How Does Low for Long Impact Credit Risk Premiums?

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Abstract

The Federal Reserve's experiments in monetary policy related to the Global Financial Crisis lasted longer than any previous easing cycle, giving rise to the question of how does a long-term, low-interest-rate environment affect the pricing of credit risk. We decompose credit default swap (CDS) rates into expected losses and credit risk premia, and show that the level of and firms' exposure to systematic default risk, controls for mis-measuring expected losses and proxies for CDS market liquidity explain more than 80% of the variation in risk premia across firms and over time. We show that in the zero lower bound period, residual risk premia are lower for high-yield debt compared to investment-grade debt—consistent with a reaching for yield interpretation. Our findings are also consistent with investors demanding compensation for ambiguity aversion related to the end of the low-rate environment, a decrease in the supply of risk capital and higher costs of trading credit risky instruments due to regulatory changes.

JEL Classifications: G12, G13, G22, G24

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1. Introduction

Just prior to the historic reduction to a zero Fed funds rate on December 16, 2008, investment-grade (IG) bond yield spreads averaged 6.51% and high-yield (HY) bonds traded at an eye-popping spread of nearly 22%.[1] Similarly, credit default swap (CDS) premia were at a near all-time high, with the median CDS rate reaching 310 basis points (bps).[2] While all three credit risk measures fell on the FOMC announcement, they remained elevated compared to pre-recession levels. Indeed, the median CDS premium stayed above 100 bps until late 2009 and high-yield bond yields remained in double-digit territory well into summer 2009. With such extreme pressure in credit markets, accommodative monetary policy is to be expected. Nor would it be surprising if near-zero rates persisted well beyond the end of the recession. However, few people would have predicted in December 2008 that such a low Fed funds rate would continue through most of the next decade.[3]

How did credit markets respond to this extraordinary stimulus? Eventually, spreads fell far enough that yields were not only back to pre-recession levels, but by the middle of the low-for-long decade, investment-grade yields reached historical lows. For example, the average A-rated bond yield fell below 2.5% in September 2012 and remained well under 4% even after the Fed funds target rose to 2% in June 2018.[4] Except for a period in 2015 and 2016 when falling energy prices drove up the average spread, the high-yield bond market also experienced record low yields in much of the period. In part, these low credit spreads reflect the reduced probability of default that accompanied one of the longest economic expansions in U.S. history (Wang (2014); Krishnamurthy and Vissing-Jorgensen (2011); Gilchrist and Zakrajsek (2013)). And, of course, risk appetites increased sharply from the panic-mode lows of late 2008.

But, did the pricing of credit risk revert to the level expected of efficient bond and CDS markets? Several factors could have resulted in a change in credit risk premia during this period. First among them is the fact that Federal Reserve policy was so unusual that investors faced the added risk associated with normalization of rates. Chairman Bernanke surprised fixed income markets in March 2009 by

[1] These figures quote the ICE Bank of America/Merrill Lynch U.S. Corporate Master Option-Adjusted Spreads for IG and HY bonds as of December 15, 2008.

[2] This median statistic is for five-year CDS rates with modified restructuring on senior unsecured debt, as of December 15, 2008. The sample include all public U.S. firms with Markit CDS coverage and a Moody's credit rating. Details on the sample construction are provided in Section 2.

[3] Orphanides (2015) notes that "liftoff" occurred between 7 and 32 months after the end of the previous three recessions while the Federal Reserve waited more than 72 months after the June 2009 end of the Great Recession to raise rates.

[4] These statistics refer to the ICE Bank of America/Merrill Lynch U.S. Corporate A Effective Yield.

announcing that rates would remain low for an extended period, and even more surprising, by explicitly stating that "extended period" meant two years. Swanson (2015) notes that, in addition to the major unconventional monetary policy announcements made by the Federal Reserve in this period, Bernanke released incremental news about these policies at almost every FOMC meeting. While Bernanke's goal was to increase transparency, his updates were necessary to alleviate concerns about how and when the low-for-long policy would end. The Taper Tantrum episode of 2013 highlights the extent to which investors were shocked by relatively small shifts in Federal Reserve policy. Not only did yields rise in this episode, but Mueller, Sabtchvesky, Vedolin, and Whelan (2017) show a sharp increase in the risk premium on Treasury bonds. Shi (2017) and Puhl, Savor, and Wilson (2016) provide evidence that uncertainty about the future path of macroeconomic conditions leads to a risk premium related to ambiguity aversion. Thus, while the low-for-long policy may have reduced expected losses on credit instruments to historic lows, credit spreads might have been even lower had risk premia fallen with expected losses.

Alternatively, the extended period of ultra-low rates may have had the opposite effect on risk premia as financial intermediaries pursued a practice of "reaching for yield" (Drechsler, Savov, and Schnabl (2018); Borio and Zhu (2012); La Spada (2018)). Drechsler, Savov, and Schnabl (2018) show theoretically how easy monetary policy effectively lowers the risk tolerance of intermediaries that reach for yield, resulting in lower risk premia. Greenwood and Hanson (2013) and Choi and Kronlund (2018) provide evidence from low-quality bonds that supports this view.

Reaching for yield may have reduced credit risk premia as a result of mispricing or effectively lowering risk aversion, but the phenomenon may also be an indication of tremendous pressures among regulated financial intermediaries that struggled to stay in business. Di Maggio and Kacpercyzk (2017) show that the low-for-long environment led to exits in the money market mutual fund (MMMF) business as funds were unable to cover their fixed costs when revenue on safe assets dropped to nearly zero. Similarly, Chodorow-Reich (2014)) and Becker and Ivashina (2015) highlight the incentive to reach for yield among life insurers and pension funds, which also face increased pressures to meet fixed obligations when low rates persist. If the low-for-long rate period caused negative operating income among financial institutions, not only might they reach for yield as a method of maintaining profitability, but they might require a higher return on equity (a higher risk premium) than in the pre-crisis period to remain providers of risk capital in credit markets.

Finally, we consider whether structural changes in credit markets after the Great Financial Crisis (GFC) contributed to increased risk premia. The Volcker Rule, which was adopted in full in April 2014, restricted the activities of bond dealers, which may have exacerbated bond market illiquidity (Bao, O'Hara, and Zhou (2018); Anderson and Stulz (2017); Dick-Nielsen and Rossi (2018)). If illiquidity requires a risk premium (Driessen (2005); De Jong and Driessen (2012)), credit spreads would not have reverted to their pre-crisis levels. Similarly, by requiring derivatives to trade on a central clearinghouse, Dodd-Frank raised the capital required to trade CDS (Boyarchenko, Gupta, Steele, and Yen (2016)). Consequently, for CDS to continue as an attractive asset class, CDS traders would have required higher risk premia.

We test for the effects of the low interest rate environment on risk premia in credit markets using Markit CDS data for public U.S. firms during the period 2002-2017. Following the methodology in Berndt, Douglas, Duffie, and Ferguson (2018), we decompose CDS rates into compensation for expected losses and risk premia, and focus on the latter component to determine how the low-for-long policy may have impacted the price of risk on credit instruments. Our benchmark panel regression includes nearly 1.3 million firm-date observations for more than 520 firms. It shows that the level of and firms' exposure to systematic default risk, controls for mis-measuring expected losses and proxies for CDS market liquidity explain more than 80% of the variation in risk premia across firms and over time. Despite the high R^2, we observe a distinct time series pattern in residual risk premia and find that residuals are generally larger post-GFC than before.

We present evidence that the higher risk premia in recent years are associated with an increase in systematic default risk exposure for IG firms. We further show that after controlling for this increased risk exposure, residual risk premia are lower for high-yield debt compared to investment-grade debt. This change in relative pricing is consistent with a reaching for yield interpretation. Note that the reaching for yield explanation applies only after controlling for the market-wide increase in credit risk premia. In isolation, a reaching-for-yield story would not explain higher risk premia.

Our findings also suggest that the zero lower bound period is associated with a reduction in the supply of risk capital and a higher required compensation for the provision of risk capital by the remaining intermediaries. Our analysis of ambiguity aversion points to higher risk premia on credit risky instruments due to more macro-economic uncertainty. Finally, the adaptation of the Dodd-Frank Act and Volcker Rule are associated with marginal increases in credit risk premia as well.

The remainder of the paper is organized as follows: Section 2 explains how we measure credit risk premia and describes the data. Section 3 visualizes the temporal and cross-sectional variation in credit risk premia. Section 4 explains the empirical methodology for predicting credit risk premia and presents results for the benchmark model. Section 5 develops hypotheses regarding the impact of low interest rates on residual credit risk premia and describes our findings. Section 6 concludes.

