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Credit risk and the transmission of interest rate shocks[☆]

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ABSTRACT

Using daily credit default swap (CDS) data, we find a positive relation between corporate credit risk and unexpected monetary policy shocks during FOMC announcement days. Positive shocks to interest rates increase the expected loss component of CDS spreads as well as a risk premium component. However, not all firms respond in the same manner. We show that firm-level credit risk is an important driver of the monetary policy response, both in credit and equity markets, and its role is not diminished by the inclusion of other risk proxies. A stylized corporate model of monetary policy, investment, and financing rationalizes our findings.

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1. Introduction

Understanding the transmission of interest rate shocks to corporations is of paramount importance to policymakers and economic researchers, as corporate borrowing is widely used to fund investment, production, labor, and other real activities. While economic theory suggests that firms obtain credit at a premium that compensates for default risk, it is still widely debated as to how corporate credit risk is affected by monetary policy. This transmission mechanism has played a crucial role in policy responses over the last two decades.[1]

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[1] The financial crisis of 2008-09 featured a number of non-financial firms whose credit spreads were disproportionately affected. Zero lower bound policy and large-scale asset purchases by the Federal Reserve during the 2008-09 Global Financial Crisis greatly helped these disproportionately affected firms (see Gilchrist and Zakrajsek (2013), Swanson and Williams (2014), and Swanson (2016)).

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In this paper, we connect unexpected interest rate movements to fluctuations in credit risk to shed more light on this transmission mechanism. To measure credit risk at the firm-level, we take advantage of daily quoted prices on the corporate, single name, credit default swap (CDS) market. Using CDS rates allows us to conveniently separate the two main components of credit spreads, an expected loss component and a credit risk premium, and independently study their reaction to monetary policy surprises.[2]

Our baseline monetary policy shock is given by 30-minute movements in the 2-year on-the-run US Treasury security surrounding FOMC announcements. We use this particular maturity as Hanson and Stein (2015) and Swanson (2021) show that forward guidance movements, present in both conventional and unconventional periods, highly relate to medium-term treasuries. To ensure that our results are driven by *pure* monetary policy disturbances, we use two additional measures that control for a central bank information effect (e.g., Romer and Romer (2000); Nakamura and Steinsson (2018)). The first shock is obtained by applying a simplified version of the procedure described in Jarocinski and Karadi (2020) to split movements of our baseline policy measure into monetary policy and non-policy related movements. The second one is a monetary policy shock developed by Bu et al. (2021) that uses the entire term structure of Treasury securities for identification purposes.

Using daily data going back to the early 2000s, we find a positive and significant relationship between unexpected monetary policy shifts and credit risk around Federal Open Market Committee (FOMC) announcement days. We document that a positive 25 basis points (bps) surprise in monetary policy leads, on average, to a 7 basis point movement in CDS spreads. The significance is robust to firm level controls and fixed effects at various levels. We additionally show that unexpected movements of interest rates significantly affect both components of credit risk: compensation related to expected losses as well as a credit risk premium component that measures additional risk compensation.

The average response of CDS spreads masks a rich heterogeneous response at the firm level. Consistent with recent evidence, we find that firm-level risk is an important driver of the response to monetary policy shocks.[3] Riskier firms, that is firms with higher ex-ante CDS spread levels, display a stronger sensitivity to monetary policy shocks than less risky firms do. Quantitatively, firms in the highest ex-ante risk quintile display an additional 17 basis points sensitivity to policy shocks.

As discussed in Chava and Hsu (2020), equity prices can also display a response to monetary shocks depending on the severity of firm-level financial constraints. We show similar effects by extending our analysis to the equity universe. Stock prices of firms with high credit risk react significantly more than stock prices of low credit risk firms. Within a 1-hour (2-day) window surrounding FOMC announcements, stock prices of high credit risk firms contract, on average, between 0.1% and 0.4% (2.1% and 3.3%) more than stock prices of low credit risk firms, in response to a 25 bps contractionary monetary surprise. These are economically large differences.

Finally, we show that the response's heterogeneity survives the inclusion of other popular proxies for credit risk. Credit risk as measured by CDS spreads, helps determine firm-level responses to monetary policy surprises more than book leverage or market capitalization do. For example, we show the role of book leverage becomes secondary for credit markets when we simultaneously control for CDS spreads. We interpret this finding as suggestive of CDS as a superior risk measure to understand the pass-through of monetary policy shocks.

In the second part of the paper, we design a stylized equilibrium model of corporate leverage, investment, and monetary policy that is able to generate heterogeneity in credit risk response to monetary policy shocks. In the model, firms maximize the present value of future, nominal cash flows over a 3-period horizon. Firms have access to debt capital markets in the second period and when issuing debt, firms agree to pay a spread on top of the risk-free rate. The spread depends on their default risk and intermediary risk aversion towards that default risk. In the final period, firms either pay back their creditors and distribute positive dividends, or they default.

We embed monetary policy into the model by assuming that central banks set short-term interest rates through a Taylor Rule. Unexpected shocks to the Taylor Rule have a direct impact on the nominal interest rates in the economy and most importantly on investor risk aversion through the stochastic discount factor (SDF). We show analytically and numerically that the sensitivity of the real SDF with respect to monetary policy matters greatly for the transmission of policy shocks. When the sensitivity is high, there are greater effects of monetary policy on credit spreads. In terms of heterogeneity, the model generates asymmetric responses by firms, as the equilibrium credit spread curve is highly convex with respect to the ex-ante market capitalization of firms and with respect to firm-level credit risk. Hence, firms with a smaller distance to default have a greater response to all sources of risk, which includes monetary policy. Interestingly, leverage is negatively related to credit risk in the model given its association with cash flow-yielding investment.

Literature review. Our paper relates work in the areas of corporate credit risk, heterogeneous effects of monetary policy, and their interaction. As greater amounts of cross-sectional and time series data have surfaced, empirical research on credit risk has flourished. A large body of work has explored corporate credit spreads in the context of firm and economy-wide dynamics (e.g., Dufresne et al. (2011); Gilchrist and Zakrajšek (2012)).

A number of papers discuss the effects of monetary policy on the corporate bond market. Javadi et al. (2017) study how FOMC actions (rate cuts, hikes, inactions, and QE interventions) affect corporate credit spreads. They find that rate cuts and QE interventions contribute to a decline in credit spreads, while FOMC inactions are associated with large increase in credit

[2] The CDS market is also less subject to investors' selling (or buying) pressures that can move bond spreads away from what their underlying credit risk would suggest (e.g., Haddad et al. (2021)).

[3] Similar findings are presented in Javadi et al. (2017), Guo et al. (2020), and Smolyansky and Suarez (2020), using credit ratings.

spreads. Guo et al. (2020) use monthly returns on a variety of corporate bonds indices and find that excess bond returns significantly decline following a monetary policy shock. More recently, Smolyansky and Suarez (2020) show that “reaching for yield” cannot explain the corporate bond market reaction to monetary policy shocks. Consistent with these studies, we document that firms with high credit risk respond substantially more to surprises. In contrast with these studies, we explore the effect of high frequency surprises on daily CDS spreads and their two components, expected losses and credit risk premia.[4]

A recent and related literature examines how monetary policy can have heterogeneous effects on firm-level outcomes. Ottonello and Winberry (2020) examine the investment and leverage response following interest rate shocks and find that firms with lower levels of risk respond the greatest. Similarly to Ottonello and Winberry (2020), we find that leverage becomes uninformative to understand the propagation of monetary policy shocks at the firm level when one takes into account other measures of credit risk. In a closely related paper, Anderson and Cesa-Bianchi (2021) examine the transmission of monetary policy shocks into credit risk, using secondary market prices of bond-based credit spreads. They also decompose credit risk into expected loss and risk premium components and show that interest rate shocks mostly affect the latter component. Furthermore, they show that higher levered firms have bond spreads that react more to policy movements. Our analysis is broadly consistent with their findings, however we depart in two significant ways. First, we show that using a market-based measure of credit risk (such as CDS rates) is more informative than using a more static accounting-based measure (such as book leverage) in understanding how monetary policy shocks propagates in credit markets. Second, we find that the expected loss component, measured using conditional default probabilities estimated by Moody’s Analytics, significantly reacts to monetary policy shocks.

Our results regarding the relative informational content of CDS also extend when we examine the cross-sectional responses of equity prices. This finding can be related to those in Corvino and Fusai (2022) and Friewald et al. (2014), who document that firm-level credit risk premiums and equity returns contain similar information and move together, and to those in Chava and Hsu (2020), who show that monetary policy has a greater impact on equity returns of firms that are more financially constrained.

2. Data

Monetary Policy Shocks. Unexpected movements in risk-free interest rates can be measured in different ways. While daily movements broadly capture the direction of a policy action, higher frequency price data better account for market expectations shortly prior to an FOMC announcement (e.g., Kuttner (2001); Gürkaynak et al. (2005)). A second, more recent literature seeks to strip out a portion of interest rate surprises that might be due to news that is non-monetary in nature. For example, an unexpected rate increase might include a component that is an upward movement in discount rates (“pure” monetary policy shock) and a residual portion revealing information regarding the state of the economy (e.g. Romer and Romer (2000); Nakamura and Steinsson (2018)).

To speak to both of these points, we use three shocks. Our first shock reflects 30-minute movements in the 2-year on-the-run US Treasury security ($2yr$), surrounding FOMC announcements. To isolate pure movements related to monetary policy, we apply the methodology from Jarocinski and Karadi (2020) to high frequency movements of the 2-year Treasury yield and obtain a second monetary measure purged of the information effect ($2yr^{MP}$, see Appendix A.5 for more details). Lastly, we use a recent measure (BRW) developed by Bu et al. (2021) which is devoid of the central bank information effect and directly captures the sensitivities of longer-term interest rates to monetary policy announcements.

In total, our dataset includes up to 256 FOMC announcement dates – the first one on July 5, 1991 and the last one on June 16, 2021. While our monetary data extends back to the1990′s, the beginning date of our regression specifications is restricted by the availability of firm-level expected default frequency (EDF) data prior to 2004.[5]

Firm-Level Data. Firm–level data come from multiple sources: data on credit default swap quotes from Markit, data on expected default frequency (EDF) from Moody’s Analytics, quarterly accounting characteristics from Compustat, and equity prices from CRSP (daily) and TAQ (minutes surrounding FOMC window). We use companies that can be unambiguously matched across the different data sources. Furthermore, we exclude from our sample financial firms (sector *Financials* in Markit), utilities (sector *Utilities* in Markit), and quasi-governmental firms (sector *Government* in Markit).

