Online Appendix to

"Crossing the Credit Channel: Credit Spreads and Firm Heterogeneity

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A Theoretical Framework

A.1 Derivations

Entrepreneurs Entrepreneurs maximize expected profits subject to the balance sheet constraint:

$$\max_{K}\{zK^{\alpha} - R^{B}B\} \tag{A.1}$$

$$s.t. \quad K = N_j + B. \tag{A.2}$$

The first order condition associated with the firm's problem is:

$$FOC(K) = \alpha z K^{\alpha-1} - R^{B} = 0. \tag{A.3}$$

Equation (A.3) pins down the credit demand schedule:

$$CS = \frac{\alpha z K^{\alpha-1}}{R}, \tag{A.4}$$

where $CS \equiv \frac{R^B}{R}$ is the credit spread and R is the known risk-free interest rate.

Financial Intermediaries Financial intermediaries maximize expected profits, subject to the incentive compatibility and the balance sheet constraints:

$$\max_{D,B}\{(1-p_j)R^{B}B - R(B-E)\} \tag{A.5}$$

$$\begin{aligned} s.t. \quad & (1-p_j)R^{B}B - R(B-E) \geq \theta(1-p_j)R^{B}B \\ & B = E + D \\ & D \geq 0. \end{aligned} \tag{A.6}$$

The problem of financial intermediaries can be solved by setting up the following Lagrangian:

$$\mathcal{L}_j^{FI} = (1-p_j)R^{B}B - R(B-E) + \lambda_j\{(1-p_j)R^{B}B - R(B-E) - \theta(1-p_j)R^{B}B\} \tag{A.7}$$

which gives the following first order conditions:

$$FOC(B) \quad : \quad \lambda_j = -\frac{(1-p_j)R^{B} - R}{(1-p_j)(1-\theta)R^{B} - R} \tag{A.8}$$

$$FOC(\lambda_j) \quad : \quad (1-p_j)R^{B}B - R(B-E) - \theta(1-p_j)R^{B}B = 0 \tag{A.9}$$

Equation (A.8) pins down the value of the Lagrange multiplier for given credit spread. Equation (A.9), which represents the financial constraint at equality, pins down the credit supply schedule. The credit supply schedules differ depending on whether the intermediary's financial constraint binds or not. In particular, credit supply is a piece-wise function with a kink where the financial constraint becomes binding:

$$CS = \begin{cases} \frac{1}{1-p_j} & \text{if } N_j < K \leq N_j + \frac{E}{\theta} \\ \frac{1}{(1-p_j)}\frac{1}{(1-\theta)}\left(1 - \frac{E}{K-N_j}\right) & \text{if } K > N_j + \frac{E}{\theta}\upsilon \end{cases} \tag{A.10}$$

When the financial constraint does not bind, the Lagrange multiplier $\lambda = 0$ and the credit supply schedule can be recovered from equation (A.8). By substituting $\frac{R^B}{R} = \frac{1}{1-p_j}$ in the $FOC(\lambda_j)$ it is possible to compute the threshold level of capital for which the constraint becomes binding, namely $K > N_j + \frac{E}{\theta}$. This expression shows that such threshold level of capital can be written in terms of the intermediary's leverage, as $\frac{K-N_j}{E} > \frac{1}{\theta}$. That is, the constraint is not binding only if the intermediaries' leverage is below a certain limit. When instead the constraint binds, the Lagrange multiplier is positive ($\lambda_j > 0$) and the credit supply schedule can be recovered from equation (A.9).

A.2 Additional Results

The Role of Capital Demand Elasticity Our theoretical framework implies that a fall in intermediaries' equity *can* lead to an increase in the EBP component of credit spreads that is greater for high-leverage firms. A key ingredient to obtain this result is a relatively elastic capital demand schedule (i.e. relatively high value of α), a feature that we need in order to match the unconditional properties of the data.[1]

To see the importance of the capital demand elasticity, consider the case of a perfectly inelastic demand schedule (i.e. $\alpha \to 0$). In our simple set up, and in contrast with our empirical findings, the safe firm would always see its credit spreads *increase more by than the risky firm* in response to a fall in intermediaries equity. This can be seen by noting that

[1] Table 7 in the main text shows that high-leverage firms have, on average, a leverage of 0.48, compared to 0.24 for low-leverage firms. This difference is very large compared to the difference in credit spreads, at 351bp and 230bp for high- and low-leverage firms respectively. For a given shape of the capital supply schedule, we need a relatively flat (i.e. elastic) capital demand schedule to match these properties. In other words, while it would be possible to match the credit spreads of high- and low-leverage firms with a steep capital demand schedule, the resulting values for leverage would be too close to each other relative to those observed in the data. Or, conversely, it would be possible to match the leverage ratio of high- and low-leverage firms with a steep capital demand curve, but that would imply values for credit spreads that are too far apart from each other relative to what we observe in the data.

the partial derivative of the supply schedule (A.10) with respect to intermediaries' equity is always smaller than zero, namely:

$$\frac{\partial CS}{\partial E} = -\frac{1}{(K-N)(1-p_j)(1-\theta)} < 0, \tag{A.11}$$

and that the cross partial derivative with respect to entrepreneurial net worth is also always smaller than zero, namely:

$$\frac{\partial^2 CS}{\partial E \partial N} = -\frac{1}{(K-N)^2(1-p_j)(1-\theta)} < 0. \tag{A.12}$$

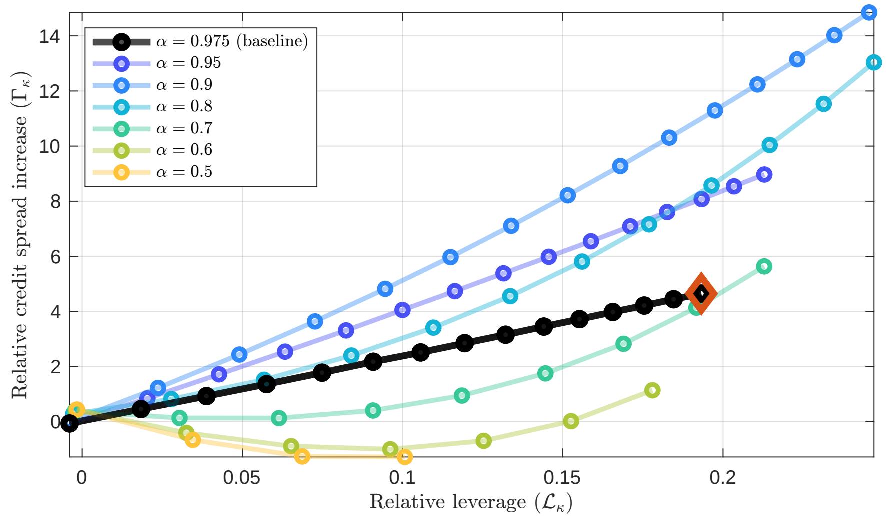
In other words, a fall in intermediaries' equity leads to an increase in credit spreads which is larger for high-net worth (low-leverage) firms.

This is in contrast to the calibrated version of the model in Section 4 in the main text, which features a relatively elastic slope of the demand schedule ($\alpha = 0.975$), and where we find that a fall in intermediaries' equity leads to an increase in credit spreads that is larger for high-leverage firms. A simple continuity argument suggests that there must be a value of α between 0 and 1 that flips the sign of the cross partial derivative (A.12). We thus consider to what extent our results are robust to different values of the capital demand elasticity. Specifically, we consider values of α from 0.5 to 0.975 (which is our baseline). We then compute the relation between Γ_k and $\mathcal{L}_k$, as we did in Figure 4 in the main text, for each value of α.

The results from this exercise are reported in Figure A.1. The thick black line reports the relation between Γ_k and $\mathcal{L}_k$ using our baseline value of $\alpha = 0.975$, and thus is identical to the black line in Figure 4 in the main text. Also, the red diamond corresponds to the baseline calibration, as reported in Figure 3 in the main text. In line with the intuition outlined above, a more inelastic capital demand schedule (a lower value of α) initially makes the relative response of high-leverage firms stronger, as shown by a steepening of the relation between Γ_κ and $\mathcal{L}_\kappa$ for $\alpha = 0.95$ and $\alpha = 0.90$, for example. But, as α reaches low-enough values, this relation reverses. The slope of the lines in Figure A.1 flattens as α falls further, and eventually becomes negative. Thus, our framework implies that, in response to a fall in intermediaries' equity, the credit spread of high-leverage firms increases by more than the credit spread of low-leverage firms only if the capital demand schedule is elastic enough.

