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Credit Risk and the Transmission of Interest Rate Shocks

Berardino Palazzo
Board of Governors of the Federal Reserve System
dino.palazzo@frb.gov

Ram Yamarthy
Office of Financial Research
ram.yamarthy@ofr.treasury.gov

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Berardino Palazzo† Ram Yamarthy‡

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Abstract

Using daily credit default swap (CDS) data going back to the early 2000s, we find a positive and significant relation between corporate credit risk and unexpected interest rate shocks around FOMC announcement days. Positive interest rate movements increase the expected loss component of CDS spreads as well as a risk premium component that captures compensation for default risk. Not all firms respond in the same manner. Consistent with recent evidence, we find that firm-level credit risk (as proxied by the CDS spread) is an important driver of the response to monetary policy shocks – both in credit and equity markets – and plays a more prominent role in determining monetary policy sensitivity than other common proxies of firm-level risk such as leverage and market size. A stylized corporate model of monetary policy, firm investment, and financing decisions rationalizes our findings.

Keywords: Credit risk, CDS, monetary policy, shock transmission, equity returns

JEL Classification: E52, G12, G18, G32

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†Federal Reserve Board, dino.palazzo@frb.gov.

‡Office of Financial Research, ram.yamarthy@ofr.treasury.gov.

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 financial institutions extend credit to firms at a premium that compensates for default risk, it is still widely debated and researched as to how corporate credit spreads are affected by interest rate shocks through monetary policy.[1] This transmission mechanism has played a crucial role in the last two decades: during the 2007-09 financial crisis and during the recent market turmoil sparked by the COVID-19 pandemic.[2]

In this paper we use higher-frequency measures of unexpected movements in interest rates and of credit risk to shed more light on the transmission of monetary policy shocks into corporate credit markets. To ensure that our results do not depend on a particular measure of monetary policy shock, we use four different measures. As introduced in Gürkaynak, Sack, and Swanson (2005), we use Target and Path measures to control for unexpected changes in the current federal funds rate targets and movements in the short-run path of interest rates, respectively. To control for term structure movements in the zero lower bound (ZLB) period, we use a measure related to large scale asset purchases (LSAP) from Swanson (2020) and a monetary policy shock developed by Bu, Rogers, and Wu (2019) that uses longer-term Treasury securities for identification purposes. Finally, to measure credit risk at the firm-level, we take advantage of daily quoted prices on the credit default swap (CDS) market. As the CDS effectively insures against a default event, its time-varying premium (referred to as a "spread") directly serves as a market-based measure of credit risk.

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. On average, we find that a 1 standard deviation surprise in monetary policy leads, on average, to a 1 basis point movement in CDS spreads. The significance is robust to multiple measurements of monetary policy, firm level controls, and fixed effects at various levels. We additionally find that unexpected movements of inter-

[1] A number of studies have focused on understanding the bank lending channel of monetary policy, liquidity transformation, and its connection to asset prices (see e.g., Drechsler, Savov, and Schnabl (2017) and Drechsler, Savov, and Schnabl (2018)). Another very recent working paper examines credit costs and monetary policy (Anderson and Cesa-Bianchi (2020)).

[2] The financial crisis of 2008-09 featured a number of non-financial firms whose credit spreads were disproportionately affected. The implementation of the zero lower bound and large-scale asset purchases by the Federal Reserve greatly helped and had a strong impact on them (see Gilchrist and Zakrajsek (2013), Swanson and Williams (2014), and Swanson (2016)). With respect to recent events in March 2020, the Federal Reserve reacted swiftly by cutting the federal funds rate to zero and by establishing corporate credit facilities with the intent to purchase Treasuries and agency MBS at an unlimited basis.

est rates significantly affect two components of credit risk: compensation related to expected losses as well as a credit risk premium component that measures additional compensation for default risk.

Not all firms respond to monetary policy in the same manner. Consistent with recent cross-sectional evidence (e.g., Javadi, Nejadmalayeri, and Krehbiel (2017), Guo, Kontonikas, and Maio (2020), and Smolyansky and Suarez (2020)), we find that firm-level risk is an important driver of the response to monetary policy shocks. 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, for firms with a 1 standard deviation higher CDS spread, a 1 standard deviation interest rate surprise marginally increases future spreads between 0.6 and 0.7 basis points. Similarly, firms in the highest risk quintile (the top 20% of the CDS rate distribution) display much stronger response relative to those in the lowest quintile. These heterogeneous sensitivities affect both the expected loss and credit risk premium components of CDS spreads.

As discussed in Chava and Hsu (2019), among others, 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. When we consider stock price changes using a 1-hour window around FOMC announcements, stock prices of high credit risk firms contract 15 basis points more than stock prices of low credit risk firms in response to a 1 standard deviation contractionary monetary surprise. When we look at the cumulative 2-day returns, stock prices of high credit risk firms contract 40 basis points more than low credit risk firms. These are economically and statistically large differences.

Financial leverage and market size can also serve as empirical and theoretically-motivated proxies for cross-sectional risk. In our study, we show that firms with higher leverage and lower market values of equity display increased sensitivities to monetary policy. However, the role of leverage and market size becomes relatively insignificant when we simultaneously control for an interaction effect using the historical level of CDS spreads. We interpret these results as suggestive of CDS as better risk measures for the pass-through of shocks into asset prices.

Finally, our paper is one of the first to separate CDS spreads into their expected loss and credit risk premium components, and study their relative importance for the pass-through of monetary policy shocks. We find that when examining the response of CDS spreads, both the credit risk premium and the expected loss channel seem to play a significant role. Meanwhile when examining the response of equity returns, regardless of time frequency (1 hour vs.

2 day returns), it always is the case that compensation for physical default probabilities matters more. These results suggest that credit risk premia and expected default affect the transmission of shocks differentially across corporate bonds and equity markets.

One major issue that arises when using CDS prices as a direct measure of credit risk is that the credit default swap is a derivative instrument that indirectly captures the financing risks that are apparent in corporate bonds. As they are not precisely the same set of instruments and not necessarily traded by the same market participants (see Augustin, Subrahmanyam, Tang, and Wang (2014)), CDS spreads, at times, may have differing levels of liquidity relative to corporate bonds, which can imply unequal levels of company-specific credit risk. This phenomenon is also known as a non-zero CDS-bond basis, as discussed in Bai and Collin-Dufresne (2019). To handle these issues, we conduct robustness on our tests to ensure that CDS-related liquidity does not affect the main dynamics. We do this by limiting our sample to security-level observations that have a larger number of reported dealer quotes and we find that our results actually become stronger. Furthermore, as discussed in recent regulatory reports from the Office of the Comptroller of the Currency (OCC), the demand for credit derivatives by financial institutions has decreased over time.[3] To ensure that our reported results are not sensitive to a particular time period with increased derivative demand and volume, we conduct analysis over different subsamples (ZLB vs. non-ZLB) and find that our results are robust, particularly when we use the monetary policy shock measure of Bu et al. (2019), which is identified using longer-term Treasury movements.

Beyond the full sample evidence, our analysis can be directly applied to the recent COVID-19 episode. Following the pandemic's adverse effect on the real economy, monetary and fiscal authorities enacted a number of large-scale stimulus programs. We focus our attention on the March 23, 2020 announcement by the Federal Reserve that established corporate credit facilities and stated an intent to purchase Treasuries and Agency mortgage-backed securities (MBS) at an unlimited basis. As this was a significant episode of expansionary monetary policy, we observe changes in CDS spreads, default probabilities, and equity returns consistent with the findings obtained using the full sample of interest rate shocks: Firms in the highest quintile of risk, as proxied by their CDS levels, are those that reacted the most. High credit risk firms' CDS prices and physical default probabilities reduced dramatically following the policy announcement relative to less risky firms. At the same time, and in a way consistent with our full-sample findings, stock returns of firms in the highest CDS category fell much more than the ones of firms in the lowest CDS category.

To help understand the heterogeneity in credit risk response to monetary policy shocks

[3] See the *Quarterly Report on Bank Trading and Derivatives Activities* from the Office of the Comptroller of the Currency, Q4 2019.

and the irrelevance of firm leverage in explaining this response once we control for CDS, we design a stylized equilibrium model of corporate leverage, investment, and monetary policy. In the model, firms seek to maximize the expected, present value of future, *nominal* cash flows over a 3-period horizon. Firms invest without leverage in the first period but have access to debt capital markets in the second period. When issuing debt, firms agree to pay a spread on top of the risk-free rate, depending 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 (aggregate) 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 a firm's credit risk.

How does the model generate this natural convexity in credit costs? Upon seeing an increase in bond yields due to a contractionary monetary shock, all firms would like to cut back on leverage. Reducing leverage is tied to a reduction in investment. Firms that are closer to default and are riskier have a low endogenous capital stock to begin with. For this reason, cutting back on investment significantly harms them the most and, in equilibrium, they are even closer to default. Hence, credit spreads of the riskiest firms increase the most following an unexpected and positive shock to interest rates.

Literature Review

Our paper relates many different strands of research, including work in the areas of monetary policy and its measurement, corporate credit risk as identified by bond and CDS markets, and the interaction between the two.

A significant portion of work in monetary economics seeks to examine whether fluctuations in the money supply and short-term interest rates have non-neutral effects on real quantities (see e.g., Christiano, Eichenbaum, and Evans (2005)). Crucial to those experiments is the identification of exogenous and unexpected shocks to interest rates. While one subset of the literature focuses on identification through structural vector-autoregressions (SVAR), another one uses high-frequency financial market data surrounding FOMC announcements. Starting with Kuttner (2001), researchers have suggested that changes in actively traded interest rate futures contracts, in 1 hour windows surrounding FOMC announcements, better identify exogenous changes in market expectations. Using a similar approach, Bernanke and Kuttner (2005) examine the link between these unexpected changes and equity market prices. Instead of using the actual change itself, Gürkaynak et al. (2005) rotate the FOMC-related movements among a number of short-term futures contracts to show that there exist 2 factors that significantly affect asset prices – a target and a future path factor. Similar to the aforementioned paper, we also use the Target and Path factors as two of our key monetary policy shock variables. The latter quantities are unable to capture movements in policy in the ZLB period as target interest rates were kept at or close to zero. To account for this point, Swanson (2020) extends the factor analysis in Gürkaynak et al. (2005) to introduce a third factor that accounts for monetary policy surprises linked to LSAP programs. In our analysis, we also use this LSAP factor but additionally account for the ZLB period using a set of shocks constructed by Bu et al. (2019). The work by Bu et al. (2019) focuses on using a wide set of zero-coupon bond yields (with maturities ranging from 1 to 30 years) to identify a monetary policy shock that is active during the ZLB.

As greater amounts of cross-sectional and time series data have surfaced, empirical research related to credit risk has flourished. To this day, financial economists have explored corporate bond-based credit spreads to make a number of statements regarding firm and economy-wide dynamics (see e.g. Dufresne, Goldstein, and Martin (2011), Gilchrist and Zakrajsek (2012)). More relevant to our study of monetary policy interactions, a number of papers discuss the effects of policy on the corporate bond market. Both Javadi et al. (2017) and Guo et al. (2020) discuss the ways in which policy-related rate movements affect corporate spreads. Both papers show that speculative or lower-rated bonds are more responsive to monetary policy. While their findings are similar in spirit to ours, they mainly explore selection issues with respect to credit ratings and do not explore how actively traded prices matter for transmission. Our paper, on the other hand, incorporates market-based CDS prices directly and compares them to slower-moving measures such as leverage. A recent paper by Smolyansky and Suarez (2020) also examines the effects of monetary policy on the corporate bond market, by disentangling two effects – a "reaching for yield" effect and an "information" effect. The authors also use monetary policy shocks identified in higher frequency and find that unanticipated policy actions lead to heterogeneity in corporate bond return responses.

In practice, as credit derivative markets substantially increased in use following the early 2000s, many banks and hedge funds have opted to trade in the liquid world of credit default swaps. The market is large and robust and the earlier cited OCC regulatory study suggests that banks alone hold more than $3.9 trillion in notional protection with respect to CDS. In our study we primarily use CDS data – that is, quotes of credit default swap spreads provided by broker dealers. There are several advantages to using CDS over corporate bond data. Our CDS data is 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, Brennan, and Marsh (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. Berndt, Douglas, Duffie, and Ferguson (2018), a related paper, discusses time series and cross sectional patterns in CDS. Among many other things, the authors show that a large portion of CDS spread movements is determined by factors outside of physical default probabilities.[4]

A recent, related literature bridges the gap between monetary policy and firm-level fundamentals, and examines how monetary policy can have heterogeneous effects on firm-level decision making. Ottonello and Winberry (2019) examine the investment and leverage response following interest rate shocks and find that firms with lower levels of risk respond the greatest. Jeenas (2019) explores similar issues as Ottonello and Winberry (2019) but stresses the role of balance sheet liquidity. In contrast with both of these studies, we explore how market-based *asset prices* respond on a daily level following an unexpected policy announcement. The daily data is particularly important as it helps with the identification of the shock transmission.

While the focus of their study is on cross sectional equity market returns, Chava and Hsu (2019) show that monetary policy has a greater impact on the returns of firms that are more financially constrained. The authors use the financial constraints measure originally constructed by Whited and Wu (2006). Our equity results are similar to theirs, in that CDS rates can be likened to a financial constraint measure. Additionally, of course, we examine the heterogeneous impact of unexpected interest rate shocks on credit risk movements and their risk premium components.[5]

In a closely related paper, Anderson and Cesa-Bianchi (2020) use secondary market prices of corporate bonds and related credit spreads as their key response variable of interest. They find that interest rate shocks indeed affect bond-based credit spreads and that more-leveraged

[4]Historically CDS have been used as a direct proxy of credit risk but in recent times, issues of liquidity have become more relevant, as the CDS-bond basis emerged in the financial crisis period (see Augustin et al. (2014) and Bai and Collin-Dufresne (2019) for more information). In our study, we are able to control for these liquidity issues by including firm-level variables that have been suggested to affect the bond basis. Furthermore, our results are robust to the use of different sample periods (full sample, ZLB, and non-ZLB).

[5]Similarly, Ozdagli (2017) explores the reaction of equity market prices to informational and financial constraint frictions. His paper shows that the stock prices of more constrained firms are less responsive to monetary policy. This result is different from the findings in Chava and Hsu (2019), however some of it may be due to differences in the type of constraint measure they use. Ozdagli (2017) focuses on using a constraint measure that is similar to monitoring costs, similar to the financial accelerator literature.

firms are more affected. Our analysis is consistent with their findings, however we show that using a market-based measure of credit risk (such as CDS) is more informative than using a more static measure such as leverage. Our results regarding the relative informational content of CDS also extend when we examine the cross-sectional responses of equity prices. These results can be related to those in Corvino and Fusai (2019) and Friewald, Wagner, and Zechner (2014) who find that firm-level credit risk premiums and equity returns contain similar information and move together.

2 Data

2.1 Monetary Policy Shocks

Unexpected movements in risk-free interest rates – as set through monetary policy – can be measured in different ways. To obtain a comprehensive picture of how such shocks affect credit risk, we use four different measures that all involve the high frequency identification approach popularized by Kuttner (2001) and Gürkaynak et al. (2005), among others.

Gürkaynak et al. (2005) conclude that at least two factors are needed to explain changes in a larger cross section of monetary policy–sensitive instruments following FOMC announcements. These two factors are determined through a principal component analysis (PCA) of *30-minute changes* in federal funds futures rates and Eurodollar futures rates. In the literature, these factors are often referred to as "Target" and "Path" factors – the former because it loads most heavily on the shortest-term interest rate contracts and the latter as it has implications for medium-term expectations of future rate movements. In our paper, we use updated versions of these two factors (see Swanson (2020) for more details).

A natural concern in the identification of monetary policy shocks is the inability of short-term rates to characterize policy when rates are at the zero lower bound, as was the case from late December 2008 through December 2015 in our sample. To address these concerns we use two additional measures. The first measure is constructed in Swanson (2020) and effectively is the third principal component from the component extraction described above. Additional restrictions are placed on this third principal component (through an orthogonal rotation of the factors) such that the third component does not affect the Target variable during the ZLB period and is relatively small prior to the ZLB. In Swanson (2020), this factor is described as a LSAP factor. Our fourth and final measure of monetary policy is developed by Bu et al. (2019) and delivers a measure that directly captures the sensitivities of longer-term interest rates to monetary policy announcements and is purged of the central bank information effect (e.g., Nakamura and Steinsson (2018)). Bu et al. (2019) employ a Fama-

Macbeth style procedure using *daily data* surrounding FOMC announcements, where the test assets include longer-term Treasury securities. The time-varying estimate (a commonly priced risk factor) that emerges from the second step is the effective monetary policy shock. In all subsequent analysis, we will refer to the latter shock as BRW.

