Internet Appendix for

Do FOMC Actions Speak Loudly?

Evidence from Corporate Bond Credit Spreads

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Abstract- In this online appendix, we conduct a series of additional robustness checks.

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1. Possible Confounding Impacts of Firm-Specific Effects

It is well-documented that current contingent claim pricing models of credit fail to generate estimates consistent with observed credit spreads (Eom et al., 2004; Huang and Huang, 2012). The most widely cited culprit is the missing firm attributes pertinent in determining default and recovery risks. The number of candidates among potential firm attributes seems innumerable. This, of course, begs a number of interesting questions: To what extent are our results about FOMC actions confounded by firm fixed effects? Do possible changes to the mainstay proxies (and determinants) of default risk—asset volatility and leverage—explain our results? To address these issues, we re-estimate our benchmark Model (3) by adding (1) firm and industry fixed effects, (2) firm equity return volatility, and (3) firm and industry leverage as well as firm size. Results of these analyses (only for FOMC action dummies) are presented in Table I.

[Insert Table I and II about here]

As is evident from Models (1) – (3) in Table I, the inclusion of firm fixed effect does change the magnitude impact of our test variables, albeit making these effects statistically more significant. The inclusion of firm fixed effects makes CUT effects economically larger and statistically even more significant (particularly during the crisis period). During the pre-crisis period, a rate cut corresponds to a 11.7 basis point drop in nonfinancials' spreads, mildly larger than our original 9.5 basis point drop, estimated without firm fixed effects. During the crisis period, a rate cut corresponds to a 30.3 basis point drop in nonfinancials' spreads, drastically larger than our original 7.6 basis point drop estimated without firm fixed effects. As reported in Table II, among financials, the inclusion of firm fixed effects makes CUT effects smaller (but still significant) during the pre-crisis period. During the crisis period, the inclusion of firm fixed effects makes the CUT effects larger albeit insignificant. During the pre-crisis period, a rate cut corresponds to a 3.4 basis point drop in financials' spreads, smaller than the 7.2 basis point drop estimated without firm fixed effects. During the crisis period, a rate cut corresponds to a 18.7 basis point drop in financials' spreads (albeit statistically insignificant), larger than the 6.9 basis point drop estimated without firm fixed effects.

The inclusion of firm fixed effects makes the no-action effect economically larger and statistically even more significant during the pre-crisis period. Interestingly though, the no-action effect becomes negative (attenuating) for non-financials while becoming much more positive (extenuating) for financials. During the pre-crisis period, a no-action corresponds to a 2.9 basis point drop, as opposed to the insignificant 0.1 basis point rise estimated originally. During the same period, a no-action corresponds to a 3.6 basis point rise in financials' spreads, as opposed to the insignificant 0.7 basis point drop estimated without firm fixed effects.

During the crisis period, a no-action corresponds to a 13.9 basis point drop, as opposed to the 16.6 basis point rise estimated originally. For the same period, a no-action corresponded to a 46.7 basis point drop in financials' spreads, as opposed to the 68.3 basis point rise estimated without firm fixed effects. In the presence of firm fixed effects, QE effects are much larger in magnitude and statistically significant. The announcement of QE corresponds to 40 basis points drop in spreads. These effects are almost three times larger than estimates without firm fixed effects. Lastly, the inclusion of firm fixed effects changes our estimates of a rate hike effect. A rate hike corresponds to a 5.2 basis point drop in spreads as opposed to the 1.4 basis point drop estimated without firm fixed effects. For financials, a HIKE corresponds to a 3.6 basis point rise in spreads, as opposed to the insignificant 0.8 basis point drop estimated without firm fixed effects.

At first glance, these results seem to suggest that in part what we originally captured are confounded by the firm-level idiosyncrasies associated with changes in the default risk. We attempt to elucidate on this point by further examining the impact of including asset volatility, leverage, and size. In a nutshell, what we find is that the inclusion of the firm-specific volatility or leverage leaves our original estimates (and their signs) virtually intact. But the inclusion of firm size results in estimated coefficients' signs that are very similar to those observed when firm fixed effects are included. This fact along with the above-mentioned regularities—for instance an attenuating NOACT effect for non-financials versus an extenuating NOACT effect for financials—lead us to conclude that firm fixed effects may actually proxy for access to capital among non-financials and exposure to systemic risk among financials.

Our results (Tables I and II) based on firm-level characteristics show that only when we include firm size do we arrive at qualitatively similar results as adding firm fixed effects. In the presence of known credit risk measures (volatility and leverage), our results remain intact. Furthermore, tables III and IV reveal that our bonds belong to a group of firms that dominate trading irrespective of FOMC announcements. The nonfinancial firms represent some of iconic U.S. corporations (AT&T, Ford Motors, GM, AOL Time Warner, etc.). These firms on average have large fixed assets and cash holdings. In essence, as noted by Rauh and Sufi (2010), these firms represent the high credit-quality sphere of borrowers who maintain a stoic, simple capital structure: senior unsecured public debt and equity. However, firms spread their debt and priority structure as they worsen in credit quality: firms use multiple types, sources, and priorities of corporate debt. Rauh and Sufi (2010, p. 4277) conclude that "…[t]he spreading of the capital structure as credit quality deteriorates is broadly consistent with models such as Park's (2000) that view the existence of priority structure as the optimal solution to manager-creditor incentive problems." Clearly a majority of firms in our sample fit the profile of borrowers that are least likely to pose a manager-creditor conflict.

[Insert Table III and IV about here]

Relatedly, Stiglitz and Weiss (1981) argue that in the downturns (and perhaps by extension financial crises), lenders ration credit in favor of high-quality borrowers. Lemmon and Roberts (2010: 555) find that indeed in the aftermath of "…the collapse of Drexel Burnham Lambert, Inc.; the passage of the Financial Institutions Reform, Recovery, and Enforcement Act of 1989; and regulatory changes in the insurance industry as an exogenous contraction in the supply of below-investment-grade credit after 1989." Our firms are less likely to face credit rationing or be shunned away from capital markets. Moreover, our firms have greater internal capital resources, thus allowing them to neutralize the adverse impacts of policy uncertainty associated with FOMC no-actions. Anecdotal evidence abounds. In the aftermath of the global financial crisis of 2008, iconic firms such as Berkshire Hathaway raised debt at negative spreads—their cost of borrowing was lower than that of the U.S. Treasury[1]. This further shows that in times of crisis and heightened uncertainty, debt investors' can find these firms a more attractive alternative and better candidate for a flight-to-quality. We thus posit that firm-specific fixed effects proxy the same latent variables for which size also proxies: lower agency costs and easier access to funds, thus an outright better candidacy for flights-to-quality.