Following Berndt et al. (2018), we use Markit to obtain data on (i) 5-year CDS quotes based on the no restructuring (XR) docclause and (ii) recovery rates. We restrict these data to contracts written on senior unsecured debt (Markit tier category *SNRFOR*). From Moody’s, we also obtain annualized, physical probabilities of default (EDF) across multiple maturities used to compute a CDS rate’s expected loss component.[6]

[4] There are several advantages to using CDS over corporate bond data. Our CDS data are often available *daily* for each firm, which allows for a better identification of the impact of monetary policy shocks. Perhaps due to the daily frequency, Blanco et al. (2005) suggest that the CDS market leads the bond market in incorporating information and determining credit risk. Similarly, Hilscher and Wilson (2017) suggest that CDS contain additional information on top of credit ratings.

[5] In Appendix A.1, we discuss our monetary policy shock measures in more details. In particular, we show that (i) BRW and $2yr^{MP}$ display significant volatility in the ZLB period, from 2009 through 2015 and (ii) surprise movements in 2-year yields are mostly dominated by the monetary component.

[6] The expected default frequency is derived from a Merton-type structural model for default prediction and accounts for stock price information, leverage, time-varying equity volatility, and other variables.

Our average (median) CDS spread is 188 (90) basis points, with an average and median recovery rate of about 40%. The average firm in our dataset has an annualized default probability of about 1% on FOMC announcement days, while half of the firms have a default probability less than 0.32%. Our matched sample has 585 unique firms with observations on both credit spreads and EDF and covers FOMC meetings from January 28, 2004 to December 11, 2019, with an average of about 300 firms each FOMC date. Additionally, our sample is tilted toward large market capitalization firms as CDS contracts predominantly cover large companies. Other details and statistics are provided in Appendix A.2 and Appendix A.3.

Expected Losses vs. Credit Risk Premia. Credit spreads can be decomposed into two components – an expected loss portion (compensation for losses in default) and a residual risk premium component (compensation for covariation between state prices and losses in default). A major part of our study examines whether interest rate shocks affect these components in different ways. To this end, we need to compute an expected loss component. Berndt et al. (2018) define the expected loss rate, EL_t, as the quantity that satisfies the CDS pricing equation under risk-neutrality assumptions:

$$(\Delta \times EL_t) \sum_{k=0}^{K-1} d_{t,(k+1)\Delta} \mathbb{E}_t\left[1 - D_{t,k\Delta}\right] = L_t \sum_{k=0}^{K-1} d_{t,(k+1)\Delta} \mathbb{E}_t\left[D_{t+k\Delta,\Delta}\right], \tag{1}$$

where the contract lasts a total of T years, Δ is the time between payments in years, and hence there are a total of $K \equiv \frac{T}{\Delta}$ periods.[7] Furthermore, L_t measures the loss given default, $D_{t,y}$ indicates default between t and $t+y$, and $d_{t,k\Delta}$ is the time t discount rate of a cash flow at $t+k\Delta$.[8] Note that the left hand side refers to all expected payments from protection buyers while the right hand side refers to expected payments from protection sellers. Because EL_t is an annualized rate, the exact premum paid over the payment horizon is $\Delta \times EL_t$, which is included on the left hand side. Appendix A.4 provides more details.

If we were to use the entire term structure of payments, as this equation suggests, computing EL_t is costly. Zero-coupon bond yields, a model of cumulative default probabilities, and data regarding losses in default are all needed. In the empirical analysis that follows, we use an approximated version of the 5-year expected loss component given by $EL_{it}^{5Y} \approx L_t \times EDF_{it}^{5Y}$, where L_t is one minus the recovery rate. While the equation looks overly-simplisitic, the motivation for it can be seen by looking at the expression of a 1-period expected loss component – $EL_t = L_t \times \mathbb{E}_t\left[D_{t,1}\right]$. Instead of a 1-period bond, we replace the EDF term with a 5-year EDF. Additionally, our approximation holds exactly under a flat term structure of default probabilities.

To ensure our approximation is sensible, we compare our value with two measures that directly use the formula in Eq. 1. One of them is a replication of Berndt et al.'s approach, involving a Nelson-Siegel-Svensson model fitted to EDF's at three different maturities. Our second measure uses a term structure of EDF data across more than three maturities. We show in Appendix A.4 that our approximation is very highly correlated and almost indistinguishable in levels from both of these alternative measures.

Fig. 1 displays a time series decomposition of the average 5-year CDS, expected loss, and risk premium components, where the expected loss uses our approximation, and the credit risk premium is a simple difference of the first two. The risk premium component plays a large role and explains much of credit spreads' variation. Over our sample, the risk premium (the expected loss) component averages about 130 (65) basis points.

3. Effects of interest rate shocks on credit risk

In the first part of the empirical analysis, we study the average effects of monetary policy shocks on credit risk and its components. The three main dependent variables are CDS spreads, expected losses, and the risk premium component. Let y_{it} denote the level of the dependent variable and ε_t^m the shock to monetary policy on date t, where t is a FOMC announcement day. To measure how monetary policy shocks trigger changes in y_{it}, we examine the linear model below:

$$\Delta y_{it} = \beta_0 + \alpha_i + \beta_m \varepsilon_t^m + \beta_X' X_{it} + \varepsilon_{it} \tag{2}$$

where $\Delta y_{it} = y_{i,t+1} - y_{i,t-1}$ and X_{it} is a set of firm-level controls. For example, if y is a quoted CDS spread and the FOMC announcement takes place on Wednesday January 4, we would take the difference between the value on Thursday January 5, ($y_{i,t+1}$) and Tuesday January 3, ($y_{i,t-1}$).[9] We scale monetary policy shocks so that β_m represents the change in CDS due to a 25 basis points change in the monetary policy shock. In the baseline regression specification, we include firm (α_i) fixed effects.[10]We also cluster standard errors at the FOMC date-firm level using the methodology developed by Correia (2016).

In Panel A of Table 1 we report results only including fixed effects. Columns 1 to 3 report the reaction of overall CDS prices, while columns 4 to 6 and 7 to 9 report the response of expected losses and credit risk premia, respectively. We

[7] As CDS premium payments are largely made on a quarterly basis in practice, Δ would be set to 0.25 years if one was to implement this equation.

[8] The expression above takes into account two additional assumptions. The first is that losses in default are conditionally independent from the realized default event. Second, conditional losses follow a martingale.

[9] The reason we add an additional day to the future value is due to the way in which Markit conducts its dealer surveys. Surveys occur throughout the day and we cannot ensure that the price quote on the FOMC day will truly incorporate responses *following* the monetary shock. Hence, we use the subsequent day's value.

[10] The Markit-based industry sectors are basic materials, consumer goods, consumer services, energy, healthcare, industrials, technology, and telecommunications services.

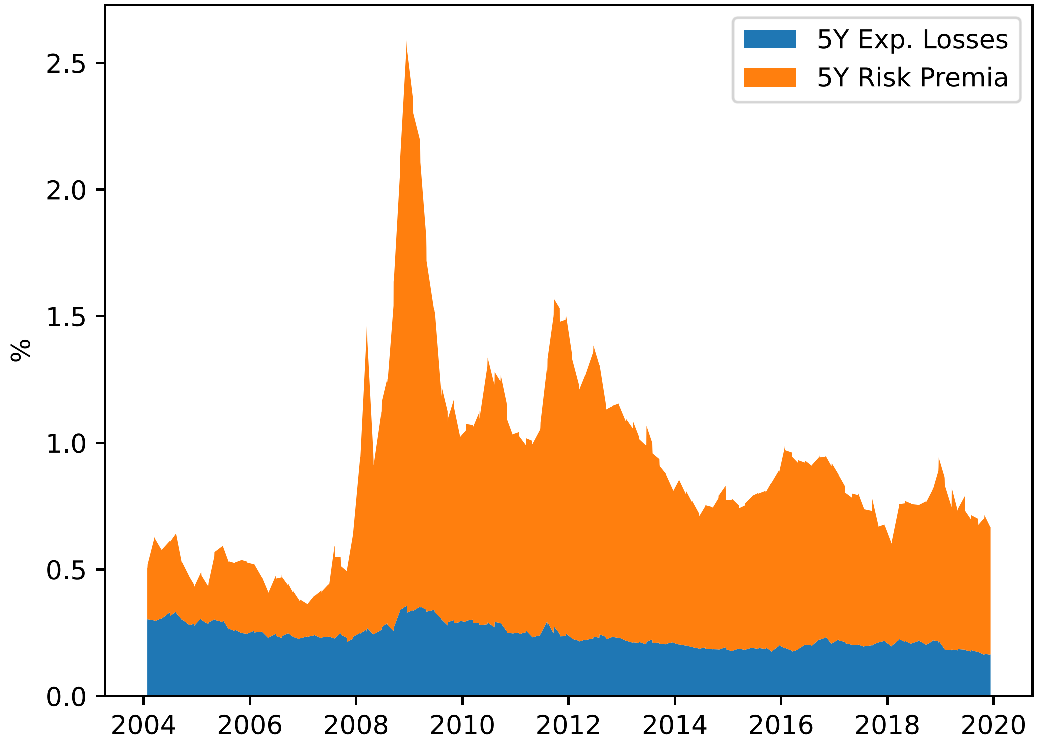


Fig. 1. CDS spreads, expected losses, and risk premia on FOMC days. This figure displays a time series decomposition of the 5-year CDS spread into expected loss and risk premium components, using the methodology discussed at the end of Section 2. Surrounding each FOMC meeting day, spreads are plotted on the day in advance, the day of, and the day following the announcement. In total, there are 129 announcement days from January 28, 2004 till December 11, 2019.

find that a 25 basis point shock to 2-year rates (row 1), is associated with a positive 7 basis point movement in CDS. For monetary shocks devoid of the information effect, as measured by $2yr^{MP}$ (row 2) and *BRW* (row 3), we find that a positive 25 bps monetary policy surprise generates a significant and positive increase in CDS spreads, between 7 and 8 bps.