In total, our dataset includes 145 FOMC announcement dates – the first one on Wednesday, January 30, 2002 and the last one on Wednesday, June 19, 2019. We include only scheduled FOMC meetings. The beginning date of our dataset is restricted by the availability of firm-level CDS data prior to 2002. Figure 1 reports the time series for all four monetary policy variables: Target, Path, and LSAP in the top panel and BRW in the bottom panel. In both panels, the gray area indicates the zero-lower bound period while the dashed lines respectively reflect key announcement dates during the ZLB for QE1, QE2, and Operation Twist. As the first three factors are comparable (arising from the same estimation), they are plotted in the same figure; meanwhile, the BRW variable is plotted separately in basis point terms. Figure 1 shows that in the pre-ZLB period the Target and Path factors are more volatile. During the ZLB period the Target and Path display less variation relative to LSAP and BRW. It is worth noting that that LSAP and BRW don't perfectly display the same behavior. On the QE1 announcement date (March 18, 2009) both of them dramatically decrease as quantitative easing was a strongly unexpected expansionary shock. However, on the QE2 and Operation Twist episodes, they show differing signs and magnitudes of response – this will play an important role later as we examine the credit risk response.

Table 1 displays summary statistics of the four monetary policy shocks used in the empirical analysis, both for the full sample (Panel A) and for two subsamples: the conventional period (Panel B) and the zero lower bound period (Panel C).[6] Within each panel, all rows provide statistics on Target, Path, LSAP, and BRW (in basis points). What was clear in the figures regarding the behavior of these shocks in the ZLB and non-ZLB periods is reinforced in Table 1. Target and Path variables have up to 25% more variation in the non-ZLB period while LSAP and BRW have up to 40% less (relative to the full-sample). Meanwhile during the ZLB period, Target and Path variables have up to 74% less variation while LSAP / BRW variables display roughly 40% more variation. This makes sense as the first two shock variables have larger loadings on shorter-end contracts.

Table 2 examines the correlations across all of our monetary policy variables and shows that in the full sample, Target, Path, and LSAP have correlations close to zero, as expected.[7]

[6] We follow Bu et al. (2019) and define the ZLB period to cover the years of 2009 to 2015. The conventional period covers the years from 2002 to 2008 and from 2016 to 2019.

[7] As the three of them are principal components to begin with, one might expect their pairwise correlation to be precisely zero. The reason this is not the case is because Swanson (2020) constructs these orthogonalized factors over a much longer sample and we are restricting the pre-built factors to a shorter time horizon, which

We also find that BRW has a small correlation with Target and larger correlation with Path ($\rho = 0.22, 0.52$ respectively). The latter makes sense as the Path factor picks up on medium-term changes in interest rates and the construction of BRW involves bond yields of different maturities. Perhaps most interestingly, LSAP and BRW don't have a strong correlation ($\rho = 0.20$ unconditionally and $\rho = 0.35$ during the ZLB) and some of this can be seen through the construction procedure itself. LSAP is simultaneously extracted with Target and Path via a PCA; meanwhile, BRW is able to pick up on long-term unexpected yield changes on QE dates without any competing factors.

2.2 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 (SIC 6000-6999 in Compustat and sector *Financials* in Markit), utilities (SIC 4900-4999 in Compustat and sector *Utilities* in Markit), and quasi-governmental and non-profit firms (SIC 9000-9999 in Compustat and sector *Government* in Markit). We also exclude firms not incorporated in the United States (Compustat foreign incorporation code different from *US*).

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 CDS contracts written on senior unsecured debt (Markit tier category *SNRFOR*)[8]. Whenever possible, we also provide the annualized, 5-year conditional probability of default (EDF) from Moody's Analytics. This ex-ante measure of default likelihood 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.

Table 3 reports the firm-level summary statistics. Panel A describes the 5-year CDS spreads (in basis points), the recovery rate, and the numbers of CDS quote contributors (i.e., composite depth) from Markit. As is standard in this data, Markit aggregates a number of quotes from CDS broker-dealers to provide an average CDS price. We have 54,886 firm-FOMC announcement day observations, which imply about 384 firms per FOMC announcement day, on average. These firms have an average (median) CDS spread of 187 (90)

can slightly tilt the correlation.

[8]We obtain very similar results using modified restructuring (MR). These results are available upon request.

bps, an average and median recovery rate of about 40%, and an average (median) number of quote contributors of 5.7 (5).

Panel B of Table 3 reports the annualized conditional probability of default (EDF). Since we have data on EDF only starting from 2004, the number of firm-FOMC announcement day observations is lower (40,223). The average firm in our dataset has an annualized probability of default of about 1% on FOMC announcement days, while half of the firms have an annualized probability of default less than 0.32%. Panel C reports accounting data from Compustat for firms that have data on CDS. Accounting data are at a quarterly level and are calculated the quarter before the FOMC announcement quarter. The average (nominal) firm size, measured as total assets (Compustat item *atq*) is about $21 billion and more than half of the firms are larger than $8.8 billion. In our dataset, we have firms as small as $13 million (Genzyme Molecular Oncology in 2002q4) and as big as $548 billion (AT&T in 2019q1). The average leverage ratio–measured as total debt (item *dlcq* plus item *dlttq*) divided by total assets–is about 32% of total assets, while the average cash-to-asset ratio (item *cheq* divided by item *atq*) is about 10% of total assets. In our sample, firms' physical investment grows, on average, by about 1% each quarter. To measure investment growth, we consider the log-change in quarterly property, plant, and equipment (item *ppentq*). We use the firm-level accounting variables described above as controls in the analysis that follows.

To conclude, Panel D reports the equity return on the day of the FOMC announcement, the return calculated around a 1-hour window (15 minutes before to 45 minutes after) around the announcement time, and the market capitalization for publicly traded firms that have data on CDS rates. All daily return and market capitalization data is from CRSP while higher-frequency data is from TAQ. The average daily return is about 0.36%, while the 1-hour window return is 0.05%. The average market capitalization is about $26 billion and more than half of the firms in our sample have a market capitalization larger than $9 billion.

3 Effects of Interest Rate Shocks on Credit Risk

In the first part of the empirical analysis we study the aggregate, homogeneous effects of movements in monetary policy measures on credit risk and its components. The two main dependent variables we focus on are CDS spreads and the expected loss component of CDS, which is meant to solely account for movements in "physical" default probabilities. To measure the latter quantity, we rely on the annualized 5-year conditional probability of default (EDF) from Moody's Analytics to measure the firm-level expected default probability and on the Markit recovery rate to measure the loss upon default so that the expected loss is calculated as $EDF \times (1 - \textit{recovery rate})$.

Let y_{it} denote the level of the dependent variable (CDS or Exp. Loss) 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:

$$\Delta y_{it} = \beta_0 + \beta_m \varepsilon_t^m + error_{it} \tag{1}$$

where $\Delta y_{it} = y_{i,t+1} - y_{i,t-1}$. 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 ($y_{i,t-1}$). The reason we add an additional day to the future value is due to the way in which Markit conducts its 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. We standardize monetary policy shocks so that β_m represents the change in CDS due to a one standard deviation (1σ) change in the monetary policy shock. In the baseline regression specification, we include firm fixed effects and cluster standard errors at the FOMC date level (i.e., residuals across firms can potentially be correlated on a given announcement day).[9]

Columns 1 to 4 in Panel A of Table 4 report the reaction of credit risk, measured using CDS prices, to the four different monetary policy shocks. For Target, Path, and BRW, we find that a 1σ monetary policy surprise generates a significant and positive increase in CDS spreads between 0.93 and 1.20 bps. This result is consistent with the results in Anderson and Cesa-Bianchi (2020), who find a positive and significant relation between weekly changes in credit spreads and monetary policy surprises. Our results are statistically significant with t-statistics between 1.81 and 3.36. Interestingly, we find that the LSAP shock does not have a significant effect on credit risk while BRW does. As previously mentioned, these results might be due to the way in which both of them are constructed: BRW is directly based on interest rate changes at the longer end of the term structure, while LSAP is the third component of a principal component decompositon.

As discussed, CDS spreads depend on an expected loss component and a credit risk premium component. In the middle columns of Table 4, we illustrate the effect of monetary policy surprises on the expected loss component. Columns 5 to 8 show that a 1σ monetary policy surprise generates a significant and positive increase in expected loss between 0.48 and 0.59 basis points (Target, Path, and BRW). Again, the estimated coefficient on LSAP is not significant.

To examine how the credit risk premium component of credit risk responds to mone-

[9] This is the most conservative level of clustering. If we change it to firm-level or industry-level results become even stronger.

tary policy shocks, we run a version of the regression where we include the expected loss component on the right hand side:

$$\Delta y_{it} = \beta_0 + \beta_m \varepsilon_t^m + \beta_{exp} \Delta \text{ExpLoss}_{it} + error_{it} \tag{2}$$

Including the ExpLoss term acts as a (rough) control for changes in compensation purely due to fluctuations in the default probability. The inclusion of the latter variable has two noteworthy effects. First, the coefficient on the Target shock becomes insignificant, while the coefficient on the Path shock becomes strongly significant. Second, and not surprisingly, the linear model's ability to explain variation in CDS spreads' changes improves (R-squared values almost double). Overall, the results in Panel A of Table 4 show that: (i) the Target shock matters more for the expected loss component of credit risk, (ii) the Path shock matters more for the risk premium component of credit risk, (iii) the BRW shock affects both components of credit risk, and (iv) the LSAP shock does not matter for credit risk.

In Panel B of Table 4, 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, 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 reduces the t-statistics marginally and has a negligible effect on the estimated coefficients of the monetary policy sensitivities. While not reported, it is worth noting that the levels of both the CDS spread and market capitalization have negative and highly significant effects on credit risk changes around FOMC announcement days.

Overall, the results in this section suggest that monetary policy shocks directly affect credit risk on FOMC announcement days. A contractionary monetary policy shock increases credit risk through compensation for expected default and the risk premium component. In the Appendix, we also show that the immediate effects of monetary policy shocks are mitigated when we examine a longer horizon of CDS changes. This result is in contrast to the positive and significant effect of monetary policy shocks on longer-horizon changes in credit spreads documented in Anderson and Cesa-Bianchi (2020). A part of our interpretation is that the differential result (relative to the credit spread data) is likely driven by the superior ability of the CDS market to reflect new information. Several studies find that the CDS market is more liquid than the bond markets and leads the latter in price discovery (see Oehmke and Zawadowski (2017) and Lee, Naranjo, and Velioglu (2018), among others).

4 Monetary Policy and Credit Risk Heterogeneity

In the previous section, the linear model treated the response of every firm's CDS or credit risk to monetary policy as uniform. In principle, it might be plausible that certain types of firms (likely those that are constrained or have greater financing issues) are more sensitive to market-wide funding shocks. In this section we test these hypotheses, focusing on how the response to monetary policy shocks varies at the firm level. In ways similar to our study and using credit rating data, Javadi et al. (2017), Guo et al. (2020), and Smolyansky and Suarez (2020) show that speculative or lower-rated bonds are more responsive to monetary policy shocks, while Anderson and Cesa-Bianchi (2020) use credit spread data to show that highly levered firms respond more. In this section, we study how credit risk heterogeneity matters for transmission of monetary policy shocks into corporate bonds and equity markets.

4.1 Cross-Sectional Credit Risk and Asset Price Response

Our first set of tests examines whether firms with higher CDS spreads are more sensitive with respect to monetary policy shocks. We conduct two types of exercises: one where we directly multiply the shock by a lagged value of the CDS spread (linear interaction) and a second where five categories of CDS spreads are created each day before the FOMC announcement day and dummy variables are multiplied by the lagged value of the CDS spread (non-linear interaction). More precisely:

$$\begin{aligned}\Delta y_{it} &= \beta_0 + \beta_y \left(\underbrace{y_{i,t-1}}_{\text{lagged spread}} \times \varepsilon_t^m \right) + \beta_X' X_{i,t-1} + \tau_t + error_{it} \\ \Delta y_{it} &= \beta_0 + \sum_{j=2}^{5} \beta_{y,j} \left(\mathbb{1}_{ij,t-1} \times \varepsilon_t^m \right) + \beta_X' X_{i,t-1} + \tau_t + error_{it}\end{aligned} \tag{3}$$

where τ_t is a FOMC date fixed effect, $X_{i,t-1}$ indicates a vector of firm-level variables (eg. fixed effects and controls from previous section) and $\mathbb{1}_{ij,t-1}$ takes a value of 1 if firm i is in CDS risk group j at $t-1$ and 0 otherwise. As an example, firms with the highest CDS spreads at $t-1$ would fall in risk group 5.

In Panel A of Table 5, we present the results for the linear interaction model.[10] We observe a significant relationship between CDS spreads and the sensitivity of contemporaneous CDS change with respect to monetary policy shocks. In terms of interpretation, coefficients are

[10] We do not include results on the LSAP shock, as it was insignificant in the baseline regressions and rest of the analysis. Results involving the LSAP shock are available upon request.

scaled such that β_y represents the additional CDS response for firms with 1σ greater CDS in the cross-section, following a 1σ shock to monetary policy. For example, firms with 1σ greater CDS have a 0.61 basis point greater response to a Target shock (column 1). The first three columns indicate that the ex-ante level of credit risk matters for the CDS response to monetary shocks: the higher the credit risk, the higher the change in CDS spreads. However, this result is only marginally significant for the BRW shock.

Columns 4 to 6 show that differences in credit risk matter for the response of the expected loss component. In this case, the interaction coefficient is highly significant across the different measures of monetary policy shocks. This is not the case for the response of the risk premium component. Columns 7 to 9 show that, when we control for the contemporaneous change in the expected loss component, only the interaction term involving the Path factor is significant.

Results are starker when we examine the non-linear specification as displayed in Panel B of the Table 5. The first three columns suggest that CDS spreads of firms in the top credit risk category respond significantly more to a 1σ monetary policy shock than firms in the bottom credit risk category (the excluded category). On average, and depending on the measure of monetary policy shock, the change in CDS spreads of firms in the top credit risk category is between 2.34 and 3.15 basis points higher. To put things into perspective, following a 40 basis point shock in BRW (about 5σ), firms in the top credit risk category witness an increase in CDS spreads about 15 basis points larger than firms in the bottom credit risk category.

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 Panel A: interaction terms involving Target and BRW shocks are highly significant for the response of the expected loss component, while the interaction term involving the Path shock is particularly significant for the response of the risk premium component.

To summarize, this section shows that firm-level heterogeneity in credit risk matters for the transmission of monetary policy shock when we study the response of CDS spreads. This response is highly non-linear and is mostly driven by firms with high credit risk. Additionally, the two components of CDS spreads, expected loss and risk premium, react with different magnitudes to monetary policy shocks.

Equity Price Response

Theoretically, credit risk is connected to equity prices as states of default depend on market values of corporations. In what follows, we ask whether ex-ante firm-level credit risk is also an important determinant of equity price responses following monetary policy shocks. Table 6 shows that this is indeed the case. Using credit risk categories, we find that stock prices of firms with high credit risk contract significantly more following an unexpected increase in interest rates. Our finding is consistent with Chava and Hsu (2019), 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 to the nonlinear interaction specification used in the previous section, however we replace the left-hand side variable with a measure of equity returns. Specifically, we use two different measures for r_{it}: a 1-hour return surrounding the FOMC window (columns 1 – 3 of the table) and a 2-day return. 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. An unexpected contractionary shock has a negative impact on equity prices through a larger discounting of future cash flows. In terms of economic magnitudes, firms in the riskiest quintile lose 7-16 basis points in the 1 hour surrounding the FOMC announcement and 40 - 58 basis points in subsequent 2 days. Losses are generally monotonically increasing across risk groups as well. To ensure there is no short-term reversal type effect, we also control for the lagged 1 day return.

4.2 Credit Risk and Other Measures of Firm-Level Risk

In this subsection, we examine how CDS compares to other measures of cross-sectional risk – namely leverage and the market capitalization of firms. These measures are all connected as theoretical measures of risk. All else equal, a higher leverage or lower market capitalization might spell problems for corporate borrowing costs and business prospects. Furthermore, recent studies have shown that leverage is an important determinant of firm-level responses to monetary policy shocks. Anderson and Cesa-Bianchi (2020) show that the response of credit spreads to monetary policy shocks is stronger for highly levered firms. Ottonello and Winberry (2019) find that firm-level investment is less responsive to monetary policy shock for firms with higher leverage. Lakdawala and Moreland (2019) document that highly levered firms became more responsive to monetary policy shocks in the aftermath of the financial crisis.

To better understand how leverage influences the transmission of monetary policy shocks, we present a baseline specification where we do not include any measures of cross sectional credit risk and solely include a leverage interaction term. After examining this specification, we add on the elasticities with respect to CDS-sorted dummies in an alternative specification.[11] Specifically:

$$
\begin{aligned}
\Delta y_{it} &= \beta_0 + \beta_{lev}\left(\underbrace{\text{lev}_{i,t-1}}_{\text{lagged leverage}} \times \varepsilon_t^m\right) + \beta_X' X_{i,t-1} + \tau_t + error_{it} \\
\Delta y_{it} &= \beta_0 + \beta_{lev}\left(\text{lev}_{i,t-1} \times \varepsilon_t^m\right) + \sum_{j=2}^{5} \beta_{y,j}\left(\mathbb{1}_{ij,t-1} \times \varepsilon_t^m\right) + \beta_X' X_{i,t-1} + \tau_t + error_{it}
\end{aligned} \tag{4}
$$

The results are reported in Table 7. In columns 1 to 6, we use the expected loss component as a dependent variable, while in columns 7 to 12 we use CDS spreads as a dependent variable and control for contemporaneous changes in the expected loss component. Table 7 shows that firms with higher leverage are more sensitive to monetary policy shocks. The expected loss component moves by an additional 0.12–0.30 basis points for firms with 1σ greater amounts of lagged leverage, while the risk premium component moves an additional 0.14–0.58 basis points.