In contrast, we find that for financials, which are similarly larger firms, the FOMC no-actions correspond with large extenuating impacts on the credit spreads. Larger financials—money center banks such Bear Sterns and Lehman Brothers—naturally have greater leverage, risky operations, and more reliance on capital markets to enhance their regulatory mandated capital requirements. In the vernacular of Wall Street post-financial crisis, these firms personify the too-big-to-fail risk. The heightened uncertainty in the face of a FOMC no-actions can undermine investors' trust in the viability of these large financial institutions as a going-concern without any intervention. Thus, we posit that in their case, firm-specific fixed effects proxy the same latent variables for which size also proxies: greater exposure to systemic risk, perhaps by the virtue of generating the majority if not all of the systemic risk.

While our previous discussions preceded results we relied on, we now discuss how we can address this concern with respect to confounding impacts of asset volatility and leverage.

we also examine the impact of inclusion of firm characteristics such as volatility and leverage. As is evident in table I and II (Models (4) – (6), we first examine possible confounding effects of asset volatility. As Bharath and Shumway (2008) demonstrate, various measures of distance-to-default are

[1] In an article titled "Glut pushes U.S. Treasury Debt Interest Rate above Berkshire Bonds," Bloomberg reporters, Daniel Kruger and Brian Keogh, write: "The bond market is saying that it's safer to lend to Warren Buffett than Barack Obama. Two-year notes sold by the billionaire's Berkshire Hathaway Inc. in February yield 3.5 basis points less than Treasuries of similar maturity, according to data compiled by Bloomberg. Procter & Gamble Co., Johnson & Johnson, and Lowe's Cos. debt also traded at lower yields in recent weeks, a situation former Lehman Brothers Holdings Inc. chief fixed-income strategist Jack Malvey calls an 'exceedingly rare' event in the history of the bond market. …" http://www.bloomberg.com/apps/news?pid=20601087&sid=aHjVRrVodt4g&pos=2

highly sensitive to the equity return volatility. In fact, for a short event study such as ours, whereby there is little known information about changes of other firm attributes, the only tangible information about changes in asset volatility is changes to stock return volatility.

It is noteworthy that we examine the veracity of our claim and check whether over the two-day window there was any filing of accounting statements or any release of analysts' reports. To do so, we utilized both COMPUSTAT quarterly and I/B/E/S databases. Interestingly, less than 5% of our sample firms have quarterly reports or analyst forecast/opinion releases during event windows.

Given that, we cannot then include almost any firm attributes in the regressions of credit spreads. This is because, in an analysis of the change in spreads, a lá Collin-DuFresne, Goldstein, Martin (2001), we require a change in attributes. These changes over our short windows are zero for virtually all our sample firms. As such, we first drop firms with quarterly statements reported or analysts forecast/opinion released. We then remedy the challenge by including changes in the firm-level equity return volatilities as a proxy for changes in the underlying asset's volatilities. To control for the impact of asset volatility, we utilize three proxies: (1) a log daily price range volatility—à la Alizadeh, Brandt, and Diebold (2002), (2) changes of the squared close-to-close of the day's stock returns, and (3) changes in the absolute value of close-to-close of day's stock returns. In choosing our proxies of instantaneous volatility, we are motivated by Alizadeh, Brandt, Diebold (2002, p. 1048). As they note, despite universal agreement that volatility is time-varying and predictable, "… the problem is that standard volatility proxies such as log absolute or squared returns are contaminated by highly non-Gaussian measurement error (e.g., Anderson and Sorensen (1997)), which produces highly inefficient Gaussian quasi-maximum likelihood estimators and similarly inefficient inferences about latent volatility." As such Alizadeh, Brandt, Diebold (2002) recommend a log range volatility; which is defined as the log of difference between daily high and daily low prices.

We find that the impact of changes in asset volatility is tenuous at best. Moreover, the inclusion of various asset volatility proxies leaves our originally estimated effects of FOMC actions unscathed. As is evident in Models (4) – (6) in table I, a rate cut has a greater attenuating impact on spreads during the pre-crisis period than the crisis period: a 10 basis point drop versus a 3 basis point drop. A rate hike is associated with a statistically significant 1.4 basis point drop during the pre-crisis period. The no-action has no significant impact during the pre-crisis period, whereas it corresponds to a 13.7 basis point rise in spreads during the crisis period. A QE corresponds to a statistically significant 13.1 basis point drop in spreads. For financials, table II, a CUT has a significant attenuating impact of 5.3 basis points on spreads only during the pre-crisis period. A NOACT has no significant impact during the pre-crisis period, whereas it corresponds to a 69.8 basis point rise in spread during the crisis period. A QE corresponds to a statistically significant 14.1 basis point drop in spreads.

To control for the impact of leverage, we utilize two proxies: (1) the firm's long-term debt to total assets, and (2) the firm's Fama-French 49 industry median leverage. We also consider firm size (total assets) decile ranking as an alternative measure of firm attributes.[2] Having controlled for leverage, the impact of FOMC actions remains basically intact. A rate cut has a greater attenuating impact on spreads during the pre-crisis period than the crisis period: a 24 basis point drop versus an 8 basis point drop. A rate hike is perhaps associated with a 4 basis point rise during the pre-crisis period. A no-action is probably associated with a 2.5 basis point increase during the pre-crisis period, whereas it corresponds to a 9 basis point rise in spreads during the crisis period. A QE corresponds to a statistically significant 13.4 basis point drop in spreads. For financials, a CUT had a significant attenuating impact of 52 basis points on spreads only during the pre-crisis period. A NOACT had no significant impact during the pre-crisis period, whereas it corresponded to a 79 basis point rise in spreads during the crisis period. A QE corresponded to a statistically insignificant 11 basis point drop in spreads.