2. Measuring Credit Risk Premia

In order to test for the effects of low-for-long on the risk premia associated with credit markets, we examine CDS rather than bond spreads. CDS premia have the advantage over bond spreads that they are less affected by illiquidity (Longstaff, Mithal, and Neis (2005); Blanco, Brennan, and Marsh (2005), 2005; Dick-Nielsen, Feldhütter, and Lando (2012)). Even if the CDS market is no more liquid than the bond market, which could be the case later in our sample, CDS data are preferred because they are based on homogeneous instruments (e.g., a five-year contract on senior unsecured debt of the issuer) rather than on bonds that differ in maturity, coupon, call protection, and seniority. By using CDS rates, we also avoid the impact of off-the-run and on-the-run Treasury bond differentials that affect the choice of a risk-free benchmark required for calculating bond spreads.

Our focus is on risk premia, which we estimate as the component of CDS rates that remains after covering expected losses (Berndt (2015), Berndt, Douglas, Duffie, and Ferguson (2018)). For a given firm, let C_t denote the time-t CDS rate. In the absence of market frictions, there exists a stochastic discount factor process M, defined so that a payment of Z_T at time T has a market value at time $t \leq T$ of $E_t(Z_T\, M_T)/M_t$, where E_t denotes expectation conditional on market information available at time t. Under these assumptions, the CDS rate satisfies

$$\Delta\, C_t \sum_{k=0}^{K-1} E_t\left((1 - D_{t,k\Delta})\frac{M_{t+(k+1)\Delta}}{M_t}\right) \;=\; \sum_{k=0}^{K-1} E_t\left(L_{t+k\Delta,\Delta} D_{t+k\Delta,\Delta}\, \frac{M_{t+(k+1)\Delta}}{M_t}\right), \qquad (1)$$

where T is the maturity of the CDS contract in years, Δ is the time between premium payments, and $K = T/\Delta$ is the number of payment periods. We use $D_{t,y}$ to denote the indicator of default of the firm in the period $(t, t+y]$ and $L_{t,y}$ to denote the conditional expected loss given default, as a fraction of notional, that would apply if the firm were to default in period $(t, t+y]$. The left-hand side of Equation (1) is the value of the premium leg of the CDS contract. The right-hand side is the value of the protection leg. The CDS rate C_t equates the market values of the two legs.

Berndt (2015) shows that if investors were risk-neutral, M_t would be deterministic and the resulting CDS rate, denoted EL_t, would solve the equation

$$\mathrm{EL}_t = \frac{\sum_{k=0}^{K-1} d_{t,(k+1)\Delta}\, E_t\left(L_{t+k\Delta,\Delta} D_{t+k\Delta,\Delta}\right)}{\Delta \sum_{k=0}^{K-1} d_{t,(k+1)\Delta}\, E_t\left(1 - D_{t+k\Delta,\Delta}\right)}, \tag{2}$$

where $d_{t,y}$ is the price at time t of a default-free zero-coupon bond with y years to maturity. For a flat and relatively low term structure of default probabilities, EL_t is a close approximation of the annualized expected rate of loss to the protection seller. Thus we will refer to it as the "expected loss rate."

The "credit risk premium," denoted RP_t, is defined to be the difference between the observed CDS rate C_t and the hypothetical CDS rate EL_t that would apply in the absence of risk aversion and market frictions. That is,

$$\mathrm{RP}_t = C_t - \mathrm{EL}_t. \tag{3}$$

The premium RP offers investors compensation for bearing credit risk. It varies with systematic risk in credit markets and firms' exposure to such risk. RP may also be affected by changes in the supply of and demand for risk capital, changes in the structure of credit markets, and regulatory changes affecting the cost of trading. In summary, we think of RP as excess compensation for protection sellers in the CDS market, above and beyond expected default losses. Note that the estimated risk premium will be sensitive to the error in estimating expected losses.

2.1 Data

We obtain daily data on CDS rates from Markit Partners, which provides composite quotes based on bid and ask quotes obtained from two or more anonymous CDS dealers. We assume that the composite CDS rate from Markit is the rate at which the market value of the default swap is zero. We restrict our analysis to CDS contracts on public U.S. firms that use the "modified restructuring" definition of default. Our CDS data apply to senior unsecured debt instruments with a maturity of five years. We use expected LGD estimates provided in the Markit database. We obtain issuer-level ratings by matching firms in the Markit database to Moody's Default and Recovery Database. Balance-sheet data are collected from Compustat, and options data from OptionMetrics. The sample period is 2002 to 2017.

To construct our estimates of the risk premia on CDS, we use two EL measures that differ in their estimates of the probability of default (PD). The first PD is provided by the Risk Management Institute (RMI) of the National University of Singapore (NUS). RMI provides, on a monthly and firm-by-firm basis, conditional default probabilities for different horizons. The NUS-RMI Credit Research Initiative Technical Report available at rmicri.org describes the prediction accuracy for RMI PDs. PD estimates from RMI have been used in studies by Madan (2014), Berndt (2015), Duan and Miao (2016) and Berndt, Douglas, Duffie, and Ferguson (2018), among others.

Our second PD estimate is based on Moody's alphanumeric senior unsecured issuer ratings. We use Moody's data on Outlook and Watchlist information to refine the alphanumeric ratings. For a given firm, a refined credit rating is defined by raising the firm's alphanumeric rating by one notch (for example from Baa2 to Baa1) if the firm is on "positive outlook" and by two notches if it is on "upgrade watch."[5] Similar but opposite adjustments are made to refined ratings for firms with a negative outlook or on downgrade watch. Berndt, Douglas, Duffie, and Ferguson (2018) find that refined ratings supply a significant amount of information about relative credit quality across firms. They also show that refined ratings exhibit substantially more time-series variation—and that they have more explanatory power for credit risk premia—than raw alphanumeric ratings.

Moody's disseminates annual default studies that report average cumulative issuer-weighted global default rates by alphanumeric senior unsecured issuer rating and maturity horizon, using data dating back to 1983. For example, Moody's 2017 annual default study reports global default rates based on data from 1983 to 2016 (see Moody's Investors Service (2017)), Moody's 2016 study reports default rates based on data from 1983 to 2015, and so on. To obtain refined-ratings-based PD estimates, we set a firm's y-year PD estimate equal to the y-year default rate reported for the firm's refined ratings category in the current year's annual default study. As a result, in any given year, a change in a firm's refined-ratings-based PD occurs only if the firm's refined rating changes.

[5]Watchlist and outlook data are available from November 15, 2003 onwards. Prior to that date, refined ratings are set equal to alphanumeric ratings. Watchlist and outlook data sometimes are in the form of "Developing" or "Uncertain." In those instances, refined ratings are again set equal to alphanumeric ratings.

Berndt, Douglas, Duffie, and Ferguson (2018) show that RMI-based estimates of expected losses are similar to those using Moody's EDFs and that both are lower than ELs based on refined ratings, especially for high-yield issuers. A possible explanation for the difference, besides the fact that EDFs and RMIs are forward-looking, point-in-time PDs that are updated frequently, is that rating agencies try to "rate through the cycle." We focus on RMI PDs and provide results for refined-ratings-based PDs as robustness checks.

2.2 Descriptive Statistics

The range of credit qualities of the firms in our data may be judged from Table 1, which categorizes firms according to their median Moody's rating over the sample period. The table shows, for each credit rating, the number of firms in our study with that median rating. As the table indicates, firms in the sample tend to be of medium credit quality. Across industry groups, ratings tend to be higher for financial, healthcare and technology firms, and tend to be lower for telecommunication services firms.

Table 1: **Distribution of firms across sectors and by credit quality** The table reports the distribution of firms across sectors and by median Moody's senior unsecured issuer ratings. The data include 650 public U.S. firms and cover the period from 2002 to 2017.

	Aaa	Aa	A	Baa	Ba	B	Caa	Ca-C	All
Basic Materials	0	0	11	20	11	3	0	0	45
Consumer Goods	0	5	16	44	23	10	4	0	102
Consumer Services	0	1	11	40	17	18	9	1	97
Energy	1	1	6	34	8	6	1	0	57
Financials	1	12	34	57	9	3	1	0	117
Healthcare	1	1	13	16	10	5	1	0	47
Industrials	1	3	17	33	13	10	5	0	82
Technology	1	1	9	12	5	6	0	0	34
Telecommunications Services	0	0	4	7	4	5	2	0	22
Utilities	0	0	6	29	5	7	0	0	47
All	5	24	127	292	105	73	23	1	650

Table 2 reports summary statistics by sector and credit rating for CDS rates, PDs, Markit estimates of recovery rates and expected losses. This table reveals substantial cross-sectional differences in CDS rates and PDs. Notably, we observe that among high-yield firms PDs based on ratings are substantially higher than RMI PDs. As a result, when PDs are based on ratings the estimates of expected losses are higher and those of credit risk premia are lower. While recovery rate estimates tend to be close to 40%, we observe a notable decrease in estimated recovery rates as credit quality decreases.

Table 2: **Descriptive statistics for CDS rates, PDs, recovery rates and expected losses** The table reports median five-year CDS rates, RMI PDs and refined-ratings-based PDs, Markit estimates of recovery rates (Rec), and expected losses. CDS rates, PDs and expected losses are reported as annualized rates, in basis points.