Shifts in the Capital Demand Schedule In the main text, we considered the transmission mechanism of monetary policy via a fall in intermediaries' equity. However, a monetary

Figure A.1 Leverage and Credit Spreads: Robustness



Note. Relation between relative credit spreads increase ($\Gamma_\kappa = \Delta CS_R - \Delta CS_{S,\kappa}$) and relative leverage ($\mathcal{L}_\kappa = L_R - L_{S,\kappa}$) for different values of the capital demand elasticity (α). Lines of different colors correspond to different values α, with the thicker black line corresponding to our baseline calibration of $\alpha = 0.975$. Different circles of a given color correspond to a different pair of risky-safe firms, obtained by varying the level of net worth (and thus leverage) of the safe firm. We report values of $\{\mathcal{L}_\kappa, \Gamma_\kappa\}$ only for equilibria where the financial constraint is binding for both firms. The red diamond denotes the relative credit spread increase in our baseline calibration described in Section 4 in the main text.

policy tightening also reduces the demand for capital via an increase in the risk free rate R (i.e. an increase in the risk free rate required on capital). As the capital demand schedule shifts downward, the equilibria for both the high-leverage and the low-leverage firms shift along their supply curves—causing, all else equal, credit spreads to fall. Note that, theoretically, a large enough shift in the capital demand schedule can dominate over the shift in the capital supply schedule—so that, in equilibrium, credit spreads fall for all firms. Our empirical results speak against this possibility: in the data, credit spreads increase in response to a monetary policy shock, implying that the shift in the capital demand schedule is small relative to the shift in the capital supply schedule.

What are the implications for the relative response of safe (low-leverage) and risky (high-leverage) firms? Because of the concavity of the capital supply schedule, the safe firm lies on a portion of the supply curve that is steeper relative to the risky firm. Thus, a downward shift in the demand schedule means that the fall in credit spreads is larger for the safe firm. This is different from Ottonello and Winberry (2020), where (due to convex supply schedules) a downward shift in the capital demand schedule could lead to a larger fall in the credit spreads of the risky firm—thus creating the possibility that, in equilibrium, high-leverage firms' spreads *fall* relative to low-leverage firms' spreads.

In sum, in our baseline calibration, a downward shift in the capital demand schedule (by reducing credit spreads more for low-leverage firms) generates the same cross-sectional patterns as an inward shift in the capital supply schedule, namely it makes high-leverage firms' credit spreads increase relative to low-leverage firms' spreads.

B Data

Corporate bond data. Corporate bond data for the United States are sourced from the Intercontinental Exchange-Bank of America Merrill Lynch (ICE-BofAML) Global Index System. We focus on bonds in the Global Corporate Index (`G0BC`) and the Global High 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.[2]

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. We also use the bond-specific ISIN codes in the data set to obtain additional characteristics on the bonds from Thomson Reuters Datastream. Specifically we merge in information on the seniority of each bond, whether the bond is callable, the issue date of the bond, the redemption date of the bond and the ISO country code of the bond. We also use the Thomson Reuters Datastream to obtain information on the coupon rate and amount issued when it is missing from the ICE BofAML data.

Event study data set. In the event study data set, the time dimension denotes FOMC meetings. In Table B.1 we summarize the characteristics of our US corporate bond sample which covers 156 FOMC meetings between August 1999 and November 2017. In any given month, each firm has on average around 4 bonds outstanding, although the distribution is positively skewed, with some firms having many bonds outstanding in any given month. The average amount issued is $631 million and the maximum amount issued is $15bn. We consider both high yield and investment grade bonds. The median credit rating is BBB2.

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

Just over 60 percent of the bond observations in our sample are callable bonds.

Table B.1 Bond Data Set: Summary Statistics

	Mean	Std. Dev.	Min	Median	Max
No. of Bonds per Firm/Month	4.2	5.2	1.0	2.0	59.0
Effective Yield (%)	4.9	2.9	0.1	4.6	38.0
Spread (%)	2.4	2.5	0.1	1.6	35.0
Coupon (%)	5.8	1.9	0.4	5.9	15.0
Amount Issued ($M)	631	549	25	500	15,000
Maturity at Issue (Years)	14.8	9.6	1.5	10.0	50.0
Time to Maturity (Years)	10.7	8.6	1.0	7.4	30.0
Effective Duration	6.8	4.1	0.0	5.8	19.7
Credit Rating (Composite)	-	-	C	BBB2	AAA
Callable (% of Observations)	61.3	-	-	-	-

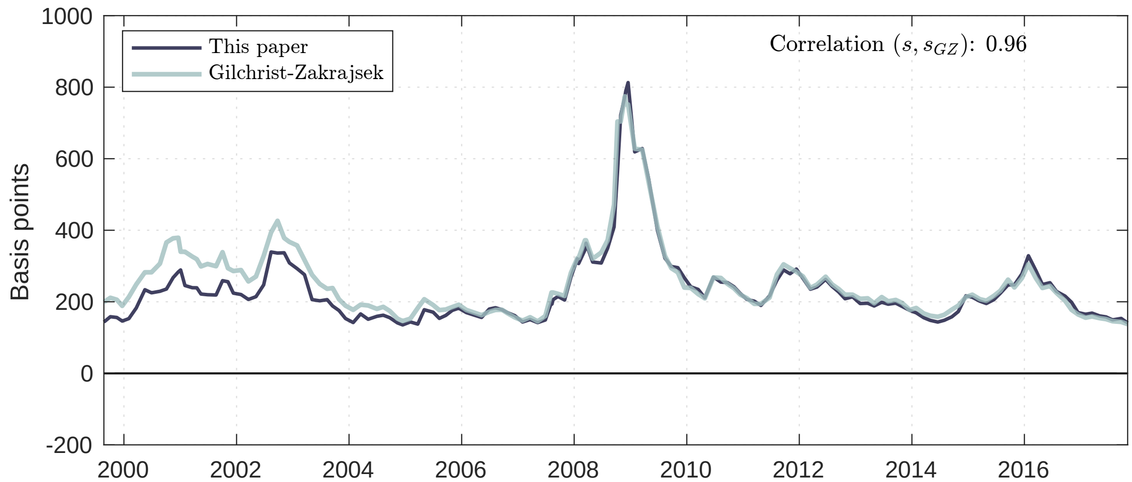
Note. Summary statistics for the 285,794 observations in the baseline specification in Column (1) of Table 2 in the main text. The sample period covers 156 FOMC meetings between August 1999 and November 2017.

Figure B.1 plots the average credit spread on outstanding bonds in our sample over the period 1999-2017. For comparison, we also plot the average credit spread calculated by Gilchrist and Zakrajsek (2012) (GZ). Our average credit spread closely tracks that of GZ other than for the period 2000-2003, for which the GZ average spread is more elevated. There are a number of reasons for the possible discrepancy between our measure and that of GZ. Firstly, the coverage of bonds in our data set differs from that of GZ. GZ use both Lehman/Warga and Merrill Lynch databases. The proportion of high yield bonds in our data set is relatively small at the beginning of our sample. If high yield bonds are more prominent in the GZ data set in these years, it may explain the elevated spreads. Secondly, the calculation of spreads is different in GZ. They construct a synthetic risk-free security with the same cash-flows as the corresponding corporate bond and then calculate the spread as the difference between the yield of the corporate bond and the yield of the synthetic security. No adjustment is made at this stage for callable bonds. In contrast, our spread measure is the "option-adjusted spread" calculated by ICE-BofAML.

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

Figure B.1 Credit Spreads: Comparison with GZ



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

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. **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 Section 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).