The magnitude of the leverage interaction term greatly reduces and its significance disappears when we include monetary policy shocks interacted with dummies based on firm-level credit risk (columns 4 to 6 and columns 7 to 9). For example, comparing column 9 to 12, we find that the effects of the BRW shock interacted with leverage shrinks from 0.58 to 0.21 and its statistical significance vanishes. Meanwhile, the estimated coefficients on the credit risk-based dummies remain very similar to the ones reported in Panel B of Table 5.

We reach a similar conclusion using equity returns as the dependent variable. The first three columns of Table 8 suggest that firms with 1σ higher leverage experience a 2 to 5 basis point additional drop in equity returns, albeit insignificant statistically. Once we add on the CDS dummies, these effects change sign and remain insignificant, while firms in the highest credit risk quintile display a large and significant response to monetary policy shocks (42 to 61 basis point drop over the 2 day window).

Overall our results suggest that credit risk, as measured by CDS spreads, is stronger and more informative than leverage to understand the heterogeneous transmission of monetary policy at the firm level.

[11] In these regressions historical leverage is included as a direct multiplicative term with the monetary policy shock, while credit risk is interacted through dummy variables. In principle, one could wonder what the effects would be if they were both treated as categorical variables. In the Appendix we explore such a specification and show that the main results presented here still hold.

Comparison to Market Size as a Risk Measure

Beyond leverage, the market value of equity (market size) serves as another candidate to measure risk in the cross-section. We study the importance of firm size in shaping the response to monetary policy shocks using the same approach as in the previous section. Table 9 reports these results.

Columns 1 to 6 show that the logarithm of market capitalization on the day prior to the FOMC day matters for the response of the expected loss component, even as we control for firm-level credit risk. Columns 1 to 3 show that firms with 1σ smaller size experience an additional and significant increase in expected loss between 0.32 and 0.55 basis point following a contractionary monetary policy surprise. When we include credit risk-based dummies, the magnitude of the coefficient of the interaction term between size and the various measures of monetary policy shocks reduces, but differently from the leverage case, the estimated coefficients do not lose their significance.

Columns 7 to 12 report the results when the dependent variable is the change in CDS spreads and we also control for the contemporaneous change in the expected loss component. In this case, size seems to play a minor role and its significance is at best marginal when we control for credit risk-based dummies. In the latter case, firms in the top credit risk quintiles still experience a much larger increase in the risk premium component than firms in the bottom category following a contractionary monetary policy surprise.

To conclude, in Table 10 we show how market size determines the cross-sectional equity response to monetary policy. In columns 1 to 3, we show that firms with a 1σ smaller size witness a significant greater reduction in equity prices in the two days following a FOMC announcement (roughly 0.1 – 0.2 percent larger). When we control for credit risk-based dummies, we find that CDS does not matter for the transmission of monetary policy into equity prices while using the Target shock. At the same time, credit risk continues to matter when we use the Path and BRW shocks. In the latter case, the estimated coefficients are smaller in magnitude than the ones reported in columns 5 and 6 of Table 6, but they continue to remain strongly significant.

4.3 Expected Default vs. Risk Premium Channel

In previous sections we focused on the transmission of monetary policy shocks onto asset prices using time-varying sorts based on CDS spreads. The use of the latter variable prevents a more granular analysis based on the expected loss and the credit risk premium component, respectively. In this section, we fill the gap and study how the heterogeneity in monetary policy response is tied to heterogeneity in expected loss and risk premium compensation.

To isolate the risk premium component, we use a technique similar to the one in Gilchrist and Zakrajsek (2013) as we project CDS spreads onto the expected loss component. The projection is run separately for each FOMC announcement, using CDS and expected loss data on the prior day.

The residual of this regression is our proxy for the firm-level credit risk premium. Given the expected loss (EL) and the risk premium (RP) measures, we calculate terciles (bottom 33%, middle 33%, and top 33%) using their distribution the day before the FOMC announcement and classify stocks in nine (3×3) categories. These categories go from the one including firms jointly in the bottom tercile of the expected loss and risk premium distributions (EL_1RP_1) to the one including firms jointly in the top tercile of both distributions (EL_3RP_3). The main specifications is given by:

$$\Delta y_{it} \;=\; \beta_0 + \sum_{k=1}^{3}\sum_{j=1}^{3} \beta^{EL_kRP_j}\left(\mathbb{1}_{i,t-1}^{EL_kRP_j} \times \varepsilon_t^m\right) + \beta_X' X_{i,t-1} + \tau_t + error_{it} \qquad (5)$$

where $\mathbb{1}_{i,t-1}^{EL_kRP_j}$ is a dummy variable that takes value of 1 if firm i belongs to tercile k ($k = 1, 2, 3$) of the expected loss distribution and tercile j ($j = 1, 2, 3$) of the risk premium distribution the day before the time t FOMC announcement. In the regression model, we exclude firms belonging to the category EL_1RP_1, so the estimated coefficients are the additional effect of monetary policy shocks relative to firms with the lowest expected loss and risk premium values.

The results are displayed in Table 11. The first 3 columns focus on the response of credit risk, as measured by changes in CDS spreads, while columns 4 to 6 focus on the response of equity prices, as measured by the 2-day return following the FOMC announcement. Table 11 shows that firms with a high expected loss are the ones displaying a significantly higher increase in CDS spreads following a contractionary monetary policy shock. Among high expected loss firms, the ones that also have a high risk premium generate a much larger response. For these firms, the estimated coefficients are very close to the estimated values in Panel B of Table 5, thus signaling that both expected loss and risk premium matter for the transmission of monetary policy shocks in CDS markets.

We reach a different conclusion when we consider the response of equity prices (columns 4 to 6). Analogous to movements in CDS markets, firms with a high expected loss are generally the ones that display a significantly larger decrease in equity prices following a contractionary monetary policy shock. Different than the CDS market however, credit risk premium does not play any role in amplifying the equity response of high expected loss firms. This result leads us to conclude that heterogeneity in credit risk premium plays a marginal role in equity markets, where the response to monetary policy shocks is mostly dictated by the level of expected default.

4.4 Application to COVID-19 Crisis

Beyond its harmful impact on public health and real economic activity, the COVID-19 pandemic caused a large disruption in financial markets. The month of March was particularly damaging as large-cap U.S. equity markets lost 13% overall and reached a trough of 25% month-to-date losses on March 23. Credit markets also displayed greater default risk and investor risk aversion as the spread between the Moody's BAA corporate bond yield and 10-year Treasury rate reached a high of 4.3% on March 23. This was the largest level going back over 5 years.

In the midst of this panic, there were a number of policy programs rolled out by U.S. monetary and fiscal authorities to counteract negative headwinds. We focus our attention on those enacted by the Federal Reserve Board on March 23, 2020. On that day the Fed decided to inject tremendous amounts of liquidity into the financial system. These monetary initiatives included but were not limited to: (1) open-ended purchases of Treasuries and agency MBS (escalated from a previous announcement), (2) the establishment of primary and secondary market corporate credit facilities, and (3) an expansion of the Money Market Mutual Fund Liquidity Facility to include state and local municipal bond purchases.

These policy interventions were both large in scope and generally unexpected by market participants, which makes them a useful event to better understand the transmission of risk across the financial system, this time following an expansionary monetary policy. In Figure 2 we display the behavior of 3 financial indicators (changes in CDS prices, EDF probabilities, and equity returns) across credit risk categories, over a 1-day and 2-day horizon directly following the policy announcement. It is evident from the top 2 panels that credit risk as a whole decreased for all firms, but most clearly for the riskiest firms. Similarly, firms in quintiles 4 and 5 are the ones that display the highest equity returns following the announcement as shown in the bottom panel of Figure 2.

In Table 12 we perform a more formal analysis of the heterogeneous responses where we project 2-day changes in each of the three variables (CDS, EDF, and equity returns), on dummy variables of the lagged CDS risk quintile. Within each response variable, we have 3 regressions. The first examines the average response; the second looks at the response per CDS risk grouping, by adding dummy variables corresponding to each quintile and excluding the bottom category. The last regression adds leverage and lagged (log) market size as control variables. All regressions use standard errors clustered at the industry level.

Columns 1, 4, and 7 display that the average response of these markets was strongly positive. CDS and EDF values reduced 23 and 16 basis points, respectively. Meanwhile stocks on average yielded 16% on the day following the policy action. Columns 2, 5, and 8 statistically confirm the message from Figure 2, which is that firms in the highest CDS quintiles were those that displayed the most amplified response to the policy action. These responses are robust to controlling for lagged leverage and market size (columns 3, 6, and 9).

In summary, firms that were riskier, as judged by their CDS levels in the last trading day before the March 23 announcement, were those that were most affected by the monetary initiatives put in place by the Federal Reserve. It is difficult to say that this impact was causal and perfectly identified, as a fiscal stimulus package was soon to be passed, and there were daily announcements regarding the state of the pandemic. That being said, due to the timing and the sheer magnitude of the monetary policy action, CDS spreads, expected default probabilities, and equity prices moved in the expected directions across credit risk categories.

5 Model

In this section, we discuss a stylized model of corporate leverage, investment, and monetary policy. Our goal is to provide a plausible mechanism that can help us understand the patterns displayed in the empirical analysis section. We particularly focus on two results: (1) the heterogeneity in response of firm credit risk to monetary policy and (2) the irrelevance of firm leverage in explaining this response, once we account for credit risk. To keep the model simple and transparent we limit it to 3 periods. In many ways, our model is similar to the one in Bhamra, Fisher, and Kuehn (2011), however we allow for endogenous investment and leverage. In what follows, we show how endogenous investment plays a key role toward generating the heterogeneity in monetary policy response.

5.1 Timeline and Structure

Over the course of a 3-period horizon ($t = 1, 2, 3$), a heterogeneous set of firms maximize the expected present value of *nominal* cash flows. The expectations are necessary to take into account 3 sources of uncertainty: variation in idiosyncratic productivity (a_t^i), variation in aggregate productivity (A_t), and potential shocks to monetary policy, (S_t). In the model, all shocks are assumed to follow AR(1) processes with persistence parameter ρ and volatility parameter σ:

$$
\begin{aligned}
a_t^i &= \rho_a a_{t-1}^i + \sigma_a \varepsilon_{a,t}^i \\
A_t - \mu_A \equiv \tilde{A}_t &= \rho_A \tilde{A}_{t-1} + \sigma_A \varepsilon_{A,t} \\
S_t &= \rho_S S_{t-1} + \sigma_S \varepsilon_{S,t}
\end{aligned}
\tag{6}
$$

where $\tilde{A}$ represents the demeaned value of aggregate productivity. All of these variables are accounted for in the firm's decision to finance investment through leverage and influence the firm-level credit spread. The presence of the firm-level productivity shock a^i ensures heterogeneity in investment and financing choices.

Period 1

At the start of the initial period, each firm begins with 1 unit of capital ($k_1^i = 1$ for all i) and draws a random, idiosyncratic shock from a stationary distribution of productivity ($a_1^i \sim \Phi_a(a)$). Similarly, aggregate variables (A_t, S_t) are also drawn from their 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_{i1}) and the discounted value of Period 2 cash flows.

More explicitly, the firm's decision problem is given by:

$$
V_1\left(A_1, S_1, a_1^i, k_1^i\right) = \underset{\{k_2\}}{\text{Max}} \;\; D_{i1} + \mathbb{E}_1\left[M_2^n W_{i,2}\right]
$$

subject to:

$$
\begin{aligned}
&W_{i,2} = \text{Max}\{0, V_{i,2}\} \\
&D_{i1} \geq 0 \text{ (No equity issuance)} \\
&D_{i1} = \Pi_{i1} - i_{i1} - \underbrace{\varphi_{k1}(k_{i1}, i_{i1})k_{i1}}_{\text{Adj. Costs to Capital}} + \tau\delta k_{i1}
\end{aligned}
\tag{7}
$$

where M_2^n represents the nominal stochastic discount factor (SDF) used to value future cash flows. While this SDF does not come from a particular agent's preferences, it can be thought of as a market-based pricing kernel that firms utilize.[12] W_{i2} represents the realized Period 2 value of the firm, bounded below by limited liability upon potential exit. Finally dividends, D_{i1}, consist of firm profits (Π), net of investment (i) and adjustment costs to investment

[12]The use of an "exogenous" pricing kernel is a popular technique in models of corporate finance and asset pricing. Models that use this approach can be found in Chen (2010) and Kuehn and Schmid (2014), among many others. The key benefit from such an approach is that the parametric modeling of the pricing kernel can help capture key features in the data, without having to close the model in general equilibrium.

($\varphi_{k1}(\cdot) \times k_1$), plus a capital depreciation tax shield with tax parameter τ and depreciation parameter δ.

There are a few things to note. First, all variables – dividends, profits, investment, etc. – represent nominal values. While this seems non-standard relative to the literature predicated on real decision making, the above problem can be recast as one where variables are normalized by their appropriate price levels and effectively real.[13] Secondly, to keep things simple, firms cannot issue equity or save cash. Finally, it is natural to ask why this initial stage exists in the model given there is no leverage decision to begin with. The purpose of the first period is to generate heterogeneity across firms before they access capital markets in Period 2. Adding leverage would help to generate dispersion across firms, but it also clouds the setup of the second period, which we use to test the effects of an interest rate shock due to monetary policy.

Period 2

After operating 1 period, firms have the opportunity to exit if the market value of continuing operations reaches its lower bound (i.e. $V_{i2} \leq 0$). If they choose to continue operations, firms now have the ability to take on debt to finance investment by engaging with financial intermediaries.

The debt contract is structured as follows. For a chosen amount of debt b_{i3} at time 2, firms owe a face value of $(1+c)b_{i3}$ at time 3, while receiving market proceeds $p_{i2}b_{i3}$ at time 2. Implicitly, p_{i2} will reflect the market priced credit risk of firm i. The pricing of the debt contract is set to break even:

$$p_{i2}b_{i,3} = \mathbb{E}_2\left[M_3^n(1-\mathbb{1}_{\{D_{i3}>0\}})(1+c)b_{i,3}\right] + \mathbb{E}_2\left[M_3^n\mathbb{1}_{\{D_{i3}<=0\}}X_{i,3}^{PD}\right] \tag{8}$$

In the above formula the left hand side reflects the time 2 proceeds lent to an individual firm. Meanwhile the right hand side is a probability weighted sum of the discounted value of (1) proceeds given no default and (2) proceeds given default. Note that the default event takes place when $D_{i3} \leq 0$ as the third period is the final one and there is no continuation value (i.e. remaining dividend proceeds are remitted to shareholders or creditors). Further, if default was to occur, the payment given default is defined as $X_{i3}^{PD} = (1-\xi)(1-\delta)k_{i3}$, where ξ represents a fractional loss of depreciated capital in period 3.

The realized final period cash flows will be $D_3 = D\left(a_3, A_3, S_3, k_3, b_3\right)$, where the first 3 variables are exogenous states and the last 2 are endogenous states (capital and debt chosen as of time 2). We can show that the price on a corporate bond with maximum payoff $(1+c)b_{i3}$

[13] Solving the nominal problem is one-to-one with a real version. See Appendix B for details.

satisfies:

$$p_2 = p\left(a_2, A_2, S_2, k_3, b_3\right) \tag{9}$$

Upon interacting with financial markets, firms are offered an entire price or interest rate schedule that contracts on next period chosen capital and debt. The latter quantities are observable to banks. The firm internalizes this price schedule and chooses capital and debt to maximize:

$$V_2\left(A_2, S_2, a_2^i, k_2^i\right) = \underset{\{k_3, b_3\}}{\text{Max}} \;\; D_{i2} + \mathbb{E}_2\left[M_3^n W_{i,3}\right]$$

subject to:

$$\begin{aligned} & W_{i,3} = \text{Max}\left\{0, D_{i,3}\right\} \\ & D_{i2} \geq 0 \text{ (No equity issuance)} \\ & D_{i2} = \Pi_{i2} - i_{i2} - \varphi_{k2}(k_{i2}, i_{i2})k_{i2} + \underbrace{p_{i2}b_{i,3}}_{\text{Debt Proceeds}} + \tau\delta k_{i2} \\ & p_{i2}b_{i,3} = \mathbb{E}_2\left[M_3^n(1 - \mathbb{1}_{\{D_{i3}>0\}})(1+c)b_{i,3}\right] + \mathbb{E}_2\left[M_3^n \mathbb{1}_{\{D_{i3}<=0\}} X_{i,3}^{PD}\right] \end{aligned} \tag{10}$$

Similar to the previous period, firms account for the present value of future cash flows, although now it 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. While our main goal is to generate cross-sectional risk in credit spreads through this mechanism, such a tax vs. distress cost tradeoff is common in the literature (see 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 possible). Cash flows to equity holders are given by:

$$\begin{aligned} \text{(No Default)} \quad & D_{i,3} = \Pi_{i,3} + (1-\delta)k_{i,3} - (1+c)b_{i,3} + \tau\left(\delta k_{i,3} + cb_{i,3}\right) \\ \text{(Default if } D_{i,3} < 0\text{)} \quad & 0 \end{aligned} \tag{11}$$

If the firm does not default (top line), 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. Conversely if the firm defaults, equity holders are wiped out and creditors receive un-depreciated capital net of deadweight losses (X^{PD}).