[2] We cannot use changes in leverage simply because the overwhelming majority (95%+) of our sample firms have no material changes to their characteristics reported. Roughly, only 5% of our firms have any accounting statement reported (per COMPUSTAT quarterly) or have any analysts reviews released (per I/B/E/S) within a five-day window of FOMC announcement dates.

Interestingly though, as is evident in Model (9) of tables I and II, when we use firm size as a control variable, the impact of FOMC actions changes almost the same way that it does when we add firm fixed effects. A rate cut has a smaller attenuating impact on spreads during the pre-crisis period than the crisis period: a 27.3 basis point drop versus a 34.2 basis point drop. A no-action has no significant impact during the pre-crisis period, but it corresponds to an 18 basis point drop in spreads during the crisis period. A QE corresponds to a statistically significant 41.3 basis point drop in spreads. For financials, a NOACT had no significant impact during the pre-crisis period, whereas it corresponded to a 54 basis point rise in spreads during the crisis period. A QE corresponded to a statistically insignificant 37 basis point drop in spreads.

Overall, we find that while asset volatility [a measure intimately related to the proxies of recovery risk (Friewald et al., 2014)] and leverage [a measure intimately related to default risk or financial distress (Dichev, 1998; Campbell et al., 2008)] matter, their inclusion does not qualitatively change our original findings, and leaves them almost quantitatively intact. This gives us comfort that our earlier findings are not irreparably contaminated by the firm's idiosyncrasies associated with default and recovery risks. However, we do find that the inclusion of firm fixed effects and similarly firm size can change the magnitude and significance of FOMC actions' effects. Except for no-action, our revised estimated effects seem to be larger and more significant. As for FOMC no-actions, the impacts become attenuating. A closer examination of our sample firms reveal that these firms account for a preponderance of corporate bond trading over the period of 2002-2010. These firms are large and have relatively smaller spreads. Together, we see these as an indication that the firm fixed effects (and firm size) proxy for a firm's candidacy of being the destination for a flight to quality. We argue that firms in our sample fit the profile of firms that are greater candidates for a flight to quality: low agency costs, greater internal liquidity, and easier access to external funds. In times of heightened uncertainty, such firms can offer lower risk, thus becoming respites for unnerved investors. This can explain while prototypical proxies of default and recovery risk don't change our results, firm fixed effects and size can have significant impacts. On the other hand, large banks with limited access to cheap time deposit funding are more likely to rely on external capital markets. These banks, by virtue of their large asset-liability duration gaps, are more susceptible to adverse economic conditions, and thus more exposed to systemic risks. Periods of great policy uncertainty may not bode well for these banks. Considering that our sample coincides with quite uncertain times—when in one instance an iconic bank like Bear Stern is almost rescued but another like Lehman has left to fail—we can even see how policy uncertainty can lead to such drastic—60 basis point by some estimates—rises in financials' spreads.

2. Information Flow

Given the inherent illiquidity of the corporate bond market (Sarig and Warga, 1989), it is conceivable that bond portfolio managers may find it difficult to readjust their portfolios accordingly on the occasion of an FOMC announcement. Alternatively, a public release of information may lead to more ex-post information asymmetry if market participants differ in their ability to process and interpret the news (Kim, and Verrecchia, 1994, 1997). These suggest there can be a pre- and/or post-announcement drift. Obviously, the inherent illiquidity of the market prevents us from performing a prototypical announcement analysis.

As we described before the prototypical accounting information changes over the short ±1 window of our study occurred virtually for none of the firms. Moreover, as noted before, less than 5% of our sample had any accounting statement reported (per COMPUSTAT quarterly data) or any analyst forecast posted in a ±5 day window (per I/B/E/S data). However, to address the above concerns, we proceed in two ways to make meaningful comparisons for our sample bonds and nonsample bonds as well as for in-sample and out-of-sample periods. In table III, we take the entire TRACE data available from 2002 to 2010. As in our paper, we first translate the intraday data into daily data using Bessembinder et al. (2009) guidelines. We then separate the sample into two groups: bonds that we have in our study (valid data for FOMC announcement dates) and all other bonds. We conduct sample comparison of major bond characteristics: yield spreads, coupon rates, age, years-to-maturity, and number of bonds per borrower firm. We use number of bonds per borrower as a proxy for dispersion of bond ownership (Davydenko and Strebulaev

2007). To gauge the overall market condition, particularly the degree of uncertainty aversion, we also use the VIX index, the so called "fear" index in the Wall Street vernacular. What is interesting is that our bonds account for a preponderance of all trades: 443,960 as opposed to 146,216 for other bonds in the entire 2002-2010 period among nonfinancial bonds. For financial bonds, we had 1,366,186 in our sample bonds as opposed to 643,925 of other bonds traded during the period of 2002-2010. Our sample bonds, except for speculative and long-term bonds, have smaller spreads, shorter age, longer maturity, and fewer bond issues outstanding. This gives us some comfort that our sample came from bonds that were perhaps more representative of the population.

To make the comparison more relevant in view of our event study design, we repeate the aforementioned but with limitations on timeframe. We chose two windows surrounding the FOMC announcement dates: a short window with ±5 days around FOMC dates, and a long window ±20 days around FOMC dates. We repeat our comparison between sample bonds and others for these two windows. The rationale is simple: during the short-window, there are potentials for information leakage. During longer periods, the confounding effects of information leakage should be less present. Similar generalities are still present. In short sample, we have 108,632 of our sample bonds' day trades as opposed to 34,254 of other bonds' day trades. In the long sample, we had 102,677 of our sample bonds' day trades as opposed to 32,955 of other bonds' day trades. Our sample bonds have smaller spreads, shorter age, and fewer bond issues outstanding.