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

Table B.2 SECTORS IN BOFAML DATA SET

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

C Monetary Policy Surprises

To construct the monetary policy surprises we closely follow the methodology detailed in Jarociński and Karadi (2020). We identify monetary policy surprises by decomposing 30-minute surprises in the S&P 500 stock market index (s_t^{eq}) and the 3-month federal funds futures contract (s_t^{FF4}) using a sign restriction procedure. Specifically, we rotate the covariance matrix of $s = (s_t^{FF4}, s_t^{eq})$ with an orthonormal matrix and keep the draws that satisfy the following sign restrictions:

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

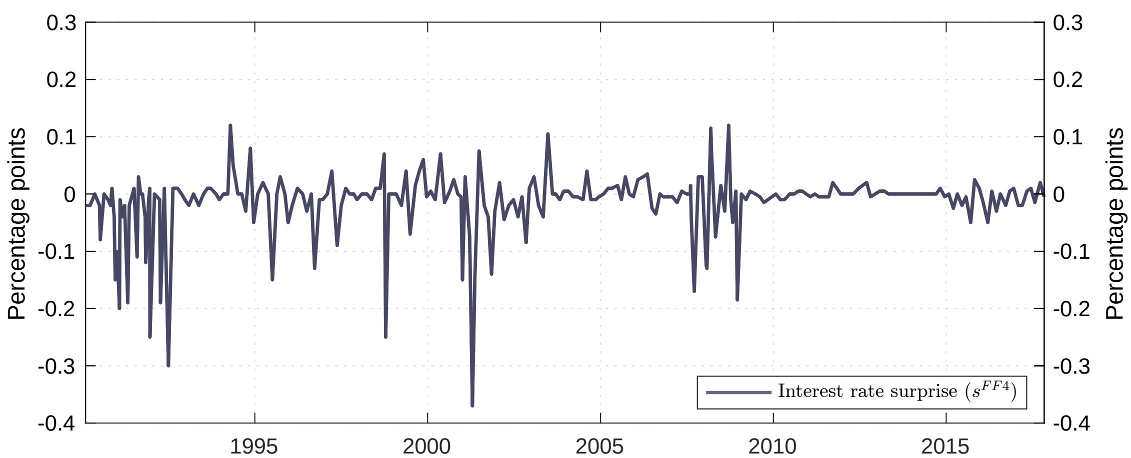
	Monetary shock (ϵ^m)	Non-monetary shock (ϵ^{other})
Equity surprise (s_t^{eq})	−	+
Interest rate surprise (s_t^{FF4})	+	+

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

For our empirical analysis, we construct time series of monetary (ϵ^m) and non-monetary (ϵ^{other}) shocks by taking the the median across $5,000$ admissible models. This means that

Figure C.1 displays the behavior of s_t^{FF4} over time, while Figure 1 in the main text displays the underlying orthogonal monetary (ϵ^m) and non-monetary (ϵ^{other}) surprises that drive s_t^{FF4}. The monetary surprise explains 70 percent of the total variance of s_t^{FF4}.

Figure C.1 HIGH FREQUENCY INTEREST RATE SURPRISES



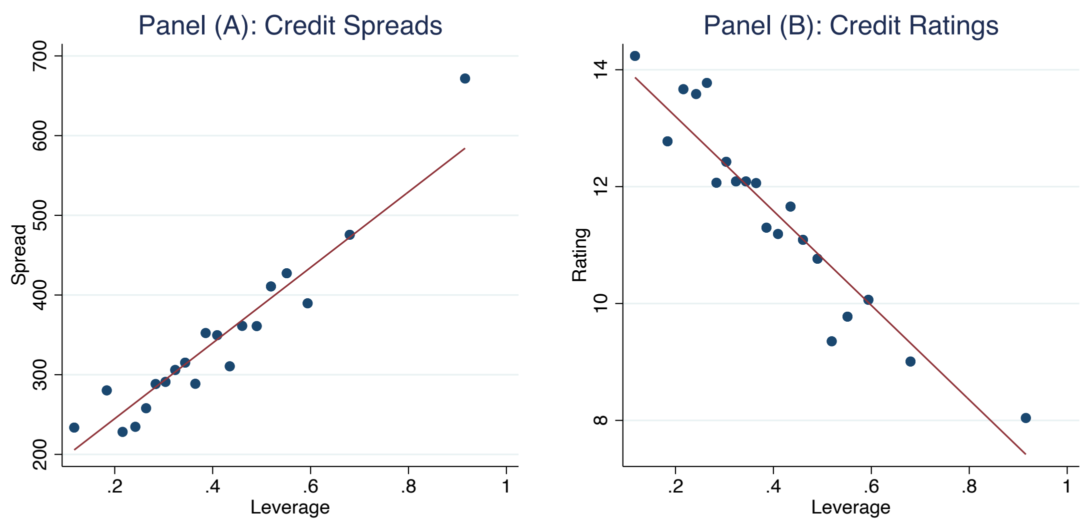
NOTE. This figure plots the raw 30-minute surprise in the 3-month ahead federal funds futures (FF4) contract (s_t^{FF4}) for each FOMC meeting in our sample.

D The Unconditional Relation Between Leverage & Credit Spreads

In our data the correlation between credit spreads and leverage is positive. Panel A of Figure D.1 reports a scatter plot of (average) firm level leverage on the horizontal axis against the (average) firm level credit spread. The right panel of Figure D.1 shows that high leverage and high credit spreads are associated with bad credit ratings—where a bad credit rating corresponds to a low number. The reduced form correlation between leverage and credit spreads is in line with the predictions from the simple model outlined in Section 4 in the main text. Moreover, the correlation between leverage and credit ratings justifies the specification of our market segmentation assumption in terms of leverage rather than credit ratings.

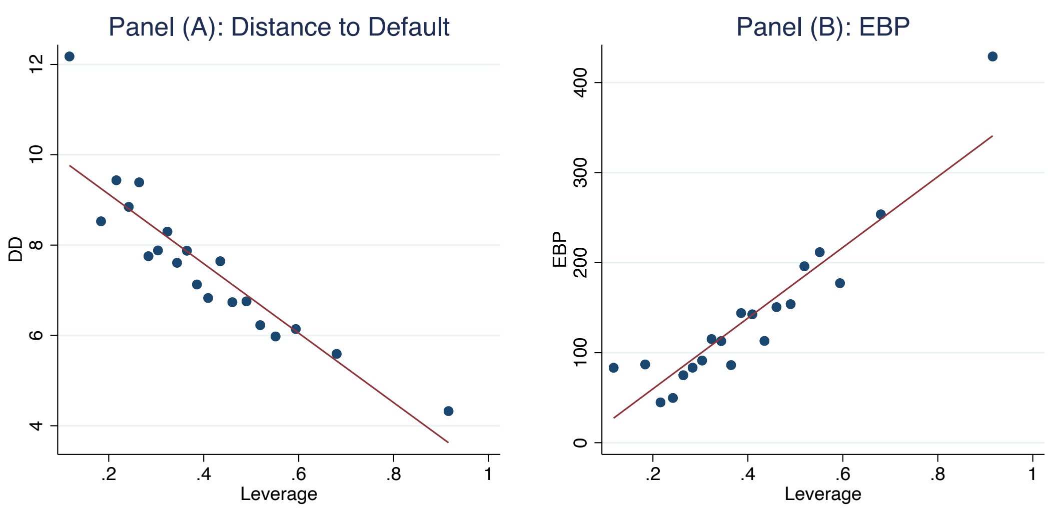
Figure D.2 decomposes the correlation between leverage and credit spreads shown in Panel (A) of Figure D.1 using the Gilchrist and Zakrajsek (2012) decomposition of credit spreads into a default component and a risk premium component. The Figure reports a scatter plot of (average) firm-level leverage on the horizontal axis against the (average) firm-level distance to default (Panel A) and the (average) firm-level EBP (Panel B). In the model, heterogeneity in entrepreneurs' net worth leads to heterogeneity in their leverage and, in turn, to heterogeneity in financial intermediaries' leverage. As a result, low net worth firms have a higher cost of external finance via two distinct channels. First, by assumption, low net worth firms face a higher default probability. Second, low net worth firms have a higher demand for credit, which leads the financial intermediary that deals with those firms to be more highly leveraged. As a result the intermediary's incentive to default is higher, which implies a higher EBP. Figure D.2 shows that the implications of the model are borne out in the data.

