Monetary Policy Surprises and Corporate Credit Spreads†

Difang Huang
Monash University
difang.huang@monash.edu

Xinjie Wang
Southern University of Science and Technology
xinjie.wang@sustech.edu.cn

Zhaodong (Ken) Zhong
Rutgers University
zdzhong@business.rutgers.edu

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Abstract

We study the effects of monetary policy surprises (MPSs) on corporate credit default swap (CDS) spreads. Using high-frequency surprises around Federal Open Market Committee (FOMC) announcements, we find a negative relation between changes in unexpected expansionary monetary policy and changes in CDS spreads using both panel regressions and time-series regressions. More importantly, we show that there is a strong cross-sectional effect of MPSs on CDS spreads. Unexpected expansionary monetary policy reduces the flight-to-safety and flight-to-liquidity phenomenon: The credit spread between investment-grade and high-yield CDSs narrows significantly following an unexpected monetary policy. Finally, we show that monetary policy affects CDS spreads through cash flow, financial constraints, and risk channels.

1 Introduction

Central banks around the world, such as the Federal Reserve in the U.S., respond to turmoils in the financial markets using monetary policy tools. The purpose of these monetary policies is typically to stimulate economies by lowering borrowing costs for corporations. However, it has been shown that the Federal Reserve has sometimes "surprised" the market by reacting to economic downturns more aggressively than the market expected (e.g., Cieslak, Morse, and Vissing-Jorgensen, 2019). The standard model of monetary policy with market imperfection suggests that "unexpected" monetary policy could result in large moves in credit spreads (e.g., Gertler and Karadi, 2015).

While prior studies provide evidence on the impact of monetary policy on credit spreads at the aggregate level (Gertler and Karadi, 2015), there is limited empirical evidence about whether and how credit spreads of individual companies may respond to monetary policy. Economic theories (e.g., Bernanke and Gertler 1989; Kiyotaki and Moore 1997) indicate that the impact of a monetary policy shock depends on a firm's financial constraints. These theories predict that security prices of firms with greater financial constraints would be more sensitive to a monetary policy shock than those with less financial constraints. The prediction implies that there may be a cross-sectional effect of monetary policy surprises (MPS) on corporate credit spreads. In this paper, we study the effects of monetary policy on a cross-section of single-name corporate credit default swap (CDS) spreads using high-frequency surprises around Federal Open Market Committee (FOMC) announcements.

The CDS market can offer an economically important distinct insight over and above that contained in the equity market. First, the CDS market is sizeable: At the end of 2016, it had an outstanding notional of around $5.2 trillion. Second, the CDS market is more liquid than the corporate bond market. A CDS, as a derivative contract, is less subject to the liquidity effect and demand pressure (e.g., Longstaff, Mithal, and Neis, 2005), whereas the credit spreads of corporate bonds contain a significant component of the liquidity effect (e.g., Bao, Pan, and Wang, 2011; Friewald, Jankowitsch, and Subrahmanyam, 2012). Third, a CDS is a standard instrument, the price of which reflects the homogeneity of the contract, whereas corporate bonds have various features and covenants that affect their prices. Hence, CDS spreads appear to be an arguably "cleaner" measure of credit risk than the credit spreads of corporate bonds. Finally, liquidity providers in the CDS market are large financial institutions.

We identify the monetary policy surprises during FOMC announcements following the method in Gertler and Karadi (2015). We use the change in Fed funds futures rates measured within a short-period window (e.g., 30 minutes) on FOMC announcement days as instrumental variables and use the same-day response in the yield of one-year government bond as the dependent variable. The fundamental identification assumption is that information about the economy on FOMC days does not affect the policy announcement, and only previously available news is relevant for policy-makers. Given this assumption, changes in Fed funds futures rates on FOMC announcement days are uncorrelated with the intraday changes in both economic and financial variables.

The CDS market may need more time to incorporate the effects of unexpected monetary policy shocks (Subrahmanyam et al. 2017; Daetz et al. 2020). Therefore, we convert the regression residuals on FOMC days into a monthly variable using the two-step approach (Barakchian and Crowe, 2013; Gertler and Karadi, 2015) and normalize the sign of the monetary policy surprises so that a positive surprise corresponds to an unexpected decrease in the interest rates, thus an expansionary monetary policy shock (Ottonello and Winberry, 2020).

We first provide evidence that the change in CDS spreads is negatively related to the MPSs. Specifically, a one basis point increase in MPSs is associated with a decrease in the firm-level credit spread of -32.65 basis points (bps), with a t-statistic of -3.02. We include various controls, including the commonly used firm characteristics, firm fixed effects, time fixed effects, and credit-rating fixed effects. The adjusted R-squared for the univariate regression is 5.6%, indicating that a change in MPSs has substantial explanatory power for the cross-sectional variation of CDS spreads. Our findings are robust when we study the aggregate credit spread index as the economic magnitude of this effect is comparable, with a change in the MPSs coefficient of -23.67 bps and a t-statistic of -4.66.

It is well known that investors shift their asset allocations away from riskier investments and into safer ones during times of market turmoil (flight to safety). It is interesting to examine whether unexpected monetary policy can reduce the flight-to-safety phenomenon. We find that the aggregate credit spread between investment-grade and high-yield firms narrows significantly following unexpected monetary policy.

We also explore the time variation and cross-sectional heterogeneity of the sensitivity of CDS spreads to MPS. Bernanke and Gertler (1989) predict that the sensitivity of assets to a monetary policy shock is greater during periods of economic slowdown. Consistent with this prediction, we find that the negative effect of MPSs on spreads is 174% higher for firms during the global financial crisis. Consistent with the prediction that security prices of firms with greater financial constraints would be more sensitive to a monetary policy shock than those with less financial constraints, the relationship between change in MPSs and change in CDS spreads is significantly stronger for three categories of firms: The coefficient is 173% higher for small firms, 40% higher for illiquid firms, and 318% higher for high-yield rated firms.

Credit spread consists of two components: expected default and risk premium. We decompose CDS spreads into these components and investigate their relationship with MPSs. Our results show that unexpected monetary policy has no significant effect on changes in default probability but does have a significant negative effect on the risk premium, suggesting that a change in MPSs leads to decreases in risk premiums but not in expected default losses.

To understand how monetary policy affects credit spreads, we examine three possible channels through which monetary policy impacts CDS spreads. In general, monetary policy can influence firms in two ways. It can impact firms directly, and it can also have an indirect impact on firms through its effects on economic conditions and the financial market. We expect that MPSs have a larger effect on firms that are more sensitive to monetary policy. We focus on three characteristics that are related to both direct and indirect monetary policy transmission: firm's cash flow, firm's financing constraints, and firm-level ambiguity and risk (Altman, 1968; Kaplan and Zingales, 1997; D'Acunto et al., 2017; Gu et al., 2018).

We first focus on firm's cash flow and identify three types of firms: firms with lower cash flow amount, firms with more cash flow volatility, and firms with longer cash flow duration. The relationship between changes in MPSs and changes in CDS spreads is significantly more substantial for these three types of firms: The coefficient is 71% higher for firms with a low amount of cash flow, 42% higher for firms with a longer cash flow duration, and 123% higher for firms with higher cash flow volatility. Our findings are consistent with the hypothesis that MPSs affect firms through cash flow related liquidity and discount rate channels.

Next, we demonstrate that MPSs have a larger impact on the CDS spreads of financially constrained firms, such as those with lower profitability and investment. For example, the change in the MPSs coefficient for firms with lower profitability is 200% higher than that for higher profitability firms. The results are similar when we consider other proxies for financing constraints, including the financial constraint index of Whited and Wu (2006). As the intensity of firms' financing constraints is positively related to firms' exposure to monetary policy, our result supports the hypothesis that monetary policy is essential for the spreads of financially constrained firms.

In addition to its impact on firms' financing constraints, MPSs can impact firm-level risk and ambiguity. We measure firms' risk and ambiguity as in Augustin and Izhakian (2020). The relationship between changes in MPSs and changes in credit spreads is 134% stronger for firms whose risk is above that of the median firm and 68% stronger for firms whose ambiguity is below that of the median firm, indicating an economically and statistically significant effect.

FOMC announcements contain information about the interest rate and the economic outlook. It is interesting to investigate the separate effects of each type of information. To this end, we decompose MPSs into two components: monetary policy shocks and central bank information shocks. We find that changes in both types of shocks lead to a decrease in credit spreads. More importantly, monetary policy shocks significantly affect default probability, while central bank information shocks significantly affect risk premium.

Our paper contributes to several strands of literature. There is a vast volume of literature studying the impact of monetary policy on firm-level quantities. Some papers focus on the low-frequency firm-level outcomes, including the quarterly or annual capital expenditure, capital investment, inventories, the number of employees, sales growth, and firm value (Bahaj et al. 2018; Cloyne et al. 2018; Jeenas, 2019; Crouzet and Mehrotra, 2020; Ottonello and Winberry, 2020).

Other papers focus on the high-frequency outcomes, including the equity return (Kuttner 2001; Gurkaynak, Sack, and Swanson, 2005; Campbell, Evans, Fisher, and Justiniano, 2012; Hanson and Stein, 2015; Corsetti, Duarte, and Mann, 2018; Foley-Fisher et al., 2018; Ozdagli, 2018; Chava and Hsu, 2019; Ozdagli and Velikov, 2020) and the credit spreads (Javadi et al. 2018; Daetz et al. 2020). Our paper contributes to this broad literature and shows that there exists a negative relation between the changes in MPSs and changes in CDS.

Second, we contribute to the strand of literature that investigates how and to what extent the effect of monetary policy varies across different firms. Serval studies show that firm-level response depends on age (Cloyne et al. 2018), size (Gertler and Gilchrist, 1994; Crouzet and Mehrotra, 2020), liquidity (Jeenas, 2019), and leverage (Kalemli-Ozcan et al. 2018). By controlling firm characteristics, we examine the effects of monetary policy on firm performance (Campbell et al., 2008; Akey, 2015; Akey and Lewellen, 2016; Gu et al., 2018) by highlighting the role of firm's cash flow (Dechow et al. 2004; Gao et al., 2018; Weber, 2018; Ozdagli, 2018), financing constraints (Gertler and Gilchrist, 1994; Gomes et al., 2016; Ozdagli and Weber, 2017), and ambiguity and risk (Augustin and Izhakian, 2020) on the response of firm-level credit spreads to MPSs.

Our paper is related to the literature on monetary policy transmission channels (Bernanke and Blinder, 1992; Christiano, Eichenbaum, and Evans, 1996; Gertler and Karadi, 2015; Paul, 2017; Nakamura and Steinsson, 2018; Jarocinski and Karadi, 2020, Neuhierl and Weber, 2019; Leombroni, Vedolin, Venter, and Whelan, 2020). We assess the transmission channels by identifying the multiple dimensions of monetary policy shocks, including the conventional mechanism whereby the Fed adjusts the current short-term interest rate and the recent information mechanism whereby the central bank influences market expectation about the future evolution of short-term interest rates. We contribute to this strand of the literature by using high-frequency instrumental variables and sign restrictions to identify monetary policy shocks from contemporaneous central bank information shocks and investigate their dynamic influences on corporate credit spreads, default probability, and risk premium. Our paper is also related to the rapidly growing literature on the influence of FOMC cycles on asset prices by focusing on the cross-section of firm-level credit risk (Lucca and Moench, 2015; Cieslak et al., 2019).

The remainder of the paper is organized as follows. We describe our data and summary statistics in Section 2. Section 3 examines the impact of unexpected monetary policy on CDS spreads. Section 4 investigates how monetary policy affects CDS spreads. Section 5 decomposes MPSs and examines the impact of the components on credit spreads. Section 6 shows the robustness of our results. Section 7 concludes the paper.