5.2 Discount Factors, Monetary Policy, and Inflation

In this subsection we describe how monetary policy and inflation are determined. These two quantities drive the the nominal stochastic discount factor that firms and intermediaries use for asset valuation.

In our model economy, market participants use the following real, exogenous pricing kernel:

$$M_t^r = \exp\left(m_t^r\right) = \exp\left(m_0 - m_A\left(A_t - \mu_A\right) - m_S S_t\right) \tag{12}$$

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 (including monetary policy). We introduce monetary policy in the model by imposing a Taylor rule, that the central bank adopts to set the short-term *nominal* 1-period interest rate in the following manner:

$$y_t^1 = i_0 + \alpha_A\left(A_t - \mu_A\right) + \alpha_\pi\left(\pi_t - \mu_\pi\right) + S_t \tag{13}$$

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 (see e.g., Gallmeyer, Hollifield, Palomino, and Zin (2017) and Song (2017)), we use the Euler equation restriction applied to a 1-period nominal risk-free security, to back out an endogenous process for inflation. More specifically:

$$p_t^{rf} = \mathbb{E}_t\left[M_{t+1}^r \frac{1}{\Pi_{t+1}}\right] = \frac{1}{\exp\left(y_t^1\right)} \qquad (\Leftrightarrow) \qquad y_t^1 = -\log \mathbb{E}_t\left[\exp\left(m_{t+1}^r - \pi_{t+1}\right)\right] \tag{14}$$

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, one can guess and verify the following inflation process, $\pi_t = \pi_0 + \pi_A \tilde{A}_t + \pi_S S_t$. Matching coefficients from the Taylor rule on the left hand side will yield the following solution to the inflation coefficients. For more details, see Appendix C.

$$\begin{aligned}
\pi_S &= \frac{1 - m_S \rho_S}{\rho_S - \alpha_\pi} \\
\pi_A &= \frac{\alpha_A - m_A \rho_A}{\rho_A - \alpha_\pi} \\
\pi_0 &= i_0 + m_0 + \frac{1}{2}\left(m_A + \pi_A\right)^2 \sigma_A^2 + \frac{1}{2}\pi_S^2 \sigma_S^2
\end{aligned} \tag{15}$$

Given the linearity of the inflation process, the nominal log SDF becomes:

$$\begin{aligned}
m_{t+1}^n &= m_{t+1}^r - \pi_{t+1} \\
&= \left(m_0 - \pi_0\right) - \left(m_A + \pi_A\right)\tilde{A}_{t+1} - \left(m_S + \pi_S\right) S_{t+1}
\end{aligned} \tag{16}$$

Equation 16 implies that any (nominal) risk premium for an asset is based on that asset's return covariance with these last 2 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:

$$p_{i2} = \mathbb{E}_2\left[M_3^n(1 - \mathbb{1}_{\{D_{i3}>0\}})(1+c)\right] + \mathbb{E}_t\left[M_3^n \mathbb{1}_{\{D_{i3}<=0\}} \frac{X_{i,3}^{PD}}{b_{i3}}\right]$$

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. $p_{i2} \downarrow$) if m_{t+1}^n is negatively affected by S_t. For this to be the case we need:

$$m_S + \pi_S > 0 \quad (\Leftrightarrow) \qquad m_S > \underline{m} \equiv \frac{1}{\alpha_\pi}. \tag{17}$$

This restriction plays a crucial role in the calibration as will be explained shortly.

5.3 Calibration

There are a number of processes in the model section that we need to specify. After-tax firm profits are given by:

$$\Pi_{it} = (1-\tau)\left(e^{\left(\tilde{A}_t + a_t^i\right)} k_{it}^{\alpha}\right) \qquad \text{for } t = 1$$
$$\Pi_{it} = (1-\tau)\left(e^{\left(\tilde{A}_t + a_t^i\right)} k_{it}^{\alpha} - f\right) \qquad \text{for } t = 2, 3$$

In both periods after-tax profits are decreasing returns to scale in capital. Production, however, requires a fixed cost ($f > 0$) only in the second and third period. 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, there are no firms that will default immediately, which simplifies the setup. Investment and adjustment costs to capital are given by:

$$i_{it} = k_{i,t+1} - (1-\delta)k_{it}$$
$$\varphi_{kt}\left(k_{it}, i_{it}\right) = \frac{\phi_{kt}}{2}\left(\frac{i_{it}}{k_{it}} - \delta\right)^2 = \frac{\phi_{kt}}{2}\left(\frac{k_{i,t+1}}{k_{it}} - 1\right)^2$$

where δ is the depreciation rate and ϕ_{kt} are time-dependent parameters. We set the quarterly depreciation rate to 2.5%. Without any adjustment costs, the firms' average level and volatility of investment are both extremely large. Further, if the 2 parameters are set to be equal ($\phi_{k1} = \phi_{k2}$), investment behavior is greatly different across the 2 periods.[14]

Table 13 describes the calibrated parameters. While the model features a stylized 3-period setup and is designed to display a mechanism, some parameters are guided by quarterly data. The steady state interest rate, i_0 is set to equal the quarterly nominal interest rate (roughly 1.1% in the data). The Taylor rule coefficients on productivity and inflation are roughly equal to those in the data.[15] The autocorrelation of idiosyncratic productivity is relatively large ($\rho_a = 0.85$) to generate persistent heterogeneity and is similar to the value in Kuehn and Schmid (2014). S_t is also persistent ($\rho_S = 0.50$) so that it is a priced state variable and can generate larger asset pricing impulse responses. The value of ρ_A is 0.50 yet as we will show, plays an inconsequential role for our study.

The conditional volatilities of aggregate productivity and monetary policy (σ_A and σ_S)

[14] If the model were extended to larger, fully dynamic setting, one parameter would control investment adjustment costs. We would be able to more easily control investment behavior.

[15] We regress three-month Treasury bill rates on the growth rate of productivity (from the San Francisco Federal Reserve) and Core CPI inflation to recover plausible coefficient values.

are chosen to roughly match the data.[16] Conditional idiosyncratic volatility (σ_a) is chosen along with the adjustment cost parameters to generate reasonable cross-sectional dispersion in investment rates. The returns to scale parameter, $\alpha = .65$, is similar to the estimated value in Hennessy and Whited (2007). The fixed costs of production, $f = 1.10$ is set to generate reasonable levels of final period default. Adjustment cost parameters (ϕ_{k1}, ϕ_{k2}) target average levels of investment of 10% per period. Finally, coupon rates, which do not affect credit spreads, are set to be positive ($c = .01$) to generate a tax advantage of debt.

Credit Spread Schedule and the Price of MP Risk

A key parameter in our setup is the real market price of risk associated with interest rate shocks, m_S.[17] To better understand its role towards credit spreads, we explore debt pricing dynamics in Figure 3. The y-axis reports the credit spread associated with a particular debt choice (high, medium, or low values of b_{i3}) for various choices of capital on the x-axis (different values of k_{i3}). We hold fixed idiosyncratic and aggregate cash flows shocks to their median values, and vary monetary policy shocks from median (solid line) to elevated (dashed) states. A couple of intuitive results hold: (1) greater amounts of debt lead to higher credit risk, holding capital fixed and (2) lower amounts of investment increase credit risk, holding debt fixed. When the economy witnesses an interest rate shock, credit spreads or credit risk increase. This is represented by a shift from a solid line to a dashed line. It is also apparent that firms that originally choose higher levels of debt witness a larger increase, when compared with those who choose lower debt levels.

To crystalize the role that m_S has on the relative monetary policy impact, and the rationale behind our m_S calibration, in Figure 4 we plot the precise difference between the dashed and solid lines following a policy shock. In the top-left figure, where m_S is at the baseline value, we see that the impact 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 impact of 15 basis points.

These dynamics shift if we examine impulse responses under a lower monetary policy price of risk ($m_S = 5$), as given in the upper-right figure. Here we see that 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 figure, 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

[16] Given persistence parameters and data volatilities we can choose values for each σ. Data for S is given to us through Taylor rule residuals.

[17] While m_A would play a larger role in a larger simulation, it is not crucial here due to our focus on monetary policy. We show later in this section that the results are robust to different values of m_A.

investors price monetary policy in their real pricing kernel. It is important to mention 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 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, throughout all 3 periods. The results of the simulation are provided in Table 14. In the first period, firms invest 10.2% on average with a cross-sectional standard deviation of 3%. As we would expect, investment rates are highly tied to productivity. Due to the lack of fixed costs, there is no realized default.

In the second period, firms have the ability to access capital markets and they take on quite a bit of leverage, roughly 68% to finance investment. The average credit spread on the debt is 8.2 basis points and serves as our measure of credit risk.[18] The ex-ante probability of default also takes on a distribution with an average value of 3.82%. Relative to the data, one might think that priced credit risk is relatively low and default rates are relatively high. This is a common issue among models without significant curvature in the SDF or risk neutral probability adjustment, as a greater number of defaults are needed to generate larger spreads. In our model economy, we abstract from such quantitative issues.

One important characteristic to note is that the model creates a strong link between investment rates and leverage (91% correlation from Table 14). The firms that choose to invest more fund their capital expenditures using significantly more leverage. Figure 5 helps understand this strong correlation. Across all panels the x-axis represents Period 2 firm-value. As the latter quantity approaches 0, firms are closer to default. In the top panel, we see that leverage decreases substantially as value diminishes. Because value is positively linked to capital stocks and investment rates, a natural positive correlation emerges.

The two other panels in Figure 5 display the behavior of asset prices. As firms get much closer to default through lower market values, likely due to poor productivity and a diminished capital stock, their ex-ante default probabilities dramatically increase (see bottom panel). This increase in default probability then manifests itself in asset prices through very

[18]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: $\frac{1+c}{p_{i2}} - \frac{1+c}{\mathbb{E}_2\left[M_3^n(1+c)\right]}$. The latter reflects the gross yield on a risk-free security.

large credit spreads (middle panel).

Effects of an Unexpected Interest Rate Shock

We now test the effects of a positive interest rate shock due to monetary policy. In terms of the simulation procedure, we re-simulate the economy keeping all idiosyncratic and aggregate shocks the same. However, we change one thing – 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. 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 15 displays the effects of a monetary shock on some moments of interest. The first column (*Baseline*) reports the baseline economy values, the second column (*MP Shock*) embeds the monetary shock, and the third shows the difference of the two. It is worth mentioning that the *Baseline* values in Table 15 do not match those from Table 14. That is because we select firms to compute relevant statistics, conditional on them not defaulting at the start of period 2 across both simulations. As the economy with the MP innovation is inherently riskier, we end up paring down some firms in the baseline economy that were on the riskier end, and do default in the shocked economy. This explains, for example, why the credit spread is lower in the joint sample as opposed to the earlier simulation.

In terms of the actual response, on average, firms reduce 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 directly consistent with the empirical analysis. The standard deviation of credit risk also increases, suggesting that the right tail of credit spreads is becoming wider. 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 impact of various parameter choices on the impulse responses discussed in the prior paragraphs. These results are presented in Table 16. We examine the same moments as previously and the second column of the table (*Baseline Change*) matches the last column of Table 15. The first set of tests we conduct are to look at the equilibrium effects of the monetary policy price of risk, m_S. In this case, the effect of m_S on the debt pricing schedules takes into account firm-level equilibrium choices of debt and capital.

In columns 3 – 5 of this table, we now incorporate their optimal decision making. The first column ($m_S = 16$), in which 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 the baseline (5.0 vs. 3.7 basis points). So too are the drop in investment rate (3.8 vs. 2.9%), increase in default ex-ante probability, and realized default rate. In the second column ($m_S = 5$), 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. 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 fluctuations in the response of credit spreads to interest rate shocks are highly tied to the investment channel. It is the reduction in firms' cash-flow generating process due to disinvestment that brings firms closer to default.

In columns 6 – 9 we examine other variables of interest. For higher values of the persistence of policy shocks ($\uparrow \rho_S$ in column 6), while fixing the volatility of S, we see that a monetary policy shock increases the credit spread response dramatically. This is intuitive as we have increased the likelihood of future interest rate hikes following a current shock. The same happens when the fixed cost increases ($\uparrow f$ in column 7). In this case, firms are more likely to default given that the cash flow process stays the same. In the final two columns of the table we show that shifts in variables related to aggregate productivity ($\uparrow m_A$ and $\uparrow \rho_A$) do not matter much for the results. This makes sense as the simulation design held aggregate risks constant.

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 17. 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 ($Q5$ represents the firms with the lowest market values in the baseline economy). The second panel does the same based on a sort of their initial credit spread ($Q5$ represents the firms with the highest credit spreads in the baseline economy). Finally the bottom panel performs the sort based on leverage ($Q5$ represents firms with the highest leverage). In essence, the sorts align with our priors on risk – lower market values, higher credit spreads, and higher leverage lead to greater risk. 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 $Q5$ – who display an average increase of 16.5 basis points. Why does this take place? 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. That is because of the inherent self-selection in the model. Firms that take on more leverage are not riskier in equilibrium. They are the ones who are more productive and use leverage toward investment that generates positive cash flows. Hence, shocks to aggregate states, such as interest rates and monetary policy, do not have a strong impact on them due to their built-up capital buffers.

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 is more influential than leverage for the transmission of monetary policy.

6 Conclusion

Using high-frequency data related to credit risk (CDS) and monetary policy (unexpected interest rate shocks surrounding FOMC days), we show that movements in monetary policy significantly affect credit risk. Consistent with recent evidence, we also find that there is significant heterogeneity in the sensitivities of firm-level credit risk and equity price response to monetary policy. Firms that are ex-ante riskier, measured by spreads, leverage, or market size, display greater sensitivites. More important, however, we show that CDS play a more prominent role in determining monetary policy sensitivity. Our stylized model is able to rationalize these findings on the basis of equilibrium self-selection.

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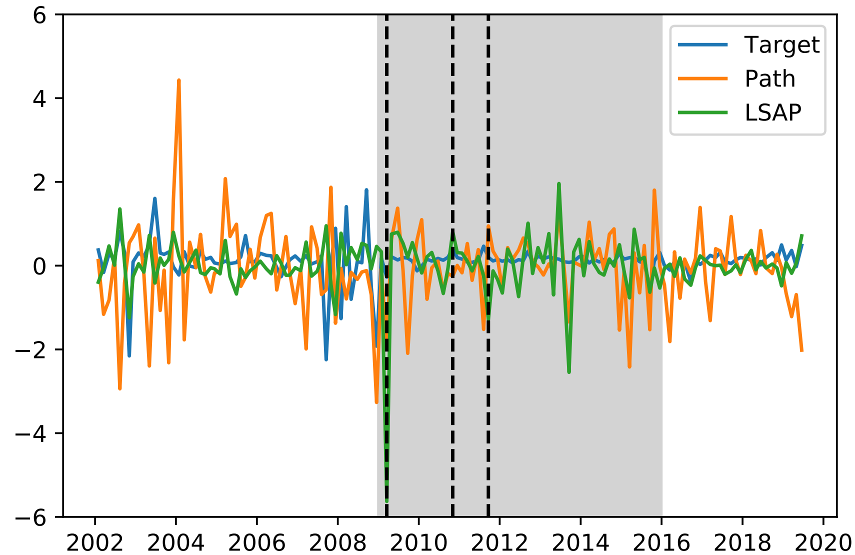
Figure 1. Monetary Policy Shocks
These figures display the monetary policy shocks used in the empirical analysis for the regularly scheduled FOMC meetings from Wednesday, January 30, 2002, to Wednesday, June 19, 2019. The top figure reports the "Target" and "Path" shocks, as initially discussed in Gürkaynak et al. (2005). The same figure also reports the "LSAP" shock as constructed in Swanson (2020). The bottom figure reports the monetary policy shock measure developed by Bu et al. (2019). In all figures the shaded area represents the zero-lower-bound (ZLB) period while the dashed lines represent key monetary policy dates for QE1 (March 18, 2009), QE2 (November 3, 2010), and Operation Twist (September 21, 2011), respectively. Target, Path, and LSAP shocks are in raw terms while BRW is in basis points. For more details regarding construction see the main text and papers cited above.