Figure D.1 Leverage and Credit spreads



Note. Binned scatter plot of (average) firm level leverage on the horizontal axis against the (average) firm level credit spread (panel A) and the average firm-level credit rating (panel B). The solid lines display the estimated relation between leverage and the credit spread / credit rating from a linear regression.

Figure D.2 Leverage, Distance to Default, and the Excess Bond Premium



Note. Binned scatter plot of (average) firm level leverage on the horizontal axis against the (average) firm level distance to default (panel A) and the average firm-level Excess Bond Premium (panel B). The solid lines display the estimated relation between leverage and the distance to default / EBP from a linear regression.

E Merton-KMV Model & Decomposing Credit Spreads

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

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

$$dV = \mu V dt + \sigma_V V dW \tag{E.1}$$

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

$$E = V\mathcal{N}(d_1) - e^{-rT}F\mathcal{N}(d_2) \tag{E.2}$$

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

$$d_1 = \frac{ln(V/F) + (r + 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}} \tag{E.3}$$

$$d_2 = d_1 - \sigma_V \tag{E.4}$$

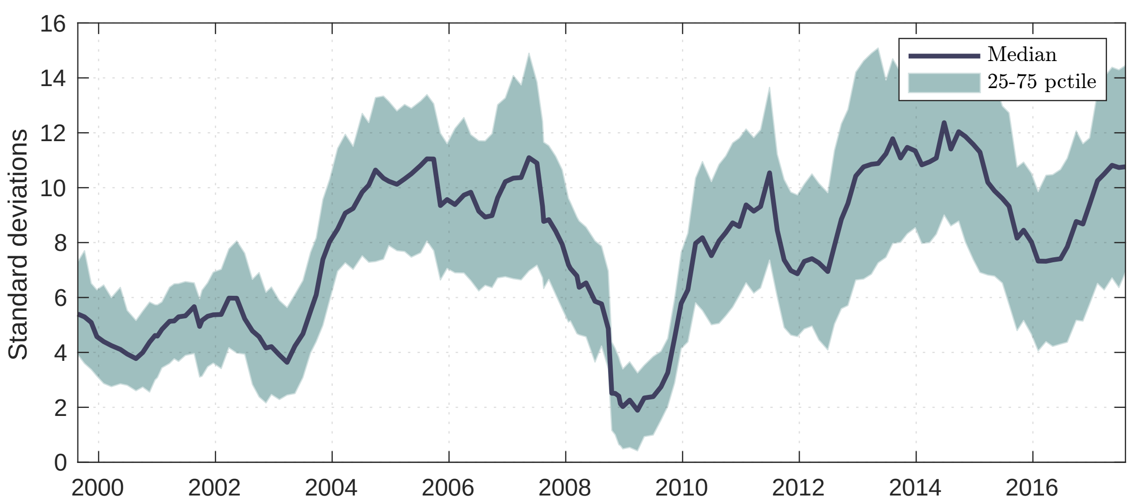
The standard Merton model supplements (E.2) with a second equation obtained from Ito's Lemma, giving two equations in two unknowns (V and σ_V) which can be solved simultaneously. But as discussed in Bharath and Shumway (2008), the volatility of market leverage means that simultaneously solving the two equations rarely provides meaningful results. Instead we use the "iterative procedure". We begin by guessing the value of asset volatility, given by $\sigma_V = \sigma_E[E/(E+F)]$, where σ_E is the volatility of the market value of equity. Using this guess, we use (E.2) to solve for the market value of the firm, V, for each day in the previous year. Using these estimates of the market value, we update our guess of σ_V by calculating the volatility of returns over the previous year. We continue this process until our guess of σ_V converges. Once the process has converged, we calculate the annual return on assets, μ, using our estimates of the market value of the firm. The distance to default for the firm is given by:

$$DD = \frac{ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}} \tag{E.5}$$

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

Figure E.1 plots the median distance to default in our data set around each FOMC date, together with the $25 - 75$ percentiles. The data suggests the distance to default of firms varies over the economic cycle, with significant variation both in the time series and in the cross-sectional dimension.

Figure E.1 The Cross-Section of the Distance to Default



Note. The figure plots the panel of the distance to default in our data set around FOMC dates. The dark solid line displays the cross-sectional median of the distance to default. The dark shaded areas display the 25-75 percentile range.Sample period: August 1999 to November 2017.

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

$$ln(cs_{ij,t}) = \lambda DD_{j,t} + \gamma X_{ij,t} + e_{ij,t} \tag{E.6}$$

where $cs_{ij,t}$ is the credit spread for firm j on bond i at time t, $DD_{j,t}$ is the firm-specific distance to default and $X_{ij,t}$ is a vector of bond-specific controls. The residuals obtained from estimating E.6 form our estimate of the bond-specific EBP.[3]

For comparability with GZ, we focus on senior unsecured bonds issued by domestic companies in the domestic currency. We exclude from our sample observations for which the spread is greater than $3,500$ basis points or below 5 basis points, bonds which have less than one year or more than thirty years to maturity and bonds which have a face value of less than $150 million. Our vector of controls $X_{ij,t}$ includes the face value of the bond, its duration, the coupon rate, and the age of the bond. Similar to GZ, we also consider a correction for the bonds that are callable.[4]

Table E.1 Credit Spreads Decomposition: OLS Regression

	(log)Spread ($ln(cs_{ij,t})$)
Distance to default	-0.0542***
	(0.0035)
log(Age)	0.0061
	(0.0047)
Log(Issuance)	-0.0225***
	(0.0085)
log(Duration)	0.2789***
	(0.0121)
log(Coupon)	0.4258***
	(0.0204)
R-squared	0.7532
Observations	941,541

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

In Table E.1 we present the results from the regression of corporate bond spreads on the distance to default and a number of bond controls (shown in equation (E.6)), which we use

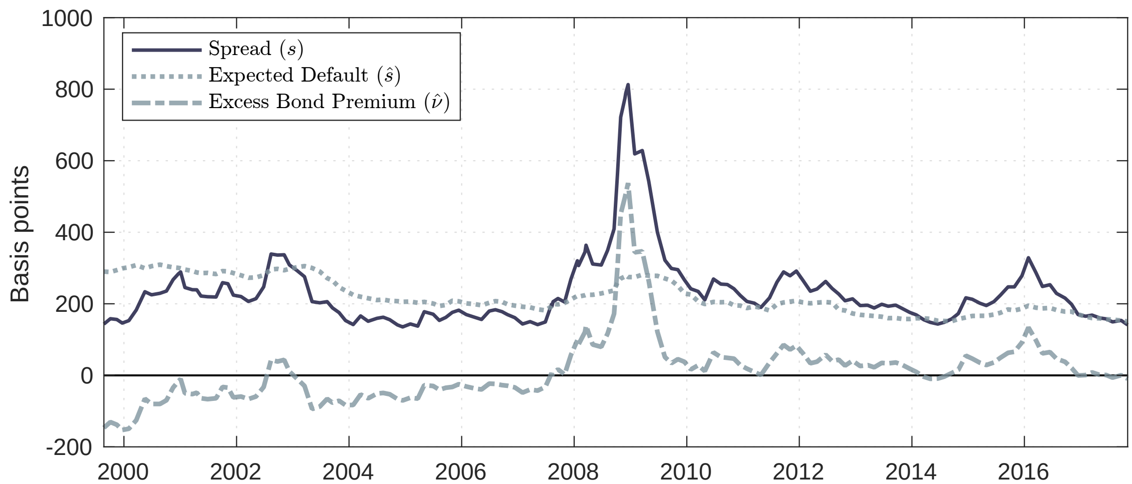
[3] Gilchrist and Zakrajsek (2012) define the excess bond premium at the aggregate level as the mean of the bond-specific excess bond premia.

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

to decompose spreads into a component associated with the probability of default and the 'excess bond premium'.