2 Data and summary statistics

2.1 CDS data

In this section, we describe our data. We obtain the end-of-day prices for single-name contracts on U.S. companies from Markit, a primary data provider for CDS data. We focus on CDS contracts with a five-year maturity, denominated in U.S. dollars, and with an MR documentation clause since they are the most liquid contracts (Blanco, Brennan, and Marsh, 2005 and Longstaff, Mithal, and Neis, 2005). The Markit data also provide the number of market makers contributing prices to the calculation of Markit's end-of-day consensus valuation. We use this number to measure liquidity in the CDS market following Qiu and Yu (2012).

We aggregate the daily CDS data to monthly CDS data. As the credit default swap market is less liquid than the equity and treasury market, the CDS market participants may need more time to incorporate the influences of monetary policy shocks in trading activity (Subrahmanyam et al. 2017; Daetz et al. 2020). Our data frequency choice is also comparable to the CDS event studies in the literature. For example, Kaviani et al. (2021) use the one-month window to study the relationship between changes in policy uncertainty and changes in CDS spreads.

To exclude abnormal observations and distressed firms, we require the CDS spread of a firm to be higher than five basis points and smaller than 1,000 basis points. During the sample period from January 2002 to December 2015, we have 461 firms and 55,036 firm-month observations with valid data for both accounting and financial variables. We present the median and quantile values of all these firms' credit default spreads conditional on a given date in Figure 1. The figure displays significant variation in cross-sectional and time-series dimensions, confirming the importance of identifying the heterogeneous effects of monetary policy on different firms.

[FIGURE 1 ABOUT HERE]

2.2 Measure the monetary policy surprises

We measure the monetary policy surprises using the high-frequency instrumental variable approach. Following Gertler and Karadi (2015), we use the movements of asset prices within the narrow time window around the FOMC meeting to identify the exogenous monetary policy changes. The FOMC meetings are scheduled for about eight times per year and there are some unscheduled FOMC meetings.[1] Follow the conventional practice in the literature, we use the yield of one-year maturity government bonds in month t, i_t^1, as our baseline monetary policy indicator[2]

[1] Our results are robust to the exclusion of unscheduled FOMC meetings and we present the results in Section 6.2.
[2] Our sample period includes the global financial crisis where the short-term interest rate reached the zero lower bound. Gertler and Karadi (2015) argue that the yield of the one-year government bond was not constrained by the zero lower bound. To further address this possible constraint (Swanson and Williams, 2014), we also use other policy indicator variables, including the two-year government bond yield and the ten-year government bond yield, as the robustness check in Section 6.1. Our empirical results are also robust to the subsample analysis excluding the period of the global financial crisis.

and consider the change in its price between 10 minutes before and 20 minutes after a FOMC announcement as the monetary policy innovation:

$$\Delta i_t^1 = i_t^1 - i_{t,-1}^1, \tag{1}$$

where Δi_t^1 is the change in the yield of one-year maturity government bonds, i_t^1 is the yield of one-year maturity government bonds 20 minutes after the FOMC meeting in month t, and $i_{t,-1}^1$ is the yield of one-year maturity government bonds 10 minutes before the FOMC meeting in month t.

The monetary policy innovation is (partly) endogenously determined by the Fed in response to the economic conditions and the financial market (Gürkaynak, Sack, and Swanson, 2005).[3] Therefore, we use the change in the asset prices of Fed funds and Eurodollar futures between 10 minutes before and 20 minutes after the FOMC announcement as external instruments:[4]

$$\Delta f_{t+j} = f_{t+j} - f_{t+j,-1}, \tag{2}$$

where the Δf_{t+j} is the change in the asset price of interest rate futures (including Fed funds futures and Eurodollar futures) for month $t + j$, f_{t+j} is the asset price 20 minutes after FOMC meeting in month t for interest rate futures expiring in $t + j$, and $f_{t+j,-1}$ is the asset price 10 minutes before the FOMC meeting in month t for interest rate futures expiring in $t + j$.[5]

As the surprises in both fed funds futures and eurodollar futures on FOMC announcement days are largely uncorrelated with change in both economic and financial variables over the announcement window period (Gertler and Karadi, 2015), we derive our measure of MPSs on

[3] The change in the one-year government bond yield is high dimensional as it includes information on the federal fund rate and treasury yield, the shock in forward guidance, and the quantitative easing (Gürkaynak, Sack, and Swanson, 2005).
[4] These assets include the current month's Fed funds futures (FF1), the three-month-ahead monthly Fed funds futures (FF4), and the six-month, nine-month and one-year ahead futures on three-month Eurodollar deposits (ED2, ED3, ED4).
[5] For $j = 0$, the surprise in futures rates measures the shock to the current interest rate (Kuttner, 2001). For $j \geq 1$, the surprise in futures rates measures the shock to forward guidance (Gürkaynak, Sack, and Swanson, 2005).

FOMC dates as the regression residual of monetary policy innovation Δi_t^1 on external instruments Δf_{t+j}:

$$\Delta i_t^1 = \alpha + \beta\, \Delta f_{t+j} + \varepsilon_t. \tag{3}$$

We show the regression results of the monetary policy innovation on various instrument sets in Appendix A and select the current month's Fed funds futures (FF1) as external instrument variable. The estimated regression residual $\widehat{\varepsilon_t}$ is expected to include the exogenous surprises in both the current funds rate and the Fed's forward guidance on further interest rates.

As the residual ε_t is a high-frequency variable and happens on FOMC days, we convert it into monthly average surprises using the two-step approach to study its persistent impact on firm-level variables (Barakchian and Crowe, 2013; Gertler and Karadi, 2015). We first cumulate the surprises on all FOMC days during the last month and then average these monthly surprises across each day of the month to investigate the dynamic impact of exogenous policy surprises on the firm's credit risk.[6]

Following Ottonello and Winberry (2020), we normalize the sign of monetary policy surprises so that a positive surprise corresponds to an unexpected decrease in the interest rates, thus an expansionary monetary policy shock. We show our measure of MPSs in Figure 2. As both MPSs and CDS spreads are highly persistent over our sample period, we regress the change in CDS spreads on MPSs change as our main regression specification, and our results are robust when we study the relationship between the level of CDS spreads and the level of MPS.

[FIGURE 2 ABOUT HERE]

[6] We also apply the approach in Gertler and Karadi (2015): First, we create a daily surprise time series by summing all FOMC day surprises; second, we derive the monthly averages of the time series and take the first-order difference of this series to obtain monthly average surprises. The results are similar.

2.3 Other control variables

We obtain firm-level accounting and financial variables from CRSP, CRSP/Compustat Merged Database, and Option Metrics. Our covariates include leverage, which is defined as the total amount of outstanding debt divided by the sum of total debt and equity; size, measured as the number of shares outstanding times the stock price at the end of the month; CDS depth, defined as the number of market makers who contribute the CDS prices; CDS volatility, defined as the volatility of the firm's five-year CDS spread measured in basis points; illiquidity, measured as the logarithm of the firm's stock illiquidity ratio, following Amihud (2002); profitability, defined as the firm's operating profits divided by firm size; momentum, calculated as the firm's cumulative continuously compounded return from month t-7 to month t-2; historical stock return volatility, measured as the firm's one-year realized stock return volatility; investment, calculated as the ratio of the firm's investment divided by total assets; average rating, defined as the Standard & Poor's long-term issuer credit rating for a firm; and firm-level ambiguity and risk based on the intraday trade and quote database (Augustin and Izhakian, 2020). We match each firm's CDS data with its balance-sheet information by firm name.

We include common macroeconomic variables from the St. Louis Federal Reserve Economic database, the expectation of economic indicators from the Survey of Professional Forecasters by the Federal Reserve Bank of Philadelphia, and the treasury yield from the Federal Reserve Board. We use the monthly average of the log S&P 500 index as our stock price index. We use the GDP deflator and the log of real GDP as the measures of the economy, and the monthly industrial production index and the consumer price index as the measures of the aggregate price level.[7] To measure the general financial conditions, we use the excess bond premium following Gilchrist and

[7] We interpolate the quarterly GDP deflator and the real GDP to monthly frequency following Stock and Watson (2010).

Zakrajsek (2012).[8] We also use the monthly average close values of the CBOE VIX Index, the TED spread, and the one-month macroeconomic uncertainty index from Jurado, Ludvigson, and Ng (2015) as additional measures for market conditions.

The FOMC announcements contain information about both the interest rate and the economic outlook (Gertler and Karadi, 2015; Nakamura and Steinsson, 2018). We use the surprises in the current month's Fed funds futures (FF1) as an external instrument variable and consider the surprise of three-month-ahead Fed funds futures (FF4) as our measure of the interest rate surprise (Gürkaynak, Sack, and Swanson, 2005). We also use the change in S&P500 between 10 minutes before and 20 minutes after an FOMC announcement as our measure of the stock price surprise.[9]

2.4 Summary statistics

Table 1 reports the summary statistics for the main variables in our data sample. Panel A shows the summary statistics for firm-level characteristics and covers all of the credit spread ratings in our sample. On average, a firm has a five-year CDS spread of 144.39 basis points and a market depth of 7.26. We also construct additional firm characteristic variables that are determinants of CDS spreads documented in the literature, including leverage, volatility, size, illiquidity, profitability, momentum, and investment (e.g., Tang and Yan, 2007, 2010; Bai and Wu, 2016). The average firm has a leverage ratio of 0.69, a realized return volatility of 0.32, a market capitalization of 9.36, a gross profitability ratio of 0.02, an illiquidity ratio of 0.01, a price momentum of 0.07, and an investment of 0.19. Panel B reports the summary statistics for the macroeconomic variables. The average values of one-year government bond yield, ten-year government bond yield, the five-by-five forward rate, and the five-year break-even rate are 1.66,

[8] The EBP variable aggregates the forward-looking information on the financial condition and real economy and improves the reliability of the explanation performance (Caldara and Herbst, 2019).
[9] This narrow window excludes the pre-FOMC announcement drift documented by Lucca and Moench (2015).

3.48, 4.67, and 1.89, respectively, and the average values for TED spread, VIX and MU are 0.44, 19.81, and 0.69, respectively.

[TABLE 1 ABOUT HERE]

3 Impact of monetary policy surprises on CDS spreads

In this section, we test the impact of MPSs on credit spreads. We also provide evidence on the flight to safety of credit spreads given unexpected monetary policy. Furthermore, we investigate time-series variation and cross-sectional heterogeneity for the relation between MPSs and CDS spreads. We further discuss the effect of MPSs on both default probability and risk premium.

3.1 Baseline results

We first regress the firm-level credit spreads on MPSs and additional control variables:

$$\Delta CS_{i,t} = \beta_0 + \beta_1 \Delta MPS_t + \beta_2 CS_{i,t-1} + \beta_3 X_{i,t} + \beta_4 Y_t + \eta_i + \delta_t + \epsilon_{i,t}, \tag{4}$$

where $X_{i,t}$ is a vector of firm-level control variables including the credit rating fixed effect for firm i at time t, Y_t is a vector of macroeconomic controls, η_i captures firm and credit rating fixed effects, δ_t captures quarter fixed effects, and $\epsilon_{i,t}$ represents the error terms.[10]

Following the literature on the determinants of CDS spreads, we include control variables, including size, illiquidity, firm leverage, profit, volatility, momentum, and investment. We add the firm fixed effects to control for the unobserved firm heterogeneity and to address the persistence in firm-level determinants. We also add the credit-rating fixed effects to alleviate the nonlinearity of credit rating and the quarter fixed effects to address the trend in monetary policy shocks. To

[10] As monetary policy surprises and credit spreads are highly persistent and correlated over time, we consider using the changes in CDS spreads as the dependent variable.

address the potential serial correlation in the unexpected monetary policy surprises (Ramey, 2016), we calculate the two-way clustered standard errors by firms and quarter (Ottonello and Winberry, 2020).