In our next approach, we extend our method to a longer timeframe of ±5 days surrounding the FOMC announcements. We utilize all bonds, our original sample bonds and any other that have valid information in the ±5 day window. We then separate our sample into four categories: CUT sample, HIKE sample, NOACT sample, and QE sample. So the CUT sample includes all bonds within ±5 days of CUT announcements that have valid prices and other necessary information. Then for every one of these samples, we run the following panel regression.

$$\Delta CSPRD_{t,t-1} = \beta_{-5}DAY_{t-5} + \beta_{-4}DAY_{t-4} + \beta_{-3}DAY_{t-3} + \beta_{-2}DAY_{t-2} + \beta_{-1}DAY_{t-1}$$
$$+ \beta_0\, DAY_t + \beta_1\, DAY_{t+1} + \beta_2\, DAY_{t+2} + \beta_2\, DAY_{t+2} + \beta_4\, DAY_{t+4} + \beta_5\, DAY_{t+5} \qquad (4)$$
$$+ \delta_1 \Delta RF^{\dagger}_{t,t-1} + \delta_2\, \Delta Slope^{\dagger}_{t,t-1} + \delta_3\, SP^{\dagger}_{t,t-1} + \delta_4\, \Delta VIX^{\dagger}_{t,t-1} + \delta_5\, \Delta FF^{\dagger}_{t,t-1} + \epsilon_{i,t}$$

Where, *CSPRD* and all other variables are as defined above. DAY_{t-i}, is a dummy variable that takes the value of 1 if the trade belongs to day $t - i$ of the ±5 days around announcement day at time t. We note that in the above regression, our variables are day-to-day changes and not ±1 day changes, which we use for our benchmark analysis. In so doing, we then can use the coefficient estimates on these day dummies as a measure of abnormal return for that day. We use the coefficient estimates and their corresponding standard errors to generate a prototypical event window visual representation of how excess spreads change. These are all reported in Figure 1 and 2.

Heuristically, we have already found patterns that are quite visible in the graphs. CUTs are associated with drops in spreads, albeit at wider confidence bounds. NOACTs during crisis correspond to a rise in both level and confidence bounds of spreads. QEs during crisis correspond to drops in the level and rise in the confidence bounds of spreads. Effects of CUTs on financial are distinctly different. Yet, QE seems to benefit them more in that confidence bounds are smaller after announcements and spreads are smaller.

Overall, except for inactions and QE, there is very little evidence on the leakage information prior to the announcement or drift afterwards. On the occasions of QE and NOACT of the crisis period, we find prolonged, continued effects exerted after the announcement. Perhaps the illiquidity of the corporate bond leads some bondholders to readjust their portfolios gradually after the announcements are made. Alternatively, given that both actions lead to greater errors in estimates that increase over time, it is also possible the inactions and QE lead to increased information asymmetry post announcement. Overall, the direction of these effects seems to be persistent.

[Insert Figures 1 and 2 about here]

Table I. Robustness analysis – firm attributes and fixed effects

This table reports the coefficients of regressing changes in credit spreads on FOMC action dummies and a host of orthogonalized control macro-level variables for the entire sample, the pre-crisis and crisis periods. Pre-crisis period is defined as August 2002 to November 2007. Crisis period is defined as December 2007 to June 2009. FOMC policy action stances are denoted by dummy variables that indicate: rate decrease (CUT), rate increase (HIKE), no change (NOACT), and quantitative easing (QE). Control variables include changes in the Treasury bill rate (RF), Treasury yield curve slope—the difference between T-bond and T-bill yields (SLOPE), VIX index, and S&P500 return (SP). Δ RngVol is the change from t – 1 to t + 1 of the range-bound volatility; defined as the log of daily high stock price minus the log of daily low stock price. Δ SqrRet is the change from t – 1 to t + 1 of the squared daily stock return. Δ AbsRet is the change from t – 1 to t + 1 of the absolute daily stock return. LTDebt is the most recently available long-term debt ratio for the firm based on quarterly COMPUSTAT data. Ind. LTDebt is the industry (49 Fama-French) median long-term debt ratio based on quarterly COMPUSTAT data. SIZE is the reverse decile ranking (largest denoted by 1 and smallest denoted by 10) of the firm's asset size based on quarterly COMPUSTAT data. For brevity, the coefficient estimates on all other control variables are not reported. Robust (heteroskedasticity and autocorrelation corrected) standard errors (see White, 1980) corrected for firm clustering are used to calculate the t-values that appear in parentheses below the coefficient estimates. Coefficients that are statistically different from zero at the 1%, 5%, and 10% levels are marked with ***, **, and *, respectively.

	Firm and Industry Fixed Effects			Stock Return Volatility Effects			Firm Leverage and Size Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. For the pre-crisis period of Aug. 2002 – Nov. 2007. (N=15,965)									
CUT	-0.117***	-0.162***	-0.097***	-0.101***	-0.101***	-0.101***	-0.189***	-0.242***	-0.273***
	(-5.91)	(-10.49)	(-5.83)	(-6.41)	(-6.38)	(-6.46)	(-2.87)	(-3.22)	(-3.34)
HIKE	-0.052***	-0.075***	-0.032***	-0.013**	-0.014**	-0.014**	0.046**	0.003	-0.026
	(-11.82)	(-9.15)	(-6.62)	(-2.21)	(-2.25)	(-2.23)	(2.20)	(0.11)	(-0.38)
NOACT	-0.029***	-0.057***	-0.009***	0.004	0.004	0.004	0.025*	-0.009	-0.038
	(-3.13)	(-6.61)	(-2.60)	(0.90)	(0.91)	(0.91)	(1.96)	(-0.97)	(-0.71)
Δ RngVol				-0.113					
				(-0.77)					
Δ SqrRet					0.334				
					(1.05)				
ΔAbsRet						0.035			
						(0.20)			
LTDebt							-0.088**		
							(-2.12)		
Ind. LTDebt								0.042	
								(0.56)	
SIZE									0.004
									(0.64)
Industry F.E.	No	Yes	Yes	No	No	No	No	No	No
Firm F.E.	Yes	No	Yes	No	No	No	No	No	No
Adj. R^2	0.1551	0.0375	0.1555	0.0367	0.0368	0.0366	0.0691	0.0650	0.0652