	CDS	PD		Rec	EL			CDS	PD		Rec	EL	
		RMI	Rtg		RMI	Rtg			RMI	Rtg		RMI	Rtg
			All							By sector			
	80	28	40	0.40	16	23	BM	89	31	44	0.40	18	26
			By rating				CG	85	29	44	0.40	17	26
Aaa	19	10	2	0.40	6	1	CS	97	34	52	0.40	20	31
Aa	27	13	6	0.40	7	3	Egy	92	38	43	0.40	22	25
A	40	15	15	0.40	9	9	Fin	78	19	25	0.40	11	15
Baa	78	25	42	0.40	14	24	Hlth	50	17	32	0.40	10	19
Ba	185	52	158	0.40	31	92	Ind	65	28	38	0.40	16	22
B	342	100	564	0.40	59	302	Tech	90	29	37	0.40	17	22
Caa	681	176	1,327	0.37	113	735	Tele	145	46	123	0.40	27	71
Ca-C	1,598	311	1,816	0.30	211	1,099	Utl	70	23	43	0.40	13	25

Figure 1 shows the time series of median five-year CDS rates and RMI PD estimates. CDS rates rose dramatically in the 2008-09 financial crisis, even though PDs only (eventually) rose modestly more than during the previous recession. CDS rates also spike in 2002 when WorldCom defaulted and again during the latter half of 2011.[6] While PDs show substantial variation over our sample period, temporal variation in CDS rates is much higher. This suggests that CDS rates vary to a large extent as a result of changes in credit risk premia.

3. Variation in Credit Risk Premia

The focus of our work is to understand how the long-term, low-interest-rate environment may have affected credit risk premia. Figure 2 plots the median credit risk premia RP, defined in Equation (3) as the CDS rate net of the expected loss rate due to default. The left side of the graph shows the daily time series of the median credit risk premia for IG firms while the right side shows the credit risk premia for HY firms. Both figures are based on RMI PDs. These graphs show that the variation in CDS rates over time (shown in Figure 1) owes more to changes in risk premia than to changes in expected losses. The median premium fluctuates dramatically during 2002–2017, and not just in the 2008–09 crisis period. For example, the median annual premium for the full sample dropped by nearly half from 2002 to 2003. From less than 30 bp in 2004–2007, the median annual premia sharply

[6]During the second half of 2011, concerns arose about European sovereign debt and the outcome of U.S. government debt ceiling negotiations.

Figure 1: **Median five-year CDS rates and RMI PDs** The figure shows the daily times series of median five-year CDS rates and median annualized five-year RMI PDs. Only those days on which data are available for 50 or more firms are shown.

increased to over 100 bp during the financial crisis. Premia remained fairly high for several years after the end of the Great Recession—between 85 and 100 basis points—before declining to lower levels. Notably, throughout the entire 2010–17 post-crisis period, median premia for IG firms remained well above their pre-crisis levels. Similarly, HY premia only returned to the lows of the mid-2000s in late 2017. If measured by ratings PDs, the pattern in credit risk premia over time is similar (see Figure B.1 in the appendix).

Credit risk premia can also be expressed per unit of expected default loss, as shown in Figure 3. The per-unit-of-EL premia for IG firms were generally lower in the pre-GFC period compared to the post-GFC period. For HY firms, we observe significant variation over time but no clear trend emerges. The equivalent time series of median ratings-based premia is shown in Figure B.2. It exhibits somewhat lower post-GFC premium-to-expected-loss ratios for IG firms.

Figure 4 shows the five-year constant maturity Treasury rate, the implied yield on a typical five-year bond if investors were risk neutral (i.e., if there were no credit risk premia), and the bond-equivalent yield obtained from CDS rates. The implied yield, shown by the red line, is simply the median expected loss from using RMI PDs added to the risk-free rate. The bond-equivalent yield is the sum of the risk-

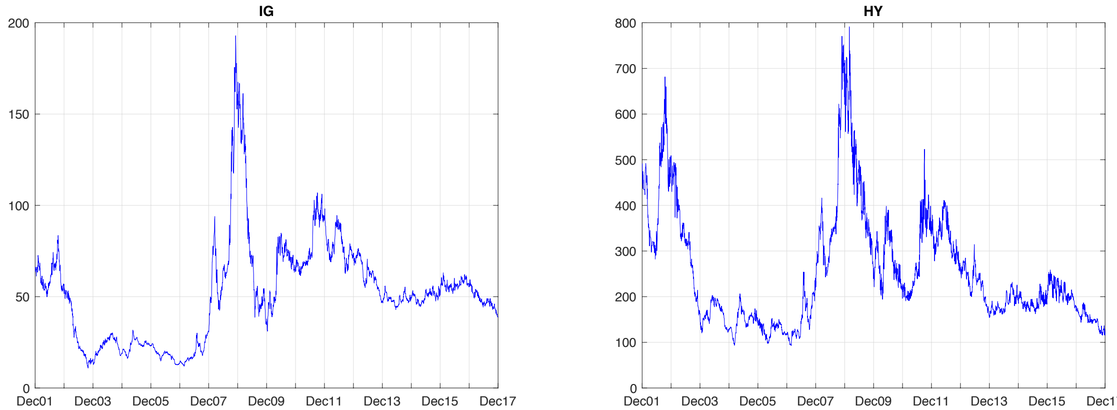

Figure 2: **Median credit risk premia** The left panel of the figure shows the daily times series of the median premium, RP, for IG firms. EL is computed using RMI PDs. Only days on which premia are available for 50 or more IG firms are shown. The right panel shows the daily median across HY firms. Only days on which premia are available for 10 or more HY firms are shown.

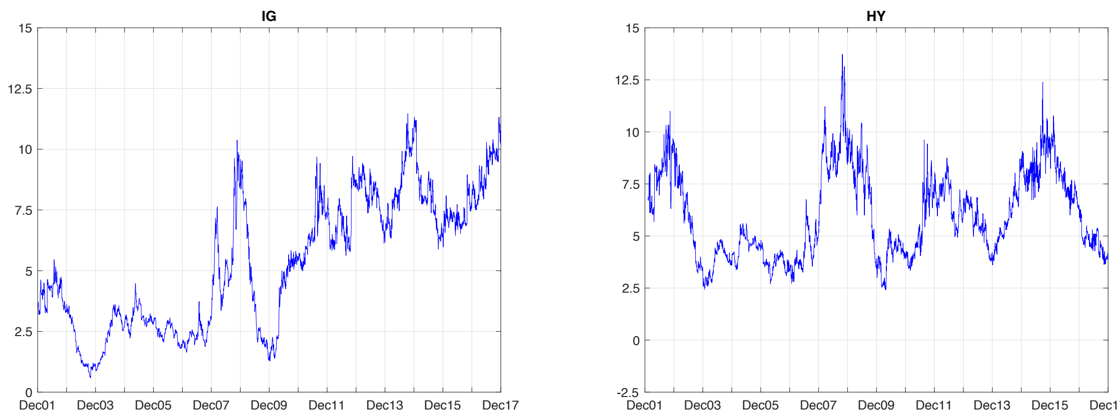

Figure 3: **Median credit risk premia per unit of expected loss** The left panel of the figure shows the daily times series of the median premium-to-expected-loss ratio, $\mathrm{RP}_t/\mathrm{EL}_t$ for IG firms. EL is computed using RMI PDs. Only days on which premia are available for 50 or more IG firms are shown. The right panel shows the daily median across HY firms. Only days on which premia are available for 10 or more HY firms are shown.

free rate and the median CDS premium. Figure 4 shows that the bond-equivalent yield averaged about 400 bps before the Great Recession, with sharply higher rates around the last two recessions. The graph also indicates that CDS rates tend to rise with expected losses and that investors perceived a high level of credit risk around the two recession periods.