In the middle columns of Table 1, we illustrate the effect of monetary policy surprises on the expected loss component. Columns 4 through 6 show that a 25 bps monetary policy surprise generates a significant and positive increase in expected loss around 3 basis points. Finally, columns 7 through 9 suggest that the pass through of monetary policy into risk premia is larger than the pass through into expected losses, as the estimated coefficients are larger. For example, the $2yr^{MP}$ suggests a 5.6 basis point movement of credit risk premia versus a 2.8 basis point movement in expected losses. As the coefficients are additive, one interpretation of the results would be that $67\%(= 5.6/8.4)$ of the average pass through occurs through the risk premia channel.

Our overall result is consistent with Anderson and Cesa-Bianchi (2021)'s findings of a positive and significant relation between weekly changes in credit spreads and monetary policy surprises that is largely driven by the risk premium channel. Differently from Anderson and Cesa-Bianchi (2021), we document that the expected losses component is also significantly associated to policy surprises. We attribute this discrepancy to different data and methodologies to compute the expected losses component.[11]

In Panel B of Table 1, we repeat the analysis in Panel A by adding a battery of firm-level control variables, known *prior to* the FOMC announcement day. At the firm level, we include the CDS spread, (log) market capitalization, book leverage ratio, cash-to-asset ratio, (log) total book value of assets, and investment growth. All daily variables are taken from the prior day and accounting variables are taken from the latest quarter preceding the announcement day. Adding firm-level control variables does not affect much the findings reported in Panel A. However, t-statistics and the estimated coefficients do shrink a bit.

Overall, the results in this section suggest that monetary policy shocks substantially affect credit risk on FOMC announcement days. A contractionary monetary policy shock increases credit risk through both the expected default and risk premium components.

[11] Anderson and Cesa-Bianchi (2021) use changes in credit spreads and directly estimate a firm-level distance to default using a Merton-KMV framework. We use changes in CDS rates and use firm-level conditional default probabilities estimated by Moody's Analytics. Additionally, we use a narrower window (2-day change) than the 1-week window that Anderson and Cesa-Bianchi (2021) use to calculate changes in credit spreads.

Table 1
Credit risk response to monetary policy shocks. This table reports the average effect of monetary policy shocks on movements in CDS, expected losses, and credit risk premia. For more details regarding the specification, see Equation (2) in the main text. In Panel A, columns 1 – 3 report the results using CDS changes as the dependent variable and three shock variables $(2yr, 2yr^{MP}, BRW)$ as key regressors. Columns 4 – 6 focus on movements in expected loss compensation as the dependent variable. Columns 7 – 9 focus on the risk premium component, the difference between CDS and expected losses. In Panel B, we include as controls firm-level variables known as of the day before the FOMC announcement. These variable are all divided by their unconditional standard deviation. We standardize monetary policy shocks so that all coefficients represent the change in CDS due to a 25 bps change in the monetary policy shock. In all regressions, we include firm fixed effects and clustered standard errors at the FOMC date and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

	Panel A: No Firm-level controls								
	Δ CDS			Δ Exp. Loss			Δ Risk Premium		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2yr	7.097***			2.338**			4.773***		
	(3.341)			(2.327)			(2.896)		
$2yr^{MP}$		8.354***			2.817**			5.569***	
		(3.598)			(2.603)			(2.965)	
BRW			7.340**			3.132***			4.069*
			(2.498)			(3.939)			(1.673)
Obs	38,229	38,229	38,229	38,229	38,229	38,229	38,229	38,229	38,229
R^2	0.017	0.018	0.019	0.013	0.014	0.020	0.012	0.012	0.011
	Panel B: With firm-level controls								
	Δ CDS			Δ Exp. Loss			Δ Risk Premium		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2yr	5.876***			2.191**			3.629**		
	(3.221)			(2.436)			(2.403)		
$2yr^{MP}$		6.983***			2.654***			4.303**	
		(3.475)			(2.768)			(2.469)	
BRW			6.159**			2.958***			2.994
			(2.155)			(3.570)			(1.278)
CDS	−0.029***	−0.029***	−0.030***	−0.007*	−0.007*	−0.007*	−0.024***	−0.024***	−0.025***
	(-3.246)	(-3.261)	(-3.271)	(−1.772)	(−1.777)	(−1.724)	(−2.740)	(−2.749)	(−2.798)
Market Cap	−0.016**	−0.016**	−0.020***	0.007	0.007	0.005	−0.023***	−0.023***	−0.025***
	(-2.242)	(-2.312)	(−2.864)	(1.467)	(1.484)	(1.092)	(−3.300)	(−3.375)	(−3.698)
Leverage	0.007**	0.008***	0.007**	0.001	0.001	0.001	0.006**	0.006**	0.006*
	(2.610)	(2.637)	(2.267)	(0.879)	(0.946)	(0.672)	(1.991)	(2.025)	(1.879)
Cash Holdings	0.003	0.004	0.004*	0.001*	0.001*	0.002**	0.002	0.002	0.002
	(1.501)	(1.588)	(1.799)	(1.677)	(1.781)	(2.083)	(1.036)	(1.100)	(1.222)
Book Assets (log)	0.009	0.009	0.010	−0.004	−0.003	−0.003	0.013**	0.013**	0.013**
	(1.443)	(1.513)	(1.592)	(−0.974)	(−0.938)	(−0.831)	(2.259)	(2.315)	(2.299)
Investment Rate	0.001	0.001	0.001	0.001	0.001	0.001	0.000	−0.000	−0.000
	(0.812)	(0.662)	(0.535)	(1.442)	(1.321)	(1.291)	(0.030)	(−0.074)	(−0.171)
Obs	34,867	34,867	34,867	34,867	34,867	34,867	34,867	34,867	34,867
R^2	0.034	0.035	0.036	0.025	0.026	0.030	0.018	0.018	0.017

4. Monetary policy and credit risk heterogeneity

In the previous section, the linear model treated the response of every firm's credit risk to monetary policy as uniform. It is plausible, however, that more financially fragile firms are more sensitive to market-wide funding shocks. In this section, we test this hypothesis by focusing on how the response to monetary policy shocks varies with firm-level credit risk, as measured by CDS spreads the day before the scheduled FOMC announcement.

4.1. Cross-Sectional credit risk and asset prices response

Our first set of tests examines whether firms with higher CDS spreads are more sensitive to interest rate shocks. Specifically, we propose a non-linear specification by interacting a quintile ranking of CDS the day before a FOMC announcement with the interest rate shock:

$$\Delta y_{it} = \beta_0 + \alpha_i + \alpha_{s,t} + \sum_{j=2}^{5} \beta_{y,j} \left(\mathbb{1}_{ij,t-1} \times \varepsilon_t^m \right) + \beta_X' X_{i,t-1} + \varepsilon_{it} \tag{3}$$

where $\mathbb{1}_{ij,t-1}$ takes a value of 1 if firm i is in CDS risk group j at $t-1$ and 0 otherwise, $X_{i,t-1}$ indicates a vector of firm-level variables (including the interacted CDS category dummies), α_i is a firm fixed effect, and $\alpha_{s,t}$ is a sector-time fixed effect.[12]

[12] The Markit-based industry sectors are basic materials, consumer goods, consumer services, energy, healthcare, industrials, technology, and telecommunications services.

Table 2
Cross-sectional credit response to monetary policy shocks. This table reports the heterogeneous effects of monetary policy shocks on credit risk due to cross-sectionally varying levels of risk, as determined by historical CDS rates. For more details regarding the specification, see Eq. (3) in the main text. In this table, firms are sorted into CDS risk quintiles based on 5-year CDS data from the day prior to FOMC announcements. Dummy variables are then interacted with monetary policy shocks. Columns 1 – 3, 4 – 6, and 7 – 9 focus on movements in CDS spreads overall, the expected loss component, and credit risk premia, respectively. Within each panel, each column from left to right uses a different shock variable ($2yr$, $2yr^{MP}$, BRW). Coefficients represent the change in CDS due to a 25bps change in the policy shock, conditional on the firm falling into that risk quintile. In all regressions, we include the firm-level controls used Panel B of Table 1, firm and sector-time fixed effects and clustered standard errors at the FOMC date and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

	Δ CDS			Δ Exp. Loss			Δ Risk Premium		
	2yr	$2yr^{MP}$	BRW	2yr	$2yr^{MP}$	BRW	2yr	$2yr^{MP}$	BRW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
shockXCDS2	0.524	0.538	0.371	0.281	0.369**	0.589***	0.225	0.155	−0.215
	(1.005)	(0.776)	(0.491)	(1.546)	(1.982)	(2.876)	(0.423)	(0.225)	(−0.297)
shockXCDS3	1.462	2.014*	1.930	1.036*	1.360*	1.670***	0.512	0.658	0.408
	(1.528)	(1.678)	(1.152)	(1.666)	(1.774)	(3.131)	(0.509)	(0.522)	(0.269)
shockXCDS4	5.249***	7.189***	4.378	1.823*	2.153**	2.898***	3.473**	5.110***	1.435
	(2.686)	(3.399)	(1.647)	(1.976)	(2.142)	(3.576)	(2.100)	(2.870)	(0.610)
shockXCDS5	15.313***	17.767***	17.002***	6.209**	7.442***	8.541***	9.347**	10.572**	8.112
	(3.247)	(3.643)	(2.681)	(2.603)	(3.102)	(3.852)	(2.167)	(2.207)	(1.629)
Obs	34,867	34,867	34,867	34,867	34,867	34,867	34,867	34,867	34,867
R^2	0.169	0.169	0.171	0.111	0.112	0.118	0.110	0.111	0.110

Firms with the highest CDS spreads at $t-1$ would fall in risk group 5, while firms with the lowest CDS spreads at $t-1$ belong to the excluded risk group 1.[13]

Table 2 reports the results. As in Table 1, the three sets of columns relate to CDS, expected loss, and risk premia sensitivities, respectively. Within a set of columns, the shocks are given by $2yr$, $2yr^{MP}$, and BRW. The first three columns suggest that CDS spreads of firms in the top credit risk category respond significantly more to a 25 bps monetary policy shock than firms in the bottom credit risk category (the excluded category). On average, and depending on the monetary policy shock, the change in CDS spreads of firms in the top credit risk category is between 15 and 18 basis points higher.

When we consider changes in the expected loss and credit premium components separately (columns 4 to 9), we find results consistent with the ones in Table 1: interaction terms involving the highest risk group, are highly significant for the response of both the expected loss and risk premium components. With the exception of the *BRW* shock, risk premium coefficients are again larger than expected loss sensitivities.