Figure E.2 plots the decomposition of average spreads into the average fitted component and the average excess bond premium using the regression results reported in Table E.1. In the five years prior to the financial crisis, the average excess bond premium was low (and largely negative). The average excess bond premium increased sharply during the financial crisis in 2008. Since the financial crisis, the average excess bond premium has fallen back, although remains at a slightly more elevated level than prior to the crisis.

Figure E.2 Credit Spreads Decomposition: Expected Default and the Excess Bond Premium

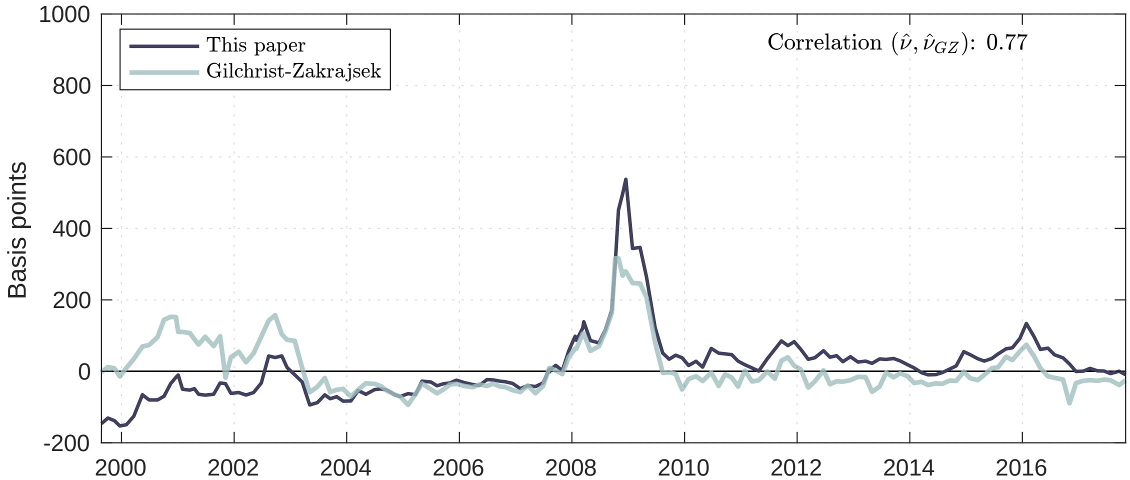


Note. The Figure plots the decomposition of average credit spreads into the average fitted component and the average excess bond premium, computed according the regression results reported in Table E.1.

Our average excess bond premium follows a similar profile to the excess bond premium calculated by GZ. The correlation over the whole sample period, from August 1999 to November 2017, is 0.77. Similar to the profiles of average spreads, shown in Figure E.3, the GZ excess bond premium is elevated relative to our measure for the period 2000-2003. Comparing our measure to the GZ excess bond premium over the period January 2003-November 2017, the correlation coefficient is 0.96.

Note that, in any case, some differences in the profile of the EBP are to be expected. Our sample period is different from the original sample used by GZ and they obtain credit spreads from different sources. Moreover, we use credit spreads data bracketing FOMC announcements for the estimation of specification (E.6), while GZ use end of month observations. The high correlation between our EBP series and GZ's original one is reassuring, suggesting that the EBP is robust to different specifications, data, and potential time variation in the

Figure E.3 Excess Bond Premium: Comparison with GZ



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

estimated coefficients.

F High Frequency Event Study: Additional Results

In this Section we describe additional results and robustness checks that are complementary to the findings reported in Section 2 in the main text.

Table F.1 reports the same exercises shown in Table 2 in the main text, but instead of using the high-leverage dummy $\ell^{High}_{j,t-1}$ (which is equal to 1 when the leverage of firm j lies above the median leverage in the distribution), we use the continuous leverage measure $L_{j,t-1}$ interacted with the monetary policy surprises. We standardize $L_{j,t-1}$ over the sample so that the coefficient γ captures the marginal impact of ϵ^m_t on $\Delta cs_{ij,t}$ for a firm whose leverage is 1 standard deviation above the average leverage in the sample.

In order to address the concern that leverage might be correlated with other firm characteristics, in the main text we run a series of 'double-interaction' regressions—see equation (2) in the main text. Similarly, Table F.2 reports the results from the estimation of equation (2) in the main text using the continuous leverage interaction $L_{j,t-1}$, rather than the high-leverage dummy $\ell^{High}_{j,t-1}$. The results are unchanged.

Tables F.3 and F.4 report the results from an exercise where we consider the interaction between monetary policy surprises and alternative proxies for financial constraints, instead of leverage. Specifically, we consider firm (log) size, sales growth, credit rating, time since IPO, a measure of the firm's distance to default (calculated using the Merton-KMV framework, detailed in Appendix E), the ratio between total debt and EBITDA, and the measure of a firm's liquid assets used in Jeenas (2018). Table F.3 considers the interaction of monetary policy surprises with high financial constraint dummies, $x^{High}_{j,t-1}$, while F.4 considers continuous measures of financial constraints, $x_{j,t-1}$.

While the fitted spreads $\hat{cs}_{ij,t}$ can explain almost 75 percent of the variation in overall credit spreads, the excess bond premium $\hat{\nu}_{ij,t}$ inherits much of the volatility of credit spreads (see Figure E.2 in Online Appendix E). Therefore, the result in Table 5 in the main text could simply reflect the higher variance of $\hat{\nu}_{ij,t}$ relative to $\hat{cs}_{ij,t}$. To check whether this is the case, we re-estimate specification (1) after standardizing both series, which we label $\widetilde{\Delta\hat{cs}}_{ij,t}$ and $\widetilde{\Delta\hat{\nu}}_{ij,t}$. The results (reported in F.5) show that the response of $\widetilde{\Delta\hat{\nu}}_{ij,t}$ is still significantly larger than $\widetilde{\Delta\hat{cs}}_{ij,t}$. This implies that the larger coefficient in Table 5 is not only due to the higher variance of $\hat{\nu}_{ij,t}$ (relative to $\hat{cs}_{ij,t}$), but also to a stronger transmission via the EBP.

Table F.6 reports the results from a simple time series regression of credit spreads (and their decomposition into fitted spreads and excess bond premium) on the monetary policy surprises. We do this by taking an average of the credit spread of all outstanding bonds at each time period t , using the amount issued with each bond as a weight.

In an additional robustness exercise, we check that our baseline findings are robust to alternative approaches to control for the information component embedded in the raw interest rate surprises s_t^{FF4}. Specifically, we consider the response of credit spreads to the monetary policy surprises calculated by Miranda-Agrippino and Ricco (2021). The results are reported in Table F.7.

Table F.8 reports the estimation results from simple regressions of credit spreads on different monetary surprises (i.e. the raw surprises, as well as the monetary and non-monetary components obtained using the approach in Jarociński and Karadi (2020)), without time-sector fixed effects and abstracting from the effect of firm leverage. The average response of credit spreads to the raw interest rate surprises (s_t^{FF4}) is estimated at 10 basis points, as shown in column (1). This estimate is almost three times smaller than the credit spread response to monetary surprises (ϵ^m), reported in column (2). The estimate in column (1) not only is smaller, but also is less statistically significant, with a p-value of 0.08 relative to a p-value of less than 0.01 in our baseline. These differences could reflect the fact that an increase in s_t^{FF4} is, in general, due to a linear combination of two forces that have opposing effects on credit spreads: (i) a monetary policy contraction (ϵ^m) that acts to increase credit spreads; and (ii) a systematic monetary policy tightening by the central bank to respond to improved demand conditions (ϵ_t^{other}), which acts to compress credit spreads (see Jarociński and Karadi, 2020). Consistent with this interpretation, the response of credit spreads to non-monetary news (ϵ_t^{other}) is strongly negative at -25 basis points (as shown in column (3) of Table F.8), even though it is not statistically significant.

Table F.9 considers the response of the distance to default measure to monetary policy surprises. The results in Column (1) show that the distance to default measure falls by 0.34 standard deviations in response to a contractionary monetary policy shock. The magnitude of the response, however, is small compared to the unconditional variance of the distance to default. The results in columns (2) and (3) are insignificant, suggesting that response of the distance to default to monetary policy does not vary systematically with firm leverage.