Since 2010, the bond-equivalent yield has been below 300 bp for the median firm in the sample, indicating that terms have been extremely favorable for corporate bond issuers in the post-GFC period. That is, even though risk premia exhibited substantial variation over the last decade, the movement in bond yields was dominated by adjustments to interest rates. As a result, debt was cheaper to issue

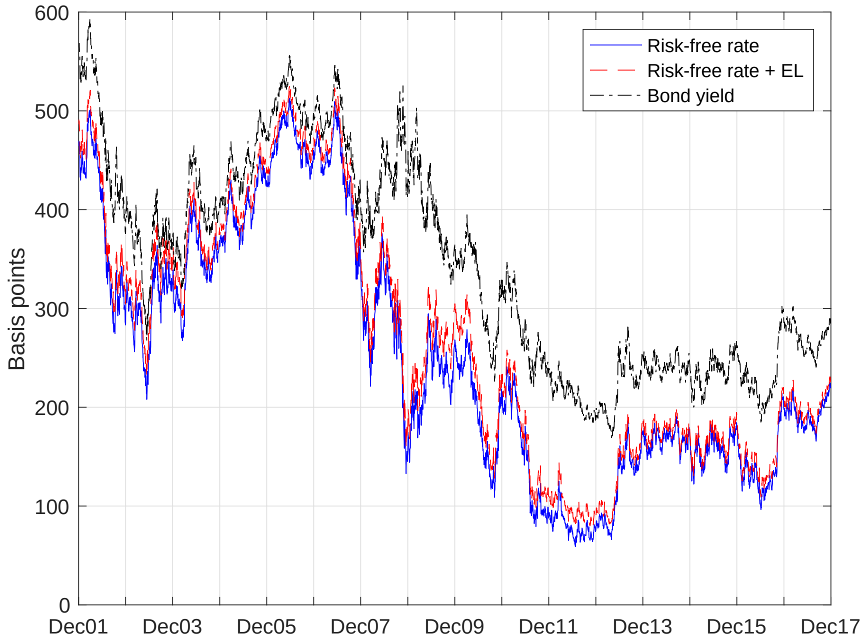

Figure 4: **Bond yields and their components** The figure shows the daily times series of Treasury rates, Treasury rates plus median expected loss rates, and Treasury rates plus median CDS rates (bond yields). The rates are annualized five-year rates. EL is computed using RMI PDs. Only those days on which data are available for 50 or more firms are shown.

for corporations as a result of the prolonged period of accommodative monetary policy, despite the offsetting effects of increased risk premia.

From 2008 onwards, several innovations in monetary policy had the potential to affect credit markets. Swanson (2015) categorizes these policies into (1) the near-zero rates; (2) forward guidance and (3) large-scale asset purchases (LSAPs). Based on changes related to these three categories, he identifies nine announcement dates during 2009-14 that were likely to have triggered significant responses to Federal Reserve policy actions. The LSAP announcements are usually associated with Quantitative Easing (QE). Wang (2014) analyzes the 3-day announcement effects in the CDS market for the five earliest of these dates and finds mixed effects. She argues that the most beneficial impact on credit spreads arose from an increase in confidence (the first QE) and from the flattening of the term structure that resulted from forward guidance.[7]

In Figures 5 and B.3 we examine bond-equivalent yields around the eight policy announcements

[7] The announcement dates are: (1) 3/18/09 for QE1; (2)11/3/10 for QE2; (3) 8/9/11 for FG through mid-2013; (4) 9/21/11 for Operation Twist; (5) 1/25/12 for FG through late 2014;(6) 9/13/12 for FG through mid-2015; (7) 12/12/12 for FG relative to unemployment and inflation expectations; (8) 12/18/13 for FOMC to taper its bond purchases; and (9) 12/17/14 for FOMC announcement on patience in normalizing monetary policy.

and consider the three components (the riskfree rate, EL, and the risk premium). The nine graphs, which are presented from the earliest date (March 18, 2009 – QE1) to the latest (December 17, 2014, the announcement regarding patience in normalizing rates), show a decline in the bond-equivalent yield from over 600 bp in the worst of the recession to a range near 200-250 bp for the other eight dates. About half the announcements lead to a lower yield on event date 0, but only QE1 and the fifth and six announcements (about forward guidance in 2013 and 2014) led to lower yields that remained low for as long as a month.

After QE1, the riskfree rate is substantially lower, especially around the time of the first FG announcement, but it varies quite a bit over the period and in between announcement dates. As expected, the taper announcement is a period when both riskfree and bond yields rise. The policy announcements have very little impact on EL and no clear pattern on credit risk premia. Thus, to the extent monetary policy announcements affected corporate interest rates, it is mainly through their impact on Treasury rates.

4. Explaining Credit Risk Premia Variation

In order to understand how the post-GFC period has affected credit risk premia, we need to understand how the market typically prices credit risk. Thus, we start with a basic model of credit spreads and expected losses to motivate our benchmark prediction model for CDS rates. Over short horizons, for small default probabilities PD and constant loss given default L, expected losses are given by $\mathrm{EL} = E(L\,D) = L\,\mathrm{PD}$, where D denotes the default indicator. CDS rates are given by

$$\begin{aligned} C &= E\left[m\,(L\,D)\right] \\ &= \mathrm{EL} + \mathrm{Cov}(m, L\,D), \end{aligned}$$

where m denotes the gross return on the stochastic discount factor. Dividing by EL and taking logs on both sides yields

$$\log\left(\frac{C}{\mathrm{EL}}\right) = \log\left(1 + \frac{1}{\mathrm{EL}}\,\beta\,L\,\mathrm{Var}(m)\right),$$

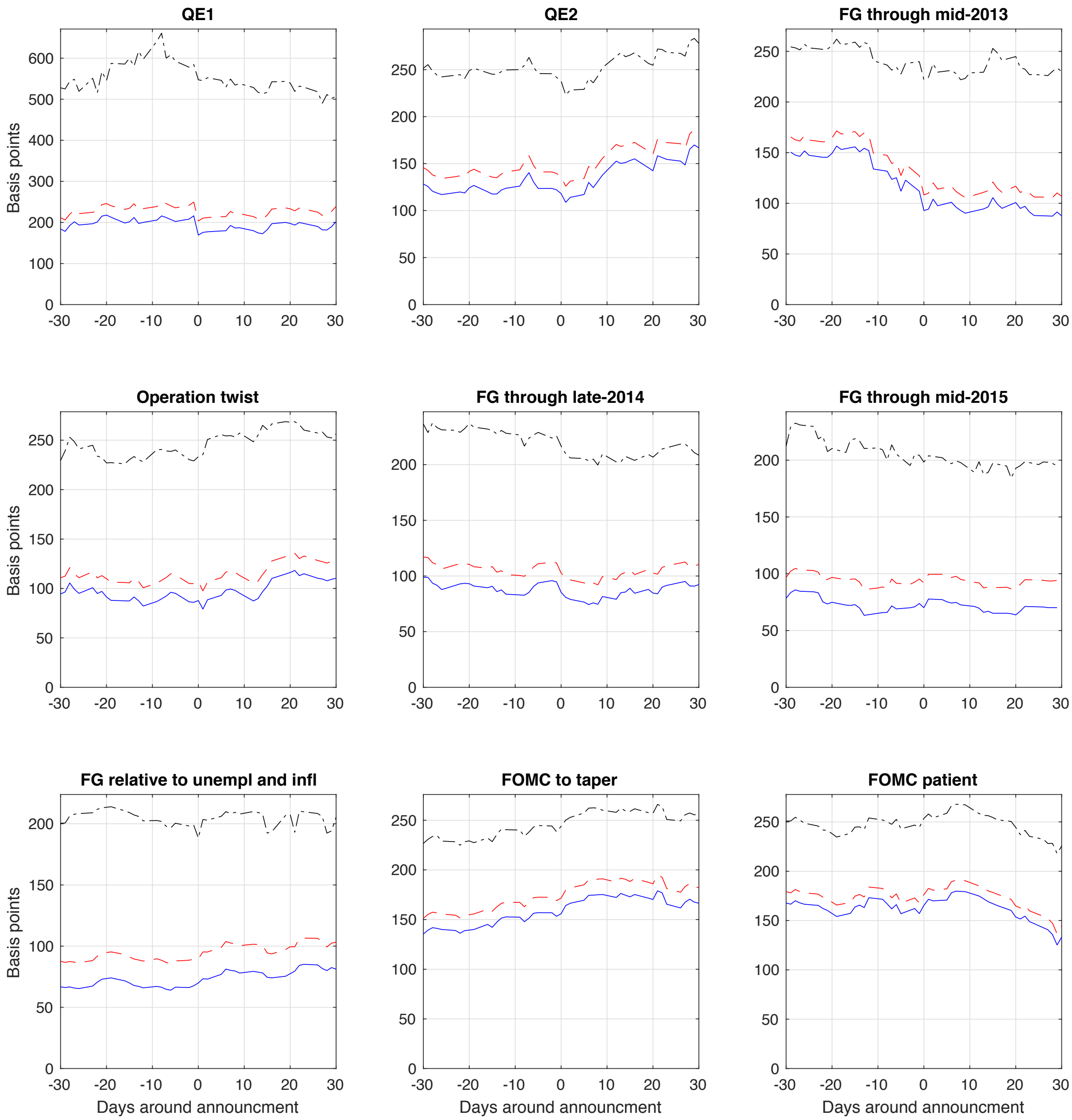

Figure 5: **Announcement effects on bond equivalent yields** The figure shows the daily five-year constant maturity Treasury rates (blue solid line), the Treasury rate plus the average five-year expected loss rate (red dashed line), and the Treasury rate plus the average five-year credit risk premium (black dash-dot line) around major unconventional monetary policy announcements, across Baa2 rated firms. EL is computed using RMI PDs.

where $\beta = \mathrm{Cov}(m, D)/\mathrm{Var}(m)$ measures the exposure to systematic default risk.[8]