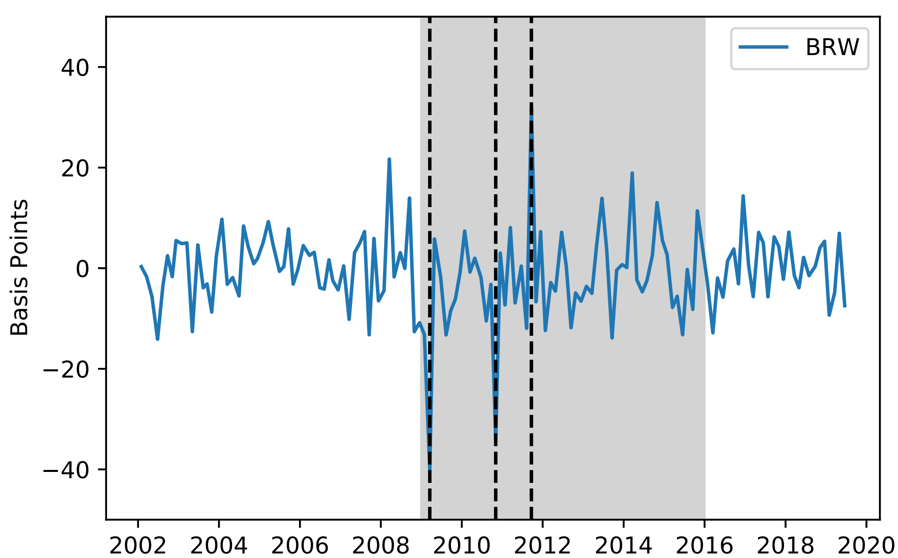


Figure 2. Financial Market Reaction to March Policy Action, by CDS Quintile
These figures display the 1- and 2-day financial market response of CDS prices, EDF (physical default) probabilities, and daily equity market returns, following the March 23, 2020, policy announcement by the U.S. Federal Reserve. Each panel reports a different response based on the median change within CDS quintiles, sorted as of March 23. The top panel reports changes of 5Y CDS prices, in basis points. The middle panel reports changes in the 5Y EDF measures. The bottom panel reports the day-after and 2-day-after returns, in percentage points.

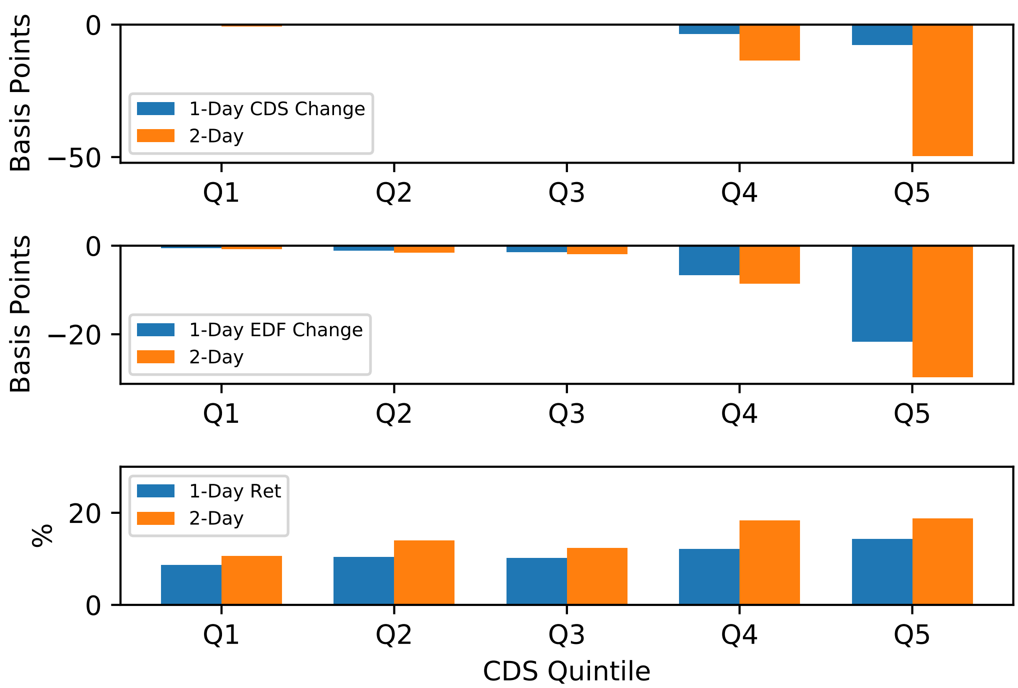


Figure 3. Schedule of Credit Spreads
This figure display the credit spread schedule that is offered to firms in the second period, as implied by the baseline set of parameters. Lines for chosen values of low, medium, and high debt are provided (blue, red, and yellow respectively) and the x-axis throughout 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.

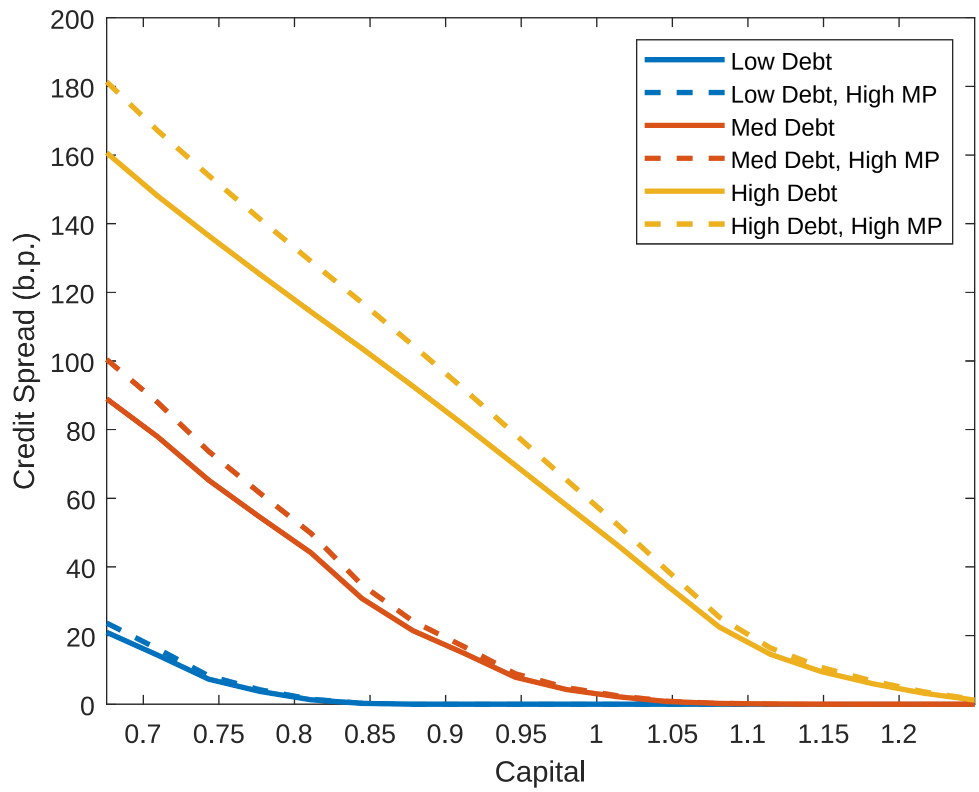
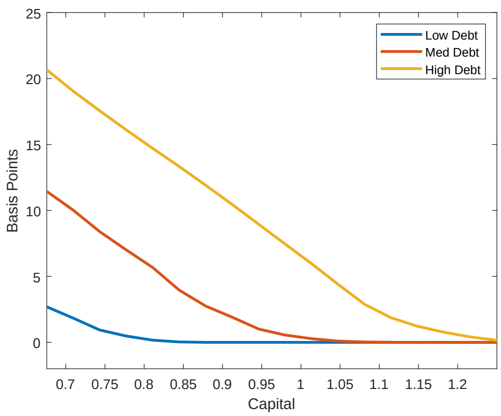
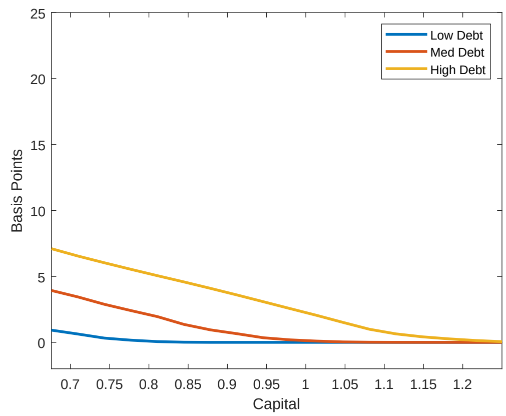


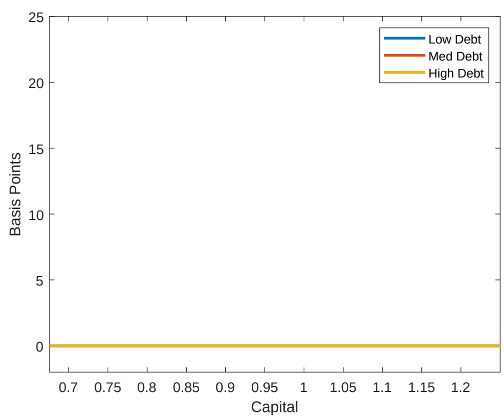
Figure 4. Difference of Credit Spreads following Monetary Shock
These figures display the difference in credit spread schedules, where one schedule accounts for a positive monetary policy shock and the other is held at steady state. The upper left panel focuses on a model environment where the real, 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 Figure 3.



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



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



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

Figure 5. Second-Period Decision-Making

These figures display the relationship between endogenous firm value and chosen leverage (top panel), resulting CDS (middle), and ex-ante default probabilities (bottom). All values are simulated second-period variables under the baseline calibration. The x-axis in all figures represents the firm value (market capitalization).

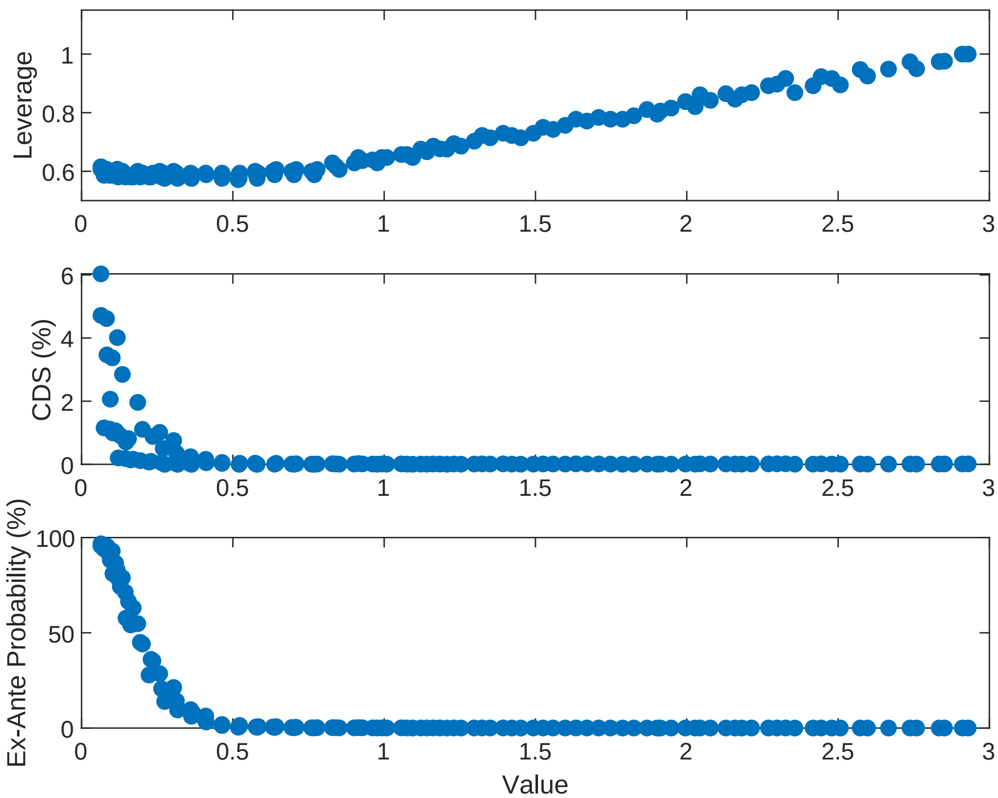


Table 1. Monetary Policy Shocks – Summary Statistics
This table reports the summary statistics for the monetary policy shocks used in the empirical analysis: Target, Path, LSAP, and BRW. Panel A reports the quantities over the entire sample. Panel B reports the quantities in periods outside the Zero Lower Bound (ZLB) period. Panel C reports the quantities using the ZLB period, which covers 2009-2015. The first 3 shocks are reported in raw terms while BRW is in basis points.

	Mean	Std. Dev.	Min	Median	Max	Obs.
			Panel A: Full Sample			
Target	0.100	0.532	-2.759	0.139	1.812	145.0
Path	-0.047	1.034	-3.266	-0.048	4.432	145.0
LSAP	0.014	0.699	-5.631	0.021	1.962	145.0
BRW (bp)	-0.836	8.635	-40.113	-0.698	31.964	140.0
			Panel B: No ZLB			
Target	0.082	0.667	-2.759	0.132	1.812	90.0
Path	-0.060	1.136	-3.266	-0.113	4.432	90.0
LSAP	0.045	0.426	-1.246	0.003	1.368	90.0
BRW (bp)	0.121	6.523	-14.131	0.319	21.703	85.0
			Panel C: ZLB			
Target	0.130	0.140	-0.534	0.143	0.465	55.0
Path	-0.025	0.851	-2.419	0.042	1.804	55.0
LSAP	-0.037	1.000	-5.631	0.142	1.962	55.0
BRW (bp)	-2.315	11.048	-40.113	-2.326	31.964	55.0

Table 2. Monetary Policy Shocks – Correlations
This table reports the correlations for the monetary policy shocks used in the empirical analysis: Target, Path, LSAP, and BRW. Panel A reports the correlation matrix over the entire sample. Panel B reports the matrix in periods outside the Zero Lower Bound (ZLB) period. Panel C reports the correlations using the ZLB period, which covers 2009-2015.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Panel A: Full Sample				
	Target	Path	LSAP	BRW
Target	1.000***	–	–	–
Path	-0.084	1.000***	–	–
LSAP	0.042	0.133	1.000***	–
BRW	0.223***	0.517***	0.204**	1.000***
Panel B: No ZLB				
	Target	Path	LSAP	BRW
Target	1.000***	–	–	–
Path	-0.107	1.000***	–	–
LSAP	-0.041	-0.157	1.000***	–
BRW	0.378***	0.561***	-0.191*	1.000***
Panel C: ZLB				
	Target	Path	LSAP	BRW
Target	1.000***	–	–	–
Path	0.078	1.000***	–	–
LSAP	0.45***	0.451***	1.000***	–
BRW	0.061	0.582***	0.348***	1.000***

Table 3. Firm-level data – Summary Statistics
This table reports the firm-level summary statistics for the observations used in the empirical analysis. Panel A reports data from Markit. For each firm, we report the the 5-year CDS spreads (in basis points), the percentage of value recovered post-default (i.e. recovery rate), and the numbers of dealers providing CDS quote contributors (i.e., composite depth). In Panel B, we report the annualized conditional probability of default (EDF) from Moody's Analytics. In Panel C, we report firm-level accounting data from Compustat. *Size* is the nominal value of total assets (Compustat item *atq* in billion of dollars). *Leverage* is total debt (item *dlcq* plus item *dlttq*) divided by total assets. *cash-to-asset* is cash and cash equivalents (item *cheq*) divided by total assets. The log-change in quarterly property, plant, and equipment is the quarterly (log) difference in net property, plant, and equipment (item *ppentq*). In Panel D, we report firm-level equity market data from CRSP. *Daily return FOMC* is the daily market return on the FOMC announcement day. *Return around FOMC* is the market return calculated over a 45-minute window around the FOMC announcement (from 15 minutes prior to the announcement to 30 minutes after the announcement). *Market cap* is the market capitalization at closing on the FOMC announcement day. All data are winsorized at the top and bottom 0.5%.