Overall, our results show that firm-level heterogeneity in credit risk matters for the transmission of monetary policy shocks. This response is highly non-linear and is driven by firms in the highest credit risk categories. Additionally, the two components of CDS spreads, expected loss and risk premium, react with different magnitudes to monetary policy shocks, with the latter playing a somewhat more prominent role.

Equity Price Response. We ask whether ex-ante credit risk also matters for monetary policy propagation into equity markets. Table 3 shows that this is indeed the case. Using credit risk categories, we find that stock prices of high credit risk firms contract significantly more following an unexpected increase in interest rates. Our finding is consistent with Chava and Hsu (2020), who show that monetary policy has a greater impact on the returns of firms that are more financially constrained.

We use a very similar approach as the non-linear interaction specification used in the previous section, however we replace the left-hand side variable with two different measures of returns – a 1-hour return surrounding the FOMC window (columns 1 to 4) and a 2-day return (columns 5 to 8). To ensure there is no short-term reversal type effect, we also control for the lagged one-day return. In addition to the three shocks used to this point, we show how stock prices react to movements in the residual component of the 2-year Treasury yield ($2yr^{NonMP}$, columns 4 and 8).

Regardless of the equity return measure, findings are qualitatively consistent in that higher credit risk firms show a larger equity price sensitivity to monetary policy shocks that are devoid of any information effect. An unexpected contractionary shock has a negative impact on equity prices through a larger discounting of future cash flows. Focusing on the $2yr^{MP}$ shock, firms in the riskiest quintile lose about 51 basis points in the one hour surrounding the FOMC announcement and 233 basis points over the subsequent 2 days. Losses are generally monotonically increasing across risk groups as well.

Consistent with the way we derive $2yr^{MP}$, its orthogonal non-monetary component ($2yr^{NonMP}$) behaves in the opposite way when we look at the 1-hour return surrounding the FOMC window. In this case, stocks in the riskiest quintile gain about 182 basis points relative to stock in the bottom credit risk quintile. However, this pattern is reversed once we use a 2-day return window.

[13] Note that there is no baseline policy shock term in the regression as we include sector-time fixed effects.

Table 3
Cross-sectional equity response to monetary policy shocks. This table reports the heterogeneous effects of monetary policy shocks on equity returns due to cross-sectionally varying levels of risk, as determined by historical CDS rates. For more details regarding the specification, see Eq. (3) in the main text. In this table, firms are sorted into CDS risk quintiles based on 5-year CDS data from the day prior to FOMC announcements. Dummy variables are then interacted with monetary policy shocks. Columns 1 – 4 focus on 1-hour returns while columns 5 – 8 focus on 2-day returns. Within each panel, each column from left to right uses a different shock variable ($2yr$, $2yr^{MP}$, BRW, $2yr^{NonMP}$). Coefficients represent the change in CDS due to a 25bps change in the policy shock, conditional on the firm falling into that risk quintile. In all regressions, we include the firm-level controls used Panel B of Table 1, firm and sector-time fixed effects and clustered standard errors at the FOMC date and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

	1-Hour Return				*2-Day Return*			
	2yr	$2yr^{MP}$	BRW	$2yr^{NonMP}$	2yr	$2yr^{MP}$	BRW	$2yr^{NonMP}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
shockXCDS2	−0.010	−0.109	−0.156***	0.502***	−0.551*	−0.680**	−0.935***	−0.143
	(−0.133)	(−1.337)	(−3.087)	(2.920)	(−1.931)	(−2.342)	(−3.291)	(−0.144)
shockXCDS3	0.073	−0.047	−0.182*	0.758***	−0.770*	−1.075**	−1.499***	0.486
	(0.756)	(−0.377)	(−1.683)	(2.814)	(−1.768)	(−2.011)	(−2.973)	(0.374)
shockXCDS4	−0.072	−0.314*	−0.356***	1.185*	−1.365**	−1.773**	−1.650***	0.154
	(−0.399)	(−1.842)	(−2.618)	(1.886)	(−1.995)	(−2.480)	(−3.255)	(0.073)
shockXCDS5	−0.134	-0.506*	−0.558***	1.816***	−2.120**	−2.331**	−3.313***	−2.006
	(−0.479)	(−1.875)	(−3.120)	(2.833)	(−2.538)	(−2.577)	(−3.730)	(−0.491)
return (lag)	0.010	0.010	0.009	0.008	−0.030	−0.032	−0.036*	−0.030
	(1.447)	(1.409)	(1.380)	(1.283)	(−1.480)	(−1.570)	(−1.813)	(−1.480)
Obs	29,432	29,432	29,432	29,432	34,866	34,866	34,866	34,866
R^2	0.520	0.520	0.521	0.521	0.393	0.393	0.395	0.392

4.2. Credit risk and other measures of firm-level risk

In this subsection, we examine if our results survive the inclusion of two related measures of credit risk – leverage and the market capitalization of firms. All else equal, higher leverage or lower market capitalization might spell problems for corporations. Furthermore, recent studies have shown that leverage is an important determinant of firm-level responses to monetary policy shocks (e.g., Lakdawala and Moreland (2021); Ottonello and Winberry (2020); Anderson and Cesa-Bianchi (2021)).

To better understand how the interaction of leverage with credit risk influences the transmission of monetary policy shocks, we use dummy variables classifying whether a firm-date observation jointly falls within a particular tercile (bottom 33%, middle 33%, and top 33%) of credit risk (i.e., CDS) and tercile of leverage. In total we have 9 categories that range from firms in a low credit risk-low leverage category (CDS_1LEV_1) to firms in a high credit risk-high leverage category (CDS_3LEV_3). The main specification is given by:

$$\Delta y_{it} = \beta_0 + \alpha_i + \alpha_{s,t} + \sum_{j=1}^{3}\sum_{k=1}^{3} \beta^{CDS_k LEV_j} \left(\mathbb{1}_{i,t-1}^{CDS_k LEV_j} \times \varepsilon_t^m \right) + \beta_X' X_{i,t-1} + \varepsilon_{it} \tag{4}$$

where $\mathbb{1}_{i,t-1}^{CDS_k LEV_j}$ is a dummy variable that takes value of 1 if firm i belongs to tercile k ($k = 1, 2, 3$) of the CDS distribution and tercile j ($j = 1, 2, 3$) of the book leverage distribution the day before the time t FOMC announcement. In Eq. 4, $X_{i,t-1}$ indicates a vector of firm-level variables (including the interacted CDS-leverage dummies), α_i is a firm fixed effect, and $\alpha_{s,t}$ is a sector-time fixed effect. In the regression model, we exclude firms belonging to the category CDS_1LEV_1, so the estimated coefficients are the additional effect of monetary policy shocks relative to firms with the lowest credit risk and lowest leverage.

Table 4 reports the results. Estimated coefficients on the interaction terms are grouped by leverage categories so that one can study how credit risk affects the propagation of monetary policy shock within each leverage category. In columns 1 to 3, we use CDS as a dependent variable; in columns 4 to 6 we use the expected loss component; in columns 7 to 9 we use the risk premium component; in columns 10 to 12 we use the 2-day equity return. For each dependent variable, we use three different monetary policy shocks: $2yr$, $2yr^{MP}$, and BRW. We also report the number of observations for each CDS-leverage category. While CDS values and leverage tend to be positively associated (their unconditional correlation is significant and equal to 0.35), there is a substantial number of firms with low (high) CDS values and high (low) leverage.

Table 4 displays that CDS values matter for the transmission of monetary policy shocks, above and beyond the (book) leverage that a firm might carry on its balance sheet. To illustrate this point, we focus on the response of CDS rates (columns 1 to 3). Our results show that high credit risk firms across leverage categories almost always witness a significantly larger response than low CDS-low leverage firms. At the same time, elevated leverage does not *consistently* increase the response to monetary policy, once we control for risk rankings determined by CDS. As an example, consider low credit risk firms.

Table 4
Cross-sectional credit response by leverage. This table reports the heterogeneous effects of monetary policy shocks on credit risk due to cross-sectionally varying levels of joint leverage and credit risk. For more details regarding the specifications, see Eq. (4) in the main text. As in earlier tables, Columns 1 – 9 focus on movements in overall CDS spreads as a dependent variable, expected losses, and credit risk premia. Additionally, Columns 10 – 12 focus on 2-day returns surrounding FOMC announcements. Within each panel the columns represent specifications using different shocks ($2yr$, $2yr^{MP}$, BRW). The interaction terms (regressors) are expressed with a notation "shock × YZ" where Y indicates the low, medium, or high credit risk tercile and Z the book leverage tercile. N is the number of observations in each credit risk-leverage category. The excluded category (low credit risk and low leverage firms) has 5,181 observations. Coefficients represent the basis point spread change due to a 25 bps change in the policy shock, conditional on the firm falling into that joint risk bucket. In all regressions, we include the firm-level controls used Panel B of Table 1, firm and sector-time fixed effects and clustered standard errors at the FOMC date and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