Table F.10 focuses just on the sample of bonds that are non-callable and reports the results from the simple specification which excludes time-sector fixed effects and abstracts from the role of leverage. It considers the decomposition of spreads into fitted spreads and the excess bond premium. The results are similar to the main results which include callable bonds, suggesting that spreads increase in response to monetary policy tightening, with almost all of the effect due to the excess bond premium.

Table F.11 also focuses on the sample of bonds that are non-callable and reports the results from specification (1) in the main text, with the decomposition of spreads into fitted spreads and the excess bond premium. The results are similar to our main results, suggesting that in response to monetary policy tightening, spreads increase more for highly leveraged firms and that the EBP accounts for most of the relative response.

Table F.1 Heterogeneous Response of Credit Spreads: Robustness To Continuous Leverage

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)	(4)	(5)
	Time-sector FE	Controls	Within Leverage	IV	Pre-crisis
MP surp.×Lev. ($\epsilon^m \times L_j$)	13.59*	13.21*			17.42***
	(7.28)	(7.54)			(5.08)
MP surp.×Lev. ($\epsilon^m \times \tilde{L}_j$)			11.40**		
			(5.46)		
1yr Rate x Lev. ($\epsilon^m \times L_j$)				12.41***	
				(0.67)	
Double clustering	Yes	Yes	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.309	0.304	0.309	-0.028	0.345
Observations	279,603	267,306	279,603	279,603	52,056

Note. Results from estimating specification (1) in the main text, namely $\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma\,(\epsilon_t^m L_{j,t-1}) + \delta L_{j,t-1} + e_{ij,t}$ and its variants described in the text, where ϵ_t^m is the monetary policy surprise; Δcs_{it} is the change in spreads between the day before the FOMC announcement and five days after the announcement; L_j is the (standardized) leverage of firm j; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $\tilde{L}_j$ is the within-firm ($L_{j,t-1} - \mathbb{E}_j[L_{j,t-1}]$) standardized leverage; *1yr Rate* is the 1-year T-bill. Standard errors (reported in parentheses) are clustered two-way, at the firm level and time level. Additional controls include firm (log) size, sales growth, 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 $p < 0.1$).

Table F.2 Heterogeneous Response of Credit Spreads to Monetary Policy: Additional Interactions (Continuous)

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	Size	Sales Growth	Credit Rating	Time IPO	DD	Debt-Ebitda	Liquid Assets
MP surp.×Lev. ($\epsilon^m \times L_j$)	13.43*	14.26*	13.54*	9.59*	13.23*	11.83*	13.83*	13.46*
	(7.32)	(7.81)	(7.35)	(5.25)	(7.16)	(7.04)	(7.81)	(7.32)
MP surp.×Size ($\epsilon^m \times X_j$)		2.64						
		(5.63)						
MP surp.×Sales growth ($\epsilon^m \times X_j$)			1.01					
			(1.86)					
MP surp.×Credit rating ($\epsilon^m \times X_j$)				-9.03				
				(8.00)				
MP surp.×Time IPO ($\epsilon^m \times X_j$)					-1.32			
					(3.51)			
MP surp.×DD ($\epsilon^m \times X_j$)						-6.92		
						(5.76)		
MP surp.×Debt-Ebitda ($\epsilon^m \times X_j$)							3.20	
							(2.89)	
MP surp.×Liquid Assets ($\epsilon^m \times X_j$)								0.86
								(1.13)
Double clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.309	0.309	0.309	0.310	0.309	0.310	0.311	0.309
Observations	279,603	279,603	279,075	277,288	279,603	277,281	251,257	279,597

Note. Results from estimating specification (2) in the main text, namely $\Delta cs_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma\,(\epsilon_t^m L_{j,t-1}) + \delta\,(\epsilon_t^m X_{j,t-1}) + \Gamma W_{j,t-1} + e_{ij,t}$, where ϵ_t^m is the monetary policy surprise; Δcs_{it} is the change in spreads between the day before the FOMC announcement and five days after the announcement; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; L_j is the (standardized) leverage of firm j; X_j is a (standardized) generic characteristic of firm j, namely size, sales growth, credit rating, time since IPO, distance to default (DD), debt-to-EBITDA ratio, and liquid assets. 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 $p < 0.1$).

Table F.3 HETEROGENEOUS RESPONSE OF CREDIT SPREADS: OTHER INTERACTIONS (HIGH/LOW DUMMY)

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Size	Sales Growth	Credit Rating	Time IPO	DD	Debt-Ebitda	Liquid Assets
MP surp.×Size ($\epsilon^m \times x_j^{High}$)	-3.18						
	(7.49)						
MP surp.×Sales growth ($\epsilon^m \times x_j^{High}$)		-6.35					
		(6.67)					
MP surp.×Credit rating ($\epsilon^m \times x_j^{High}$)			-14.26				
			(8.97)				
MP surp.×Time IPO ($\epsilon^m \times x_j^{High}$)				-3.30			
				(5.58)			
MP surp.× DD ($\epsilon^m \times x_j^{High}$)					-7.27		
					(9.22)		
MP surp.× Debt-Ebitda ($\epsilon^m \times x_j^{High}$)						22.55**	
						(10.57)	
MP surp.×Liquid Assets ($\epsilon^m \times x_j^{High}$)							1.24
							(3.97)
Double clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.320	0.320	0.321	0.320	0.321	0.310	0.320
Observations	285,272	284,732	283,076	285,332	283,069	251,257	285,262

NOTE. Results from estimating equation (1) in the main 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; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $x_{j,t-1}^{High} = 1$ when a given characteristic (X) of firm j, namely size, sales growth, credit rating, time since IPO, distance to default (DD), debt-to-EBITDA ratio, and liquid assets lies above the median of its distribution (and zero otherwise). Standard errors (reported in parenthesis) are clustered at the firm level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

Table F.4 Heterogeneous Response of Credit Spreads: Other Interactions (Continuous)

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Size	Sales Growth	Credit Rating	Time IPO	DD	Debt-Ebitda	Liquid Assets
MP surp.×Size ($\epsilon^m \times X_j$)	-2.00						
	(5.17)						
MP surp.×Sales growth ($\epsilon^m \times X_j$)		-0.25					
		(2.33)					
MP surp.×Credit rating ($\epsilon^m \times X_j$)			-14.31				
			(9.21)				
MP surp.×Time IPO ($\epsilon^m \times X_j$)				-3.64			
				(4.16)			
MP surp.×DD($\epsilon^m \times X_j$)					-13.52*		
					(7.40)		
MP surp.×Debt-Ebitda ($\epsilon^m \times X_j$)						1.27	
						(2.24)	
MP surp.×Liquid Assets ($\epsilon^m \times X_j$)							0.04
							(1.36)
Double clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.320	0.320	0.322	0.320	0.322	0.310	0.320
Observations	285,272	284,732	283,076	285,332	283,069	251,257	285,262

Note. Results from estimating equation (1) in the main 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; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $X_{j,t-1}$ is a (standardized) generic characteristic of firm j, namely size, sales growth, credit rating, time since IPO, distance to default (DD), debt-to-EBITDA ratio, and liquid assets. Standard errors (reported in parenthesis) are clustered at the firm level. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

Table F.5 EXPECTED DEFAULT AND EXCESS BOND PREMIUM: STANDARDIZED SERIES

	(1)	(2)
Dep. Variable:	Default Risk, Standardized ($\widetilde{\Delta\hat{cs}}$)	Exc. Bond Premium, Standardized ($\widetilde{\Delta\hat{\nu}}$)
MP surp. (ϵ^m)	0.49	0.72**
	(0.30)	(0.30)
Double clustering	Yes	Yes
Time-sector FE	No	No
R-squared	0.030	0.033
Observations	285,794	285,794