Indexing firms by subscript i, and assuming $\log(C_i)$ is measured with noise ε_i, we have

$$\log\left(\frac{C_i}{\mathrm{EL_i}}\right) = \log(\beta_i) - \log(\mathrm{EL}_i) + \log(L_i) + \log(\mathrm{Var}(m)) + z_i + \varepsilon_i \tag{4}$$

[8]We thank Darrell Duffie for discussions related to this approach.

where $z_i = \log\left(1 + \frac{\text{Cov}(m, L_i D_i)}{\text{EL}_i}\right) - \log\left(\frac{\text{Cov}(m, L_i D_i)}{\text{EL}_i}\right)$ is smaller when $\text{Cov}(m, L_i D_i)/\text{EL}_i$ is larger.[9]

At a given point in time, we use $\overline{D}_k$ to denote the ex-post realized average default rate for rating category k over the next period. For firm i, let $k(i)$ denote the associated rating. We take the view that $E(D_i|\overline{D}_{k(i)}, m) = \overline{D}_{k(i)}$, meaning any systematic component of default risk at the firm level is captured by the ratings-wide performance of the firms in that rating category. Using the tower property of conditional expectations, we can show that

$$\text{Cov}(m, D_i) \quad = \quad E(mD_i) = E\left[E(mD_i|\overline{D}_{k(i)}, m)\right] = E(m\overline{D}_{k(i)}) = \text{Cov}\left(m, \overline{D}_{k(i)}\right). \tag{5}$$

In particular, $\beta_i = \beta_j$ for all firms i and j in the same rating category at a given point in time. Equation (5) assumes $E(m) = 0$. The result that betas are equal within a rating category can also be obtained when the $E(m) = 0$ assumption is replaced assuming constant default probabilities $E(D_i)$ within each rating class.

Since β is the same for firms of a given rating, we estimate it using the regression $D_i = \alpha_i + \beta_{k(i)}\widetilde{m} + \epsilon_i$, where $\widetilde{m}$ denotes a market performance variable (e.g., the realized market average default rate). The regression is implemented as

$$\text{PD}_i \quad = \quad \alpha_i + \beta_{k(i)} E(\widetilde{m}) + u_i, \tag{6}$$

where u_i are white noise measurement errors. Following Hilscher and Wilson (2016), we refer to β as "failure beta."

To estimate Equation (6), we measure PD_i by the one-year firm-level RMI PD and $E(\widetilde{m})$ as the median one-year RMI PD. The estimation is performed on the set of all firms that are present both in the RMI database and Moody's DRD database. The sample contains about 2,500 firms and covers the period from 1990 to 2017. Equation (6) is implemented as a panel-data regression with firm fixed effects. Figure 6 shows that the estimated failure betas are an increasing, concave function of firm default risk that is roughly linear in the log-log space.

With the log-linear approximation $\log(\beta_i) = a + b' \log(\text{EL}_i)$, with $b' \in (0, 1)$, Equation (4) can be

[9] For small positive x, $\log(1 + x)$ is close to x. As x increases above 1, $\log(1 + x)$ approaches $\log(x)$. As shown in Figure 3, $\text{Cov}(m, L\,D)/\text{EL}$ tends to be far above 1.

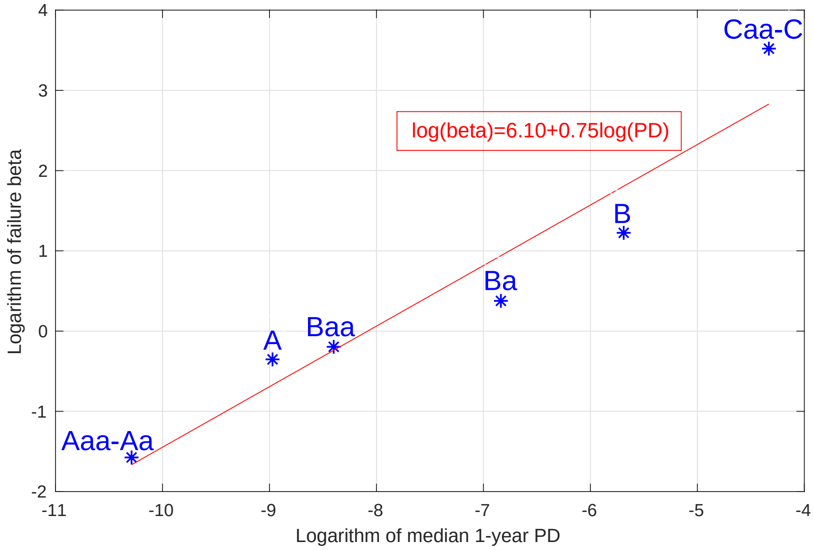

Figure 6: **Failure beta versus PD estimates** The figure shows the failure beta versus the one-year RMI PD estimate, logarithmic, by Moody's issuer rating. Failure betas are estimated using all firms with both PDs in the NUS RMI database and rating information from Moody's. The PD associated with rating k is the median PD, across firms with rating k and over time. The sample period is 1990–2017.

rewritten as

$$\log\left(\frac{C_i}{\mathrm{EL_i}}\right) = a + b\log\left(\mathrm{EL}_i\right) + \log(L_i) + \log\left(\mathrm{Var}(m)\right) + z_i + \varepsilon_i, \tag{7}$$

where $b = b' - 1 < 0$. Motivated by Equation (7), our benchmark model of credit risk premia is specified as

$$\log\left(\frac{C_t^i}{\mathrm{EL}_t^i}\right) = a + b\log(\mathrm{EL}_t^i) + X_t^i\, b_X' + Y_t\, b_Y' + \varepsilon_t^i, \tag{8}$$

where b_X and b_Y are coefficient vectors to be estimated. We use X_t^i and Y_t to denote vectors of firm-specific and macro-economic predictor variables that proxy for the level of aggregate risk—i.e., for $\log\left(\mathrm{Var}(m)\right)$—and control for mismeasurement of expected losses or market frictions. Mis-measurement of expected losses and CDS-market liquidity factors have been studied by Berndt, Douglas, Duffie, and Ferguson (2018), Driessen (2005), Blanco, Brennan, and Marsh (2005), Bai, Collin-Dufresne, Goldstein, and Helwege (2015), Chen, Collin-Dufresne, and Goldstein (2009), De Jong and Driessen (2012), Ericsson, Reneby, and Wang (2015), Han and Zhou (2016), and Tang and Yan (2010).

Table 3 reports the results. We present two specifications that vary according to the measure of expected losses, where the PD is approximated by RMI or ratings. As expected, we find that the absolute value of the regression coefficient on $\log(\mathrm{EL}_t^i)$ is less than one in both regressions. This implies that default risk premia—per unit of expected losses—tend to decrease as expected losses increase. This is also in line with the literature on the credit spread puzzle, which finds that the excess bond spread over and above expected losses is proportionately higher for investment grade bonds compared to high yield bonds (Huang and Huang (2012), Eom, Helwege, and Huang (2004), Berndt (2015)).

Note that each specification includes ratings and sector indicator variables as controls. In unreported results, these rating indicators are significantly different from the left out category of Baa2 and the omitted sector of consumer goods. In the RMI regressions, the coefficients on the ratings indicators are also monotonically increasing with credit risk, while they are mostly increasing with credit risk in the ratings-based specification. Table 3 includes implied volatilities from the firm's at-the-money and out-of-the-money equity options, allowing us to capture an element of skewness as well as overall uncertainty. These variables may also capture mismeasurement of expected losses. While RMI is a forward-looking measure of PDs and ratings are not, both regressions show that ratings momentum is significant. Firms that were recently upgraded have lower risk premia while firms that were recently downgraded command a higher premium. In addition to these variables, indicators for recent upgrades to investment-grade (IG) and for recent downgrades to speculative-grade (SG) are significant and consistent with a role for ratings momentum.

The benchmark estimation results suggest that a significant portion of the estimated risk premia owes to the sensitivity of the individual firm to systematic risk. In both regressions, the VIX and the skewness of the S&P 500 index are significantly positive. Besides the VIX, we also measure macroeconomic uncertainty with the University of Michigan consumer confidence index. The higher consumer confidence, the lower the risk premium. Finally, we include a proxy for CDS market liquidity. Table 3 includes two proxies for CDS liquidity: (1) the number of CDS quotes provided for the firm, which reflects the liquidity of the reference entity's CDS and (2) a proxy for CDS market liquidity, which is the inverse of the aggregate amount of CDS notional principal outstanding (obtained from ISDA and BIS and adjusted for double-counting). Both measures indicate that the risk premium is lower when liquidity is higher. The regressions in Table 3 have R-squares in the range of 0.73 to 0.83 and in both specifications the explanatory variables have similar coefficients and levels of significance.