We report the results in Table 2. The results in column (1) suggest that the relationship between change in MPSs and change in CDS spreads is negative and statistically significant (t-statistic = -3.03). In this univariate regression, change in MPSs attains an explanatory power of 5.6%, and the magnitude of the coefficient indicates that, on average, a one basis point change in MPSs results in a CDS spread that is 44.85 bps lower.

Next, we add the firm-specific control variables and macroeconomic variables to the baseline specification and show the regression results in column (2) and column (3) of Table 2, respectively. Their coefficients have the expected signs, confirming the conclusions in the existing literature. In column (4), we add the year fixed effects and show that neither the magnitude nor the statistical significance of the changes in MPSs is affected. While the additional control variables do absorb a significant amount of the variation in CDS spreads, the change in MPSs still has significant explanatory power as a one basis point change in MPSs is associated with a 32.65 bps decrease in credit spreads (t-statistic = -3.02). We conclude that the negative relationship between change in MPSs and change in CDS spreads holds at the individual level.

[TABLE 2 ABOUT HERE]

3.2 Aggregate analysis

In this section, we extend our analysis of the relationship between MPSs and credit spreads by using the credit spread index constructed as the monthly equal weight mean of all firms' CDS spreads to alleviate the credit spread correlation across firms.[11] Equation (5) shows our econometric specification:

$$\Delta CSIndex_t = \beta_0 + \beta_1 \Delta MPS_t + \beta_2 CSIndex_{t-1} + \beta_3 X_t + \delta_t + \epsilon_{i,t}, \tag{5}$$

where the ΔMPS_t is the change of MPS, X_t is a vector of control variables, δ_t is the quarter fixed effects, and the dependent variable $\Delta CSIndex_t$ is the change in the credit spread index.

Table 3 reports the regression results. Column (1) shows that the coefficient of change in MPSs is -34.17 bps (t-statistic = -6.45), confirming an economically relevant and statistically significant effect. The adjusted R-square is 20.2%, showing that unexpected monetary policy changes have substantial explanatory power for the variation in the change in the credit spread index.

Next, we add the lagged credit spread index in our baseline regression to alleviate the mean reversion in CDS spreads and show the results in column (2). The effect of change in MPSs on the change in credit spreads is not affected in terms of economic magnitude and statistical significance.

We also add a variety of variables for macroeconomic conditions, including asset price surprises and interest rates, to address the concern that monetary policy's response to a change in economic uncertainty could affect the credit spreads. We report the results in column (3). The term changes in MPSs have a substantial negative effect on changes in the aggregate credit spread index, with a coefficient of -35.18 bps (t-statistic = -6.15).

We further add controls for market expectation, macroeconomic indicators, and economic uncertainty and present the results in column (4). The coefficient on VIX indicates the positive relationship between economic uncertainty and CDS spreads, consistent with the hypothesis that heightened economic uncertainty may lead to higher credit spreads (Gulen and Ion, 2016). Crucially, in this specification, the change in the MPSs coefficient remains negative (-23.67) and

[11] For each firm in our data sample, we use the CDS trading volume data from Markit and calculate the credit spread for each individual firm as the trade volume-weighted mean of all CDS spreads issued by this firm.

statistically significant (t-statistic = -4.66). The magnitude of the coefficient is slightly lower than those in previous specifications, implying that macroeconomic conditions explain a portion of the negative relationship between MPSs and CDS spreads. In sum, our results demonstrate that the negative relation between MPSs and changes in credit spreads holds for both the aggregate and firm-level credit spreads.

[TABLE 3 ABOUT HERE]

3.3 Flight to safety

Next, we study the flight-to-safety effect for the relationship between monetary policy and credit spreads and present our findings in Table 4. We focus on the aggregate credit spread index constructed for investment-grade firms and high-yield firms. We also consider differences in aggregate credit spread indexes between certain credit ratings (i.e., BBB minus AAA, BBB minus AA, BB minus AAA, and BB minus AA). The investment-grade index consists of CDSs with an S&P credit rating of BBB or higher, while the high-yield index includes those with a credit rating of BB or lower.

A comparison of the results in columns (1) and (2) of Table 4 shows that the impact of MPSs is greater for the high-yield index than for the investment-grade index as the estimated coefficients are -52.84 bps and -9.15 bps, respectively. The higher sensitivity of the high-yield spread is consistent with the structural models (Huang and Huang, 2012) which indicate that credit risk constitutes a smaller portion of investment-grade credit spreads and a larger portion of high-yield credit spreads.

Next, we examine whether the spreads among CDS contracts within the investment-grade ratings are sensitive to a change in MPS. BBB is the lowest rating for investment grade, and AAA/AA is the highest rating for investment grade. Column (3) shows the spread between AAA and BBB, and column (4) shows the spread between AA and BBB. The coefficients of ΔMPSs are statistically insignificant, suggesting that the spreads between investment grades are not sensitive to changes in MPS.

Finally, we examine whether the spreads of CDS contracts between the investment-grade and the high-yield firms are sensitive to a change in MPS. In columns (5) and (6), the coefficients of ΔMPSs are negative and highly significant. These results show that the spreads between high-yield and investment-grade firms are highly sensitive to a change in MPS. Furthermore, MPSs significantly reduce the flight-to-safety effect.

[TABLE 4 ABOUT HERE]

3.4 Time-series variation and cross-sectional heterogeneity relation between monetary policy surprises and CDS spreads

We study whether the effects of MPSs on credit spreads are time-varying over the sample period and cross-sectionally heterogeneous. We first test the time variation between the change in credit spreads and the change in MPSs by interacting this variable with a dummy variable that takes the value one during the global financial crisis and zero otherwise.[12] We show the regression results in column (1) of Table 5. The negative and statistically significant interaction term suggests that the effect of a change in MPSs on the change in credit spreads was amplified during the global financial crisis.

Next, we examine whether the effect of MPSs on CDS spreads is heterogeneous across firms of different sizes. Large firms are in a better financial condition and consequently have lower CDS spreads (Ericsson et al., 2009). We compute firm size as the number of total shares outstanding

[12] The global financial crisis is defined according to the NBER-defined recession dates (between December 2007 and June 2009 in our sample period). Kelly et al. (2016) demonstrate that the impact of a firm's idiosyncratic risk and industry-level jump risk on CDS spreads changed during the global financial crisis.

times the stock price at the end of a given month and interact MPSs with a dummy variable, Small firm, that takes the value one if the size of a firm is below that of the median for all firms in that year and zero otherwise. We add this interaction term to our baseline specification and report the results in column (2) of Table 5. The change in the MPSs coefficient remains negative and significant, and the interaction term coefficient is negative and significant, both in the economic (coefficient = -30.70) and statistical (t-statistic = -4.40) sense. Our results imply that the relationship between MPSs and changes in credit spreads is much stronger for small-size firms.

Similarly, we study the cross-sectional heterogeneity of firm's illiquidity in the relation between change in MPSs and change in credit spreads. As documented by Das and Hanouna (2009), a firm's illiquidity is related to its credit spread through the capital structure arbitrage channel, as a decrease in illiquidity leads to larger arbitrage activity in the CDS market. As a firm's illiquidity is not directly observed, we use the price impact measure in Amihud (2002) based on daily stock return and volume data as our primary illiquidity measure and create a dummy variable, Illiquid firm, that equals one if a firm's level of liquidity is below that of the median for all firms in that year and zero otherwise. We add this interaction term to our baseline specification and present the estimation results in column (3) of Table 5. We find that the interaction term coefficient is negative in magnitude (coefficient = -16.52) and statistically significant (t-statistic = -3.16). The estimates show that the effects of a change in MPSs on changes in credit spreads are much stronger for illiquid firms.

We also study the cross-sectional heterogeneity of firm's credit rating in column (4) of Table 5 using the HY dummy variable, which equals one if a firm's rating is high yield and zero otherwise, as a proxy for credit rating. We show that the interaction coefficient is still always negative (coefficient = -56.40) and highly significant (t-statistic = -4.36). These findings suggest that the credit spreads of firms with a high-yield rating are more sensitive to a change in MPS, consistent with our results in Section 3.3.

[TABLE 5 ABOUT HERE]

3.5 Default probability and risk premium

In this section, we decompose firm-level credit spread into expected default and risk premium and investigate their relationship with MPSs (Berndt et al., 2018).

Our decomposition approach is similar to that in Bharath and Shumway (2008). We assume that the logarithm of CDS spreads is linearly correlated with the expected default probability measures and compute the expected default probability using the distance to default (DTD) measure in Merton (1974).[13] We also add other firm-level controls—market leverage, liquidity, and size—at the firm level and use the credit rating fixed effects to capture additional information to that obtained using Merton's measure of default risk. We estimate the following model:

$$\ln\left(CS_{i,t}\right) = \beta_0 + \beta_1 DTD_{i,t} + \beta_2 X_{i,t} + \epsilon_{i,t}, \tag{6}$$

where $CS_{i,t}$ is the firm i's CDS spread, $DTD_{i,t}$ is firm i's distance to default, and $X_{i,t}$ include other control variables (including the credit rating fixed effects). Following Bharath and Shumway (2008), we show the amount of the credit spreads explained by firm-level variables as follows:

$$DP_{i,t} = \exp\left(\hat{\beta}_0 + \hat{\beta}_1 DTD_{i,t} + \hat{\beta}_2 X_{i,t} + \hat{\sigma}^2/2\right), \tag{7}$$

where $\hat{\sigma}^2$ is the estimated error term variance. The $DP_{i,t}$ term captures the default probability embedded in the credit spread. The remaining term $RP_{i,t} = CS_{i,t} - DP_{i,t}$ captures risk premiums.

[13] The variable DTD is robust to the model misspecification (Jessen and Lando, 2015) and a large body of literature (see Bharath and Shumway, 2008; Bai and Wu, 2013; Colonnello et al., 2014; Ericsson et al., 2009, for example) provides strong empirical support for the implications of Merton's model using CDS spreads in a linear regression framework. We also consider the volatility adjustment of the DTD measure (Jessen and Lando, 2015) to alleviate the large jump in firm's value during the financial crisis and derive similar results.

We use the changes in the two components as dependent variables in our baseline specification to study their relationship with changes in MPS. Table 6 shows our results. In columns (1) and (2), we use the changes in the firm-level default probability component as the dependent variables. The coefficient of change in MPSs is positive (coefficient = 4.74) and insignificant (t-statistic = 1.74). In columns (3) and (4), we use the changes in the firm-level risk premium components as the dependent variables, and the coefficients of ∆MPSs are negative (coefficient = -48.03) and highly significant (t-statistic = -3.60). These results show that there is an insignificant positive effect for changes in default probability and a significant negative effect on the risk premium, suggesting that a change in monetary policy shock leads to decreases in risk premiums but not in expected default losses. We discuss this effect further in Section 5.

[TABLE 6 ABOUT HERE]

4 How does monetary policy affect CDS spread?

In this section, we explore the channels through which a change in MPSs affects the credit spread. We do so by investigating how this relationship differs across each firm's monetary policy exposure. We focus on three firm characteristics that are associated with the transmission mechanisms of monetary policy, namely, cash flow, financial constraints, and firm-level ambiguity and risk, following the important contributions made in the asset pricing and corporate finance literature (see Kaplan and Zingales, 1997; Campbell et al., 2008; D'Acunto et al., 2017; Gu et al., 2018).