	Mean	Std. Dev.	Min	Median	Max	Obs.
			Panel A: Markit			
5-year cds (bps)	187	281	9	90	2,301	54,886
recovery rate (%)	39.20	3.17	20.00	40.00	50.00	54,886
composite depth	5.73	3.60	2.00	5.00	33.00	54,886
			Panel B: Moody's			
5-year expected default (%)	1.03	2.31	0.05	0.32	20.04	40,223
			Panel C: Compustat			
size ($ billion)	20.60	37.62	0.01	8.83	548.38	37,933
leverage	0.32	0.19	0.00	0.29	2.44	37,881
cash-to-assets	0.10	0.10	0.00	0.07	0.81	37,925
log change in PPENT	0.01	0.09	-1.10	0.00	1.52	37,686
			Panel D: Equity Returns			
Daily return FOMC (CRSP, %)	0.36	2.37	-7.30	0.17	11.60	36,598
Return around FOMC (TAQ, %)	0.04	1.06	-8.81	0.04	10.51	34,358
Market cap ($ billion)	26.17	50.74	0.02	9.91	1157.80	36,574

Table 4. Credit Risk Response to Monetary Policy Shocks
This table reports the effect of the different measures of monetary policy shocks on movements in CDS and its expected loss component. For more details regarding the specifications, see Equations (1) and (2) in the main text. In Panel A, columns 1 to 4 report the results using CDS changes as the dependent variable and the four monetary policy shocks as key regressors. Columns 5 to 8 focus on movements in expected loss compensation as the dependent variable. Columns 9 to 12 show the results for changes in CDS after we control for the contemporaneous change in expected loss compensation. In Panel B, we include as controls the firm-level variables listed in Panel C of Table 3 and the (log) market capitalization the day before the FOMC announcement day. We standardize monetary policy shocks so that all coefficients represent the change in CDS due to a 1σ change in the monetary policy shock. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Panel A: Baseline												
Dependent Variable	Δ *CDS*				Δ *Exp. Loss*				Δ *CDS*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Target	0.926**				0.485**				0.753			
	(2.000)				(2.613)				(1.435)			
Path		1.087***				0.329*				1.208***		
		(3.501)				(1.741)				(3.796)		
BRW			1.198**				0.596***				1.072**	
			(2.469)				(3.985)				(2.285)	
LSAP				0.045				-0.062				0.046
				(0.092)				(-0.209)				(0.098)
Δ Exp. Loss									0.431***	0.429***	0.425***	0.443***
									(7.144)	(7.559)	(7.457)	(7.366)
Obs	54,573	54,573	54,115	54,573	40,001	40,001	39,641	40,001	40,001	40,001	39,641	40,001
R^2	0.023	0.025	0.027	0.016	0.031	0.027	0.036	0.024	0.064	0.071	0.070	0.060
S.E. FOMC date	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	No	No	No	No	No	No	No	No	No	No	No	No

Table 4. (Continued)

Panel B: Firm-level controls

Dependent Variable	Δ *CDS*				Δ *Exp. Loss*				Δ *CDS*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Target	0.851*				0.479***				0.693			
	(1.814)				(2.821)				(1.329)			
Path		1.094***				0.320*				1.180***		
		(3.358)				(1.800)				(3.603)		
BRW			1.257**				0.586***				1.043**	
			(2.376)				(3.525)				(2.112)	
LSAP				0.032				-0.108				0.030
				(0.061)				(-0.388)				(0.065)
Δ Exp. Loss									0.440***	0.438***	0.436***	0.450***
									(7.187)	(7.558)	(7.633)	(7.422)
Obs	36,280	36,280	35,978	36,280	33,549	33,549	33,247	33,549	33,549	33,549	33,247	33,549
R^2	0.034	0.037	0.040	0.029	0.034	0.030	0.039	0.028	0.076	0.082	0.083	0.073
S.E. FOMC date	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 5. 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. For more details regarding the specifications, see Equation (3) in the main text. Panel A below refers to a set of regressions with a direct, multiplicative term between monetary policy shocks and the one-day lagged CDS value. Meanwhile Panel B focuses on specifications that sort firms into CDS risk quintiles based on data from the day prior, and interact these risk quintiles with monetary policy shocks. Within each panel, columns 1 to 3 report the results using CDS changes as the dependent variable. Columns 4 to 6 focus on movements in expected loss compensation as the dependent variable. Columns 7 to 9 show the results for changes in CDS after we control for the contemporaneous change in expected loss compensation. In Panel A, we standardize variables such that the coefficient on the interaction term represents the change in CDS due to a 1σ change in the monetary policy shock, for a firm with 1σ larger historical CDS. In Panel B, coefficients represent the change in CDS due to a 1σ change in the policy shock, conditional on the firm falling into that risk quintile. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Panel A: Direct Interaction Effects									
Dependent Variable	Δ *CDS*			Δ *Exp. Loss*			Δ *CDS*		
	Target	Path	BRW	Target	Path	BRW	Target	Path	BRW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
shockXCDS	0.608**	0.560**	0.679*	0.351***	0.362**	0.454***	0.464	0.578**	0.635
	(2.049)	(2.255)	(1.686)	(3.290)	(2.193)	(2.866)	(1.546)	(2.034)	(1.561)
CDS lagged	-0.009*	-0.007	-0.006	-0.003	-0.001	-0.000	-0.010*	-0.008	-0.007
	(-1.862)	(-1.316)	(-0.977)	(-1.171)	(-0.586)	(-0.004)	(-1.882)	(-1.347)	(-0.991)
Δ Exp. Loss							0.331***	0.331***	0.327***
							(6.925)	(7.181)	(6.991)
Obs	54,573	54,573	54,115	40,001	40,001	39,641	40,001	40,001	39,641
R^2	0.137	0.136	0.139	0.106	0.105	0.110	0.174	0.174	0.178
S.E. FOMC date	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm and Time F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	No	No	No	No	No	No	No	No	No

Table 5. (Continued)

Panel B: Non-Linear Interaction Effects

Dependent Variable	Δ *CDS*			Δ *Exp. Loss*			Δ *CDS*		
	Target	Path	BRW	Target	Path	BRW	Target	Path	BRW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
shockXCDS2	0.079	0.219***	0.189	0.042	-0.018	0.054*	0.102	0.266***	0.180
	(0.544)	(2.931)	(1.395)	(1.384)	(-0.474)	(1.793)	(0.598)	(3.058)	(1.305)
shockXCDS3	0.255	0.405***	0.488	0.245	0.160	0.311***	0.163	0.445***	0.411
	(0.869)	(2.684)	(1.509)	(1.584)	(1.284)	(3.088)	(0.479)	(2.783)	(1.318)
shockXCDS4	0.608	1.148***	1.102**	0.491**	0.247	0.627***	0.335	1.316***	0.928*
	(1.240)	(3.252)	(2.035)	(2.173)	(1.258)	(3.448)	(0.617)	(3.757)	(1.809)
shockXCDS5	2.452**	2.343***	3.152***	1.328***	0.915*	1.691***	2.124*	2.711***	2.769**
	(2.559)	(3.162)	(2.755)	(3.125)	(1.889)	(3.709)	(1.948)	(3.479)	(2.553)
Δ Exp. Loss							0.343***	0.343***	0.337***
							(7.056)	(7.470)	(7.316)
Observations	36,280	36,280	35,978	33,549	33,549	33,247	33,549	33,549	33,247
R^2	0.153	0.153	0.158	0.110	0.107	0.117	0.184	0.186	0.189
S.E. FOMC date	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm and Time F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 6. 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. The results below are determined through a regression specification very similar to the second line of Equation (3) in the main text, with equity returns as the dependent variable instead. Throughout the table, firms are sorted into CDS risk quintiles based on one day lagged values of CDS spreads, and these risk quintile rankings are interacted with monetary policy shocks. Columns 1 to 3 report the results using 1-hour equity returns surrounding FOMC announcements, as the dependent variable. Columns 4 to 6 focus on movements in 2-day returns surrounding the announcement. We standardize variables such that coefficients represent the % change in equity returns due to a 1σ change in the policy shock, conditional on the firm falling into that risk quintile. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Dependent Variable	*1-Hour Return*			*2-Day Return*		
	Target	Path	BRW	Target	Path	BRW
	(1)	(2)	(3)	(4)	(5)	(6)
shockXCDS2	-0.028**	-0.013	-0.025*	-0.097**	-0.089	-0.185***
	(-2.338)	(-0.879)	(-1.728)	(-2.036)	(-1.583)	(-3.288)
shockXCDS3	-0.036*	0.005	-0.045	-0.231**	-0.123	-0.345***
	(-1.905)	(0.265)	(-1.614)	(-2.418)	(-1.243)	(-2.902)
shockXCDS4	-0.074**	-0.025	-0.088**	-0.256*	-0.227*	-0.423***
	(-2.266)	(-0.766)	(-2.456)	(-1.847)	(-1.820)	(-3.407)
shockXCDS5	-0.150***	-0.073	-0.155***	-0.400***	-0.413***	-0.584***
	(-2.835)	(-1.645)	(-3.592)	(-2.633)	(-2.615)	(-3.049)
ret lag	0.003	0.004	0.003	-0.035*	-0.034	-0.036*
	(0.409)	(0.499)	(0.361)	(-1.677)	(-1.578)	(-1.722)
Observations	29,594	29,594	29,594	36,279	36,279	35,977
R^2	0.467	0.465	0.467	0.338	0.338	0.340
S.E. FOMC date	Y	Y	Y	Y	Y	Y
Firm and Time F.E.	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Table 7. 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 risk as determined by historical leverage. For more details regarding the specifications, see Equation (4) in the main text. Columns 1 to 3 report the effects of leverage directly interacted (multiplicatively) with policy shocks, on movements in CDS compensation due to expected losses. Columns 7 to 9 focus on the overall CDS, while controlling for contemporaneous movements in expected losses. Meanwhile, in columns 4 to 6 and 10 to 12, regressions further include dummy interaction terms that are determined by 1-day lagged levels of CDS risk. For leverage interaction terms, we standardize variables such that coefficients represent the basis point change due to an additional 1σ movement in leverage, following a 1σ change in the policy shock. For dummy interaction terms, coefficients represent the basis point change due to a 1σ change in the policy shock, conditional on the firm falling into that risk quintile. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Dependent Variable	Δ *Exp. Loss*			Δ *Exp. Loss*			Δ *CDS*			Δ *CDS*		
	Target	Path	BRW	Target	Path	BRW	Target	Path	BRW	Target	Path	BRW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TargetXlev	0.213**			0.045			0.143			-0.133		
	(2.173)			(0.649)			(1.097)			(-1.499)		
PathXlev		0.121			-0.027			0.467**			0.084	
		(0.986)			(-0.362)			(2.425)			(0.653)	
BRWXlev			0.303**			0.0454			0.581**			0.213
			(2.504)			(0.662)			(2.068)			(1.09)
Δ Exp. Loss							0.352***	0.351***	0.352***	0.343***	0.343***	0.337***
							(7.348)	(7.439)	(7.441)	(7.064)	(7.475)	(7.297)
shockXCDS2				0.037	-0.016	0.049*				0.117	0.259***	0.158
				(1.242)	(-0.441)	(1.778)				(0.663)	(2.928)	(1.107)
shockXCDS3				0.234	0.167	0.298***				0.195	0.426**	0.352
				(1.467)	(1.342)	(3.197)				(0.548)	(2.546)	(1.044)
shockXCDS4				0.460**	0.258	0.602***				0.425	1.281***	0.814
				(2.07)	(1.365)	(3.692)				(0.728)	(3.731)	(1.562)
shockXCDS5				1.276***	0.944**	1.638***				2.276**	2.620***	2.523**
				(3.172)	(2.144)	(4.021)				(1.992)	(3.568)	(2.427)
Observations	33549	33549	33247	33549	33549	33247	33549	33549	33247	33549	33549	33247
R^2	0.105	0.104	0.107	0.11	0.107	0.117	0.178	0.179	0.182	0.184	0.186	0.189
S.E. FOMC date	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm and Time F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 8. Cross-Sectional Equity Response by Leverage
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 leverage. The regressions are very similar to the ones in Equation (4), with 2-day equity returns as the dependent variable instead. Columns 1 to 3 report the effects of leverage directly interacted (multiplicatively) with policy shocks, on 2-day returns. Meanwhile, in columns 4 to 6, regressions further include dummy interaction terms that are determined by 1-day lagged levels of CDS risk. For leverage interaction terms, we standardize variables such that coefficients represent the % return due to an additional 1σ movement in leverage, following a 1σ change in the policy shock. For dummy interaction terms, coefficients represent the % return due to a 1σ change in the policy shock, conditional on the firm falling into that risk quintile. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Dependent Variable	*2-Day Return*			*2-Day Return*		
	Target	Path	BRW	Target	Path	BRW
	(1)	(2)	(3)	(4)	(5)	(6)
TargetXlev	-0.024			0.029		
	(-0.688)			(0.939)		
PathXlev		-0.055			0.007	
		(-1.589)			(0.232)	
BRWXlev			-0.058			0.026
			(-1.531)			(0.880)
ret lag				-0.035*	-0.034	-0.036*
				(-1.677)	(-1.578)	(-1.723)
shockXCDS2				-0.101**	-0.0897	-0.188***
				(-2.073)	(-1.597)	(-3.314)
shockXCDS3				-0.238**	-0.125	-0.352***
				(-2.454)	(-1.235)	(-2.900)
shockXCDS4				-0.274*	-0.229*	-0.437***
				(-1.882)	(-1.786)	(-3.468)
shockXCDS5				-0.430***	-0.420***	-0.613***
				(-2.859)	(-2.641)	(-3.152)
Observations	36,279	36,279	35,977	36,279	36,279	35,977
R^2	0.336	0.336	0.336	0.338	0.338	0.340
S.E. FOMC date	Y	Y	Y	Y	Y	Y
Firm and Time F.E.	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Table 9. 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 risk as determined by historical market size. The regressions are very similar to the ones in Equation (4), with market size replacing leverage. Columns 1 to 3 report the effects of log market size directly interacted (multiplicatively) with policy shocks, on movements in CDS compensation due to expected losses. Columns 7 to 9 focus on the overall CDS, while controlling for contemporaneous movements in expected losses. Meanwhile, in columns 4 to 6 and 10 to 12, regressions further include dummy interaction terms that are determined by 1-day lagged levels of CDS risk. For market size interaction terms, we standardize variables such that coefficients represent the basis point change due to an additional 1σ movement in leverage, following a 1σ change in the policy shock. For dummy interaction terms, coefficients represent the basis point change due to a 1σ change in the policy shock, conditional on the firm falling into that risk quintile. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Dependent Variable	Δ *Exp. Loss*			Δ *Exp. Loss*			Δ *CDS*			Δ *CDS*		
	Target	Path	BRW	Target	Path	BRW	Target	Path	BRW	Target	Path	BRW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TargetXmrkt	-0.420***			-0.245***			-0.166			0.375		
	(-2.979)			(-2.728)			(-0.913)			(1.263)		
PathXmkt		-0.317*			-0.198*			-0.369*			0.422*	
		(-1.873)			(-1.663)			(-1.677)			(1.915)	
BRWXmkt			-0.545***			-0.330***			-0.462**			0.163
			(-3.437)			(-2.633)			(-1.969)			(0.569)
Δ Exp. Loss							0.351***	0.349***	0.348***	0.345***	0.345***	0.338***
							(7.293)	(7.379)	(7.313)	(7.119)	(7.471)	(7.294)
shockXCDS2				-0.074**	-0.131**	-0.133**				0.28	0.506***	0.272
				(-2.308)	(-1.999)	(-2.024)				(0.979)	(2.984)	(0.993)
shockXCDS3				0.014	-0.033	-0.042				0.516	0.857***	0.584
				(0.114)	(-0.343)	(-0.459)				(0.866)	(2.674)	(0.972)
shockXCDS4				0.174	-0.0145	0.146				0.819	1.872***	1.165
				(1.092)	(-0.118)	(1.121)				(0.917)	(3.484)	(1.369)
shockXCDS5				0.849***	0.528*	1.007***				2.855*	3.534***	3.105**
				(3.154)	(1.676)	(3.499)				(1.849)	(3.799)	(2.105)
Observations	33,549	33,549	33,247	33,549	33,549	33,247	33,549	33,549	33,247	33,549	33,549	33,247
R^2	0.109	0.107	0.115	0.111	0.108	0.119	0.178	0.179	0.182	0.184	0.187	0.189
S.E. FOMC date	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm and Time F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 10. Cross-Sectional Equity Response by Market Size
This table reports the heterogeneous effects of monetary policy shocks on equity returns, due to cross-sectionally varying levels of risk as determined by market size. The regressions are very similar to the ones in Equation (4), with 2-day equity returns as the dependent variable instead and market size replacing leverage. Columns 1 to 3 report the effects of market size directly interacted (multiplicatively) with policy shocks, on 2-day returns. Meanwhile, in columns 4 to 6, regressions further include dummy interaction terms that are determined by 1-day lagged levels of CDS risk. For market size interaction terms, we standardize variables such that coefficients represent the % return due to an additional 1σ movement in market size, following a 1σ change in the policy shock. For dummy interaction terms, coefficients represent the % return due to a 1σ change in the policy shock, conditional on the firm falling into that risk quintile. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Dependent Variable	*2-Day Return*			*2-Day Return*		
	Target	Path	BRW	Target	Path	BRW
	(1)	(2)	(3)	(4)	(5)	(6)
TargetXmkt	0.167***			0.133***		
	(3.361)			(3.610)		
PathXmkt		0.110*			0.0253	
		(1.951)			(0.626)	
BRWXmkt			0.183***			0.099**
			(2.998)			(2.263)
lagged return				-0.033	-0.033	-0.036*
				(-1.610)	(-1.569)	(-1.743)
shockXCDS2				-0.0317	-0.0744	-0.130***
				(-0.586)	(-1.573)	(-2.823)
shockXCDS3				-0.108	-0.099	-0.241***
				(-1.166)	(-1.311)	(-2.849)
shockXCDS4				-0.0925	-0.194**	-0.281***
				(-0.644)	(-2.002)	(-3.314)
shockXCDS5				-0.149	-0.365***	-0.381***
				(-1.212)	(-3.360)	(-3.051)
Observations	36,279	36,279	35,977	36,279	36,279	35,977
R^2	0.338	0.337	0.339	0.339	0.338	0.340
S.E. FOMC date	Y	Y	Y	Y	Y	Y
Firm and Time F.E.	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Table 11. Cross-Sectional Credit Response: Ex-Ante Default vs. Risk Premium Channel
This table reports the heterogeneous effects of monetary policy shocks on credit risk, due to cross-sectionally varying levels of risk as determined separately by the expected loss upon default (EL) and the credit risk premium (RP). For more details regarding the construction of these measures and exact specifications, see Equation (5) in the main text. For all dummy interaction terms, coefficients in columns 1 to 3 (4 to 6) represent the basis point (percentage) change due to a 1σ change in the policy shock. The variable N is the number of firms in each category. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Dependent Variable		*Δ CDS*			*2-Day Return*	
	Target	Path	BRW	Target	Path	BRW
	(1)	(2)	(3)	(4)	(5)	(6)
shockX(EL1RP2)	0.011	-0.293**	0.165	-0.040	0.026	-0.050
(N=3,262)	(0.030)	(-2.416)	(0.626)	(-0.674)	(0.468)	(-0.943)
shockX(EL1RP3)	-0.524	-0.167	-0.074	-0.266	-0.051	-0.184*
(N=2,862)	(-0.782)	(-0.552)	(-0.173)	(-1.199)	(-0.444)	(-1.800)
shockX(EL2RP1)	0.124	-0.433**	0.104	-0.163***	0.028	-0.183**
(N=4,356)	(1.456)	(-2.348)	(0.894)	(-2.815)	(0.620)	(-2.464)
shockX(EL2RP2)	0.245	-0.036	0.546*	-0.300***	-0.050	-0.443***
(N=4,759)	(0.749)	(-0.260)	(1.654)	(-2.879)	(-0.625)	(-3.196)
shockX(EL2RP3)	0.703	0.166	1.049	-0.335	-0.079	-0.458***
(N=1,996)	(1.005)	(0.311)	(1.681)	(-1.939)	(-0.647)	(-3.175)
shockX(EL3RP1)	0.0359	0.500	0.726**	-0.583***	-0.260**	-0.657***
(N=1,137)	(0.141)	(1.656)	(2.489)	(-3.182)	(-2.188)	(-3.564)
shockX(EL3RP2)	-0.267	0.738*	1.500***	-0.260	-0.257**	-0.460**
(N=3,360)	(-0.769)	(1.912)	(2.813)	(-1.360)	(-2.079)	(-2.322)
shockX(EL3RP3)	2.461**	2.369***	3.173***	-0.549***	-0.355**	-0.627***
(N=6,495)	(2.235)	(3.436)	(2.682)	(-2.933)	(-2.241)	(-3.026)
lagged return				-0.032	-0.030	-0.034
				(-1.500)	(-1.350)	(-1.597)
Observations	33,554	33,554	33,252	33,553	33,553	33,251
R^2	0.161	0.162	0.166	0.351	0.350	0.353
S.E. FOMC date	Y	Y	Y	Y	Y	Y
Firm and Time F.E.	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Table 12. Financial Market Response to March Policy Action