Table 3: **Explaining credit risk premia variation** The table reports the results of the panel data regression (8). In the first column, expected losses EL are measured using RMI PDs, in the second column they are measured using refined-ratings-based PDs. IV_{atm} and IV_{otm} are the firm-level standardized 91-day put-implied volatilities at a Delta of –50% and –20%. IV_{atm} and IV_{otm} denote similar volatilities for the aggregate stock market. Refined ratings dummies identify the firm- and date-specific Moody's rating, adjusted for watchlist and outlook status. Recent upgrade/downgrade dummies are one if the firm's alphanumeric rating has been upgraded/downgraded in the past six months, and zero otherwise. CSENT is the University of Michigan Consumer Sentiment index. We also control for the number of CDS quotes provided to Markit for a given firm on a given date. The market total CDS notional outstanding is sourced from ISDA and BIS, and is measured in trillions of U.S. dollars, adjusted for double-counting. Credit spreads and expected losses are measured in basis points of notional, and implied volatility is measured in nominal terms. The benchmark refined rating category is Baa2 and the benchmark sector is Consumer Goods. Driscoll-Kraay standard errors that are robust to heteroskedasticity, autocorrelation and cross-sectional dependence are reported in parentheses. The data cover 522 public U.S. firms and nearly 1.3 million firm-date observations. The sample period is 2002-2017.

	RMI	Rtg
Constant	10.226	9.760
	(0.331)	(0.320)
log(EL)	-0.940	-0.735
	(0.003)	(0.018)
$\log(IV_{atm})$	0.727	0.856
	(0.019)	(0.017)
$\log(IV_{otm}/IV_{atm})$	0.826	0.823
	(0.040)	(0.039)
Recent upgrade	-0.036	-0.040
	(0.004)	(0.004)
Recent downgrade	0.123	0.122
	(0.007)	(0.007)
Recent upgr HY to IG	-0.053	-0.051
	(0.015)	(0.015)
Recent dngr IG to HY	0.108	0.098
	(0.017)	(0.018)
$\log(IV_{atm}^{SPX})$	0.199	0.157
	(0.039)	(0.040)
$\log(IV_{otm}^{SPX}/IV_{atm}^{SPX})$	3.118	3.120
	(0.160)	(0.165)
log(CSENT)	-1.281	-1.318
	(0.088)	(0.088)
Nbr of CDS quotes	-0.013	-0.010
	(0.002)	(0.001)
1/CDS notional	0.529	0.535
	(0.048)	(0.047)
Refined rating dummies	Yes	Yes
Sector dummies	Yes	Yes
R^2	0.831	0.729
RMSE	0.464	0.464

We use the residuals from these regressions to analyze how credit risk premia have been affected by the prolonged low interest rate environment. Figure 7 shows the daily time series of median residuals associated with the RMI regression in column 2 of Table 3.

The figure also shows the inverse of the Fed funds rate in red, indicating that the high level of the line from December 2008 on until December 2015 is when interest rates are at the zero lower bound. We

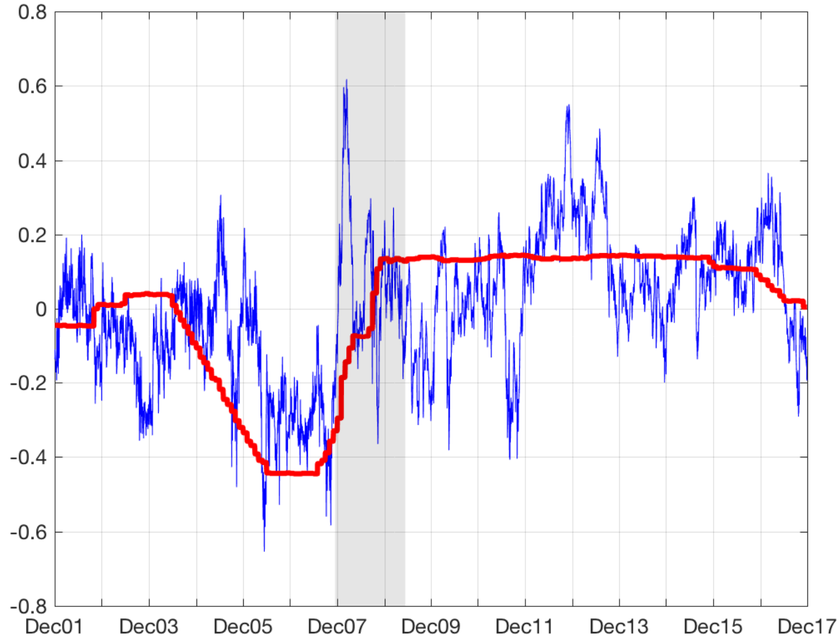

Figure 7: **Residuals** The figure shows—in the solid blue line—the daily time series of median residuals in the benchmark regression reported in column 1 of Table 3. EL is measured using RMI PDs. The red line is the negative Fed funds rate, shifted and scaled to have the same first two sample moments as the time series of median residuals. The shaded area indicates the NBER recession period from December 2007 to June 2009.

find that residuals are generally larger post-GFC than before. The lowest risk premia occur during the period when short-term interest rates were rising, which is consistent with earlier studies on reaching for yield (Adrian and Shin (2010), Rajan (2006), Becker and Ivashina (2015). While the magnitude of the typical risk premium in the Great Recession is multiples higher than that of the previous recession in 2001, both recessions are followed by a sharp decline in risk premia. However, the average over the later period is substantially higher. Since the regressions in Table 3 control for systematic risk exposure, the level of systematic risk, market frictions and expected losses, the increased risk premia in the low-for-long period are hypothesized to be related to factors that have not been important under other monetary policy regimes.

5. Explaining the Residual Variation in Credit Risk Premia

Our null hypothesis is that the residual risk premia obtained in Section 4 tend to be the same in the pre- and post-crisis period. This would be the case if the low interest rates from 2008 to 2016 only affected the expected losses and level of systematic risk in credit markets in the sense that all other pricing implications of unconventional monetary policy are limited to Treasury yields. We consider four alternative hypotheses: (i) post-GFC ambiguity aversion results in higher risk premia compared to periods with less extreme monetary policy; (ii) reaching for yield leads to unusually low risk premia for risky debt; (iii) the low-for-long period leads to declines in operating income among financial firms when revenue fails to cover expenses, which causes the remaining firms to demand a higher risk premium; and (iv) structural changes in the post-crisis period reduced the amount of risk capital available in credit markets, driving up risk premia.

We consider each hypothesis in turn. It is also possible that the null hypothesis is accepted, but the typical CDS premium in the low-for-long period is affected by a change in firms' exposure to systematic risk from before to after the crisis. That is, the price of risk may not have changed as a result of the time spent at the zero lower bound (ZLB) but the risk of the firms operating in this environment may not be constant over the whole sample period. Thus, our first test in this section focuses on changes in systematic risk exposure.

5.1 Changes in systematic default risk exposure

Figure 8 shows the time series of failure betas by letter rating.[10] For a given year, failure betas are estimated according to Equation (6) using data available until the end of the previous year. We find that the failure betas for IG firms are higher in 2002 and from 2010 onwards, and lower in between. Thus we postulate that some of the increase in residual credit risk premia during the post-GFC period observed in Figure 7 was associated with higher exposure to systematic default risk for IG firms.

Hypothesis 1 *Higher exposure to systematic default risk post-GFC, measured using failure betas, is associated with higher credit risk premia.*

We examine this hypothesis with two sets of regressions. In the first specification we simply add the failure beta to the set of predictor variables in Table 3. In the second specification we again add the failure beta but force the coefficient on log(EL) to be –1 as suggested by Equation (4). The results are reported in Table B.1 in the appendix.

Regardless of the specification, failure betas are significantly positive in each regression. Thus, the changes in systematic default risk exposure for IG firms observed in Figure 8 account for some of the

[10] Figure 8 shows the time series of failure betas for A, Baa, Ba and B rated firms, which covers most of the firms in our sample. The time series of failure betas for Aaa–Aa and Caa–C rated firms are shown in Figure B.4 in the appendix.