	Firm and Industry Fixed Effects			Stock Return Volatility Effects			Firm Leverage and Size Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B. For the crisis period of Dec. 2007 – Jun. 2009. (N=8,811)									
CUT	-0.303***	-0.311***	-0.315***	-0.033*	-0.033*	-0.032*	-0.077***	-0.081***	-0.342***
	(-6.21)	(-6.65)	(-6.49)	(-1.68)	(-1.68)	(-1.67)	(-2.61)	(-3.03)	(-6.17)
NOACT	-0.139***	-0.156***	-0.152***	0.137***	0.137***	0.136***	0.093***	0.088***	-0.180***
	(-2.73)	(-3.16)	(-2.98)	(7.02)	(7.03)	(7.03)	(2.84)	(3.16)	(-3.42)
QE	-0.400***	-0.421***	-0.414***	-0.131***	-0.131***	-0.131***	-0.134***	-0.134***	-0.413***
	(-7.18)	(-8.17)	(-7.42)	(-7.33)	(-7.35)	(-7.34)	(-4.59)	(-5.01)	(-6.99)
Δ RngVol				0.036					
				(0.19)					
Δ SqrRet					0.009***				
					(3.92)				
ΔAbsRet						0.112			
						(0.97)			
LTDebt							0.019		
							(0.23)		
Ind. LTDebt								0.050	
								(0.46)	
SIZE									0.035***
									(5.57)
Industry F.E.	No	Yes	Yes	No	No	No	No	No	No
Firm F.E.	Yes	No	Yes	No	No	No	No	No	No
Adj. R^2	0.3151	0.1069	0.3160	0.0973	0.0973	0.0975	0.1025	0.0948	0.1055

Table II. Robustness analysis for financials – firm attributes and fixed effects

This table reports the coefficients of regressing changes in credit spreads on FOMC action dummies and a host of orthogonalized control macro-level variables for the entire sample, the pre-crisis and crisis periods. Pre-crisis period is defined as August 2002 to November 2007. Crisis period is defined as December 2007 to June 2009. FOMC policy action stances are denoted by dummy variables that indicate: rate decrease (CUT), rate increase (HIKE), no change (NOACT), and quantitative easing (QE). Control variables include changes in the Treasury bill rate (RF), Treasury yield curve slope—the difference between T-bond and T-bill yields (SLOPE), VIX index, and S&P500 return (SP). Δ RngVol is the change from t – 1 to t + 1 of the range-bound volatility; defined as the log of daily high stock price minus the log of daily low stock price. Δ SqrRet is the change from t – 1 to t + 1 of the squared daily stock return. Δ AbsRet is the change from t – 1 to t + 1 of the absolute daily stock return. LTDebt is the most recently available long-term debt ratio for the firm based on quarterly COMPUSTAT data. Ind. LTDebt is the industry (49 Fama-French) median long-term debt ratio based on quarterly COMPUSTAT data. SIZE is the reverse decile ranking (largest denoted by 1 and smallest denoted by 10) of the firm's asset size based on quarterly COMPUSTAT data. For brevity, the coefficient estimates on all other control variables are not reported. Robust (heteroskedasticity and autocorrelation corrected) standard errors (see White, 1980) corrected for firm clustering are used to calculate the t-values that appear in parentheses below the coefficient estimates. Coefficients that are statistically different from zero at the 1%, 5%, and 10% levels are marked with ***, **, and *, respectively.

	Firm and Industry Fixed Effects			Stock Return Volatility Effects			Firm Leverage and Size Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. For the pre-crisis period of Aug. 2002 – Nov. 2007. (N=10,851)									
CUT	-0.034*	0.205***	0.186***	-0.053**	-0.054**	-0.053**	-0.466***	-0.520***	-0.465***
	(-1.81)	(9.51)	(8.61)	(-2.28)	(-2.21)	(-2.17)	(-2.82)	(-2.67)	(-2.88)
HIKE	0.036***	0.256***	0.256***	-0.005	-0.005	-0.005	0.186**	0.152**	0.198
	(2.75)	(38.98)	(37.62)	(-0.67)	(-0.66)	(-0.67)	(2.60)	(2.31)	(1.64)
NOACT	0.034***	0.255***	0.254***	-0.006	-0.006	-0.006	0.009	-0.014	0.034
	(2.77)	(37.41)	(36.50)	(-0.76)	(-0.78)	(-0.75)	(0.41)	(-0.46)	(0.50)
Δ RngVol				0.200					
				(1.13)					
Δ SqrRet					1.754				
					(0.98)				
ΔAbsRet						0.392*			
						(1.65)			
LTDebt							-0.024		
							(-0.59)		
Ind. LTDebt								0.356	
								(0.82)	
SIZE									-0.003
									(-0.44)
Industry F.E.	No	Yes	Yes	No	No	No	No	No	No
Firm F.E.	Yes	No	Yes		No	No	No	No	No
Adj. R^2	0.0699	0.0270	0.0701	0.0245	0.0247	0.0248	0.0371	0.0371	0.0366

	Firm and Industry Fixed Effects			Stock Return Volatility Effects			Firm Leverage and Size Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B. For the crisis period of Dec. 2007 – Jun. 2009. (N=8,811)									
CUT	-0.187	-0.157	-0.216*	0.058	0.040	0.054	0.089	0.107	-0.161
	(-1.47)	(-1.25)	(-1.68)	(1.19)	(0.85)	(1.00)	(1.01)	(1.21)	(-0.98)
NOACT	0.467*	0.448*	0.438*	0.698***	0.639***	0.640***	0.771***	0.795***	0.536*
	(1.95)	(1.94)	(1.82)	(3.64)	(3.12)	(3.02)	(3.19)	(2.73)	(1.88)
QE	-0.395**	-0.359**	-0.417***	-0.140***	-0.142***	-0.112*	-0.119	-0.105	-0.373*
	(-2.52)	(-2.45)	(-2.63)	(-3.75)	(-2.95)	(-1.83)	(-1.07)	(-1.39)	(-1.98)
Δ RngVol				1.791**					
				(2.04)					
Δ SqrRet					0.916				
					(0.22)				
ΔAbsRet						1.487			
						(1.07)			
LTDebt							-0.144		
							(-0.34)		
Ind. LTDebt								-1.233	
								(-0.88)	
SIZE									0.026
									(1.20)
Industry F.E.	No	Yes	Yes	No	No	No	No	No	No
Firm F.E.	Yes	No	Yes		No	No	No	No	No
Adj. R^2	0.1499	0.1056	0.1525	0.1086	0.0985	0.1016	0.1047	0.1057	0.0994

Table III. Comparison among same and other bonds for the entire period of 2002 to 2010 across ratings and maturities

This table reports mean and median (in brackets) of a number of bond/firm attributes for the same bonds as the original sample and other bonds which have valid data in any of the days during the period of Jan 1, 2002 to December 31, 2010. The mean equality (Wilcoxon test) and distribution equality (Kolmogorov test) are not reported for brevity but all are significant at 1% level. Number of bonds is the number of outstanding bond issues for the same firm.