4.1 Cash flow channel

There are myriad ways that a firm's cash flow can influence the transmission of monetary policy to credit spreads. Cash is the most liquid asset for firms and therefore is directly linked with monetary policy as the cost of cash holding is determined by the short-term interest rate. A firm with more cash is more sensitive to unexpected monetary policy shocks as a sudden increase in the short-term interest rate would increase cash holding cost (Gao et al., 2018). Therefore, we hypothesize that a firm with more cash flow is more responsive to MPSs.

4.1.1 Cash flow amount

We compute each firm's cash flow amount by firm's cash amount scaled by firm size, as is standard in the literature. Cash flow exhibits considerable variation across firms for a given time and overtime for a given firm. To identify the firms with more cash flow in each year, we create a dummy variable $D_{CF\ Amount}$ that equals one if a firm's cash flow amount is above that of the median of all firms in the same year and zero otherwise. Then, we interact the dummy variable with the change in MPSs to study our hypothesized channel.

We add this variable and the interaction term between $D_{CF\ Amount}$ and ΔMPSs to our baseline specification. We show our results in column (1) of Panel A in Table 7. We focus on the coefficient of the interaction term as it quantifies how cash flow amount impacts the relationship between the change in MPSs and change in CDS spreads. The interaction term coefficient is negative (-17.47) and statistically significant (t-statistic = -3.22). Given the coefficient on the change in MPSs is -24.47, these estimates imply that the relationship between change in MPSs and change in CDS spread is 71% stronger for firms with more cash flow, confirming our hypothesis that a firm with more cash flow is more sensitive to a change in MPSs.

4.1.2 Cash flow duration

Following the present value model, firms that are expected to have more cash flow in the future are more sensitive to monetary policy, consistent with the hypothesis that firms' cash flow in the future is more affected by a change in the short-term interest rate (Dechow et al., 2004; Weber, 2018).

We calculate a firm's cash flow duration following Dechow et al. (2004). To address the outliers in this estimated variable, we adopt the approach in Nagel (2005) and create a dummy variable $D_{CF\ Duration}$ that equals one if a firm's cash flow duration is above that of the median of all firms in the same year and zero otherwise. We add both $D_{CF\ Duration}$ and $D_{CF\ Duration} \times \Delta MPSs$ variables to our baseline specification and show our results in column (2) of Panel A in Table 7. While the dummy variable $D_{CF\ Duration}$ is not statistically significant, the interaction term is negative (-11.77) and statistically significant (t-statistic = -1.99), supporting the hypothesis that the credit spreads of firms with longer cash flow duration are more responsive to a change in MPS. The coefficient magnitude implies that the relationship between change in MPSs and change in CDS spreads is 42% stronger for firms with longer cash flow duration than for their counterparts.

4.1.3 Cash flow volatility

Ozdagli (2018) documents that cash flow volatility influences a firm's monetary policy sensitivity. On the one hand, volatility is related to a firm's cash flow duration as a firm with higher volatility may have a higher likelihood of default and a lower cash flow duration. On the other hand, a firm with lower volatility may have a smaller option value to delay investment and a higher probability of increasing cash flow duration, thus increasing its reliance on external financing.

We calculate each firm's cash flow volatility using the standard deviation of cash flow over the last 20 quarters of cash flow and create a dummy variable $D_{CF\ Volatility}$ that equals one for firms whose cash flow volatility is above that of the median for all firms in the same year and zero otherwise. We add this variable and its interaction term with changes in MPSs to our baseline specification. We present the results in column (3) of Panel A in Table 7. The interaction term coefficient is negative (-21.27) and statistically significant (t-statistic = -3.31), supporting the hypothesis that high cash flow volatility heightens the influence of MPSs on credit spreads. This effect is very large in terms of economic magnitude: The response to unexpected monetary policy changes for a firm with high cash flow volatility is 123% larger than that for a firm with low cash flow volatility.

4.2 Financial constraints channel

Another channel of monetary policy transmission is the credit channel (Gertler and Gilchrist, 1994; Bernanke and Gertler, 1995; Bernanke and Kuttner, 2005). A large volume of literature shows that that the equity returns of financially constrained firms are more responsive to unexpected changes in monetary policy and less responsive to expected changes in monetary policy (Perez-Quiros and Timmermann, 2000; Lamont et al., 2001; Ozdagli, 2018; Chava and Hsu, 2020). In this section, we focus on the credit channel of monetary policy transmission and study the disproportionate effect of MPSs on the credit spreads of financially constrained firms.

4.2.1 Whited and Wu's (2006) index

We create a financial constraint index, following Whited and Wu (2006), as our financial constraints proxy (see Ozdagli, 2018 for more details). We create a dummy variable $D_{WhitedWu}$, which equals one if the financial constraint index of a firm is above that of the median for all firms in the same year and zero otherwise, to identify financially constrained firms. We then interact the dummy variable with the change in MPSs to study the credit channel of monetary policy transmission.

We add the $D_{WhitedWu}$ and $D_{WhitedWu} \times \Delta$MPSs variables to our baseline specification and show the estimation results in column (1) of Panel B in Table 7. The interaction term is negative (-30.71) and statistically significant (t-statistic = -4.39), confirming our hypothesis that the credit spreads of financially constrained firms are more responsive to MPSs. The estimated magnitude of this effect is economically large: The effect of a change in MPSs on the change in credit spreads is 173% larger for firms with lower financial constraints, suggesting that the credit spreads of financially constrained firms are more sensitive to changes in MPS.

4.2.2 Profitability

Gomes et al. (2016) show that monetary policy affects the balance sheet of firms through their nominal obligations to lenders and expect that less profitable firms are more sensitive to monetary policy due to sticky leverage mechanisms. Following Ozdagli and Weber (2017), we use firm-level operating profitability as the proxy for nominal rigidities as an expansionary monetary policy shock leads to an increase in input costs and a decrease in firms' profits, thus increasing their credit spreads. Therefore, we should expect the effect of monetary policy shocks to be smaller for firms with higher profitability.

We create a dummy variable $D_{\text{Profitability}}$ that equals one if the profitability of a firm is below that of the median for all firms in the same year and zero otherwise. We add this variable and its interaction term with changes in MPSs to our baseline specification. We present the estimation results in column (2) of Panel B in Table 7. The interaction term coefficient is negative (-32.37) and statistically significant (t-statistic = -4.26). Given the change in the MPSs coefficient is -16.13, the interaction term implies that the relationship between monetary policy and credit spreads is about twice as strong for firms with lower profitability, confirming our hypothesis that a firm with higher profitability is less sensitive to a change in MPS.

4.2.3 Investment

As shown in Gertler and Gilchrist (1994) and Kashyap, Lamont, and Stein (1994), financially constrained firms are more conservative in their investment decisions and may choose projects with lower volatility and shorter duration. Therefore, firms with more investment may need to rely more on external financing, disproportionately affected by monetary policy. Ottonello and Winberry (2020) show that high leverage firms respond to unexpected expansionary monetary policy shock by reducing investment more than low-leverage firms. This investment channel of monetary policy transmission through financial frictions suggests that firms with more investment should be more responsive to MPSs.

We add the dummy variable $D_{Investment}$, which equals one if the short-term investment of a firm is above that of the median for all firms in that year and zero otherwise, and the interactions with the change in MPSs to our baseline specification and show the estimation results in column (3) of Panel B in Table 7. The interaction term is negative (-27.67) and statistically significant (t-statistic = -4.56), consistent with the hypothesis that changes in credit spreads are more sensitive to changes in MPSs for firms with more investments. The coefficient magnitudes imply that the relation between MPSs changes and changes in credit spreads is 149% stronger for such firms, representing a sizeable economic effect.

4.3 Firm-level ambiguity and risk channel

Ambiguity is defined by the conditions under which the probability of future events is unknown (Knight, 1921). There is a large body of literature on the effect of ambiguity preference on equity risk premium, options pricing, firm leverage, and credit risk. Augustin and Izhakian (2020) study the role of ambiguity in pricing credit spreads and find that both ambiguity and risk have economically significant effects on CDSs. In this section, we explore this mechanism and hypothesize that firms with a higher level of risk and lower level of ambiguity should be more sensitive to unexpected monetary policy shocks.

4.3.1 Firm-level ambiguity

Following Augustin and Izhakian (2020), we compute the monthly ambiguity for each firm using intraday stock return data. We create a dummy variable $D_{Ambiguity}$ that equals one if the ambiguity of a firm is below that of the median for all firms in the same month and zero otherwise. We add this dummy variable and the interaction term with the change in MPSs to our baseline specification. We present the empirical results in column (1) of Panel C in Table 7. The interaction term is negative (-16.73) and statistically significant (t-statistic = -2.50). The implied magnitude shows that the impact of change in MPSs on change in CDS spreads is 69% stronger for firms with lower ambiguity and suggests that such firms are more sensitive to changes in MPS, consistent with the contributions in the ambiguity literature.

4.3.2 Firm-level risk

As shown in Augustin and Izhakian (2020), firm-level risk has an economically significant influence on CDS spreads. We compute firm-level risk as the monthly standard deviation of each firm's daily returns using intraday data and create a dummy variable D_{Risk} that equals one if the monthly firm-level risk of a firm is above that of the median for all firms in that year and zero otherwise. We add this variable and its interaction term with the change in MPSs to our baseline specification and show the empirical results in column (2) of Panel C in Table 7. The interaction term is negative (-20.42) and statistically significant (t-statistic = -2.42) and implies that the impact of a change in MPSs on change in credit spreads is 134% greater for firms with higher firm-level risk, confirming that riskier firms are more sensitive to changes in monetary policy shocks.

[TABLE 7 ABOUT HERE]

5 Decomposition of Monetary Policy

FOMC announcements contain information about the interest rate and the economic outlook (Gertler and Karadi, 2015; Nakamura and Steinsson, 2018). In this section, we decompose MPSs into two components using the information embedded in the high-frequency co-movement of both stock prices and short-term Fed funds future rates around FOMC announcements.

We show the FOMC surprises of both three-month futures rates and the stock price in Figure 2. As we can see, some positive stock market surprises accompany positive three-month futures rates surprises and some negative stock market surprises accompany negative three-month futures rates surprises. These co-movements between stock price surprise and interest rate surprise are not limited to a particular period. They remain similar if we use an alternative measure of interest rate surprise, including the surprises in the current month's Fed funds futures (FF1) and in the six-month, nine-month and one-year ahead futures on three-month Eurodollar deposits (ED2, ED3, ED4).

[FIGURE 3 ABOUT HERE]

The standard monetary policy shocks predict that over FOMC announcements there is a negative co-movement between stock price surprise and interest rate surprise (Melosi, 2017). To explain this counterintuitive fact, we attribute these co-movements to two structural shocks inherent in monetary policy announcements. We identify these two shocks: The first one is the monetary policy shock that predicts the negative co-movement between interest rate surprise and stock price surprise, and the second one is the central bank information shock that predicts the positive co-movement between interest rate surprise and stock price surprise.[14]

[14] We derive the two shocks under the assumption that the announcement surprises are affected only by these two announcement shocks and that in each month we observe a linear combination of the two shocks with different shares (Gilchrist, Lopez-Salido, and Zakrajsek, 2015; Boyarchenko, Haddad, and Plosser, 2016).

To decompose MPSs into these two shocks, we follow the approach in Jarocinski and Karadi (2020). We present the technical details of the decomposition methods, including the sign restriction (Rubio Ramirez, Waggoner, and Zha, 2010), the rotate priors (Giacomini and Kitagawa, 2015), and the penalty on sign restrictions in the Appendix B.