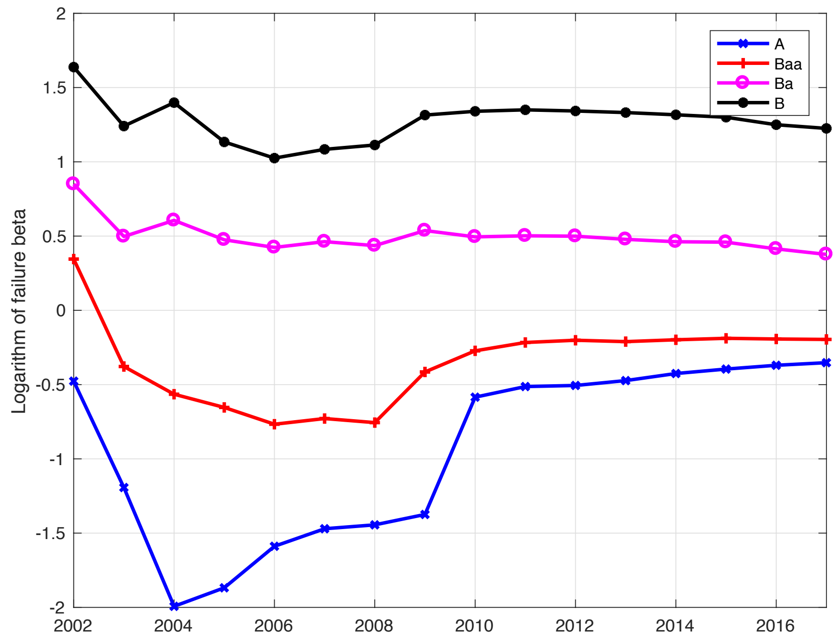

Figure 8: **Failure beta by rating** The figure shows the time series of failure betas by letter rating. For a given year, failure betas are estimated according to Equation (6) using data until the end of the previous year for firms that are covered by both the NUS RMI database and the Moody's DRD database.

higher risk premia in recent years. For example, all else the same, in the first specification the ratio of CDS rate to RMI-based expected loss rate is estimated to be $\exp(0.106 \times \log(0.76/0.66)) - 1 = 16\%$ higher when the failure beta increases from the 2009 Baa value of 0.66 to the 2010 Baa value of 0.76. By controlling for failure beta we are able to explain some of the cross-sectional variation in residual risk premia, as shown in Figure B.5 in the appendix. We note, however, that the explanatory power of the regressions is not much greater with the inclusion of failure beta, reflecting the difficulty in raising an already high R^2. We also note that temporal changes in the distribution of firms in the sample across the default risk spectrum should not be driving our results, as the regression controls for expected losses.

5.2 Ambiguity aversion

Evidence in Swanson (2015) suggests that investors were very unsure about the path of interest rate normalization after the Federal Reserve lowered rates in December 2008. We posit that monetary policy was so unusual in the post-crisis period that investors would demand a risk premium for the lack of clarity about future rates (Orphanides (2015), Dahlhaus and Gambetti (2018)). This hypothesis is based on the work of Puhl, Savor, and Wilson (2016), who find that FOMC announcements lead to an ambiguity risk premium in S&P 500 options. Similarly, Shi (2017) provides evidence that credit markets exhibit aversion to ambiguity.

To examine the effect of ambiguity aversion on credit risk premia we test two related hypotheses. First, we measure the level of uncertainty with the dispersion of macroeconomic forecasts reported in the Blue Chip Financial Forecasts. Specifically, we proxy ambiguity A with the interdecile range of the distribution F of individual forecasts in each quarter:

$$A_t \quad = \quad F_t^{-1}(0.9) - F_t^{-1}(0.1). \tag{9}$$

Shi (2017) analyzes the period 1985 to 2010 using dispersion of GDP forecasts, which we also examine in unreported results.[11] Given the focus on low interest rates after his period ends, we consider the dispersion of forecasts for the Fed funds rate. We use this measure to test the first hypothesis about macroeconomic uncertainty:

Hypothesis 2(a) *Ambiguity aversion, measured by the interdecile range of interest rate forecasts, is associated with an increase in the measured risk premium on CDS.*

Another measure of ambiguity is the volatility of volatility (VoV), suggested by Agarwal, Arisoy, and Naik (2017). Motivated by their results, we use the range of implied volatilities as a proxy for VoV:

$$\mathrm{VoV}_m \quad = \quad \log\left[\max_{t\in m}\{\mathrm{IV}_t\}\right] - \log\left[\min_{t\in m}\{\mathrm{IV}_t\}\right], \tag{10}$$

where the max and min are taking over all trading days t in a given month m. We calculate VoV at both the market aggregate and the firm levels.

Hypothesis 2(b) *Ambiguity aversion, measured by VoV, is associated with an increase in the measured risk premium on CDS.*

Table B.2 in the appendix shows our estimates of the impact of ambiguity aversion on credit risk premia. On the left side of the table we report the ambiguity measure related to the dispersion of

[11] We do not find that the GDP forecast range to be a significant predictor of residual credit risk premia.

interest rate forecasts. We find that ambiguity about future Fed funds rates has a significantly positive impact on credit risk premia. A one-standard deviation increase in FF range (see Table A.1) raises the fitted ratio of CDS rate to expected loss rate by about $\exp(0.39 \times 0.10) - 1 = 4\%$.

On the right side of Table B.2 we present the results of the model that tests Hypothesis 2(b). We compute VoV at the firm level and find that this measure of ambiguity aversion has a significantly positive impact on credit risk premia. With interpret this to mean that uncertainty about the firm's expected loss estimate is a source of ambiguity aversion. In unreported results, we also calculate market VoV but do not find significance. We attribute this result to the high time-series correlation between market volatility—which is included in the benchmark specification—and market VoV.

5.3 Reaching for yield

Rather than increasing the risk premium on credit instruments through ambiguity aversion, the low-for-long period may have led to lower yields through the reaching for yield phenomenon. The impetus to reach for yield may owe to a combination of low interest rates and agency problems or regulatory arbitrage (Becker and Ivashina (2015)). Thus, it need not involve mispricing or unusually low risk premia, but Hanson and Stein (2015), Adrian and Shin (2010), and Chodorow-Reich (2014) argue that increased demand for higher-yielding investments leads to higher prices on such assets and thus lower risk premia. Aramonte, Lee, and Stebunovs (2015) show theoretically that reaching for yield in a low interest rate environment effectively lowers risk aversion. The impact on risk premia could be for the riskiest asset classes as a whole, such as when investors are more willing to purchase any type of high yield bond to access higher yielding securities, or it could be for a specific set of bonds within an asset class. We test for evidence that risk premia are lower in the period after the crisis with two approaches. The first approach is simply to consider the low-interest period after the global financial crisis (July 2009 onwards) or, alternatively, the ZLB period, which is defined by the days on which the effective Fed funds rate is less than 25 basis points.

Hypothesis 3(a) *Reaching for yield in the low-interest period after 2009 leads to lower credit risk premia for riskier debt compared to the pre-recession period. Reaching for yield in the ZLB period is associated with lower risk premia on riskier credits.*

Chodorow-Reich (2014) provides evidence that reaching for yield occurs in the ZLB period but not for all institutions in all years during the period. In contrast, Di Maggio and Kacpercyzk (2017) argue that the impetus to reach for yield increases the longer market expects interest rates to remain low, which would cover most of the post-GFC crisis.

Since the time period indicator variable may not fully capture the reaching for yield effects we also consider the issuer quality measure for the corporate bond market proposed by Greenwood and Hanson (2013). We construct a similar measure of (low) issuer quality, ISS, defined as the average one-year RMI PD across firms in the highest quintile of debt issuance minus the average PD across firms in the lowest quintile of debt issuance. The time series of ISS is shown in Figure 9. Note that ISS is low towards the end of a recession (2002 and 2009) and high in the boom of the mid-2000s, which is when the Fed funds rate is highest in our sample. The variable is high again after the GFC ends—in 2010–2014—when the Fed funds rate is at the zero lower bound.

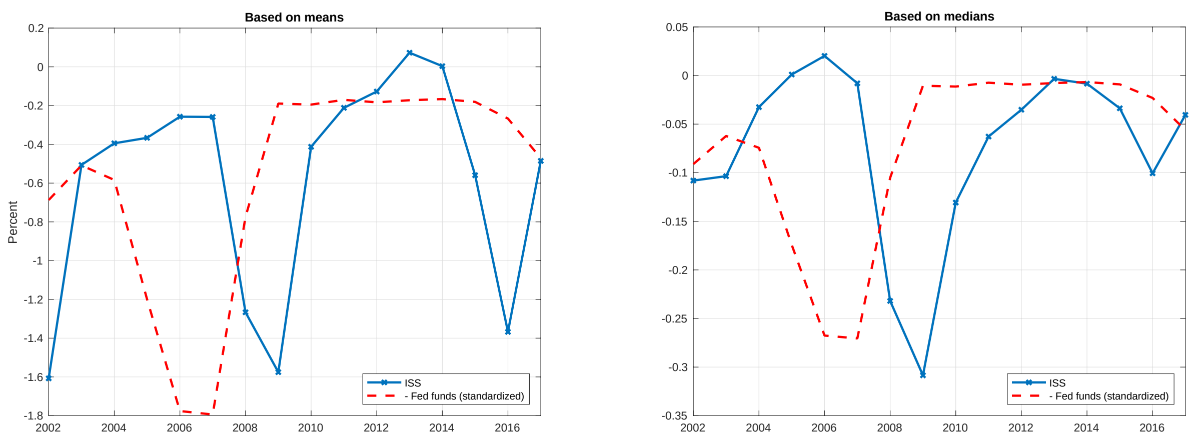

Figure 9: **Issuer quality** The figure shows the times series of issuer quality ISS. In the left plot, ISS is the average one-year RMI PD for the firms that issue large amounts of debt (firms in the highest quintile of debt issuance) minus the average PD of firms that issue little debt (firms in the lowest quintile of debt issuance). In the right plot, ISS is computed using median instead of average PDs. The red dashed line shows the negative Fed funds rate, shifted and scaled to have the same first two sample moments as ISS.

