm-level controls, including size, real sales growth, and leverage.

The resulting relative impulse responses for total debt and investment, captured by the coefficient γ^h, are reported in Figure B1, 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 and the relative response only becomes statistically significant around three years after the shock. The results show that the patterns uncovered with the high-frequency event study regressions also hold at business cycle frequency, with high-leverage firms being more responsive than low leverage firms to monetary policy changes.

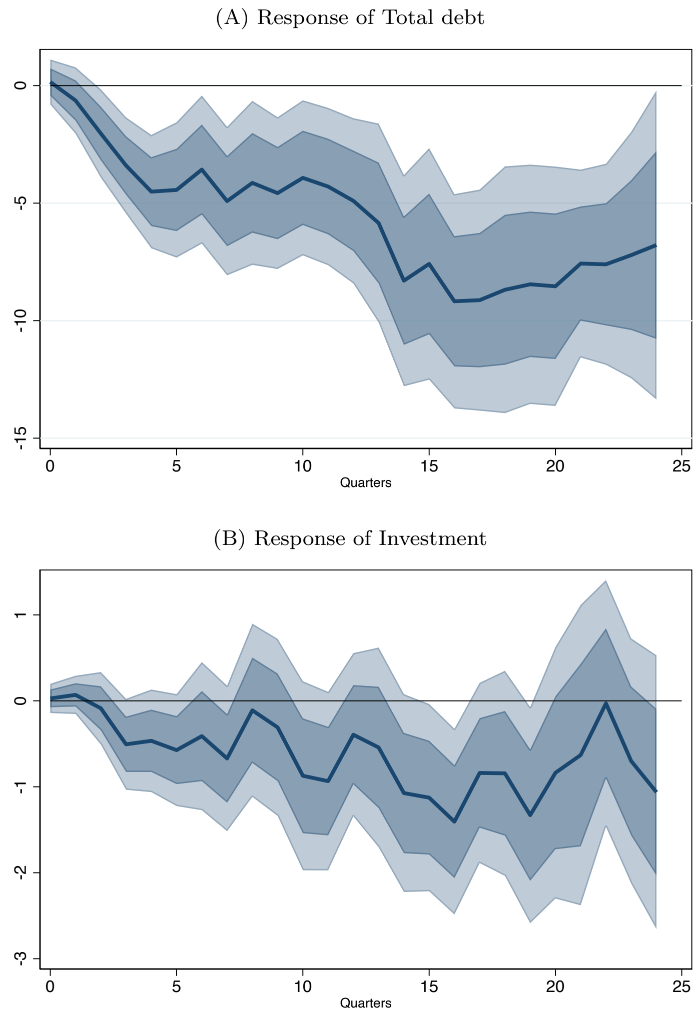

Figure B1. Heterogeneous Responses of Debt and Investment

Note: Relative impulse response of total debt and investment. The impulse responses (γ^h) are estimated with the local projection specification in (B1), namely $y_{j,\tau+h} - y_{j,\tau-1} = \alpha_j^h + \beta_{sct,\tau} + \gamma^h \epsilon_\tau^m \ell_{j,\tau-1} + \sum_{p=1}^{P} \Gamma_p W_{j,\tau-p} + e_{j,\tau+h}$, where $h = 0, 1, 2, ..., 24$; j; ϵ_τ^m is the monetary policy surprise; α_i is a bond fixed-effect; $\beta_{sct,\tau}$ is a quarter-sector fixed effect; $\ell_{j,\tau-1} = 1$ when firm j's leverage lies above the median of the leverage distribution (and zero otherwise); and $W_{j,\tau}$ is a vector of (lagged) firm-level controls, including size, real sales growth, and leverage. The shaded areas display 68 and 90 percent confidence intervals based on two-way clustered (quarter and firm) standard errors.