	Δ *CDS*			Δ Exp. Loss			Δ Risk Premium			2-Day Return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						Low Leverage						
shockXML	0.973	1.872	1.440	1.546*	1.645	1.986***	−0.610	0.248	-0.561	-1.091**	-1.102*	-1.269**
(N=3,982)	(1.061)	(1.652)	(0.970)	(1.883)	(1.654)	(3.273)	(−0.522)	(0.177)	(-0.426)	(-2.353)	(-1.881)	(-2.264)
shockXHL	6.146**	8.642***	4.380	3.290**	4.353***	3.293***	3.281	4.952*	0.726	-1.430	-1.997*	-1.240**
(N=2,426)	(2.019)	(2.632)	(1.435)	(2.501)	(2.983)	(3.750)	(1.217)	(1.735)	(0.258)	(-1.456)	(-1.785)	(-2.199)
						Medium Leverage						
shockXLM	0.248	0.603	−0.413	0.030	0.011	−0.037	0.078	0.488	−0.463	−0.099	0.245	0.269
(N=4,202)	(0.614)	(1.179)	(−0.686)	(0.300)	(0.081)	(−0.171)	(0.154)	(0.806)	(−0.576)	(−0.436)	(0.955)	(0.876)
shockXMM	1.546	2.030	1.091	0.710**	0.774**	1.350***	0.824	1.215	−0.182	−0.490	−0.522	-0.906*
(N=4,065)	(1.449)	(1.480)	(0.630)	(2.189)	(2.008)	(2.785)	(0.868)	(0.989)	(−0.110)	(−1.400)	(−1.178)	(−1.977)
shockXHM	12.245***	15.191***	11.459**	4.095***	4.971***	5.250***	8.170***	10.211***	6.576	−1.863***	−2.076***	−2.034***
(N=3,454)	(3.278)	(3.881)	(2.160)	(2.714)	(3.090)	(3.527)	(2.652)	(3.182)	(1.550)	(−3.057)	(−3.139)	(−2.819)
						High Leverage						
shockXLH	−0.804	−1.106**	−1.407**	0.052	−0.097	−0.191	−1.016**	−1.180**	−1.448*	0.545	1.112***	1.212**
(N=2,431)	(−1.621)	(−2.133)	(−2.204)	(0.362)	(−0.587)	(−0.541)	(−2.011)	(−2.233)	(−1.856)	(1.628)	(3.230)	(2.168)
shockXMH	2.413**	3.368***	2.682*	1.085	1.486	0.807	1.545	2.002*	2.164*	−0.987**	−0.935	-0.653
(N=3,582)	(2.103)	(2.766)	(1.869)	(1.445)	(1.624)	(1.654)	(1.426)	(1.688)	(1.703)	(−2.005)	(−1.635)	(−1.251)
shockXHH	11.659***	13.865***	13.097**	4.971**	5.691**	7.621***	6.692	8.193	4.859	−1.636**	−1.498*	−2.432***
(N=5,553)	(2.717)	(2.958)	(2.236)	(2.222)	(2.558)	(3.707)	(1.557)	(1.623)	(0.979)	(−2.198)	(−1.858)	(−2.847)
return (lag)										-0.030	-0.032	-0.036*
										(−1.487)	(−1.574)	(−1.802)
Obs	34,867	34,867	34,867	34,867	34,867	34,867	34,867	34,867	34,867	34,866	34,866	34,866
R^2	0.167	0.168	0.168	0.109	0.110	0.116	0.109	0.110	0.109	0.393	0.393	0.395

Among these firms, larger leverage does not imply a larger response; in fact, high leverage and low CDS firms have a *smaller* response than low leverage and low CDS firms.[14]

Columns 4 to 6 show that similar conclusions hold for the response of the expected loss component. For the risk premium component (columns 7 to 9) we also find a similar pattern, but the estimated coefficients are only significant in a few cases. Lastly, columns 10 to 12 report the response of equity prices over a 2-day window. Again, the reaction of high credit risk firms is significantly larger than that of low credit risk ones, across all leverage groups. Meanwhile leverage seems to play an inconsistent role in shaping stocks' response across credit risk categories.

Comparison to Market Size as a Risk Measure. Table 5 reports the results when we sort our firms in 9 categories that range from firms in the low credit risk-low market capitalization (CDS_1MKT_1) to firms in the high credit risk-high market capitalization category (CDS_3MKT_3). In this case, the excluded category is low credit risk and high market capitalization (CDS_1MKT_3), as they should contain the least risky firms.[15]

As in the leverage case, credit risk matters for the transmission of monetary policy shock independently from firm size, as measured by market capitalization. Columns 1 to 3 in Table 5 show that small (large) high credit risk firms have a significantly larger response than large and low credit risk firms between 9 and 12 (15 and 17) basis points. A similar conclusion holds for the response of the expected loss component (columns 4 to 6) and the credit risk component (column 7 to 9), albeit in some cases the larger response of high credit risk firms is not statistically different than the one of large and low credit risk firms. Columns 10 to 12 report the response of stock returns. Again, high credit risk firms witness a much larger drop in their equity prices independently from their market capitalization. For example, small (large) high credit risk firms have a 2-day return between 1.7% and 2.8% (2.7% and 3.1%) lower that the return of low credit risk and high market capitalization firms.

[14] The notable exception is for firms with high CDS values. In this case, high- and medium-leverage firms are twice as sensitive to monetary policy surprises than low-leverage firms.

[15] Table 5 shows that credit risk's association with market capitalization is stronger than its association with book leverage, as indicated by the relatively small number of observations in the low (high) credit risk and low (high) market capitalization category. The overall correlation between credit risk and market capitalization is significant and equal to -0.52.

Table 5
Cross-sectional credit response by market size. This table reports the heterogeneous effects of monetary policy shocks on credit risk due to cross-sectionally varying levels of joint market size and credit risk. For more details regarding the specifications, see Eq. (4) in the main text. As in earlier tables, Columns 1 – 9 focus on movements in overall CDS spreads as a dependent variable, expected losses, and credit risk premia. Additionally, Columns 10 – 12 focus on 2-day returns surrounding FOMC announcements. Within each panel the columns represent specifications using different shocks ($2yr$, $2yr^{MP}$, BRW). The interaction terms (regressors) are expressed with a notation "shock × YZ" where Y indicates the low, medium, or high credit risk tercile and Z the market size tercile. N is the number of observations in each credit risk-market size category. The excluded category (low credit risk and large market capitalization firms) has 8,456 observations. Coefficients represent the basis point spread change due to a 25 bps change in the policy shock, conditional on the firm falling into that joint risk bucket. In all regressions, we include the firm-level controls used Panel B of Table 1, firm and sector-time fixed effects and clustered standard errors at the FOMC date and firm level. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

	Δ CDS			Δ Exp. Loss			Δ Risk Premium			2-Day Return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						Small size						
shockXLL	−0.582	−1.412	0.005	0.388	0.990	0.962	−1.387	−2.994	−1.499	−0.181	−0.531	−1.087
(N= 574)	(−0.370)	(−0.702)	(0.002)	(0.750)	(1.562)	(1.556)	(−0.703)	(−1.376)	(−0.552)	(−0.209)	(−0.634)	(−1.329)
shockXML	−0.131	0.358	1.224	2.391	2.755	2.797***	−2.353	-2.154	−1.335	−1.508**	−1.702**	−1.855**
(N= 3,282)	(−0.155)	(0.347)	(1.473)	(1.596)	(1.511)	(2.771)	(-1.158)	(−0.862)	(−0.892)	(−2.210)	(−2.070)	(−2.325)
shockXHL	9.331***	11.741***	12.415***	5.724***	6.730***	8.194***	3.623	5.027	3.890	−1.742**	−1.975**	−2.851***
(N= 7,387)	(2.619)	(3.164)	(2.819)	(2.657)	(3.089)	(3.967)	(1.086)	(1.319)	(1.110)	(−2.182)	(−2.341)	(−3.266)
						Medium size						
shockXLM	−0.781	−1.068	−0.294	0.255**	0.180	0.103	−1.158	−1.373	−0.455	−0.206	−0.108	-0.485
(N=2,978)	(−1.138)	(−1.346)	(−0.377)	(2.505)	(1.195)	(0.594)	(−1.414)	(−1.444)	(−0.593)	(−0.706)	(−0.317)	(−1.557)
shockXMM	1.605*	1.976*	2.370*	0.875**	1.154**	1.220***	0.722	0.724	1.227	−0.898*	−1.198**	−1.160**
(N=5,659)	(1.796)	(1.839)	(1.874)	(1.983)	(2.129)	(3.244)	(0.804)	(0.680)	(1.115)	(−1.798)	(−2.117)	(−2.466)
shockXHM	12.776***	15.205***	8.060*	1.974	2.806*	2.676***	11.072***	12.800***	5.191	−1.614**	−2.126**	−2.003***
(N= 3,091)	(4.126)	(5.026)	(1.814)	(1.431)	(1.867)	(3.255)	(3.853)	(4.293)	(1.265)	(−1.993)	(−2.505)	(−3.405)
						Large size						
shockXMH	2.701**	3.720***	2.713	0.463**	0.579**	0.646**	2.412**	3.215**	2.231	−0.660	−0.883	−1.395***
(N=2,834)	(2.257)	(2.706)	(1.565)	(2.060)	(2.003)	(2.327)	(2.166)	(2.523)	(1.248)	(−1.586)	(−1.630)	(−3.389)
shockXHH	15.665***	16.714***	15.049**	1.670	2.189**	1.631***	14.376***	14.687***	13.658**	−2.720**	−3.034**	−3.111***
(N=616)	(4.566)	(4.348)	(2.475)	(1.624)	(2.024)	(2.782)	(4.528)	(3.889)	(2.265)	(−2.446)	(−2.500)	(−3.603)
return (lag)											−0.032	-0.036*
											(−1.575)	(−1.810)
Obs	34,867	34,867	34,867	34,867	34,867	34,867	34,867	34,867	34,867	34,867	34,866	34,866
R^2	0.167	0.168	0.168	0.111	0.111	0.118	0.111	0.111	0.109	0.393	0.393	0.395

Overall, our results suggest that the role of credit risk, as measured by CDS spreads, in shaping the heterogeneous transmission of monetary policy in corporate bonds and equity markets is little affected by firm-level book leverage or market capitalization.

5. Model

In the second part of the paper, we present a stylized model of corporate leverage, investment, and monetary policy to help us understand two main empirical results: (1) the heterogeneity in response of firm credit risk and (2) the inability of firm leverage in explaining this response. To keep the model simple and transparent we limit it to 3 periods. In many ways, our model is similar to Bhamra et al. (2011), but we allow for endogenous investment and leverage.

5.1. Timeline and structure

Over the course of 3 periods ($t = 1, 2, 3$), a heterogeneous set of firms maximize the expected present value of *nominal* cash flows.[16] The expectations are over three variables: idiosyncratic productivity (a_t^j), variation in aggregate productivity (A_t), and shocks to monetary policy, (S_t). These independent shocks follow AR(1) processes with persistence parameter ρ and volatility parameter σ:

$$\begin{aligned} a_t^j &= \rho_a a_{t-1}^j + \sigma_a \varepsilon_{a,t}^j; \\ A_t - \mu_A \equiv \tilde{A}_t &= \rho_A \tilde{A}_{t-1} + \sigma_A \varepsilon_{A,t}; \\ S_t &= \rho_S S_{t-1} + \sigma_S \varepsilon_{S,t}; \end{aligned} \tag{5}$$

where $\tilde{A}$ represents the demeaned value of aggregate productivity. The presence of the firm-level productivity shock a^j ensures heterogeneity in investment and financing choices.