5.1 Monetary policy shocks and central bank information shocks

We depict monetary policy shocks and central bank information shocks over time in Figure 3. These two types of shocks are negatively correlated during our sample period, consistent with the theoretical model on the information channel of monetary policy transmission that predicts investors view these shocks as negatively associated with each other (see Melosi, 2017 for a detailed description).

[FIGURE 4 ABOUT HERE]

The central bank information shocks are not congregated at a particular period but are highly correlated with monetary policy and market conditions over our sample. At the beginning of the sample period, January 2002, there is a series of negative central bank information shocks during the dot-com bubble as the Fed decreased the short-term interest rate from about 6% to 1% to stimulate the condition of the market. These observations are consistent with the theoretical predictions on the Taylor interest rate rules and the moderate nature of the pace of recovery (Taylor, 2007; Bernanke, 2010). The FOMC statements during this period consistently linked the easy stance of policy to weak demand conditions and high economic uncertainty with downside risks. The positive co-movement of interest rates and stock market changes after most of these announcements suggest that the worse-than-expected outlook of the FOMC led agents to update their views about the economic prospects downwards. The central bank information shocks surged during the global financial crisis that happened in August 2007. Over this period, the financial market and economic outlook deteriorated significantly, as discussed in Bernanke (2015), and the FOMC meeting announced no change in the Fed fund interest rate while expressing negative opinions on the economic outlook. In particular, at its regular meeting on August 7, 2007, the FOMC indicated an increase in the downside risks of the economy in its announcement. In the following conference call on August 16, 2007, the FOMC confirmed that downside risks had increased dramatically. In accordance with the negative shock caused by central bank information, the stock market declined and the short-term interest rates decreased over the whole month.

5.2 Change in two shocks and credit spread, default probability, and risk premium

In this section, we assess the relevance of the decomposition of monetary policy on credit spread. As in Nakamura and Steinsson (2018), monetary policy shocks are associated with lower nominal stickiness and higher financial frictions. Central bank information shocks are based on FOMC communications and have persistent effects in terms of improving financial conditions, producing an upswing in the economic outlook, and tightening monetary policy.

We use changes in monetary policy shocks and central bank information shocks as independent variables in our baseline model to investigate their relationship with changes in credit spread, default probability, and risk premium. Table 8 presents our results. The dependent variables are firm’s CDS spread in columns (1) and (2), firm’s default probability in columns (3) and (4), and firm’s risk premium in columns (5) and (6). As the first two columns demonstrate, both the changes in monetary policy shocks and in central bank information shocks have a significant adverse effect on changes in credit spread, suggesting that a change in both types of shocks leads to a decrease in credit spread. In columns (3) and (4), we replicate the exercise using default probability at the firm level as a dependent variable and show that a significant negative influence exists for a change in monetary policy shocks but not for a change in central bank information shocks. In columns (5) and (6), we use the firm-level measures of a risk premium as the dependent variable and show that a significant negative effect exists for a change in central bank information shocks but not for a change in monetary policy shocks.

The standard New Keynesian model predicts monetary policy shocks using two key components: financial frictions and nominal rigidities (Gertler and Karadi, 2011). A positive shock in monetary policy leads to lower expected losses for creditors and lower credit spreads through the decrease in financial frictions and nominal rigidities, consistent with the “Merton effect” hypothesis that there is a positive relation between unexpected monetary policy shocks and credit spread. The communications of central banks can guide growth expectations and decision-making for economic agents even if the communications contain little information on fundamentals (Morris and Shin, 2002). Jarocinski and Karadi (2020) provide a theoretical framework to show that unexpected central bank communication can influence agents’ decisions independently from monetary policy shocks and argue that central bank information shocks are in line with the information on states of the financial market conditions. They predict that positive unexpected central bank information shocks lead to a lower risk premium and easier credit conditions through central banks’ connections with financial intermediaries as the providers of liquidity. Our empirical results confirm the prediction of the theoretical findings, with a large, negative, and significant ΔMP coefficient for both credit spread and default probability and a large, negative, and significant ΔCB coefficient for both credit spread and risk premium.

[TABLE 8 ABOUT HERE]

6 Robustness checks

6.1 Other proxy for monetary policy indicators

Our results rely on using the one-year government bond yield as the monetary policy indicator. In this section, we consider other potential proxies for monetary policy indicators to confirm the relationship between changes in MPSs and changes in CDS spread and compare our empirical results with those using different proxies.

As Gertler and Karadi (2015) argue, there is some degree of central bank leverage over the one-year government bond yield, and the zero lower bounds did not constrain the Fed's ability to adjust the one-year government bond yield during the global financial crisis. To further address this concern regarding the Fed's ability to manage the short-term government bond interest rate (Swanson and Williams, 2014), we use other policy indicator variables, including the two-year government bond yield and the ten-year government bond yield, as a robustness check.

Table 9 shows the results when we use two-year government bond yield and ten-year government bond yield as additional proxies for monetary policy indicators in the regression specifications given by Equation (4). Our results show that the changes in the MPSs coefficient always remain negative and statistically significant and therefore alleviate the concern that there exist other variables that may explain the relationship between changes in MPSs and CDS spreads.

[TABLE 9 ABOUT HERE]

6.2 Other sample period

In this section, we consider whether our results are robust to the sample period's choice. As shown in Lakdawala and Moreland (2019), compared with the period before the global financial crisis, the high-leverage firms are more sensitive to monetary policy surprises after the global financial crisis. To address the exceptional conditions around the global financial crisis and the unconventional monetary policy (Crouzet and Mehrotra, 2020), we conduct the subsample analysis by excluding the global financial crisis period, the unscheduled FOMC announcements, and zero-lower bound period. We show the results in Table 10. Our results confirm that the relationship between changes in the MPSs coefficient and CDSs changes is negative and statistically significant.

[TABLE 10 ABOUT HERE]

7 Conclusion

In this paper, we document that change in CDS spreads is negatively related to change in unexpected monetary policy. These results hold in both panel regressions and time-series regressions. We focus on the cross-sectional effects of monetary policy. The credit spread between investment-grade and high-yield firms decreases following unexpected monetary surprises. The credit spread between liquid and illiquid firms also decreases following unexpected monetary surprises. These results suggest that MPSs can significantly reduce flight to safety and flight to liquidity in the credit market.

We explore three channels through which a change in unexpected monetary policy affects credit spreads. The first channel is the cash flow channel. The relation between unexpected monetary policy and CDS spreads is stronger for firms with more cash flow, firms with high cash flow duration, and firms with low cash flow volatility. The second channel is the financial constraints channel. The relationship between unexpected monetary policy and CDS spreads is stronger for firms with lower financial constraints, higher profitability, and more investment. The third channel is risk channel. The relation is stronger for firms with higher risk and lower ambiguity.

We decompose MPSs into monetary policy shock and central bank information shock and investigate its implications for credit risk, default probability, and risk premium. We show that there is an insignificant positive effect of change in MPSs on changes in default probability and a significant negative effect on risk premium. We further find that changes in monetary policy shocks have a significant impact on default probability, while changes in central bank information shocks have a significant effect on risk premium.

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Table 1: Summary statistics

This table reports the summary statistics of our data sample. All variables are measured at a monthly frequency from January 2002 through December 2015. Panel A reports summary statistics for credit spread and firm specific variables. Panel B reports summary statistics for the macroeconomic variables. CDS spread is the firm's five-year CDS spread measured in basis points. CDS volatility is the volatility of the firm's five-year CDS spread measured in basis points. CDS depth is the number of market makers contributing prices to the calculation of Markit's end-of-day consensus valuation. Log(Size) is the log of firm's stock market capitalization. Leverage is the firm's ratio of liabilities over total assets. Log(Amihud) is the natural logarithm of firm's stock illiquidity ratio (Amihud, 2002). Profitability is the firm's operating profits divided by total assets. Momentum is the firm's cumulative continuously compounded return from month t-7 to month t-2. Volatility is the firm's one-year realized stock return volatility. Investment is the firm's one-year realized stock return volatility. The average rating is the Standard & Poor's long-term issuer credit rating for a firm (the ratings range from the highest to lowest as follows: AAA, AA, A, BBB, BB, B, and C, and we use number 1 for C, number 2 for B,…, number 7 for AAA), FF4 surprise is the monthly average of the change between 10 minutes before and 20 minutes after the FOMC announcement in the three-month-ahead futures rate (FF4), following Gertler and Karadi (2015). S&P 500 surprise is the monthly average of the change between 10 minutes before and 20 minutes after the FOMC announcement in the S&P 500 index, following Jarocinski and Karadi (2020). 5y-5y forward rate is the monthly average of the five-year, five-year forward inflation expectation rate. 5y breakeven rate is the monthly average of the five-year breakeven inflation rate. Expected GDP is expected change in the GDP index. Expected CPI is expected change in the CPI index. CPI is the monthly consumer price index. Industrial Production is the monthly industrial production index. S&P500 is the monthly average of the S&P 500 index. The GDP deflator is the monthly GDP deflator (implicit price deflator). Real GDP is the monthly real gross domestic product. EBP (GZ) is the monthly excess bond premium in Gilchrist and Zakrajsek (2012) and Favara, Gilchrist, Lewis, and Zakrajsek (2016). TED spread is the difference in the spreads between the three-month Libor rate and the three-month Treasury rate. VIX is the closing value of the CBOE volatility index. MU is the one-month-ahead index of macroeconomic uncertainty in Jurado, Ludvigson, and Ng (2015).

Panel A: Firm-level variables

	N	Mean	SD	Median	Min	Max
CDS spread	55036	144.39	75.11	167.06	10.54	834.44
Depth	55036	7.26	6.09	4.12	2.00	21.32
Log(Size)	55036	9.36	9.31	1.32	6.43	12.43
Leverage	55036	0.69	0.68	0.17	0.31	1.23
Log(Amihud)	55036	0.01	0.01	0.01	0.00	0.08
Profitability	55036	0.02	0.02	0.02	-0.02	0.08
Momentum	55036	0.07	0.06	0.23	-0.56	0.90
Volatility	55036	0.32	0.28	0.17	0.13	1.07
Investment	55036	0.19	0.19	0.35	-2.80	1.85
Average Rating	55036	3.94	1.15	4.00	1.00	7.00

Panel B: Macro variables

	N	Mean	SD	Median	Min	Max
MPS	168	0.00	0.16	0.00	-0.66	0.36
ΔMPS	167	0.00	0.15	0.00	-0.56	0.71
FF4 surprise	168	0.00	0.04	0.00	-0.26	0.19
S&P500 surprise	168	0.00	0.49	0.00	-2.62	1.71
One-year gov bond yield	168	1.66	1.73	1.07	0.10	5.22
Ten-year gov bond yield	168	3.48	1.02	3.69	1.53	5.28
5y-5y forward rate	168	4.67	1.02	4.93	2.45	6.58
5y breakeven rate	168	1.89	0.63	1.98	-1.41	2.86
Expected GDP	168	2.52	1.14	2.65	-2.06	4.62
Expected CPI	168	2.05	0.75	2.06	-0.66	3.56
CPI	168	535.34	8.60	536.57	518.18	547.29
Ind. Prod.	168	459.41	4.90	460.38	446.67	466.92
S&P500	168	716.78	23.5	715.29	662.95	765.54
GDP deflator	168	458.89	7.61	460.30	443.67	470.57
Real GDP	168	955.84	6.00	956.26	941.61	967.65
EBP (GZ)	168	0.00	0.72	-0.22	-1.10	3.12
TED spread	168	0.44	0.42	0.27	0.14	2.10
VIX	168	19.81	8.73	17.31	10.96	61.18
MU	168	0.69	0.10	0.67	0.56	1.08