	All Bonds Other Bonds	All Bonds Same Bonds	Investment Grade Bonds Other Bonds	Investment Grade Bonds Same Bonds	Speculative Grade Bonds Other Bonds	Speculative Grade Bonds Same Bonds	Short-term Bonds Other Bonds	Short-term Bonds Same Bonds	Long-term Bonds Other Bonds	Long-term Bonds Same Bonds
Non-Fin.	146,216	443,960	100,004	344,577	46,212	99,383	97,135	286,299	49,081	157,661
Credit Spread	3.018	2.656	1.911	1.658	5.413	6.118	3.150	2.435	2.758	3.058
	[1.68]	[1.35]	[1.22]	[1.02]	[3.98]	[4.86]	[1.29]	[0.98]	[2.21]	[2.00]
Coupon	6.091	6.279	5.976	5.933	6.339	7.477	5.607	5.957	7.048	6.863
	[6.55]	[6.38]	[6.50]	[6.00]	[6.94]	[7.50]	[5.70]	[5.88]	[7.00]	[6.88]
Age	5.462	5.220	5.669	4.688	5.013	7.064	4.742	4.699	6.887	6.166
	[5.00]	[5.00]	[6.00]	[4.00]	[4.00]	[7.00]	[4.00]	[4.00]	[7.00]	[7.00]
Yrs.-to-Mat.	7.732	8.210	8.202	7.867	6.713	9.398	3.069	3.251	16.959	17.214
	[4.00]	[5.00]	[4.00]	[5.00]	[5.00]	[6.00]	[3.00]	[3.00]	[17.00]	[18.00]
Num. Bonds	9.624	8.007	10.472	8.364	7.787	6.769	10.227	8.871	8.429	6.438
	[6.00]	[6.00]	[7.00]	[6.00]	[4.00]	[6.00]	[6.00]	[7.00]	[5.00]	[5.00]
VIX	19.771	21.317	19.480	21.304	20.402	21.363	19.404	20.611	20.498	22.599
	[16.86]	[18.53]	[16.42]	[18.47]	[18.13]	[19.00]	[16.30]	[17.63]	[18.17]	[20.33]
Financials	643,925	1,366,186	431,659	1,263,111	212,266	103,075	577,890	1,085,479	66,035	280,707
Credit Spread	3.115	2.349	2.136	1.896	5.107	7.897	3.175	2.365	2.597	2.288
	[1.93]	[1.24]	[1.45]	[1.12]	[3.86]	[5.79]	[1.93]	[1.16]	[1.88]	[1.54]
Coupon	5.238	5.542	5.157	5.454	5.403	6.623	5.140	5.419	6.091	6.019
	[5.20]	[5.50]	[5.05]	[5.45]	[5.38]	[6.75]	[5.10]	[5.38]	[6.00]	[5.85]
Age	3.305	3.468	3.304	3.385	3.306	4.488	3.287	3.738	3.454	2.426
	[3.00]	[3.00]	[3.00]	[3.00]	[3.00]	[4.00]	[3.00]	[3.00]	[2.00]	[2.00]
Yrs.-to-Mat.	3.970	5.284	4.629	5.342	2.629	4.574	2.756	3.372	14.587	12.678
	[3.00]	[4.00]	[3.00]	[4.00]	[2.00]	[3.00]	[2.00]	[3.00]	[10.00]	[9.00]
Num. Bonds	18.227	14.942	17.404	14.782	19.902	16.899	18.958	14.914	11.829	15.049
	[21.00]	[20.00]	[21.00]	[20.00]	[21.00]	[21.00]	[21.00]	[20.00]	[17.00]	[20.00]
VIX	19.078	22.478	20.020	22.286	17.164	24.839	18.878	22.495	20.831	22.415
	[15.32]	[19.99]	[16.86]	[19.75]	[13.42]	[22.64]	[14.96]	[19.96]	[18.68]	[20.02]

Table IV. Comparison among same and other bonds for sub-periods surrounding FOMC meetings

This table reports mean and median (in brackets) of a number of bond/firm attributes for the same bonds as the original sample and other bonds who have valid data for two periods: immediately surrounding FOMC meeting (±5 days), and, further out ($-20 \le t \le -15$ and $15 \le t \le 20$). The p-values for mean equality (Wilcoxon test) and distribution equality (Kolmogorov test) are also reporter. Rating maps alphanumeric rating into a numerical variable. To be precis, AAA=1, AA+=2, AA=3, AA-=4, etc. Number of bonds refers to the number of outstanding bond issues for the same firm.

	$-5 \le t \le 5$		Mean Equal {Dist. Equal}	$-20 \le t \le -15$ and $15 \le t \le 20$		Mean Equal {Dist. Equal}
	Other Bonds	Same Bonds	*p*-value	Other Bonds	Same Bonds	*p*-value
Nonfinancials	N = 34,254	N = 108,632		N = 32,955	N = 102,677	
Credit Spread	3.021	2.683	0.000	3.069	2.720	0.000
	[1.67]	[1.35]	{0.000}	[1.73]	[1.40]	{0.000}
Coupon	6.074	6.271	0.095	6.043	6.270	0.639
	[6.55]	[6.38]	{0.160}	[6.55]	[6.38]	{0.560}
Age	5.618	5.283	0.051	5.569	5.305	0.070
	[6.00]	[5.00]	{0.004}	[6.00]	[5.00]	{0.045}
Yrs.-to-Mat.	7.731	8.211	0.859	7.819	8.212	0.586
	[4.00]	[5.00]	{0.267}	[4.00]	[5.00]	{0.821}
Rating	11.326	10.201	0.003	11.225	10.228	0.328
	[11.00]	[9.00]	{0.000}	[10.00]	[10.00]	{0.378}
Num. Bonds	8.532	8.016	0.000	8.407	8.197	0.011
	[6.00]	[6.00]	{0.000}	[6.00]	[6.00]	{0.135}
VIX	19.965	21.784	0.715	19.751	21.419	0.001
	[16.73]	[18.89]	{0.000}	[17.26]	[18.88]	{0.000}
Financials	N = 153,429	N = 339,015		N = 149,355	N = 321,805	
Credit Spread	3.128	2.387	0.000	3.302	2.430	0.000
	[1.97]	[1.26]	{0.000}	[2.03]	[1.33]	{0.000}
Coupon	5.242	5.532	0.192	5.248	5.531	0.081
	[5.20]	[5.50]	{0.015}	[5.20]	[5.50]	{0.003}
Age	3.347	3.497	0.076	3.334	3.503	0.078
	[3.00]	[3.00]	{0.111}	[3.00]	[3.00]	{0.072}
Yrs.-to-Mat.	3.988	5.273	0.481	3.989	5.255	0.023
	[3.00]	[4.00]	{0.704}	[3.00]	[4.00]	{0.106}
Rating	9.978	7.957	0.004	10.054	7.982	0.338
	[9.00]	[7.00]	{0.000}	[9.00]	[7.00]	{0.006}
Num. Bonds	96.349	14.906	0.007	95.918	15.077	0.000
	[21.00]	[20.00]	{0.249}	[21.00]	[20.00]	{0.000}
VIX	19.336	22.935	0.060	19.302	22.523	0.000
	[15.54]	[20.63]	{0.000}	[16.30]	[20.27]	{0.000}