Period 1. At the start of the initial period, firm j begins with 1 unit of capital and draws a random, idiosyncratic shock from the stationary distribution of productivity ($a_1^j \sim \Phi_a(a)$). Similarly, aggregate variables (A_t, S_t) are also drawn from their

[16] Solving the nominal problem is one-to-one with a real version. See Appendix C.1 for details.

stationary distributions. Based on the initial state, each firm decides to invest in additional capital, seeking to maximize the sum of a current dividend (D_{j1}) and the discounted value of Period 2 cash flows. More explicitly, the firm's decision problem is given by:

$$V_1\left(A_1, S_1, a_1^j, k_1^j\right) = \underset{\{k_2\}}{\text{Max}} \quad D_{j1} + \mathbb{E}_1\left[M_2^n W_{j,2}\right] \tag{6}$$

subject to a limited liability constraint ($W_{j,2} = \text{Max}\left\{0, V_{j,2}\right\}$), a no equity issuance constraint ($D_{j1} \geq 0$), and the following dividend constraint:

$$D_{j1} = \Pi_{j1} - i_{j1} - \varphi_{k1}(k_{j1}, i_{j1})k_{j1} + \tau\delta k_{j1}. \tag{7}$$

M_2^n is the nominal stochastic discount factor (SDF) used to value future nominal cash flows. While this SDF does not come from particular agent's preferences, it can be thought of as a market-based pricing kernel that firms utilize (e.g., Chen (2010); Kuehn and Schmid (2014)). W_{j2} is the realized Period 2 value of the firm, bounded below by limited liability upon potential exit. Finally dividends, D_{j1}, consist of firm profits (Π), net of investment (i) and investment adjustment costs ($\varphi_{k1}(\cdot) \times k_1$), plus a capital depreciation tax shield with tax parameter τ and depreciation parameter δ. In summary, the purpose of the first period is to generate heterogeneity across firms before they access capital markets in Period 2.

Period 2. After operating 1 period, firms have the opportunity to exit if the market value of continuing operations falls below zero. If they choose to continue operations, firms now have the ability to take on debt to finance investment. The debt contract is structured as follows. For a chosen amount of debt b_{j3} at time 2, firms owe a face value of $(1+c)b_{j3}$ at time 3, while receiving market proceeds $p_{j2}b_{j3}$ at time 2. Implicitly, p_{j2} will reflect the market priced credit risk of firm j. The pricing of the debt contract is set to break even:

$$p_{j2}b_{j,3} = \mathbb{E}_2\left[M_3^n(1 - \not{\Bbbk}_{\{D_{j3}>0\}})(1+c)b_{j,3}\right] + \mathbb{E}_2\left[M_3^n \not{\Bbbk}_{\{D_{j3}<=0\}} X_{j,3}^{PD}\cdot\right] \tag{8}$$

In the above formula the left hand side reflects lent proceeds to a firm, while the right hand side is a probability weighted sum of the discounted value of (1) proceeds in a non-default state and (2) proceeds given default ($D_{j3} \leq 0$). Further, if default was to occur, the payment to creditors reflects deadweight losses and is given by $X_{j3}^{PD} \equiv (1-\xi)(1-\delta)k_{j3}$, where $\xi < 1$. It can be shown that debt prices (p_{j2}) are a function of current shocks (a_2^j, A_2, S_2) and capital and debt policies (k_3^j, b_3^j).

At the start of period 2, firms are offered an entire price or interest rate schedule. As chosen policies are observable to banks, the firm internalizes this price schedule and chooses capital and debt to maximize:

$$V_2\left(A_2, S_2, a_2^j, k_2^j\right) = \underset{\{k_3, b_3\}}{\text{Max}} \quad D_{j2} + \mathbb{E}_2\left[M_3^n W_{j,3}\right] \tag{9}$$

subject to a limited liability constraint ($W_{j,3} = \text{Max}\{0, D_{j,3}\}$), a no-equity issuance constraint ($D_{j2} \geq 0$), and the following dividend constraint and debt pricing equation:

$$D_{j2} = \Pi_{j2} - i_{j2} - \varphi_{k2}(k_{j2}, i_{j2})k_{j2} + \underbrace{p_{j2}b_{j,3}}_{\text{Debt Proceeds}} + \tau\delta k_{j2}$$

$$p_{j2}b_{j,3} = \mathbb{E}_2\left[M_3^n(1 - \not{\Bbbk}_{\{D_{j3}>0\}})(1+c)b_{j,3}\right] + \mathbb{E}_2\left[M_3^n \not{\Bbbk}_{\{D_{j3}<=0\}} X_{j,3}^{PD}\right]. \tag{10}$$

Similar to the previous period, firms account for the present value of future cash flows, which is simply a dividend payment at period 3. Firms now have an incentive to take on debt due to its tax shield and they trade off this incentive with a borrowing cost that increases with the size of debt (e.g., Hennessy and Whited (2005)). There is again no equity issuance or savings, and dividends include a term accounting for debt proceeds.

Period 3. The final period involves no decision making. Upon realizing idiosyncratic and aggregate shocks, the firm operates, liquidates capital, and repays debt. If the firm does not default, equity holders receive profits and un-depreciated capital, repay the face value of corporate debt and receive a tax shield on depreciated capital and debt coupon payments. In this case, cash flows to equity holders are given by, $D_{j,3} = \Pi_{j,3} + (1-\delta)k_{j,3} - (1+c)b_{j,3} + \tau\left(\delta k_{j,3} + cb_{j,3}\right)$. Conversely if the firm defaults, equity holders are wiped out ($D_{j,3} = 0$) and creditors receive un-depreciated capital net of deadweight losses (X^{PD}).

5.2. Discount factors, monetary policy, and inflation

In the economy, market participants use an exogenous, real pricing kernel given by $M_t^r = \exp\left(m_t^r\right) = \exp\left(m_0 - m_A(A_t - \mu_A) - m_S S_t\right)$. By construction, M_t^r is always positive and is a function of the de-meaned aggregate risk, A_t, and the monetary shock, S_t. The market prices of risk, m_A and m_S, determine the sensitivity of credit spreads to aggregate shocks. We introduce monetary policy by imposing a Taylor rule adopted by the central bank to set the short-term *nominal* 1-period interest rate:

$$y_t^1 = y_0 + \alpha_A(A_t - \mu_A) + \alpha_\pi(\pi_t - \mu_\pi) + S_t, \tag{11}$$

where the short-term yield, y_t^1 is a linear function of growth and inflation, with the addition of a persistent interest rate shock term (S_t).

Taking a similar approach as many endowment models (e.g., Gallmeyer et al. (2017) and Song (2017)), we use the Euler equation restriction applied to a 1-period nominal risk-free security to infer an endogenous process for inflation:

$$p_t^{rf} = \mathbb{E}_t\left[M_{t+1}^r \frac{1}{\Pi_{t+1}}\right] = \frac{1}{\exp\left(y_t^1\right)} \qquad (\Leftrightarrow) \qquad y_t^1 = -\log \mathbb{E}_t\left[\exp\left(m_{t+1}^r - \pi_{t+1}\right)\right] \tag{12}$$

where p_t^{rf} represents the risk-free price on a short-term nominal bond. Using the conditional log-normality of the nominal SDF we can arrive at two main results.

Proposition 1. *Inflation (π_t) is endogenous and a linear function of productivity and the interest rate shock. As a result, the nominal SDF is also linear in these states.*

To show the first result, we guess and verify that $\pi_t = \pi_0 + \pi_A \tilde{A}_t + \pi_S S_t$. Matching coefficients from the Taylor rule on the left hand side yields:[17]

$$\pi_S = \frac{1 - m_S\rho_S}{\rho_S - \alpha_\pi}; \qquad \pi_A = \frac{\alpha_A - m_A\rho_A}{\rho_A - \alpha_\pi};$$
$$\pi_0 = y_0 + m_0 + \frac{1}{2}(m_A + \pi_A)^2\sigma_A^2 + \frac{1}{2}\pi_S^2\sigma_S^2. \tag{13}$$

Given the linearity of the inflation process, the nominal (log) SDF m_{t+1}^n becomes:

$$m_{t+1}^n = m_{t+1}^r - \pi_{t+1} = (m_0 - \pi_0) - (m_A + \pi_A)\tilde{A}_{t+1} - (m_S + \pi_S)S_{t+1} \tag{14}$$

Eq. 14 implies that any (nominal) risk premium for an asset is based on that asset's return covariance with the shock terms $\tilde{A}_{t+1}$ and S_{t+1}.

Proposition 2. *Suppose firms hold their policies fixed and there is a positive interest rate shock ($\uparrow S_t$). Corporate bond prices drop and yields increase if and only if the real SDF is significantly sensitive to the interest rate shock. This required level of significance is measured by a threshold $\underline{m}$, for which m_S must be greater than $\underline{m}$.*

Recall from a previous discussion that the bond price in (8) can be rewritten as follows:

$$p_{j2} = \mathbb{E}_2\left[M_3^n(1 - \mathbb{1}_{\{D_{j3}>0\}})(1+c)\right] + \mathbb{E}_t\left[M_3^n \mathbb{1}_{\{D_{j3}<=0\}} \frac{X_{j,3}^{PD}}{b_{j3}}\right]$$

Holding firm policies and other non-monetary policy shocks fixed, the payoffs in both parts of the corporate bond price do not fluctuate as a result of an interest rate shock. In order for prices to move, M_3^n must be sensitive to S_2. Hence, corporate bond yields and credit risk only increase (i.e. $p_{j2}\downarrow$) if m_{t+1}^n is negatively affected by S_t. For this to be the case we need:

$$m_S + \pi_S > 0 \qquad (\Leftrightarrow) \qquad m_S > \underline{m} \equiv \frac{1}{\alpha_\pi}. \tag{15}$$

5.3. Calibration

After-tax firm profits in period 1, $\Pi_{jt} = (1-\tau)\left(e^{\left(\tilde{A}_t + a_t^j\right)}k_{jt}^\alpha\right)$, are decreasing returns to scale in capital. In the subsequent two periods, we add a fixed cost ($f > 0$). The purpose behind this choice is that a large enough f serves as a convenient way to generate default and credit spreads. Also, with no costs in the first period, firms will not default immediately. Investment is standard and given by $i_{jt} = k_{j,t+1} - (1-\delta)k_{jt}$. Meanwhile, adjustment costs are given by $\varphi_{kt}\left(k_{jt}, i_{jt}\right) = \frac{\phi_{kt}}{2}\left(\frac{i_{jt}}{k_{jt}} - \delta\right)^2$, where δ is the depreciation rate and ϕ_{kt} are time-dependent parameters. Without any adjustment costs, the firms' average level and volatility of investment are both extremely large.