Table 2: Effects of MPSs on CDS spreads

This table reports the estimates of panel regressions examining the impact of MPSs on CDS spreads where the dependent variable is the monthly change of credit default spreads for a given firm. The detailed description of the variables is provided in the notes to Table 1. The sample period is from January 2002 through December 2015. The two-way clustered standard errors are reported in parentheses below the coefficient estimates. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
ΔMPS	-44.85***	-47.88***	-29.95**	-32.65***
	(14.78)	(12.92)	(11.35)	(10.80)
Lagged CDS spread		-0.05***	-0.05***	-0.06***
		(0.01)	(0.01)	(0.01)
Size		4.40**	6.51***	1.08
		(1.91)	(1.79)	(1.86)
Log(Amihud)		49.95	-219.18***	-90.64
		(88.06)	(65.66)	(63.47)
Leverage		4.30	18.02***	7.48*
		(3.49)	(4.73)	(4.07)
Profit		-119.08***	-179.62***	-137.45***
		(30.66)	(34.07)	(30.04)
Volatility		-4.57	-15.12**	7.97
		(14.59)	(6.93)	(7.26)
Momentum		-4.80	-2.39	-3.51
		(5.13)	(4.36)	(4.40)
Investment		2.85	4.62	4.32
		(3.46)	(4.08)	(3.94)
FF4 surprise			5.51	18.63
			(22.34)	(15.77)
S&P500 surprise			0.66	0.19
			(2.22)	(2.20)
5y breakeven rate			4.56	6.44*
			(3.16)	(3.54)
Expected GDP			3.50**	5.63***
			(1.44)	(1.59)
Expected CPI			3.98**	2.97
			(1.76)	(2.63)
TED spread			-2.74	-21.10**
			(6.30)	(7.87)
VIX			1.49***	2.23***
			(0.22)	(0.31)
MU			9.99	28.84
			(26.72)	(29.95)
Constant	-0.17	-34.00	-117.04***	-92.95*
	(1.86)	(20.73)	(34.04)	(43.08)
Firm Fixed Effect	YES	YES	YES	YES
Credit Rating Fixed Effect	YES	YES	YES	YES
Quarter Fixed Effect	NO	NO	NO	YES
Firm Quarter Double Clustering	YES	YES	YES	YES
Adjusted R-squared	0.056	0.091	0.147	0.181
Observations	54,203	54,203	54,203	54,203

Table 3: Aggregate analysis

This table reports the estimates of time-series regressions examining the impact of changes in MPSs on changes in CDS spreads where the dependent variable is the monthly change of the credit default spread index. A detailed description of the variables is provided in the notes to Table 1. The sample period is from January 2002 through December 2015. The two-way clustered standard errors are reported in parentheses below the coefficient estimates. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
ΔMPS	-34.17***	-39.40***	-35.18***	-23.67***
	(5.30)	(5.30)	(5.72)	(5.08)
Lagged CDS spread		-0.06***	-0.08***	-0.27***
		(0.02)	(0.02)	(0.04)
FF4 surprise			-11.53	4.07
			(24.10)	(17.49)
S&P500 surprise			-3.41*	1.16
			(1.84)	(1.45)
5y-5y forward rate			-0.66	-2.80**
			(0.83)	(1.31)
5y breakeven rate			-2.60	7.34***
			(1.87)	(2.65)
Expected GDP				1.49
				(1.30)
Expected CPI				3.73*
				(1.97)
CPI				0.39
				(1.73)
Ind. Prod.				-0.35
				(0.52)
S&P500				-0.04
				(0.13)
GDP deflator				1.44
				(2.27)
Real GDP				-1.25
				(1.02)
TED spread				-3.51
				(4.00)
VIX				1.82***
				(0.21)
MU				21.87
				(16.71)
Constant	-0.30	8.30***	18.85**	490.00
	(0.87)	(2.49)	(7.72)	(636.09)
Adjusted R-squared	0.202	0.263	0.287	0.659
Observations	167	167	167	167

Table 4: Flight to safety

This table reports the results of time-series regressions examining the impact of changes in MPSs on changes in CDS spreads. The dependent variables are the monthly changes of CDS index constructed separately for investment-grade firms in column (1), high-yield firms in column (2), the difference between BBB and AAA in column (3), the difference between BBB and AA in column (4), the difference between BB and AAA in column (5), and the difference between BB and AA in column (6). A detailed description of the variables is provided in the notes to Table 1. The sample period is from January 2002 through December 2015. The two-way clustered standard errors are reported in parentheses below the coefficient estimates. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

	IG	HY	BBB-AAA	BBB-AA	BB-AAA	BB-AA
	(1)	(2)	(3)	(4)	(5)	(6)
ΔMPS	-9.15**	-52.84***	-1.10	-5.48	-36.76***	-40.96***
	(4.40)	(10.14)	(4.88)	(5.90)	(9.61)	(9.81)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.680	0.603	0.606	0.373	0.609	0.496
Observations	167	167	167	167	167	167

Table 5: Subsample analysis

This table reports the results of panel regressions examining how a firm's characteristics impact the relationship between changes in MPSs and changes in CDS spreads where the dependent variable is the monthly change in the credit default spread for a given firm. We focus on the recession period in column (1), where the dummy variable *USREC* equals one if the month is in the NBER recession period and zero otherwise; firm's size in column (2), where *Small firm* is a dummy variable that equals one if the size of a firm is below that of the median for all firms in that year and zero otherwise; firm's liquidity in column (3), where *Illiquid firm* is a dummy variable that equals one if the liquidity of a firm is below that of the median for all firms in that year and zero otherwise; and firm's average rating in column (4), where *HY* is a dummy variable that equals one if the rating of a firm is high yield and zero otherwise. Controls are the same as in column (4) of Table 2. A detailed description of the variables is provided in the notes to Table 1. The sample period is from January 2002 through December 2015. The two-way clustered standard errors are reported in parentheses below the coefficient estimates. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
ΔMPS	-13.51**	-17.75*	-41.47***	-17.72*
	(5.96)	(8.21)	(10.57)	(8.17)
ΔMPS×USREC	-23.49***			
	(7.69)			
ΔMPS×Small firm		-30.70***		
		(6.97)		
ΔMPS×Illiquid firm			-16.52***	
			(5.22)	
ΔMPS×HY				-56.40***
				(12.95)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Credit Rating Fixed Effect	YES	YES	YES	YES
Quarter Fixed Effect	YES	YES	YES	YES
Firm Quarter Double Clustering	YES	YES	YES	YES
Adjusted R-squared	0.186	0.190	0.186	0.184
Observations	54,203	54,203	54,203	54,203

Table 6: Default probability and risk premium

This table reports the relation between changes in MPSs and changes in the two components of credit spreads. The first component is the fraction of the total spread that compensates investors for expected default losses (columns 1 and 2). The second component is the remaining fraction of the credit spread, intended to reflect the bond risk premium (columns 3 and 4). The decomposition method is based on Gilchrist and Zakrajsek (2012). A detailed description of the variables is provided in the notes to Table 1. The sample period is from January 2002 through December 2015. The two-way clustered standard errors are reported in parentheses below the coefficient estimates. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

	Default probability		Risk premium	
	(1)	(2)	(3)	(4)
ΔMPS	6.20**	4.74	-54.97***	-48.03***
	(2.48)	(2.73)	(15.62)	(13.37)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Credit Rating Fixed Effect	YES	YES	YES	YES
Quarter Fixed Effect	NO	YES	NO	YES
Firm Quarter Double Clustering	YES	YES	YES	YES
Adjusted R-squared	0.008	0.009	0.022	0.029
Observations	54,203	54,203	54,203	54,203

Table 7: Subsample analysis: Cash flow, financing constraint, firm-level risk, and ambiguity

This table reports the results of panel regressions examining the transmission channel of monetary policy on firm-level CDS spreads where the dependent variable is the monthly change in credit default spread for a given firm. We focus on exposure to a firm's cash flow, financing constraints, and ambiguity. In Panel A, we use a dummy variable $D_{CF\ Amount}$ that equals one if the cash flow amount of a firm is above that of the median for all firms in that year and zero otherwise in column (1); a dummy variable $D_{CF\ Duration}$ that equals one if the cash flow duration of a firm is above that of the median for all firms in that year and zero otherwise in column (2); and a dummy variable $D_{CF\ Volatility}$ that equals one if the cash flow volatility of a firm is above that of the median for all firms in that year and zero otherwise in column (3). In Panel B, we use a dummy variable $D_{WhitedWu}$ that equals one if the financial constraint index of a firm is above that of the median for all firms in that year and zero otherwise in column (1), where we proxy for financial constraints using the index created by Whited and Wu (2006) following the approach in Ozdagli (2018); a dummy variable $D_{Profitability}$ that equals one if the operating profitability (nominal rigidities) of a firm is above that of the median for all firms in that year and zero otherwise in column (2); and a dummy variable $D_{Investment}$ that equals one if the investment of a firm is above that of the median for all firms in that year and zero otherwise in column (3). In Panel C, we use a dummy variable $D_{Ambiguity}$ that equals one if the ambiguity of a firm is below that of the median for all firms in that year and zero otherwise in column (1), where we proxy for ambiguity using the monthly variance of the outcome probabilities following Augustin and Izhakian (2020), and a dummy variable D_{Risk} that equals one if the risk of a firm is above that of the median for all firms in that year and zero otherwise in column (2), where we proxy for risk using the monthly lagged variance of intraday five-minute equity returns following Augustin and Izhakian (2020). Controls are the same as in column (4) of Table 2. A detailed description of the variables is provided in the notes to Table 1. The sample period is from January 2002 through December 2015. The two-way clustered standard errors are reported in parentheses below the coefficient estimates. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Panel A: Cash flow

	(1)	(2)	(3)
ΔMPS	-24.47**	-27.73***	-17.24**
	(8.43)	(8.90)	(8.14)
$D_{CF\ Amount}$	2.10		
	(2.23)		
$\Delta MPS \times D_{CF\ Amount}$	-17.47***		
	(5.43)		
$D_{CF\ Duration}$		-4.93	
		(3.49)	
$\Delta MPS \times D_{CF\ Duration}$		-11.77*	
		(5.89)	
$D_{CF\ Volatility}$			4.12
			(2.58)
$\Delta MPS \times D_{CF\ Volatility}$			-21.27***
			(6.42)
Controls	YES	YES	YES
Firm Fixed Effect	YES	YES	YES
Credit Rating Fixed Effect	YES	YES	YES
Quarter Fixed Effect	YES	YES	YES
Firm Quarter Double Clustering	YES	YES	YES
Adjusted R-squared	0.186	0.185	0.201
Observations	54,203	54,203	54,203

Panel B: Financing constraint

	(1)	(2)	(3)
ΔMPS	-17.75*	-16.13*	-18.54*
	(8.38)	(8.90)	(8.82)
$D_{WhitedWu}$	-5.76		
	(4.61)		
$\Delta MPS \times D_{WhitedWu}$	-30.71***		
	(6.99)		
$D_{Profitability}$		0.99	
		(2.81)	
$\Delta MPS \times D_{Profitability}$		-32.37***	
		(7.60)	
$D_{Investment}$			-0.87
			(1.37)
$\Delta MPS \times D_{Investment}$			-27.67***
			(6.06)
Controls	YES	YES	YES
Firm Fixed Effect	YES	YES	YES
Credit Rating Fixed Effect	YES	YES	YES
Quarter Fixed Effect	YES	YES	YES
Firm Quarter Double Clustering	YES	YES	YES
Adjusted R-squared	0.189	0.186	0.185
Observations	54,203	54,203	54,203