References

Alizadeh, S., Brandt M.W., and Diebold, F.X. (2002) Range-based estimation of stochastic volatility models *Journal of Finance* 57, 1047-1091.

Anderson, T.G., and Sorensen, B.E. (1997), GMM and QML asymptotic standard deviations in stochastic volatility models, *Journal of Econometrics* 76, 397-403

Bessembinder, H., Kahle, K.M., Maxwell, W.F., and Xu, D. (2009) Measuring abnormal bond performance, *Review of Financial Studies* 22, 4219–4258.

Bharath, S. T., and Shumway. T. (2008) Forecasting default with the Merton distance to default model, *Review of Financial Studies* 21, 1339–69.

Campbell, J.Y., Hilscher, J., and Szilagyi, J. (2008) In search of distress risk, *Journal of Finance* 63, 2899–2939.

Collin-Dufresne, P., Goldstein, R., and Martin, J.S. (2001) The determinants of credit spread changes, *The Journal of Finance* 56, 2177-2207.

Dichev, I.D. (1998) Is the risk of bankruptcy a systematic risk? *Journal of Finance* 53, 1131–1147.

Eom, Y.H., Helweg, J., and Huang, J. (2004) Structural models of corporate bond pricing: An empirical analysis, *Review of Financial Studies* 17, 499-544.

Friewald, N., Wagner, C., and Zechner, J. (2014) The Cross-Section of Credit Risk Premia and Equity Returns, *The Journal of Finance* 69, 2419–2469

Huang, M., and Huang, J. (2012) How much of the corporate-treasury yield spread is due to credit risk? *Review of Asset Pricing Studies* 2, 153-202.

Kim, O., and Verrecchia, R.E. (1997) Pre-announcement and event-period information, *Journal of Accounting and Economics* 24, 395-419.

Kim, O., and Verrecchia, R.E. (1994) Market liquidity and volume around earnings announcements, *Journal of Accounting and Economics* 17, 41-67.

Lemmon, M. and Roberts, M.R. (2010) ‘The Response of Corporate Financing and Investment to Changes in the Supply of Credit’, *Journal of Financial and Quantitative Analysis*, 45(3), pp. 555–587

Rauh, J.D., and Sufi, A. (2010) Capital structure and debt structure, *Review of Financial Studies* 23, 4241-4280.

Sarig, O., and Warga, A. (1989) Some empirical estimates of the risk structure of interest rates. *Journal of Finance* 44, 1351-1360.

Davydenko, S.A, and, Strebulaev, I. (2007). Strategic Actions and Credit Spreads: An Empirical Investigation. *The Journal of Finance*, 62(6), 2633-2671.

Stiglitz, J.E., and Weiss, A. (1981) Credit rationing in markets with imperfect information, *American Economic Review* 71, 393-410.