While the model features a stylized 3-period setup and is designed to display a mechanism, some of the baseline parameters are guided by data. For example, the steady state interest rate, Taylor rule coefficients, and aggregate shock parameters are based on quarterly interest rate and macroeconomic data. Further, S_t is assumed to be persistent so that it is a priced state variable that can generate significant impulse response functions. More details regarding the baseline parameters are given in Appendix C.3.

To gain better intuition of the credit spread dynamics in the model, we explore the credit spread schedule offered to firms in Figure 2. While these quantities do not reflect firm choices (they are in "partial equilibrium"), they are of interest as they reflect the multi-dimensional nature of the debt supply curve. The y-axis in Figure 2 reports the credit spread associated with a particular debt choice (high, medium, or low values of b_{j3}) for various choices of capital on the x-axis (different values of k_{j3}). We hold fixed idiosyncratic and aggregate cash flows shocks to their median values, and vary

[17] For more details, see Appendix C.2.

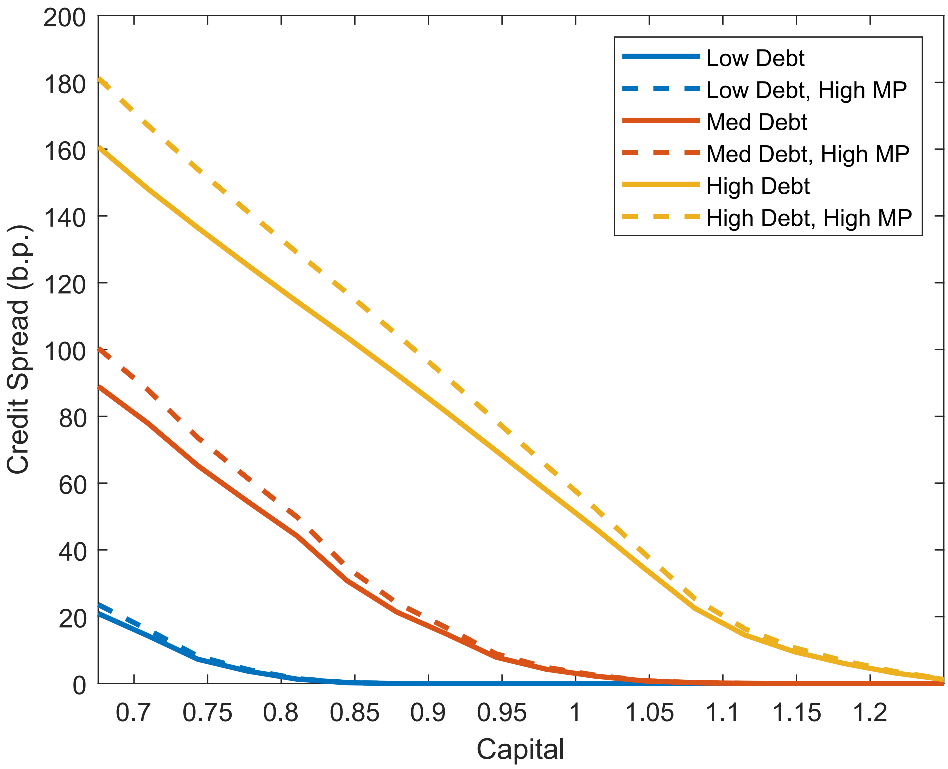


Fig. 2. Schedule of credit spreads This figure display the credit spread schedule that is offered to firms in the second period, as implied by the baseline set of parameters. Lines for chosen values of low, medium, and high debt are provided (blue, red, and yellow respectively) and the x-axis throughout is the value of chosen capital. All shocks are kept at their steady state values except for the dashed lines, which each account for a contractionary shock to monetary policy. Credit spreads are in basis points. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

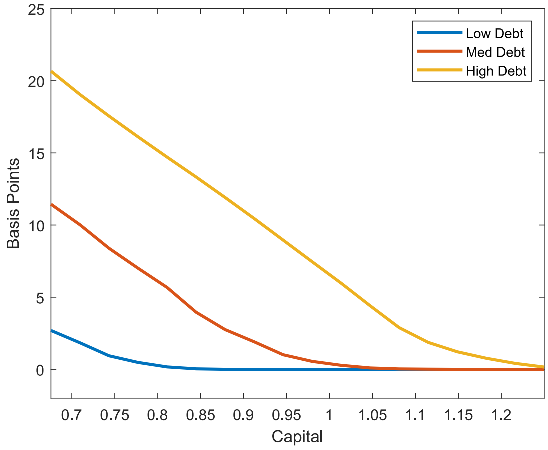
monetary policy shocks from median (solid line) to elevated (dashed) states. A few intuitive results hold: (1) a greater amount of debt leads to higher credit risk, holding capital fixed and (2) a lower amount of investment increases credit risk, holding debt fixed. When the economy witnesses an interest rate shock, credit spreads increase, as a shift from a solid line to a dashed line indicates. It is also apparent that firms that originally choose higher levels of debt witness a larger increase.

A key parameter in our setup is m_S, the price of risk associated with interest rate shocks. To better highlight its role on the relative monetary policy effect, in Fig. 3 we plot the difference between the dashed and solid lines in Fig. 2 following a policy shock. The top-left panel, where m_S is at the baseline value, shows that the effect of a shock is greatest for firms with greater leverage (i.e. fixing capital and moving vertically). For a firm that takes on 0.8 units of capital and high levels of debt, a high value of m_S leads to a monetary policy effect of 15 basis points. Under a lower monetary policy price of risk ($m_S = 5$), as given in the upper-right panel, the effect of monetary policy is weakened and for the same 0.8 units of capital and high levels of debt, the increase is now 5 basis points. Finally, in the bottom panel, we set $m_S = \underline{m}$, the threshold value from *Proposition 2*. In this scenario the response is non-existent. In summary, the effects of monetary policy are highly tied to m_S – the extent to which intermediaries price monetary policy in their real pricing kernel. It is important to reiterate that the results presented above are from a “partial equilibrium” thought experiment. They keep firm policy functions fixed as we examine the impact on credit risk. In the next subsection we examine equilibrium effects and heterogeneity.

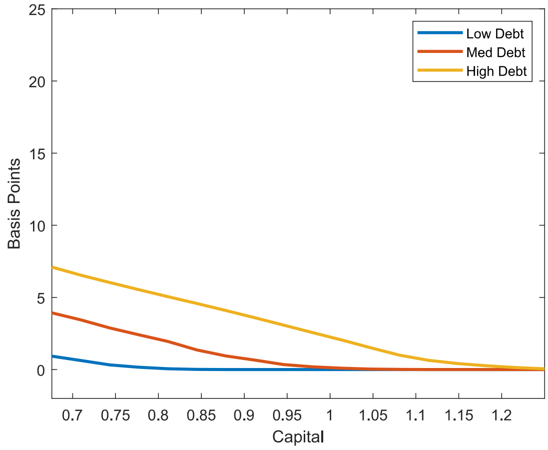
5.4. Quantitative results

To better assess the model’s ability to replicate some of the empirical findings, we simulate and examine firm-level cross-sectional moments using an artificial panel of 10,000 firms. Throughout the baseline simulation we keep monetary policy and aggregate productivity at their steady state values. The firm-level decision variables, from the second period, are provided in the first column of Table 6.[18] It is clear that firms take on a great deal of leverage (about 68%) to finance investment. The average credit spread on the debt, our measure of credit risk[19], is 6.7 basis points, while the ex-ante probability of default is about 3.5%. Relative to the data, one might think that priced credit risk is relatively low and default rates are

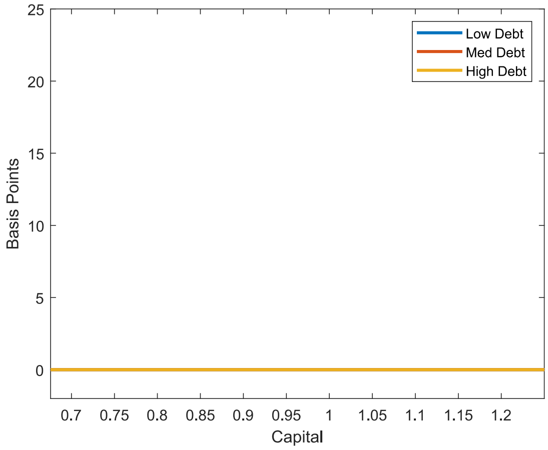
[18] As firms have access to capital markets in the 2nd period, and are subject to monetary shocks at this point, we only present results related to this period in the main text, for brevity sake. Appendix C.3 discusses the baseline moments across all three periods.



(a) Baseline Price of Risk ($m_S = 12$)



(b) Lower Price of Risk ($m_S = 5$)



(c) Negligible Price of Risk ($m_S = \underline{m}$)

Fig. 3. Difference of credit spreads following monetary shock These figures display the difference in credit spread schedules, where one schedule accounts for a positive monetary policy shock and the other is held at steady state. The upper left panel focuses on a model environment where the real, market price of monetary risk is significantly positive (the baseline). The upper right panel sets the real, market price of monetary risk to a lesser, negligible amount. Finally the bottom most panel sets the price of risk to the threshold value described in the text, $\underline{m}$. In each figure, various lines for low, medium, and high debt are provided (blue, yellow, and red, respectively). In the case of the Baseline panel, each line is the difference between the solid and dashed lines in Fig. 2. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 6
Aggregate effects of monetary policy shock. This table displays simulated moments from the model, based on a panel of 10,000 firms, across two different shock environments. In the first column ("Baseline"), aggregate cash flow and interest rate shocks are kept at steady state, while idiosyncratic shocks are simulated continuously. In the second column ("MP Shock"), aggregate and idiosyncratic cash flow shocks are exactly the same as before. However the interest rate shock at time 2 is raised. The third column merely reflects the arithmetic difference between the 2 columns. In columns 4 through 8 ($m_S = 16$ onwards), we examine the impact of a parameter change on the monetary policy impulse. Hence, these last columns are comparable to the *Change* column, under the baseline parameters. Underlying firms are fixed to be those that do not default across both simulations at the start of period 2. For more details see main text.