Panel C: Firm-level risk and ambiguity

	(1)	(2)
ΔMPS	-24.42**	-15.29*
	(9.62)	(7.46)
$D_{Ambiguity}$	12.68**	
	(4.56)	
$\Delta MPS \times D_{Ambiguity}$	-16.73**	
	(6.69)	
D_{Risk}		-12.02
		(7.37)
$\Delta MPS \times D_{Risk}$		-20.42**
		(8.45)
Controls	YES	YES
Firm Fixed Effect	YES	YES
Credit Rating Fixed Effect	YES	YES
Quarter Fixed Effect	YES	YES
Firm Quarter Double Clustering	YES	YES
Adjusted R-squared	0.182	0.191
Observations	54,203	54,203

Table 8: Monetary policy surprise and central bank information

This table reports the relation between changes in MPSs (and its two decomposed shocks) and changes in the credit spreads, the default probability, and the risk premium. We decompose MPSs into two components using the information embedded in the high-frequency co-movement of both short-term Fed fund futures rates and stock prices around policy announcements. The decomposition method is similar to that in Jarocinski and Karadi (2020). The default probability and risk premium are defined in the notes to Table 6. The detailed description of the variables is provided in the notes to Table 1. The sample period is from January 2002 through December 2015. The two-way clustered standard errors are reported in parentheses below the coefficient estimates. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

	CDS spread		Default probability		Risk premium	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔMP Shock	-48.84***	-43.34***	-47.58***	-40.02***	-1.27	-3.32
	(14.15)	(11.86)	(13.61)	(10.92)	(2.13)	(2.34)
ΔCB Shock	-49.27***	-43.61***	-4.79	2.95	-44.47**	-46.56**
	(14.24)	(11.92)	(4.55)	(4.98)	(15.21)	(15.52)
Controls	YES	YES	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES	YES	YES
Credit Rating Fixed Effect	YES	YES	YES	YES	YES	YES
Quarter Fixed Effect	YES	YES	YES	YES	YES	YES
Firm Quarter Double Clustering	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.085	0.119	0.060	0.067	0.057	0.057
Observations	54,203	54,203	54,203	54,203	54,203	54,203

Table 9: Robustness: Alternative measure of MPS

This table reports the results of panel regressions examining the relationship between changes in CDS spreads and alternative measures of changes in MPSs where the dependent variable is the monthly change in the CDS index in columns (1) and (2) and the dependent variable is the monthly change in the CDS index constructed separately for investment-grade and high-yield firms in columns (3) and (4). In Panel A, we use the ten-year government bond rate as the alternative measure of the monetary policy indicator. In Panel B, we use the two-year government bond rate as the alternative measure of the monetary policy indicator. Controls are the same as in column (4) of Table 2. A detailed description of the variables is provided in the notes to Table 1. The sample period is from January 2002 through December 2015. The two-way clustered standard errors are reported in parentheses below the coefficient estimates. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Panel A: Monetary policy indicator is ten-year government bond rate

	Full sample		Subsample	
	CDS spread		IG	HY
	(1)	(2)	(3)	(4)
ΔMPSs Alternative	-14.53**	-16.41**	-9.70*	-33.12***
	(6.50)	(7.22)	(4.42)	(9.03)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Credit Rating Fixed Effect	YES	YES	YES	YES
Quarter Fixed Effect	NO	YES	YES	YES
Firm Quarter Double Clustering	YES	YES	YES	YES
Adjusted R-squared	0.172	0.184	0.180	0.262
Observations	54,203	54,203	39,707	14,495

Panel B: Monetary policy indicator is the two-year government bond rate

	Full sample		Subsample	
	CDS spread		IG	HY
	(1)	(2)	(3)	(4)
ΔMPSs Alternative	-21.08**	-23.50***	-14.20**	-46.33***
	(7.49)	(7.05)	(5.37)	(11.86)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Credit Rating Fixed Effect	YES	YES	YES	YES
Quarter Fixed Effect	NO	YES	YES	YES
Firm Quarter Double Clustering	YES	YES	YES	YES
Adjusted R-squared	0.168	0.181	0.182	0.266
Observations	54,203	54,203	39,707	14,495

Table 10: Robustness: Alternative sample period

This table reports the results of panel regressions examining the relationship between changes in CDS spreads and changes in MPSs where the dependent variable is the monthly change in the CDS index in columns (1) and (2) and the dependent variable is the monthly change in the CDS index constructed separately for investment-grade and high-yield firms in columns (3) and (4). In Panel A, we exclude the period of the global financial crisis from March 2008 to June 2009 (following the NBER recession indicator). In Panel B, we exclude the period of the zero lower bound from January 2008 to December 2015 (following the Gertler and Karadi, 2015). In Panel C, we exclude the period of the unscheduled FOMC meeting period. Controls are the same as in column (4) of Table 2. A detailed description of the variables is provided in the notes to Table 1. The whole sample period is from January 2002 through December 2015. The two-way clustered standard errors are reported in parentheses below the coefficient estimates. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Panel A: Excluding the global financial crisis period

	Full sample		Subsample	
	CDS spread		IG	HY
	(1)	(2)	(3)	(4)
ΔMPS	-25.60***	-20.24**	-9.78***	-43.65**
	(7.65)	(7.02)	(3.07)	(18.32)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Credit Rating Fixed Effect	YES	YES	YES	YES
Quarter Fixed Effect	NO	YES	YES	YES
Firm Quarter Double Clustering	YES	YES	YES	YES
Adjusted R-squared	0.140	0.151	0.155	0.227
Observations	49,222	49,222	35,855	13,366

Panel B: Excluding the zero lower bound period

	Full sample		Subsample	
	CDS spread		IG	HY
	(1)	(2)	(3)	(4)
ΔMPS	-52.72***	-41.02***	-30.31***	-66.83***
	(10.05)	(10.00)	(6.57)	(20.53)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Credit Rating Fixed Effect	YES	YES	YES	YES
Quarter Fixed Effect	NO	YES	YES	YES
Firm Quarter Double Clustering	YES	YES	YES	YES
Adjusted R-squared	0.239	0.249	0.245	0.344
Observations	30,463	30,463	22,809	7,653

Panel C: Excluding the unscheduled FOMC meeting period

	Full sample		Subsample	
	CDS spread		IG	HY
	(1)	(2)	(3)	(4)
ΔMPS	-14.66*	-20.11*	-10.55*	-44.09**
	(7.59)	(9.67)	(5.33)	(18.73)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
Credit Rating Fixed Effect	YES	YES	YES	YES
Quarter Fixed Effect	NO	YES	YES	YES
Firm Quarter Double Clustering	YES	YES	YES	YES
Adjusted R-squared	0.164	0.172	0.180	0.238
Observations	47,687	47,687	34,909	12,777

Figure 1. The Cross-Section of CDS spread

In this figure, we depict the panel data of spread of credit default swap. The dark dashed line displays the cross-sectional median of credit spreads. The grey shaded areas display the 25-75 percentile range. The sample period is from January 2002 through December 2015.

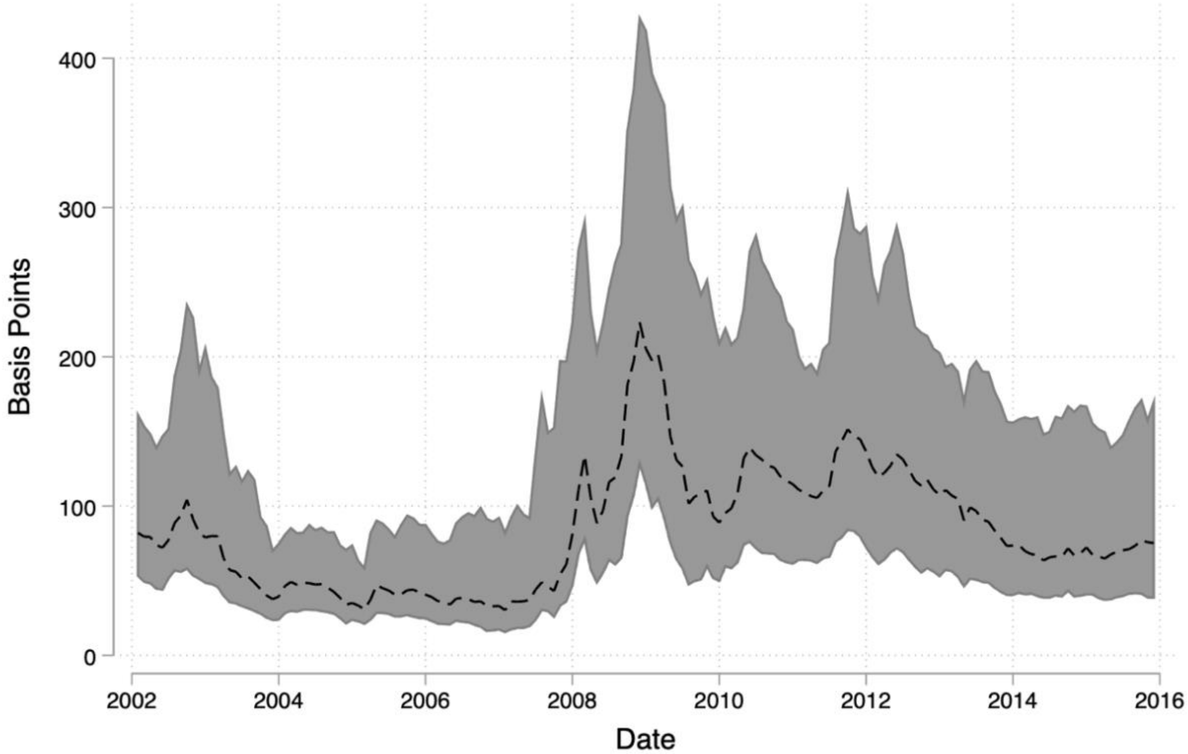


Figure 2. The Time Series of Monetary Policy Surprises

In this figure, we depict the MPSs derived from the two-stage least square regression using the surprise in the asset price of Fed funds and Eurodollar futures as external instruments to identify unexpected monetary policy shocks from the one-year government bond yield as the monetary policy indicator (Gertler and Karadi, 2015). The sample period is from January 2002 through December 2015.