This table reports the change in CDS (columns 1 to 4), expected default probabilities (columns 5 to 8), and equity returns (columns 9 to 12) after the Federal Reserve Board's announcement of a series of stimulus programs on March 23, 2020. For each variable, we calculate the change from March 23 to March 25, 2020. For each quantity, we run four regressions. In the baseline regression, we report the average change. In the second regression, we control for CDS categories, calculated using quintiles based on the latest available CDS data prior to March 23, 2020. In the third regression, we control for leverage. In the fourth regression, we also control for (log) market capitalization, calculated using the latest available data prior to March 23, 2020. * Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Dependent Variable	Δ *CDS*			Δ *EDF*			*2-Day Return*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	-22.51***	-3.967***	92.18	-15.98***	-1.367***	-95.82	16.03***	10.90***	9.483
	(-7.165)	(-6.948)	(1.117)	(-5.031)	(-4.010)	(-0.965)	(12.269)	(4.157)	(0.361)
dummy2		0.0419	-2.974		-3.362*	1.102		2.617	2.751*
		(0.039)	(-0.540)		(-1.900)	(0.199)		(1.522)	(1.952)
dummy3		-2.324	-6.273		-7.705**	1.31		3.261**	3.531**
		(-1.167)	(-0.734)		(-2.656)	(0.13)		(2.959)	(2.127)
dummy4		-19.20***	-29.15**		-13.94**	-4.721		7.574	7.702**
		(-5.338)	(-3.251)		(-2.473)	(-0.437)		(1.453)	(2.216)
dummy5		-64.09***	-76.72***		-42.64***	-25.04**		10.70*	11.36***
		(-7.884)	(-4.653)		(-3.585)	(-2.318)		(1.875)	(3.553)
Leverage			-27.69			-10.04			-4.420
			(-1.112)			(-0.428)			(-0.573)
Lagged size			-3.556			3.946			0.120
			(-1.006)			(0.925)			(0.100)
Observations	340	340	233	254	254	232	236	236	233
R^2	0.000	0.197	0.199	0.000	0.140	0.146	0.000	0.081	0.076

Table 13. Parameters and Calibrated Values
This table provides calibrated values for key parameters of interest in the model. For more details see main text.

Parameter	*Notes*	*Value*
i_0	steady state nominal int.	0.011
α_a	TR coefficient on agg productivity	0.1
α_π	TR coefficient on inflation	0.9
ρ_A	AC1 of agg productivity	0.5
ρ_S	AC1 of mon policy shock	0.5
ρ_a	AC1 of idio productivity	0.85
σ_A	conditional vol of agg productivity	0.007
σ_S	conditional vol of mon policy shock	0.004
σ_a	conditional vol of idio productivity	0.2
$exp\,(m_0)$	steady state real SDF	0.994
m_A	real market price of risk of agg productivity	0.5
m_S	real market price of risk of mon policy shock	12
α	returns to scale parameter	0.65
f	fixed costs of production	1.10
δ	capital depreciation	0.025
ϕ_{k1}	capital adjustment cost, period 1	12
ϕ_{k2}	capital adjustment cost, period 2	5.75
τ	corporate tax rate	0.25
c	coupon rate	0.01
ξ	capital losses upon default	0.4

Table 14. Baseline Moments (No Shock)
This table displays simulated moments from the model, based on a panel of 10000 firms. Aggregate cash flow and interest rate shocks are kept at steady state, while idiosyncratic shocks are simulated continuously. The top panel focuses on the first period, the middle panel focuses on the second period where firms have access to leverage, and the third period reports the realized default rate. For more details see main text.

Moment	Value
First-Period	
Avg i / k	0.102
Std i / k	0.03
Corr(i/k, prod)	0.929
Realized Def Rate (%)	0
Second-Period	
Avg i / k	0.101
Std i / k	0.035
Avg b / k	0.682
Std b / k	0.11
Avg Credit Spread (b.p.)	8.161
Std Credit Spread (b.p.)	43.999
Avg Ex-Ante Def Prob (%)	3.82
Std Ex-Ante Def Prob (%)	14.246
Realized Def Rate (%)	0.17
Corr(i/k, prod)	0.924
Corr(b/k, prod)	0.907
Corr(Credit Spread, prod)	-0.353
Corr(Credit Spread, value)	-0.241
Corr(i/k, b/k)	0.803
Third-Period	
Realized Def Rate (%)	3.666
Recovery Rate — Default	0.346

Table 15. Aggregate Effects of Monetary Policy Shock
This table displays simulated moments from the model, based on a panel of 10000 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. 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*
	Second-Period Decisions		
Avg i / k	0.102	0.073	-0.029
Std i / k	0.034	0.032	-0.002
Avg b / k	0.683	0.673	-0.01
Std b / k	0.111	0.106	-0.004
Avg Credit Spread (b.p.)	6.695	10.356	3.661
Std Credit Spread (b.p.)	35.845	59.045	23.2
Avg Ex-Ante Def Prob (%)	3.46	4.283	0.824
Std Ex-Ante Def Prob (%)	13.022	14.621	1.599
Realized Def Rate (%)	0.17	0.55	0.38

Table 16. Comparative Statics of Monetary Policy Effects

This table displays the effect of various model parameter choices on the change in firms' second period statistics due to monetary policy. The second column ("Baseline Change") displays the change in firm-level statistics under baseline parameters and mirrors the last column of Table 15. Columns 3 – 5 discuss shifting values of the monetary policy price of risk, m_S. Columns 6 and 7 respectively increase the persistence of interest rate shocks (ρ_S) and the fixed cost of production (f). The last two columns increase the price of risk with respect to the aggregate productivity shock (m_A) and the persistence of the aggregate productivity shock (ρ_A). Changes in firm statistics are computed from simulated model moments, based on a panel of 10,000 firms, across 2 different shock environments. For more details see main text.

Moment	*Baseline Change*	$m_S = 16$	$m_S = 5$	$m_S = \underline{m}$	$\rho_S = .65$	$f = 1.30$	$m_A = 1.00$	$\rho_A = .65$
Avg i / k	-0.029	-0.038	-0.01	0	-0.056	-0.03	-0.028	-0.029
Std i / k	-0.002	-0.003	-0.001	0	-0.003	-0.001	-0.002	-0.002
Avg b / k	-0.01	-0.013	-0.004	0	-0.016	-0.006	-0.01	-0.01
Std b / k	-0.004	-0.006	-0.002	0	-0.01	-0.003	-0.004	-0.004
Avg Credit Spread (b.p.)	3.661	5.008	1.311	0	7.746	7.914	3.737	3.67
Std Credit Spread (b.p.)	23.2	18.478	6.125	0	39.065	27.651	23.192	23.215
Avg Ex-Ante Def Prob (%)	0.824	1.236	0.323	0	1.774	2.081	0.813	0.826
Std Ex-Ante Def Prob (%)	1.599	2.491	0.729	0	3.907	2.123	1.599	1.605
Realized Def Rate (%)	0.38	0.8	0.15	0	1.56	3.69	0.38	0.38

Table 17. 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

A Additional Results

- In Table A1, we show that monetary policy shock effects on CDS spreads are mitigated when changes are measured using a longer future time horizon. This result is in contrast to the positive and significant effect of monetary policy shocks on weekly changes in credit ratings documented in Anderson and Cesa-Bianchi (2020) and it is likely driven by the superior ability of the CDS market to reflect new information.[19] In column 1 to 3 of Table A1, we run the specification in Equation 1 using $\Delta y_{it}^{w} = y_{i,t+5} - y_{i,t-1}$ as the dependent variable, that is the difference between the CDS spread 5 trading days after the FOMC announcement day and the CDS spread the day before the FOMC announcement day (i.e., a weekly change). The effect of monetary policy shock on weekly changes in CDS spreads is still positive, but its magnitude is smaller and significance is marginal. The statistical significance disappears if we control for (i) contemporaneous changes in expected default (Columns 4 to 6) and (ii) the change in CDS spread observed during the first day after the FOMC announcement day (Columns 7 to 9). These results make clear that the marginal significance in Columns 1 to 3 is entirely due to changes in CDS spreads during the first day after the FOMC announcement day. One way of interpreting these results is that CDS markets price in monetary policy at a very fast pace, perhaps even relative to traditional corporate bond markets.

- As discussed in Augustin et al. (2014) and Bai and Collin-Dufresne (2019) the underlying liquidity of credit default swaps is one reason why CDS may differ from corporate bonds, in terms of their priced credit risk (also known as a non-zero CDS-bond basis). We examine whether liquidity has an effect on the heterogeneous impact that interest rate shocks have on credit risk in Table A2. The Markit database allows us to examine this through the number of dealers that provide a CDS quote. We limit our sample to CDS observations with market depth greater than 5, which is the median throughout the sample. In columns 1 to 3 of the Table it is evident that the asymmetric impact of policy shocks is potentially stronger once we place these limitations. Quintile 5 firms have close to a 4 basis point impact following a standard deviation shock to monetary policy. Columns 4 to 6 echo this message, using expected loss compensation as the dependent variable (.9 to 1.7 basis point impact for the riskiest firms). Columns 7 to 9 suggest that despite limiting our sample and choosing the most liquid, informative prices, policy shocks continue to impact CDS through the risk premium channel as well.

- In an effort to understand the time-varying robustness of our results and the effect of the ZLB, we examine the credit risk sensitivities to monetary policy within and outside the ZLB period, defined as 2009 through 2015. Table A3 presents these results. In Panel A, which focuses on movements in CDS surrounding FOMC announcements, columns 1 to 3 all suggest that both Target and Path variables have significant effects on CDS in the non-ZLB period. BRW shocks are economically, but

[19] The CDS market is more liquid than the bond markets and leads the latter in price discovery (e.g., Oehmke and Zawadowski (2017) and Lee et al. (2018), among others.).

not statistically, significant. In columns 4 to 6 of the same Panel, in the ZLB period, Target seems to be fully mitigated while the coefficient estimates on Path haven't changed dramatically. Interestingly, BRW is the only variable that shows up as significant, which speaks to its value as a measure of unexpected LSAP-related policy. Panels B and C show similar effects using the expected loss component and credit risk premia as dependent variables. In summary it seems that within the ZLB period, the reduced variability in Target and Path diminish their effects on credit risk. Meanwhile longer-maturity changes in the term structure, as picked up by BRW shocks in the ZLB, manifest themselves significantly in credit risk movements.

- In the main body of the paper, we test the ability of credit risk to better explain cross-sectional heterogeneity in monetary policy responses relative to leverage and market capitalization. In those specifications, leverage and market capitalization are incorporated through direct multiplicative interaction terms with the policy shock term. In Table A4 we instead use dummy variables classifying whether a firm-date observation jointly falls within a particular tercile of credit risk (i.e., CDS) and tercile of leverage (in total 9 such dummy variables). In Table A4, we show that within a CDS tercile, leverage doesn't play any relevant role on the monetary policy response, while within a leverage quintile, credit risk certainly amplifies the response. Results hold for both equity return and CDS responses, following the FOMC announcement. We also conduct the same tests in Table A5, where we base the double-sorting on CDS and market capitalization. Variables are ranked in increasing order, which implies $CDS3$ and $MKT1$ (i.e., high CDS and small size) is the riskiest group. While ranking increases in market capitalization do seem to have an effect, CDS continues to be relatively significant. To a large extent, these results mirror those in the main text using multiplicative interaction terms.

B Nominal vs. Real Decision Making

Due to the fundamental theorem of asset pricing (see Cochrane (2005), among many others), we know there exists a positive real discount factor, M^r_{t+1}, such that the real price on an asset that pays off X^r_{t+1} in real units next period is given by:

$$q^r_t = \mathbb{E}_t\left[M^r_{t+1}X^r_{t+1}\right]$$

If we transform this into nominal prices, with a price level of P_t we receive:

$$\begin{aligned} \frac{q^n_t}{P_t} &= \mathbb{E}_t\left[M^r_{t+1}\frac{X^n_{t+1}}{P_{t+1}}\right] \\ (\Leftrightarrow) \qquad q^n_t &= \mathbb{E}_t\left[M^r_{t+1}\left(\frac{P_t}{P_{t+1}}\right)X^n_{t+1}\right] = \mathbb{E}_t\left[M^n_{t+1}X^n_{t+1}\right] \end{aligned}$$

where the nominal SDF, $M^n_{t+1} \equiv M^r_{t+1}/\Pi_{t+1}$.

Applying this same concept to the firm's time 1 problem in the model (without loss of generality):

$$
\begin{aligned}
& V_1(\dots) = \underset{\{k_2\}}{\text{Max}} \;\; D_{i1} + \mathbb{E}_1\left[M_2^n W_{i,2}\right] \\
(\Leftrightarrow) \qquad & \frac{V_1(\dots)}{P_1} = \underset{\{k_2\}}{\text{Max}} \;\; \frac{D_{i1}}{P_1} + \mathbb{E}_1\left[M_2^r \frac{W_{i,2}}{P_2}\right]
\end{aligned}
$$

The bottom equation represents a real version of the original optimization. We can see that the problems are equivalent with one another.