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

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

	(1)	(2)	(3)
Dep. Variable:	Spread (Δcs)	Default Risk ($\Delta\hat{cs}$)	Exc. Bond Premium ($\Delta\hat{\nu}$)
MP surp. (ϵ^m)	22.45***	1.78	20.67***
	(6.57)	(1.30)	(6.09)
Double clustering	No	No	No
Time-sector FE	No	No	No
R-squared	0.071	0.012	0.070
Observations	156	156	156

NOTE. Results from estimating a simple time series regression of credit spreads (and their decomposition into fitted spreads and excess bond premium) on the monetary policy surprises, namely $y_t = \alpha_i + \beta\epsilon_t^m + e_t$, where $y_{it} = \Delta cs_t, \Delta\hat{cs}_t, \Delta\hat{\nu}_t$; ϵ_t^m is the monetary policy surprise, Δcs_t, $\Delta\hat{cs}_t$, and $\Delta\hat{\nu}_t$ are the change in spreads, fitted spreads and the excess bond premium between the day before the FOMC announcement and five days after the announcement, respectively, on average across all outstanding bonds at each time t (using the amount issued with each bond as a weight); α_i is a constant. Standard errors are reported in parentheses. Credit spreads are measured in basis points and the size of the surprise is normalized so that it corresponds to a 25 basis points increase in the 1-year T-bill. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

Table F.7 Miranda-Agrippino and Ricco (2020) Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable:	Spread (Δcs)	Default Risk ($\Delta \hat{cs}$)	Exc. Bond Premium ($\Delta \hat{\nu}$)	Spread (Δcs)	Default Risk ($\Delta \hat{cs}$)	Exc. Bond Premium ($\Delta \hat{\nu}$)
MP surp.×Lev. ($\epsilon^m \times \ell_j^{High}$)	11.46*	0.81	10.66*			
	(6.51)	(0.95)	(5.65)			
MP surp.×Lev. ($\epsilon^m \times L_j$)				11.98**	0.76	11.22**
				(4.90)	(0.68)	(4.44)
Double clustering	Yes	Yes	Yes	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.341	0.444	0.331	0.344	0.444	0.334
Observations	52,056	52,056	52,056	52,056	52,056	52,056

Note. Results from estimating $y_{it} = \alpha_i + \beta_{sct,t} + \gamma(\epsilon_t^m \ell_{j,t-1}^{High}) + \delta \ell_{j,t-1}^{High} + e_{ij,t}$ and $y_{it} = \alpha_i + \beta_{sct,t} + \gamma(\epsilon_t^m L_{j,t-1}) + \delta L_{j,t-1} + e_{ij,t}$, 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 from Miranda-Agrippino and Ricco (2021); $\Delta cs_{ij,t}$, $\Delta \hat{cs}_{ij,t}$, 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; $\ell_{j,t-1}^{High} = 1$ when firm j leverage lies above the median of the leverage distribution (and zero otherwise); L_j is the standardized leverage of firm j; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect. 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 $p < 0.1$).

Table F.8 Average Response of Credit Spreads: Monetary Vs. Non-Monetary Surprises

Dep. Variable: Δcs_{ij}	(1)	(2)	(3)
Indep. Variable:	Interest rate surp. (s^{FF4})	Monetary surp. (ϵ^m)	Non-monetary surp. (ϵ^{other})
MP surprise	10.15*	27.68**	-24.91
	(5.86)	(10.62)	(16.47)
Time-Sector FE	No	No	No
Double clustering	Yes	Yes	Yes
R-squared	0.030	0.034	0.031
Observations	285,794	285,794	285,794

Note. Results from estimating the specification $y_{ij,t} = \alpha_i + \beta \epsilon_t^m + e_{ij,t}$, with different high frequency surprises. In column (1) the independent variable is the raw FF4 surprise (s_t^{FF4}); column (2) is the baseline monetary surprise (ϵ_t^m); and 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; 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 $p < 0.1$).

Table F.9 Response of Distance to Default to Monetary Shocks

	(1)	(2)	(3)
Dep. Variable:	Distance to Default (Δdd)	Distance to Default (Δdd)	Distance to Default (Δdd)
MP surp (ϵ^m)	-0.34**		
	(0.16)		
MP surp.×Lev. ($\epsilon^m \times \ell_j^{High}$)		0.06	
		(0.04)	
MP surp.×Lev. ($\epsilon^m \times L_j$)			0.05
			(0.03)
Double clustering	Yes	Yes	Yes
Time-sector FE	No	Yes	Yes
R-squared	0.028	0.372	0.372
Observations	285,794	279,603	279,603

Note. Results from estimating $y_{ij,t} = \alpha_i + \beta\epsilon_t^m + e_{ij,t}$ and $y_{it} = \alpha_i + \beta_{sct,t} + \gamma(\epsilon_t^m \ell_{j,t-1}^{High}) + \delta\ell_{j,t-1}^{High} + e_{ij,t}$ and $y_{it} = \alpha_i + \beta_{sct,t} + \gamma(\epsilon_t^m L_{j,t-1}) + \delta L_{j,t-1} + e_{ij,t}$, where $y_{it} = \Delta dd_{ij,t}$ is the change in the distance to default between the day before the FOMC announcement and five days after the announcement; ϵ_t^m is the monetary policy surprise; $\ell_{j,t-1}^{High} = 1$ when firm j leverage lies above the median of the leverage distribution (and zero otherwise); L_j is the standardized leverage of firm j; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect. Standard errors (reported in parentheses) are clustered two-way, at the firm level and time level. 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 $p < 0.1$).

Table F.10 Expected Default and Excess Bond Premium: Non-Callable Bonds

	(1)	(2)	(3)
Dep. Variable:	Spread (Δcs)	Default Risk ($\Delta \hat{cs}$)	Exc. Bond Premium ($\Delta\hat{\nu}$)
MP surp. (ϵ^m)	32.89***	3.03*	29.86***
	(10.41)	(1.62)	(10.13)
Double clustering	Yes	Yes	Yes
Time-sector FE	No	No	No
R-squared	0.037	0.023	0.034
Observations	110,493	110,493	110,493

Note. Results from estimating $y_{ij,t} = \alpha_i + \beta\epsilon_t^m + e_{ij,t}$, where $y_{it} = (\Delta cs_{ij,t}, \Delta\hat{cs}_{ij,t}, \Delta\hat{\nu}_{ij,t})$; ϵ_t^m is the monetary policy surprise, $\Delta cs_{ij,t}$, $\Delta\hat{cs}_{ij,t}$, and $\Delta\hat{\nu}_{ij,t}$ are the change in spreads, fitted spreads and the excess bond premium between the day before the FOMC announcement and five days after the announcement, respectively; α_i is a bond fixed-effect. The sample only includes non-callable bonds. 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 $p < 0.1$).

Table F.11 EXPECTED DEFAULT AND EXCESS BOND PREMIUM: HETEROGENEITY, NON-CALLABLE BONDS

	(1)	(2)	(3)
Dep. Variable:	Spread (Δcs)	Default Risk ($\Delta \hat{cs}$)	Exc. Bond Premium ($\Delta \hat{\nu}$)
MP surp.×Lev. ($\epsilon^m \times \ell_j^{High}$)	16.99***	-0.17	17.16***
	(6.23)	(0.53)	(6.46)
Double clustering	Yes	Yes	Yes
Time-sector FE	Yes	Yes	Yes
R-squared	0.402	0.522	0.388
Observations	107,187	107,187	107,187

NOTE. Results from estimating specification (1) in the main text, namely $y_{ij,t} = \alpha_i + \beta_{sct,t} + \gamma(\epsilon_t^m \ell_{j,t-1}^{High}) + \delta\ell_{j,t-1}^{High} + e_{ij,t}$, where 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; $\ell_{j,t-1}^{High} = 1$ when the leverage of firm j lies above the median of the leverage distribution (and zero otherwise); α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect. The sample only includes non-callable bonds. 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 $p < 0.1$).

G 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 (details reported in Appendix B). 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:

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

where $y_{j,\tau}$ is debt or investment of firm j in quarter τ; $\beta_{sct,\tau}$ is a quarter-sector fixed effect; $\ell_{j,\tau-1}^{High}$ 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.