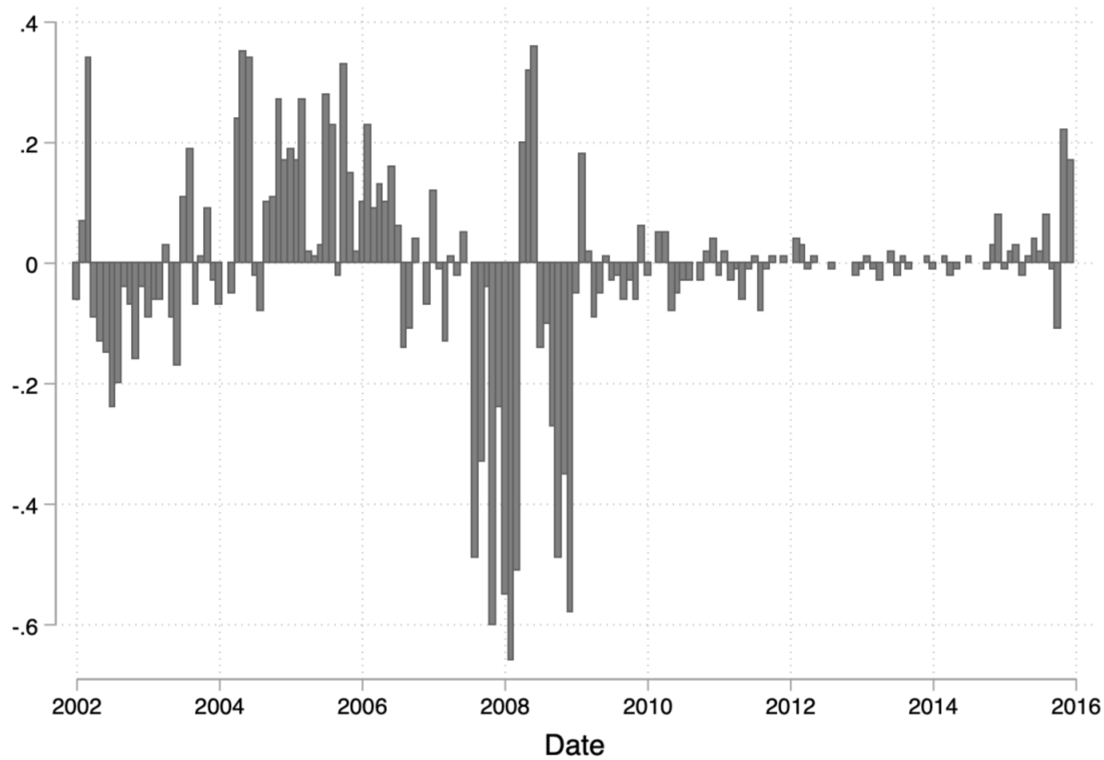


Figure 3. Interest rate and stock price surprises

In this figure, we depict the scatter plot of interest rate and stock price surprises where the change in the three-month Fed funds futures around FOMC announcements is shown in the x-axis and the change in the S&P500 index around FOMC announcements is shown in the y-axis. The sample period is from January 2002 through December 2015.

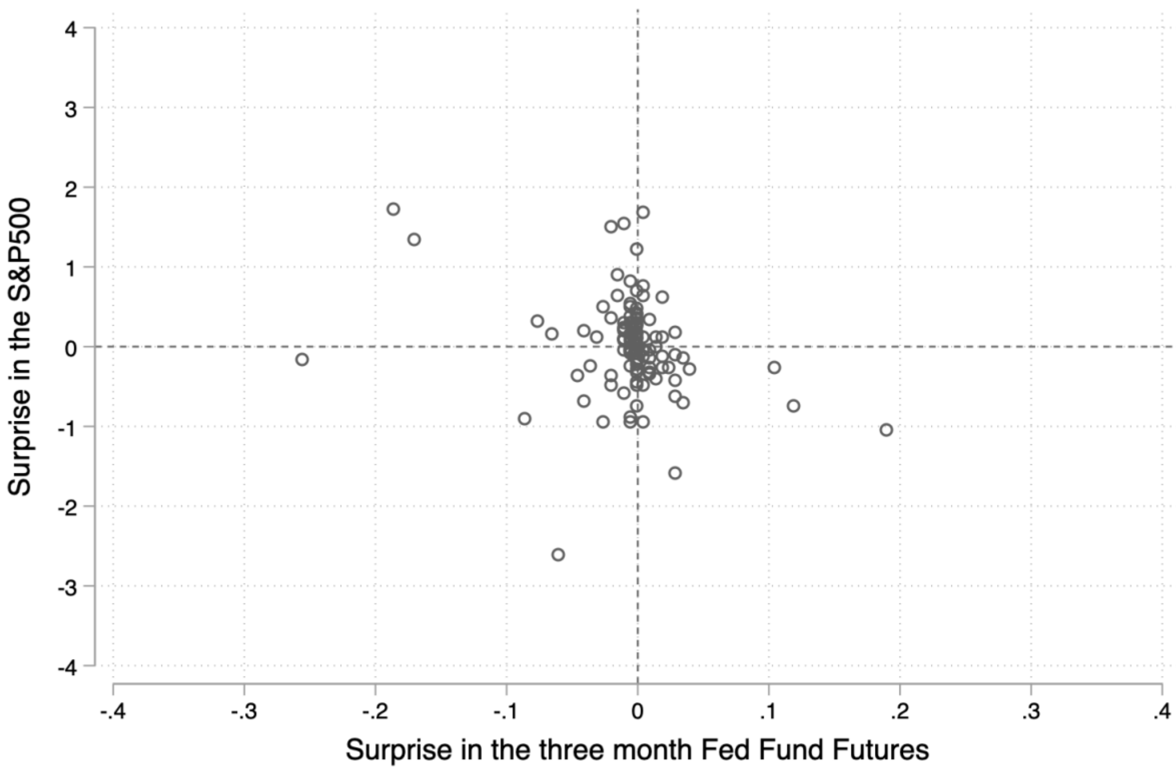
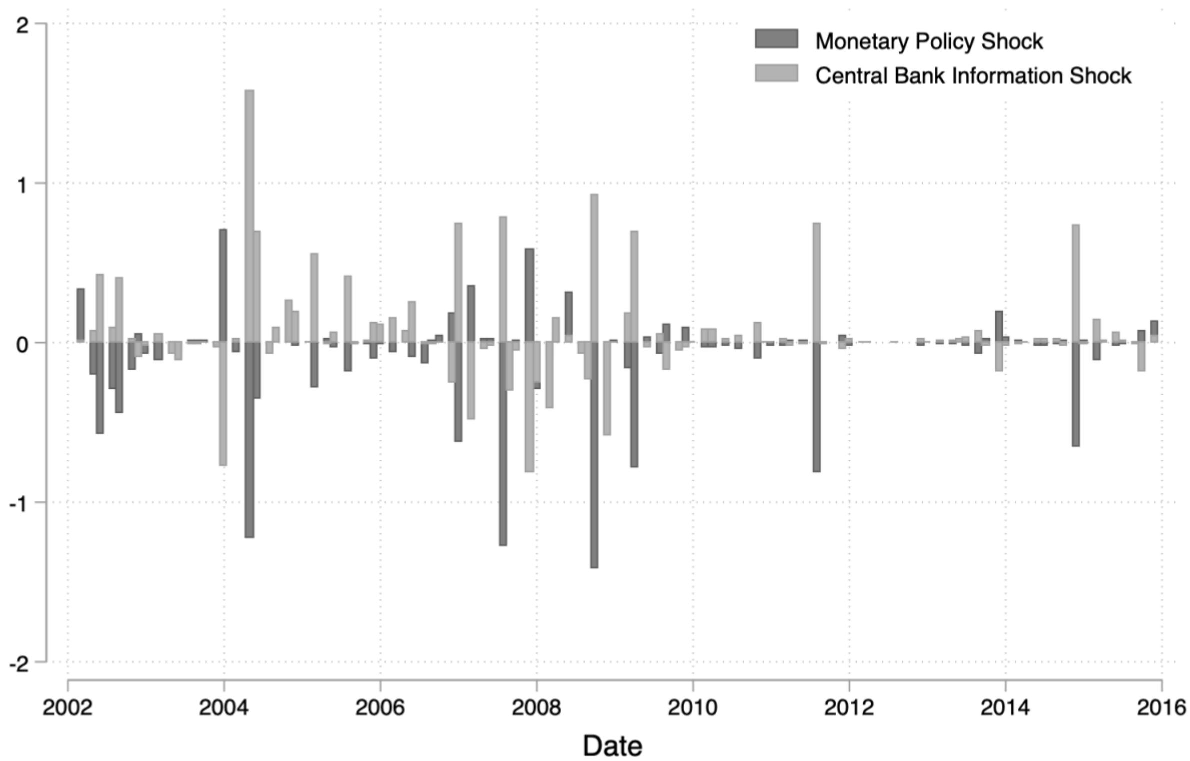


Figure 4. Decomposition of monetary policy surprises

In this figure, we depict the two shocks to the monetary policy surprises following the approach in Jarocinski and Karadi (2020) with monetary policy shock and central bank information shock. The sample period is from January 2002 through December 2015.



Appendix

Appendix A. The validity of instrument variable

In the main context, we use the one-year government bond yield as the policy indicator and the one-month federal fund future rate (FF1) as an instrumental variable and measure the surprises in both policy indicator and instrument variable in 30-minute window of each FOMC announcement. We present the instrument variable's validity by using various future rate surprises, including FF1, FF4, ED2, ED3, and ED4, and show the results in Table A1.

We show each column's regression results that the one-year government bond yield as a policy indicator and the various future rates. Stock et al. (2002) suggest that to avoid the weak instrument problem, the first-stage regression's F-statistics should be larger than 10. Based on Table A1, the best instrumental variable is FF1, which explains 15 percent innovation of one-year government bond yield and has the F-statistic of 31.22. Therefore, our choice of FF1 as an instrument variable permits us to establish convincing and robust results without the concern of weak instrument issues.

[TABLE A1 ABOUT HERE]

Appendix B. Bayesian approach for the decomposition of monetary policy

We introduce our approach to identify both the central bank information shock and monetary policy shock from the high-frequency monetary policy announcements. We make two assumptions to isolate these two shocks while imposing no restrictions on corporate credit default swap:

Assumption 1. The monetary policy surprises is composed of the central bank information shock and monetary policy shock.

Assumption 2 (Jarocinski and Karadi, 2020). The monetary policy shock is associated with an increase (decrease) in the interest rate and a decrease (increase) in stock prices. The central bank information shock is related to an increase (decrease) in interest rates and stock prices.

As we measure the monetary policy surprises using the asset price change between 10 minutes before and 20 minutes after the FOMC announcement, the Assumption 1 is justified since the monetary policy surprises is unlikely to incorporate other unrelated shocks during the FOMC announcement. Assumption 2 separates the two shocks from the monetary policy surprises. As suggested in most models, the tightening monetary policy implies the negative correlation between stock prices and interest rates. Therefore, we think this effect as the monetary policy shock. On the other hand, the positive correlation between stock prices and interest rate reflects shocks beyond the standard asset pricing theory, and we regard it as central bank information shock.

We compute the two shocks under the assumption that there exists a uniform prior on the space of rotations (Rubio-Ramirez, Waggoner and Zha, 2010). Based on Assumption 1, we impose the block-Choleski structure on the monetary policy surprises with the two shocks forming the first block. Based on Assumption 2, we impose the sign restrictions on the two shocks following Rubio-Ramirez, Waggoner and Zha (2010). For each simulation using the posterior draw, we compute the lower-triangular Choleski decomposition C and multiply C with matrix $Q = \begin{pmatrix} Q^* & 0 \\ 0 & I \end{pmatrix}$, where Q^* is the QR decomposition based on the standard normal distribution. We repeat the process until we find the Q such that the sign restrictions for CQ is satisfied.

Table A1: First stage regression of policy indicator on various instrumental variable sets

This table reports the results of first stage regressions examining the impact of instrumental variables on changes in policy indicator where the independent variables are FF1, FF4, ED2, ED3, and ED4. The sample period is from January 2002 through December 2015. The two-way clustered standard errors are reported in parentheses below coefficient estimates. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
FF1	1.41***					1.87***
	(0.25)					(0.56)
FF4		1.65***				-1.14
		(0.35)				(1.19)
ED2			1.41***			-0.41
			(0.31)			(1.67)
ED3				1.22***		-0.41
				(0.28)		(2.98)
ED4					1.14***	1.53
					(0.28)	(1.86)
Constant	-0.01	-0.02	-0.02	-0.02	-0.02	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Adjusted R-squared	0.15	0.11	0.10	0.09	0.09	0.18
F-statistics	31.22	22.38	20.52	18.63	17.15	7.46
Observations	168	168	168	168	168	168