C Deriving Endogenous Inflation

As discussed in the main text, the real SDF will take the form:

$$m_t^r \equiv \log\left(M_t^r\right) = m_0 - m_A\left(A_t - \mu_A\right) - m_S S_t$$

The central bank will follow an interest rate policy that is a linear function of the growth and inflation environments:

$$y_t^1 = i_0 + \alpha_A\left(A_t - \mu_A\right) + \alpha_\pi\left(\pi_t - \mu_\pi\right) + s_t$$

In the above equation the only process / parameter that is unknown is π_t. This will be pinned down by the Euler equation for the short-term interest rate (i.e. it will be an endogenous process). We guess and verify the following endogenous process for inflation.

$$\pi_t^{guess} = \pi_0 + \pi_A \tilde{A}_t + \pi_S S_t$$

Verification of the inflation process will amount to finding $\{\pi_0, \pi_A, \pi_S\}$ such that no-arbitrage holds.
The no-arbitrage condition for short-term interest rates:

$$y_t^1 = -\log\left(\mathbb{E}_t\left[M_{t+1}^n\right]\right) = -\log\left(\mathbb{E}_t\left[\exp\left(m_{t+1} - \pi_{t+1}\right)\right]\right)$$

The LHS is already given through the Taylor rule policy. The RHS will be implied by the fundamental dynamics:

$$
\begin{aligned}
y_t^{implied} &= -\log\left(\mathbb{E}_t\left[\exp\left(m_{t+1}^r - \pi_{t+1}\right)\right]\right) = -\log\left(\mathbb{E}_t\left[\exp\left(**\right)\right]\right) \\
&= -\mathbb{E}_t\left[**\right] - \frac{1}{2}\mathbb{V}\mathrm{ar}_t\left[**\right]
\end{aligned}
$$

The bottom result is due to the conditional log-normality. With some algebra:

$$\begin{aligned}
\mathbb{E}_t[**] &= m_0 - \pi_0 - (m_A + \pi_A)\rho_A \tilde{A}_t - (m_S + \pi_S)\rho_S S_t \\
\mathbb{V}\mathrm{ar}_t[**] &= (m_A + \pi_A)^2 \sigma_A^2 + (m_S + \pi_S)^2 \sigma_S^2
\end{aligned}$$

$$\begin{aligned}
\Longrightarrow \quad y_t^{implied} &= \left\{\pi_0 - m_0 - \frac{1}{2}(m_A + \pi_A)^2 \sigma_A^2 - \frac{1}{2}(m_S + \pi_S)^2 \sigma_S^2\right\} \\
&+ \{(m_A + \pi_A)\rho_A\}\tilde{A}_t + \{(m_S + \pi_S)\rho_S\} S_t
\end{aligned}$$

Substituting our guessed inflation process, the Taylor rule (y_t^1) policy can be re-written as:

$$\begin{aligned}
y_t^1 &= i_0 + \alpha_A \tilde{A}_t + \alpha_\pi (\pi_t - \mu_\pi) + S_t \\
&= i_0 + (\alpha_A + \alpha_\pi \pi_A)\tilde{A}_t + (\alpha_\pi \pi_S + 1) S_t
\end{aligned}$$

If we match up coefficients of $y_t^{implied}$ and y_t^{TR}, we receive:

$$\pi_S \rho_S = 1 + \alpha_\pi \pi_S \quad \Longrightarrow \quad \pi_S = \frac{1 - m_S \rho_S}{\rho_S - \alpha_\pi}$$

$$(m_A + \pi_A)\rho_A = \alpha_A + \alpha_\pi \pi_A \quad \Longrightarrow \quad \pi_A = \frac{m_A \rho_A - \alpha_A}{\alpha_\pi - \rho_A}$$

$$\text{First equality} \quad \Longrightarrow \quad \pi_0 = i_0 + m_0 + \frac{1}{2}(m_A + \pi_A)^2 \sigma_A^2 + \frac{1}{2}\pi_S^2 \sigma_S^2$$

As a result the nominal log SDF can be written as:

$$\begin{aligned}
m_{t+1}^n &= m_{t+1} - \pi_{t+1} \\
&= (m_0 - \pi_0) - (m_A + \pi_A)\tilde{A}_{t+1} - (m_S + \pi_S) S_{t+1}
\end{aligned}$$

Any nominal, risk premium for an asset (its conditional expected returns) will be based on that asset's return covariance with these last two shock terms.

Table A1. Credit Risk Response to Monetary Policy Shocks – Weekly Changes
This table reports the effect of monetary policy shocks on weekly CDS changes. The main regression specification is very similar to that in Equation (1), except we replace the left hand side variable by a weekly CDS change, $y_{i,t+5} - y_{i,t-1}$, where t reflects the FOMC announcement day. Columns 1 to 3 report the baseline results, which only include monetary policy shocks as explanatory variables. Columns 4 to 6 report the results when we include the change in the quoted CDS spread measured the day after the FOMC announcement day (most commonly used throughout the analysis). Columns 7 to 9 report the results when we include (i) the change in the quoted CDS spread measured the day after the FOMC announcement day, (ii) the contemporaneous weekly change in the expected loss component of CDS, and (iii) the firm-level variables listed in Panel C of Table 3 and the (log) market capitalization the day before the FOMC announcement day as control variables. We standardize monetary policy shocks so that all coefficients represent the change in CDS due to a 1σ change in the monetary policy shock. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Target	0.995			-0.168			-0.216		
	(0.908)			(-0.229)			(-0.233)		
Path		1.724**			0.364			0.193	
		(2.352)			(0.724)			(0.362)	
BRW			1.313			-0.192			-0.500
			(1.372)			(-0.298)			(-0.887)
Δ_dCDS				1.256***	1.252***	1.256***	1.205***	1.202***	1.203***
				(27.498)	(26.947)	(26.759)	(26.043)	(25.474)	(25.589)
Δ_w Exp. Loss							0.320***	0.320***	0.328***
							(7.280)	(7.225)	(7.454)
Dependent Variable		Δ_w CDS			Δ_w CDS			Δ_w CDS	
Observations	54,573	54,573	54,115	54,573	54,573	54,115	33,548	33,548	33,246
R^2	0.018	0.022	0.020	0.430	0.430	0.430	0.459	0.459	0.461
S.E. FOMC date	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	No	No	No	No	No	No	Y	Y	Y

Table A2. Cross-Sectional Credit Response to Monetary Policy Shocks – Liquidity

This table reports the heterogeneous effects of monetary policy shocks on credit risk, while controlling for liquidity. The regression specification tested below is very similar to the second line in Equation (3) however we limit our sample to CDS observations with composite depth (i.e. number of quotes) larger than 5. As in earlier tables, CDS risk quintiles are determined through lagged values of CDS, the day prior to the FOMC announcement. Columns 1 to 3 report the results using CDS changes as the dependent variable. Columns 4 to 6 focus on movements in expected loss compensation as the dependent variable. Columns 7 to 9 show the results for changes in CDS after we control for the contemporaneous change in expected loss compensation. Coefficients represent the basis point change in credit risk due to a 1σ change in the policy shock, conditional on the firm falling into that lagged risk quintile. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
shockXCDS2	0.001	0.314**	-0.117	-0.007	-0.112**	-0.034	0.016	0.360**	-0.123
	(0.003)	(2.414)	(-0.340)	(-0.158)	(-1.950)	(-0.701)	(0.055)	(2.431)	(-0.351)
shockXCDS3	0.500	0.893***	0.580	0.079	0.060	0.164*	0.487	0.969***	0.492
	(1.053)	(3.448)	(0.803)	(1.230)	(0.733)	(1.689)	(0.902)	(3.414)	(0.689)
shockXCDS4	0.599	1.803***	1.160	0.284	0.172	0.353**	0.301	2.146***	0.928
	(0.629)	(3.280)	(0.906)	(1.409)	(0.840)	(2.094)	(0.278)	(3.664)	(0.736)
shockXCDS5	3.938***	4.189***	3.750	1.387***	0.905	1.738**	3.190**	4.553***	2.930
	(2.641)	(3.068)	(1.615)	(2.889)	(1.507)	(2.350)	(2.054)	(3.500)	(1.375)
Δ Exp. Loss							0.569***	0.576***	0.580***
							(7.540)	(7.699)	(7.561)
Dependent Variable		Δ CDS			Δ Exp. Loss			Δ CDS	
Observations	16,520	16,520	16,352	15,253	15,253	15,085	15,253	15,253	15,085
R^2	0.288	0.285	0.285	0.116	0.109	0.117	0.340	0.346	0.341
S.E. FOMC date	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm and Time F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Depth	> 5	> 5	> 5	> 5	> 5	> 5	> 5	> 5	> 5

Table A3. Cross-Sectional Credit Response to Monetary Policy Shocks – ZLB Subsamples

This table reports the heterogeneous effects of monetary policy shocks on credit risk, when examining subsamples determined by the zero-lower bound (ZLB) period. The regression specification tested below is very similar to the second line in Equation (3) however we examine the response separately, in the period outside of the 2009 – 2015 ZLB period (columns 1 to 3) and within that period (columns 4 to 6). In Panel A, the key outcome variable is the change in CDS spread surrounding the FOMC announcement. Meanwhile Panels B and C focus on the expected loss component of the CDS and the credit risk premium, respectively. As in earlier tables, CDS risk quintiles are determined through lagged values of CDS, the day prior to the FOMC announcement. Coefficients represent the basis point change in credit risk due to a 1σ change in the policy shock, conditional on the firm falling into that lagged risk quintile. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Panel A: CDS						
	Target	Path	BRW	Target	Path	BRW
shockXCDS2	0.0749	0.202**	0.0592	0.118	0.243	0.311***
	(0.532)	(2.532)	(0.204)	(0.403)	(1.571)	(2.816)
shockXCDS3	0.198	0.411***	0.0399	1.138	0.371	0.677**
	(0.653)	(3.266)	(0.062)	(0.859)	(0.929)	(2.368)
shockXCDS4	0.634	1.023***	0.392	-0.139	1.472*	1.411**
	(1.220)	(2.800)	(0.342)	(-0.078)	(1.886)	(2.654)
shockXCDS5	2.599**	2.267***	3.272	-0.425	2.606	2.996**
	(2.594)	(3.319)	(1.438)	(-0.105)	(1.523)	(2.102)
Observations	20,809	20,809	20,507	15,457	15,457	15,457
R^2	0.156	0.150	0.153	0.178	0.182	0.188
S.E. FOMC date	Y	Y	Y	Y	Y	Y
Firm and Time F.E.	Y	Y	Y	Y	Y	Y
ZLB	No	No	No	Y	Y	Y

Table A3. (Continued)

Panel B: Expected losses

	Target	Path	BRW	Target	Path	BRW
shockXCDS2	0.0509	-0.0233	0.0562	-0.199***	-0.0154	0.061*
	(1.591)	(-0.428)	(0.883)	(-2.910)	(-0.292)	(1.954)
shockXCDS3	0.249	0.208	0.289*	0.0520	0.0320	0.332**
	(1.639)	(1.422)	(1.678)	(0.142)	(0.176)	(2.655)
shockXCDS4	0.503**	0.314	0.643*	-0.0472	0.118	0.660***
	(2.093)	(1.420)	(1.676)	(-0.055)	(0.331)	(3.104)
shockXCDS5	1.316***	1.264***	2.064**	0.936	0.212	1.640***
	(3.050)	(2.962)	(2.178)	(0.417)	(0.211)	(2.973)
Observations	18,141	18,141	17,839	15,395	15,395	15,395
R^2	0.110	0.107	0.111	0.131	0.131	0.147
S.E. FOMC date	Y	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y	Y
ZLB	No	No	No	Y	Y	Y

Panel C: Credit Risk Premia

	Target	Path	BRW	Target	Path	BRW
shockXCDS2	0.0885	0.265**	0.048	0.204	0.248*	0.283***
	(0.521)	(2.500)	(0.144)	(0.719)	(1.662)	(2.692)
shockXCDS3	0.107	0.496***	-0.0109	1.121	0.355	0.546**
	(0.294)	(3.329)	(-0.016)	(0.936)	(0.959)	(2.140)
shockXCDS4	0.381	1.302***	0.291	-0.113	1.425*	1.156**
	(0.642)	(3.431)	(0.243)	(-0.075)	(1.994)	(2.460)
shockXCDS5	2.389**	2.986***	3.430	-0.852	2.524	2.354*
	(2.046)	(3.784)	(1.425)	(-0.244)	(1.595)	(1.852)
Δ Exp. Loss	0.278***	0.280***	0.289***	0.415***	0.412***	0.388***
	(6.040)	(6.495)	(6.223)	(4.917)	(5.206)	(4.995)
Observations	18,141	18,141	17,839	15,395	15,395	15,395
R^2	0.187	0.187	0.190	0.208	0.212	0.214
S.E. FOMC date	Y	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y	Y
ZLB	No	No	No	Y	Y	Y

Table A4. Cross-Sectional Credit Response: CDS vs. Leverage by Category
This table reports the heterogeneous effects of monetary policy shocks on credit risk and equity returns, due to cross-sectionally varying levels of risk as determined by historical credit default swap spreads (CDS) and leverage (LEV). Dummy variables for each variable take 3 possible values and are interacted with one another and the monetary shock term. For all dummy interaction terms, coefficients in columns 1 to 3 (4 to 6) represent the basis point (percentage) change due to a 1σ change in the policy shock. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Dependent Variable	*Δ CDS*			*2-Day Return*		
	Target	Path	BRW	Target	Path	BRW
	(1)	(2)	(3)	(4)	(5)	(6)
shockX(CDS1LEV2)	-0.0130	-0.224***	-0.129	-0.00458	0.148**	0.178**
	(-0.126)	(-2.884)	(-1.423)	(-0.076)	(2.220)	(2.523)
shockX(CDS1LEV3)	0.141	-0.134	-0.00749	0.0951	0.148**	0.312***
	(0.887)	(-1.635)	(-0.046)	(1.272)	(2.210)	(3.432)
shockX(CDS2LEV1)	0.0362	0.0511	0.376	-0.188	-0.0319	-0.180
	(0.189)	(0.342)	(1.199)	(-1.600)	(-0.443)	(-1.624)
shockX(CDS2LEV2)	0.242	0.315**	0.425	-0.153*	0.0247	-0.168**
	(0.648)	(2.441)	(1.229)	(-1.948)	(0.542)	(-2.208)
shockX(CDS2LEV3)	0.490	-0.147	0.673**	-0.197	-0.0563	-0.162
	(1.494)	(-0.773)	(2.180)	(-1.478)	(-0.639)	(-1.541)
shockX(CDS3LEV1)	1.794**	1.326**	1.738*	-0.354*	-0.125	-0.225
	(2.064)	(2.170)	(1.973)	(-1.827)	(-0.882)	(-1.447)
shockX(CDS3LEV2)	2.511***	1.899***	2.077**	-0.292**	-0.223**	-0.402***
	(3.095)	(3.264)	(2.235)	(-2.390)	(-2.463)	(-2.929)
shockX(CDS3LEV3)	1.426*	1.733**	2.690**	-0.294*	-0.280**	-0.409**
	(1.738)	(2.562)	(2.368)	(-1.750)	(-2.330)	(-2.368)
ret_win_lag				-0.0350	-0.0338	-0.0364
				(-1.655)	(-1.590)	(-1.741)
Observations	36280	36280	35978	36279	36279	35977
R^2	0.152	0.152	0.156	0.338	0.338	0.340
S.E. FOMC date	Y	Y	Y	Y	Y	Y
Firm and Time F.E.	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Table A5. Cross-Sectional Credit Response: CDS vs. Market Size by Category
This table reports the heterogeneous effects of monetary policy shocks on credit risk and equity returns, due to cross-sectionally varying levels of risk as determined by historical credit default swap spreads (CDS) and market capitalization (MKT). Dummy variables for each variable take 3 possible values and are interacted with one another and the monetary shock term. For all dummy interaction terms, coefficients in columns 1 to 3 (4 to 6) represent the basis point (percentage) change due to a 1σ change in the policy shock. In all regressions, we include firm fixed effects and cluster standard errors at the FOMC date level.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

Dependent Variable	*Δ CDS*			*2-Day Return*		
	Target	Path	BRW	Target	Path	BRW
	(1)	(2)	(3)	(4)	(5)	(6)
shockX(CDS1MKT1)	-0.0536	-0.424	0.0425	-0.208*	-0.0756	-0.300**
	(-0.116)	(-1.156)	(0.078)	(-1.965)	(-0.755)	(-2.096)
shockX(CDS1MKT2)	-0.0289	-0.0960	0.00622	-0.145*	-0.0151	-0.134**
	(-0.387)	(-0.973)	(0.071)	(-1.869)	(-0.348)	(-2.150)
shockX(CDS2MKT1)	-0.0328	-0.0117	0.121	-0.398**	-0.150	-0.442***
	(-0.282)	(-0.099)	(1.072)	(-2.586)	(-1.209)	(-2.696)
shockX(CDS2MKT2)	0.224	0.275**	0.665**	-0.200**	-0.107	-0.321***
	(0.868)	(2.206)	(2.584)	(-2.346)	(-1.539)	(-3.116)
shockX(CDS2MKT3)	0.469	-0.141	0.559	-0.120	0.107*	-0.377***
	(1.391)	(-0.602)	(1.582)	(-1.206)	(1.758)	(-3.619)
shockX(CDS3MKT1)	1.409**	1.487**	2.520***	-0.439***	-0.310**	-0.617***
	(2.327)	(2.565)	(2.920)	(-2.811)	(-2.208)	(-3.073)
shockX(CDS3MKT2)	1.825**	1.785***	1.679**	-0.288	-0.231*	-0.333***
	(2.462)	(3.557)	(2.180)	(-1.545)	(-1.756)	(-2.688)
shockX(CDS3MKT3)	2.406**	2.182***	1.749	-0.183	-0.521***	-0.882***
	(2.441)	(3.550)	(1.304)	(-0.862)	(-3.602)	(-4.805)
ret_win_lag				-0.0339	-0.0335	-0.0365
				(-1.626)	(-1.579)	(-1.758)
Observations	36280	36280	35978	36279	36279	35977
R^2	0.151	0.152	0.155	0.339	0.338	0.341
S.E. FOMC date	Y	Y	Y	Y	Y	Y
Firm and Time F.E.	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y