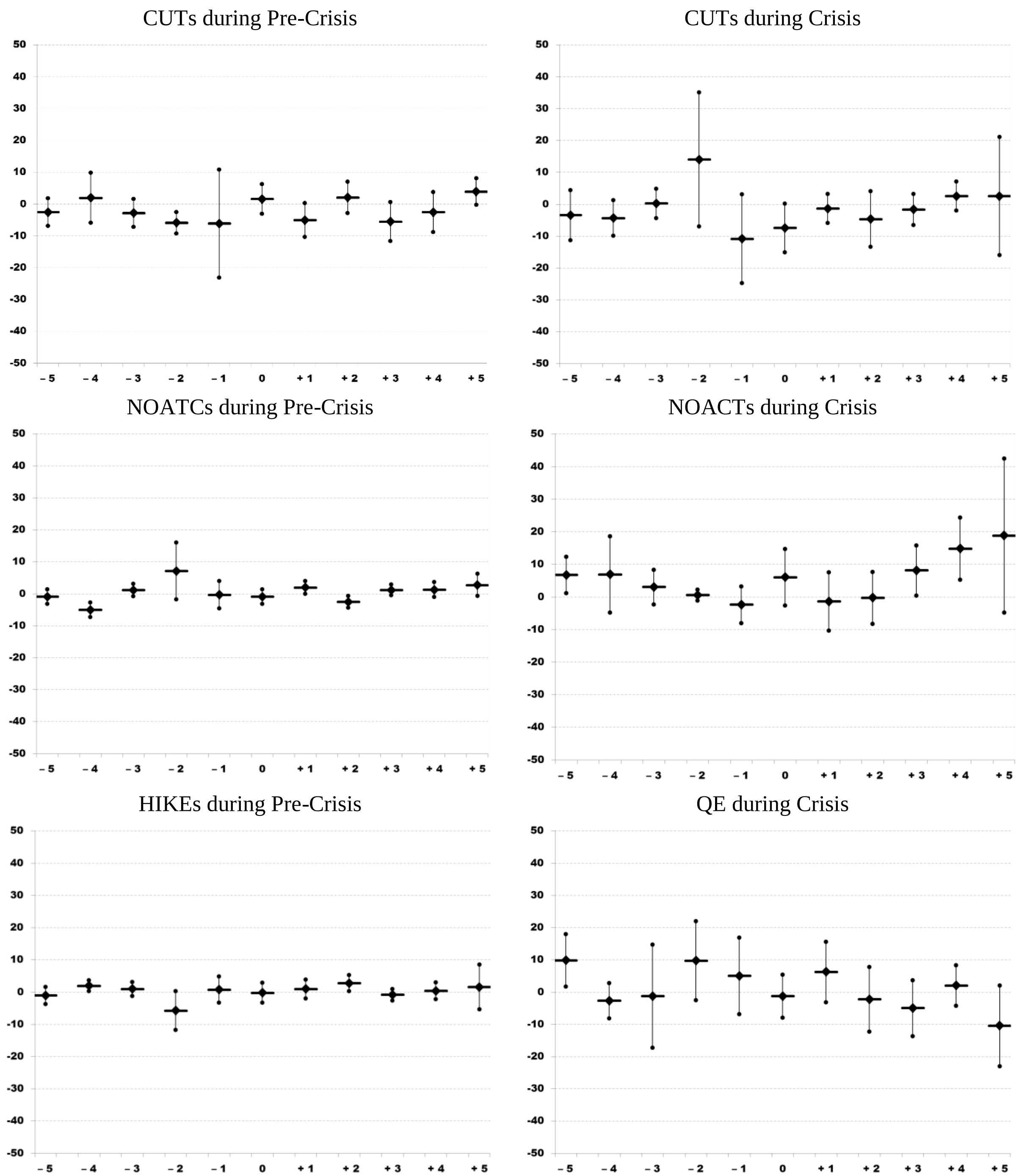

Figure 1. Changes in credit spreads of non-financial bonds surrounding FOMC action dates. This graph depicts the coefficient estimates (and 95% confidence bounds) of day dummies for the window of time ± 5 days around action dates. For each action, we run panel regression of day-to-day changes in the credit spread on our control variables and a series of event-day dummies. The control variables are same of benchmark model.

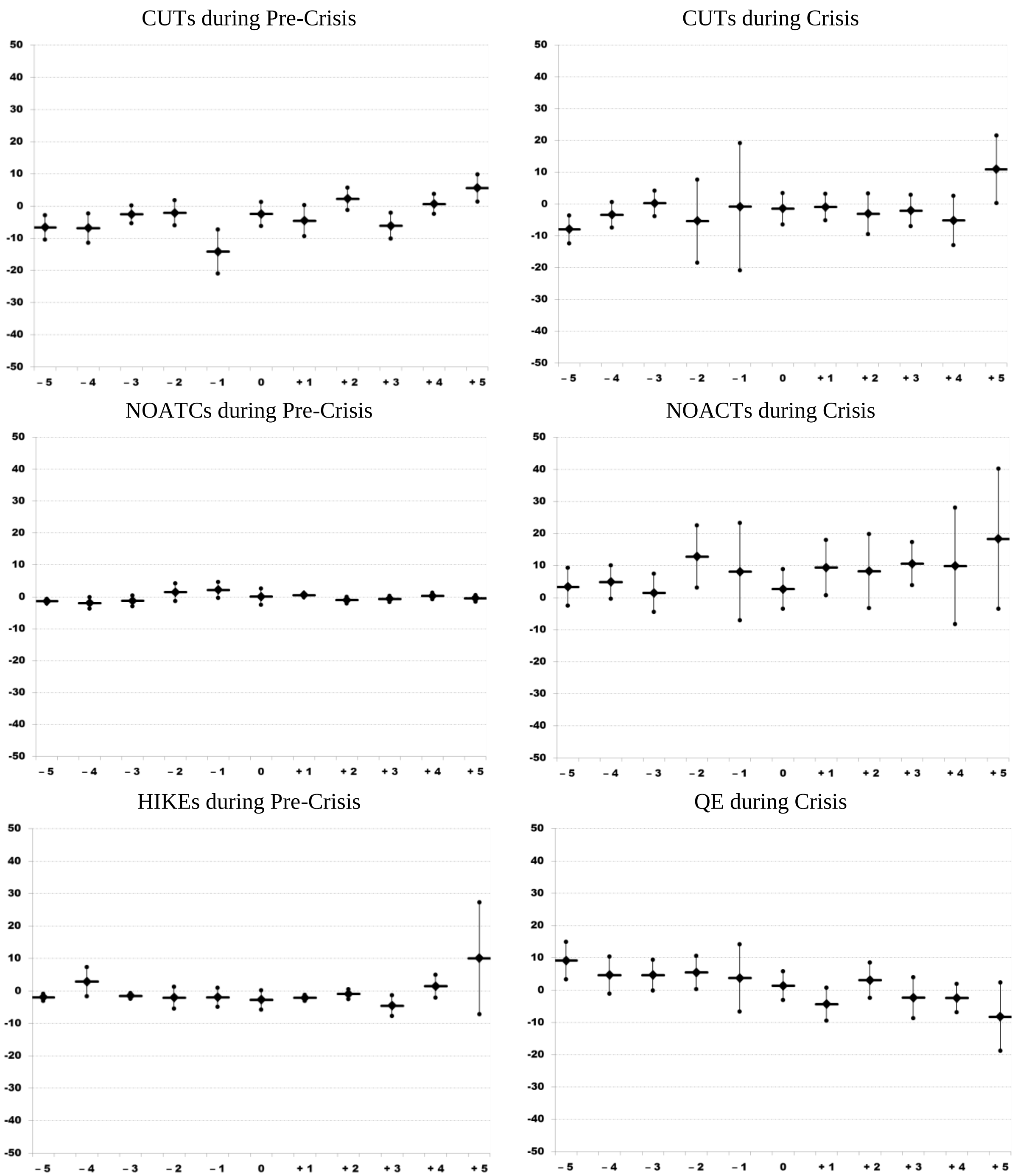

Figure 2. Changes in credit spreads of financial bonds surrounding FOMC action dates. This graph depicts the coefficient estimates (and 95% confidence bounds) of day dummies for the window of time ± 5 days around action dates. The corresponding panel regression is akin to the benchmark model with the exception in any day within the event window, all corporate bonds with valid information are used for the analysis. The dependent variable is day-to-day changes in the credit spread. The control variables are same of benchmark model.