Moment	*Baseline*	*MP Shock*	*Change*	$m_S = 16$	$m_S = 5$	$m_S = \underline{m}$	$\rho_S = 0.65$	$f = 1.30$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg i / k	0.102	0.073	−0.029	−0.038	−0.01	0	−0.056	−0.03
Std i / k	0.034	0.032	−0.002	−0.003	−0.001	0	−0.003	−0.001
Avg b / k	0.683	0.673	−0.01	−0.013	−0.004	0	−0.016	−0.006
Std b / k	0.111	0.106	−0.004	−0.006	−0.002	0	−0.01	−0.003
Avg Credit Spread (b.p.)	6.695	10.356	3.661	5.008	1.311	0	7.746	7.914
Std Credit Spread (b.p.)	35.845	59.045	23.2	18.478	6.125	0	39.065	27.651
Avg Ex-Ante Def Prob (%)	3.46	4.283	0.824	1.236	0.323	0	1.774	2.081
Std Ex-Ante Def Prob (%)	13.022	14.621	1.599	2.491	0.729	0	3.907	2.123
Realized Def Rate (%)	0.17	0.55	0.38	0.8	0.15	0	1.56	3.69

relatively high. This is a common issue among models without significant curvature in the SDF or risk neutral probability adjustment, as larger default probabilities are needed to generate larger spreads. In our model economy, we abstract from such quantitative issues.

Effects of an Unexpected Interest Rate Shock. To test the effects of a contractionary monetary policy shock, we re-simulate the economy keeping all idiosyncratic and aggregate shocks the same. However, we change one aspect – we positively shock S_2 by 1%. Based on the baseline and “impulse” economies, we take the difference of firm activity in the second period to understand the impact of monetary policy.[20] The second column of Table 6 displays the effects of a monetary shock on the second period moments of interest, while the third shows the difference of the baseline and the shocked economy.

In terms of the response, firms reduce average investment rates by 3% (of starting capital) following the monetary shock, which accompanies a slight reduction of leverage. The reduction of capital stock leads credit spreads to increase by 3.7 basis points. This result is qualitatively consistent with the empirical analysis. The standard deviation of credit risk also increases, suggesting a wider right tail of credit spreads. The increase in credit spreads coincides with a 82 basis point increase in the ex-ante default probability.

To better understand the mechanism of the model, we can explore the effect of various parameter choices on the impulse response discussed in the prior paragraph. In Table 6, columns 4 and beyond reflect the relative difference between a shocked economy and the baseline, while shifting one parameter at a time. The first set of tests look at the equilibrium effects of the monetary policy price of risk, m_S. In the fourth column, where the MP price of risk is greater than the baseline value of m_S, we see that the credit spread increase due to the policy shock is larger relative to that of the baseline (5.0 vs. 3.7 basis points). So too are the drop in investment rate (3.8 vs. 2.9%), increase in ex-ante default probability, and realized default rate. In the fifth column, we reduce the price of risk below the value of the baseline, and the direction goes the other way. Here, credit spreads only increase at a rate of 1.3 basis points. Finally we show that when $m_S = \underline{m}$ there is no effect on quantities and prices, as we would have expected from Proposition 2. In summary, these counterfactuals suggest that intermediary risk aversion towards policy shocks (m_S) plays a crucial role toward the ability of firms to optimally respond to policy. Another clear message from these counterfactuals is that the response of credit spreads to interest rate shocks is tied to endogenous investment.

In columns 7 and 8 we examine other two variables of interest. For higher values of the persistence of policy shocks ($\uparrow \rho_S$ in column 7), while fixing the volatility of S, we see that a monetary policy shock increases the credit spread response dramatically, due to an increase in the likelihood of future interest rate hikes. The same happens when the fixed cost increases ($\uparrow f$ in column 8). In this case, firms are more likely to default, all else equal.

Heterogeneous Responses. A significant portion of our empirical analysis discusses the heterogeneous response of CDS to monetary policy. Our model economy also allows us to perform a similar analysis, whose results are reported in Table 7. In each panel, we compare firms that make choices in the baseline economy with their sister firms that do the same in the economy subject to an increase in S_2. The top panel sorts firms into quintiles based on their initial market value, starting with the largest (i.e., riskiest) firms in the bottom quintile. The second panel does the same based on a sort of their initial credit spread. Finally the bottom panel performs the sort based on leverage. In essence, the sorts align with our priors on risk – lower market values, higher credit spreads, and higher leverage lead to greater risk, all else equal. Within each panel and each quintile, we examine the percentage change in investment, leverage, market values, and asset prices by comparing a firm in the baseline environment with its counterpart in the shocked policy environment.

The top panel presents a stark image. While credit spreads have gone up by 3.7 basis points, the bulk of the increase is among the riskiest firms – those in $Q5$. Upon seeing an increase in bond yields due to the monetary shock, firms are required to cut back on leverage and investment. While the reduction in leverage helps firm value, cutting back investment has a large impact on market valuations and distance to default. This manifests itself as those firms in $Q5$ post the largest decrease in market value (-26.8%). When we sort on credit spreads a similar picture emerges. Firms that ex-ante had the highest credit spreads display the largest increase in credit spreads (12.2 b.p.) following the monetary policy shock. The channel is exactly the same and mirrors the valuation sort. Finally, the picture flips when we examine leverage. Those firms that have the most leverage display a very small increase in credit spreads. This result emerges due to the inherent self-selection in the model. Firms that take on more leverage are not riskier in equilibrium. In fact, these firms are the ones that are more productive and build up larger capital stocks.

In summary, the model suggests that the response of credit risk (and equity returns) to monetary policy is heterogeneous across risk categories. However the underlying measure of risk matters. While sorts on ex-ante credit risk operate as we would expect them to, leverage is a less clean measure, because it is tied strongly with cash flow-yielding investment. This latter insight in the model might also explain, in the data, why CDS spreads are more influential than leverage for the transmission of monetary policy.

[19] While in real life there are small differences in the pricing of CDS and corporate credit spreads (often referred to as the CDS-bond basis), in the model there would be no difference, due to the perfect and complete nature of information. Model-based credit spreads serve as a perfect barometer of credit risk. We compute them as: $\frac{1+c}{p_{j2}} - \frac{1+c}{\mathbb{E}_2\left[M_3^n(1+c)\right]}$. The latter reflects the gross yield on a risk-free security.

[20] Note that Period 1 values do not change, as the interest rate shock is kept at steady state ($S_1 = 0$) in both economies.

Table 7
Distributional effects of monetary policy shock. This table displays percentage changes of simulated firm moments (investment, leverage, market value, credit spreads, and default probabilities), based on firms within a particular sorting. The top panel sorts on historical levels of market valuation. The second and third panels respectively sort on credit spread and leverage. The percentage is computed by comparing a firm in the baseline environment with its own self in the shocked policy environment (for more details see main text). The historical value is based on the level of said variable in the baseline environment. Investment, leverage, and value are all in terms of percentage point deviations. Credit spreads and ex-ante default probabilities are simple differences of variables.

Metric	*Q1*	*Q2*	*Q3*	*Q4*	*Q5*	*Average*
Sorting on Initial Value (Left to Right, Increasing in Risk)						
Δ Investment (% Chg)	−2.936	−2.801	−2.057	−2.944	−2.695	−2.675
Δ Leverage (% Chg)	-4.379	−5.325	-4.496	−2.722	−3.239	-4.032
Δ Value (% Chg)	−9.37	−11.044	−12.797	−15.422	−26.791	−15.311
Δ Credit Spread (b.p.)	0.179	−0.056	−0.317	0.993	16.521	3.661
Δ Ex-ante Def Prob (%)	0.003	-0.002	-0.021	0.234	3.686	0.824
Sorting on Credit Spread (Left to Right, Increasing in Risk)						
Δ Investment (% Chg)	−2.918	−2.939	−2.28	−2.622	−2.638	−2.675
Δ Leverage (% Chg)	−1.983	−4.114	−4.129	−5.531	−5.08	−4.032
Δ Value (% Chg)	−14.88	−10.692	−12.408	−12.546	−25.571	−15.311
Δ Credit Spread (b.p.)	3.176	0.231	-0.101	-0.545	12.228	3.661
Δ Ex-ante Def Prob (%)	0.561	0.007	0.025	0.022	2.871	0.824
Sorting on Leverage (Left to Right, Increasing in Risk)						
Δ Investment (% Chg)	−2.86	−2.691	−2.161	−2.793	−2.967	−2.675
Δ Leverage (% Chg)	−2.349	−4.391	−4.557	−5.211	−4.548	−4.032
Δ Value (% Chg)	−21.031	−22.498	−12.688	−10.832	−9.217	−15.311
Δ Credit Spread (b.p.)	16.739	−10.193	−0.256	−0.035	0.1	3.661
Δ Ex-ante Def Prob (%)	2.079	2.002	−0.018	−0.003	0	0.824

6. Conclusion

Monetary policy surprises significantly affect firm-level credit risk. Consistent with recent evidence, we document that both components of firm-level credit risk (i.e., the expected loss and the risk premium components) and equity prices respond more to monetary policy surprises when firms have higher credit risk, as measured by their CDS spreads. Additionally, the importance of firm-level credit risk for the propagation of monetary policy shocks does not diminish when we contemporaneously control for book leverage and market size, two characteristics commonly associated with firm-level risk.

To rationalize the heterogenous response of credit risk and the noisiness of leverage as a risk indicator, we construct a stylized three-period model that features endogenous financing and investment decisions together with a monetary authority that sets short term interest rates. Central to our results is an intermediary pricing kernel for which larger prices of risk related to interest rate shocks correspond to larger responses of credit spreads and real quantities. We show in the model economy that firms with higher ex-ante spreads, that are closer to default, are those that are more sensitive to interest rate shocks. Meanwhile, firms with higher leverage are able to afford such debt capacity due to their fundamental strength and, as a result, their credit spreads are less sensitive to monetary policy shocks.

Overall, our work suggests that a simple and intuitive measure such as leverage might not be as effective as a more direct measure of credit risk such as CDS spreads, to understand the pass through of monetary policy at the firm level.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2022.06.004.

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