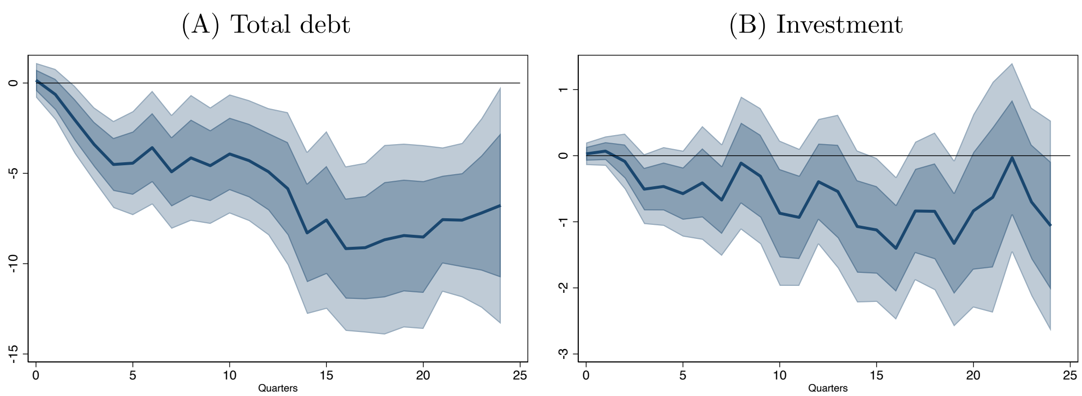
The resulting relative impulse responses for total debt and investment, captured by the coefficient γ^h, are reported in Figure G.1, in Panel A and Panel B, respectively. Panel A shows that the relative response of total debt for high-leverage firms becomes negative and statistically significant shortly 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.

First, we compare our results on debt and investment to Cloyne et al. (2018), Jeenas (2018), and Ottonello and Winberry (2020) by estimating our specification on pre-crisis data. Relative to these studies, our sample of firms is smaller (as we keep only firms for which we can match credit spread data) and the series of monetary surprises is different. Figure G.2 reports the relative impulse responses based on specification (G.1) for total debt (Panel A) and investment (Panel B). As in our full sample results, the impulse responses in Figure G.2 show that high-leverage firms contract their debt and investment by more than low-leverage firms. Again, as in our baseline, the relative response on debt is more precisely estimated than the relative response of investment.

Second, as discussed in the main text, Ottonello and Winberry (2020) argue that it is important to use *within-firm* variation in leverage—rather than the firm's leverage in the previous quarter—as an interaction variable, to control for permanent differences in firm leverage. We therefore estimate specification (G.1) for debt and investment using a dummy variable that is based on *within-firm* variation in leverage, namely $\mathcal{L}_{j,t-1} = L_{j,t-1} - \mathbb{E}_j[L_{j,t-1}]$, as an interaction variable. Figure G.3 shows that our results are not materially affected by the definition of the interaction variable.

In sum, the results in this Section 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.

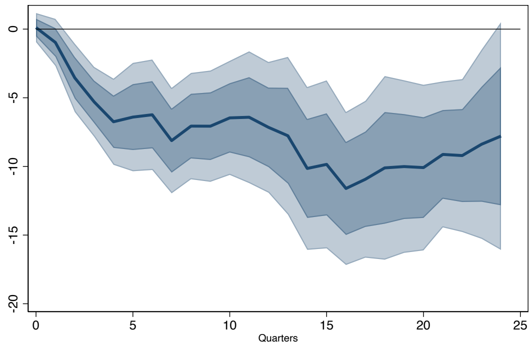
Figure G.1 HETEROGENEOUS RESPONSES OF DEBT AND INVESTMENT



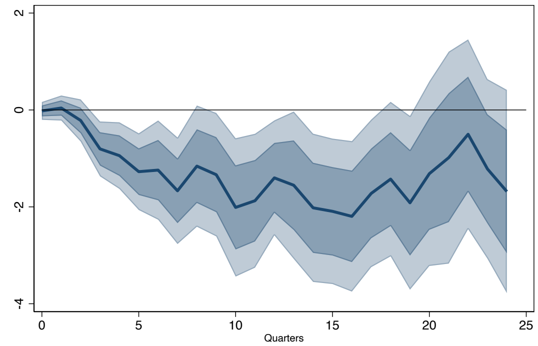
NOTE. Relative impulse response of total debt and investment. The impulse responses (γ^h) are estimated with the local projection specification in (G.1), namely $y_{j,\tau+h} - y_{j,\tau-1} = \alpha_j^h + \beta_{sct,\tau} + \gamma^h \epsilon_\tau^m \ell_{j,\tau-1}^{High} + \sum_{p=1}^{P} \Gamma_p W_{j,\tau-p} + e_{j,\tau+h}$, 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; $\ell_{j,\tau-1}^{High} = 1$ when firm j 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.

Figure G.2 Heterogeneous Response of Debt and Investment: Pre-Crisis Sample

(A) Total debt



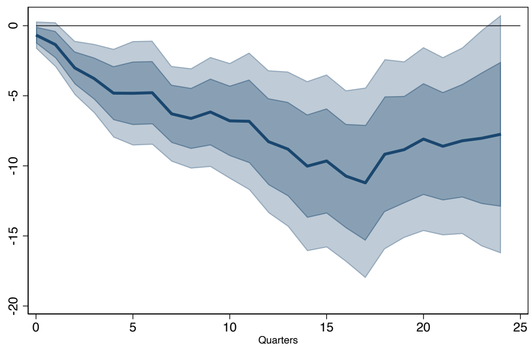
(B) Investment



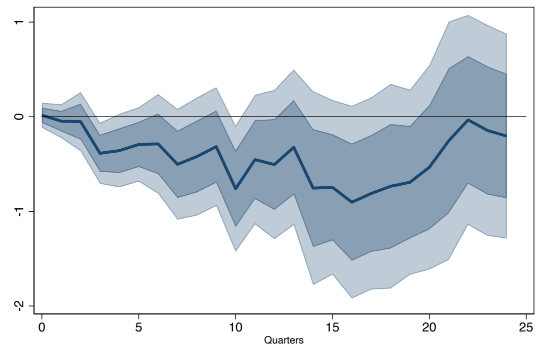
Note. Relative impulse response of total debt and investment with data up to 2007 Q4. The impulse responses (γ^h) are estimated with the local projection specification in (G.1), namely $y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta_{sct,t} + \gamma^h \epsilon_\tau^m \ell_{j,t-1}^{High} + \sum_{p=1}^{P} \Gamma_p W_{j,t-p} + e_{j,t+h}$, where $h = 0, 1, 2, ..., 24$; j; ϵ_τ^m is the monetary policy surprise; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $\ell_{j,t-1}^{High} = 1$ when firm j leverage lies above the median of the leverage distribution (and zero otherwise); the vector $W_{j,t}$ includes firm-level controls, namely leverage, size, real sales growth and current assets share. The shaded areas display 68 and 90 percent confidence intervals based on two-way clustered (quarter and firm) standard errors.

Figure G.3 Heterogeneous Response of Debt and Investment: Pre-Crisis Sample & Within-Firm Leverage

(A) Total debt



(B) Investment



Note. Relative impulse response of total debt and investment with data up to 2007:Q4. The impulse responses (γ^h) are estimated with the local projection specification in (G.1), namely $y_{j,t+h} - y_{j,t-1} = \alpha_j^h + \beta_{sct,t} + \gamma^h (\epsilon_\tau^m \mathcal{L}_{j,t-1}) + \sum_{p=1}^{P} \Gamma_p W_{j,t-p} + e_{j,t+h}$, where $h = 0, 1, 2, ..., 24$; j; ϵ_τ^m is the monetary policy surprise; α_i is a bond fixed-effect; $\beta_{sct,t}$ is a time-sector fixed effect; $\mathcal{L}_{j,t-1}1$ is defined by $L_{j,t-1} - \mathbb{E}_j[L_{j,t-1}]$; the vector $W_{j,t}$ includes firm-level controls, namely leverage, size, real sales growth and current assets share. The shaded areas display 68 and 90 percent confidence intervals based on two-way clustered (quarter and firm) standard errors.

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