We sharpen our definition of reaching for yield to include only those years at the zero lower bound when issuer quality is low or decreasing. More precisely, we consider ZLB years where ISS exceeds its trailing 3-year average. These years are 2010–2014.

Hypothesis 3(b) *Reaching for yield is high in periods when interest rates are low and issuer quality is low or decreasing. Reaching for yield is associated with lower risk premia on lower quality credits.*

Our findings related to Hypotheses 3(a) and 3(b) are summarized in Table B.3. Given that the post-GFC and ZLB dummies are highly correlated with other benchmark predictor variables, we report results for the residual credit risk premia computed in Table B.1 rather than unconditional risk premia.[12] The post-GFC and ZLB indicators suggest the opposite relative effect on HY and IG debt. While residual risk premia for IG firms are higher during the ZLB period, they are lower for HY firms. Thus the relative price of HY debt is higher in the ZLB period. The results on relative prices supports the hypothesis that reaching for yield lowers risk premia on riskier bonds. Similarly, when interest rates are low and ISS is high or increasing—indicating that the refined proxy for reaching for yield is high—the risk premia on HY firms decreases relative to the risk premia on IG debt.[13]

5.4 Operating costs

An alternative effect of the low rate environment could occur as a result of the extreme pressure on the operating income of financial intermediaries. Borio and Zhu (2012) and Chodorow-Reich (2014) point to the administrative costs of running these firms, which may exceed revenue when yields on safer assets fall in an easy money period. Chodorow-Reich (2014) and Di Maggio and Kacpercyzk (2017) provide evidence that the low interest rates put extreme pressure on MMMFs, such that they not only were incentivized to reach for yield to cover expenses but some funds failed to cover their expenses and were forced to exit the industry. The remaining firms in the industry would not be willing to provide capital to credit markets unless the return was high enough to compensate for the risk.

While MMMFs are not participants in the CDS market, the pressure to cover fixed costs is not unique to MMMFs. Chodorow-Reich (2014) notes that defined-benefit pension funds also face fixed expenditures that are less likely to be covered in a low rate environment and Borio and Zhu (2012) argue that the ZLB has a negative impact on profits in the presence of such fixed costs at insurers and banks as well. Hence, we expect the pressure on MMMFs to be correlated with the pressures on other financial intermediaries that focus on fixed-income investments and are limited in their ability to increase revenue in the low-rate environment. If the low rate environment reduces the profitability of intermediaries that concentrate their assets in the fixed income sector, then exit and the threat of exit will shift the supply curve of capital in credit markets inward. The result would be a higher risk

[12] We also computed results for the residual credit risk premia from the benchmark regression in Table 3. The findings were qualitatively similar to those in Table B.3, but with somewhat lower levels of significance for the RFY × HY variable.

[13] The result is significant for both IG and HY debt when RMI-based expected loss rates are used. For ratings-based expected loss rates we obtain the same signs but the HY regression coefficient is not statistically significant.

premium on credit market instruments in the low-for-long period:

Hypothesis 4 *Pressure from abnormally low revenues relative to fixed costs leads to exit of financial intermediaries. The remaining providers of risk capital require a higher risk premia on credit risky instruments.*

The results of our tests of Hypothesis 4 are shown in Table B.4 in the appendix. The regressions on the left side of the table measure the pressure on profits with the operating costs—defined as the difference between the average MMMF expense ratio and the T-bill rate—whereas the regressions on the right side of the table split out the effects of the expense proxy according to the firm's rating. We expect that the negative effects on profitability and thus the supply curve will be greatest for IG debt that has exceptionally low yields during the ZLB period. The table shows that the change in operating costs is associated with higher credit risk premia. As expected, the impact is greatest on IG bonds.

5.5 Regulation

Finally, we consider the impact of regulations on the structure of corporate credit markets. The low-for-long period includes two major regulatory changes that may have affected CDS pricing. One is the element of the Volcker Rule that attempts to limit proprietary trading by investment banks. This rule was included in Dodd-Frank, which was passed in 2010, but implementation of the rule was delayed until regulators could decide how best to execute Congress' directive. An on-going debate in the literature (Bao, O'Hara, and Zhou (2018), Dick-Nielsen and Rossi (2018), Anderson and Stulz (2017)) considers whether the Volcker Rule reduced dealers' willingness to provide liquidity in the corporate bond market. The disruption to the corporate bond market would have an impact on trading in the CDS market (Zawadowski and Oehmke (2012), Boyarchenko, Gupta, Steele, and Yen (2016)). Thus, the first of two hypotheses related to the structure of the market posits that the negative impact on dealer participation in the corporate bond market reduces the capital available for risk-sharing in corporate credit markets:

Hypothesis 5(a) *The expected implementation of the Volcker Rule after 2010 and its actual implementation in April 2014 reduced the amount of risk capital available in the CDS market, leading remaining traders to only participate if the risk premium was higher than before the rule.*

Another regulatory change in the low-for-long period is the requirement that derivatives trade on an exchange. Boyarchenko, Gupta, Steele, and Yen (2016) note that the CDS-basis is impacted by the initiation of central counterparties (CCPs), which they argue results from the fact that the rule effectively requires investors in the CDS market to hold more capital. For example, prior to this regulation, AIG was able to avoid full payment of mark-to-market variation margin until ratings triggered collateral calls in 2008 (McDonald and Paulson (2015)). Had AIG attempted to sell the \$527 b. in notional CDS it had on the books in 2007 after the CCP requirement, it would have required a much larger capital base. Aldasoro and Ehlers (2018) show that the market share of central counterparties (CCPs) grows to over half of the notional amount outstanding by 2017. The sharp increase from zero market share in 2010 comes at the expense of securities firms and banks. Hence, if the cost of participating in the CDS market increases as a result of the CCPs, the return to providing risk capital in the CDS market would have fallen and the supply of capital would decrease. The result would be an inward shift in the supply curve of CDS capital and an increase in the price required of suppliers. Our second hypothesis related to the structure of the market is:

Hypothesis 5(b) *The increased share of CCPs in the CDS market raises the cost of providing capital and increases the required risk premium on CDS.*

If the higher capital requirements involved in CDS trading lead to higher premia, then the amount of capital in the financial system will be related to credit risk premia. Given the existence of CCPs in the later part of the sample period, we also consider the role of bank and insurer capital ratios.

Tables B.5 and B.6 in the appendix report the results of our tests of Hypotheses 5(a) and 5(b). The tables show that indicator variables for post-Dodd Frank years and post-Volcker Rule years are significantly positive, in line with Hypothesis 5(b). The effect of CCPs in the derivatives market also sharply raises the required return on capital in CDS markets. The coefficients on capital ratios for banks and for insurers are both significantly positive in their respective regressions. While the reaching for yield literature often argues that excess capital is put to work in boom times with riskier bets (e.g., Rajan (2006), Adrian and Shin (2010)), the capital ratio variables suggest the opposite—that financial intermediaries require a higher risk premium when capital is high and they will take a lower risk return when capital is scarce. A more plausible explanation is that the period of high risk premia coincides with periods of higher capital due to changes in regulation.

6. Concluding Remarks

The Federal Reserve undertook extraordinary measures to combat the Global Financial Crisis (GFC), including lowering interest rates to the zero lower bound (ZLB) for an extended period of time. While the lower Fed funds rate reduced the overall cost of borrowing for corporate issuers, as can be seen in lower bond equivalent yields, credit risk premia in the post-GFC period did not return to pre-crisis levels. This was especially true for investment grade (IG) firms.

To come to this conclusion we decompose credit default swap (CDS) rates into expected losses and credit risk premia. After controlling for known factors that contribute to credit risk premia, we find that the residuals from our benchmark model tend to be higher in the post-GFC period. We investigate the unexpected change in credit risk premia and find that several factors have an effect on CDS market pricing.

First, firms with traded CDS contracts may have become riskier in the ZLB period, either because their fundamental business changes or because investors' perceptions of their risks changed. We find evidence that estimates of systematic default risk exposure increased in the post-GFC period, leading to higher risk premia.

Another possibility is that uncertainty about macroeconomic policy led to a higher risk premium related to ambiguity aversion. Using the dispersion of forecasts on the Fed funds rate and firm-level volatility of volatility, we find some support for ambiguity aversion as a factor. This suggests that the Federal Reserve's efforts at transparency, while greatly increased over its history, might be improved upon further.

We also find support for a role for "reaching for yield." Specifically, while median credit risk premia are higher, the riskiest firms in the sample experienced lower credit risk premia relative to IG firms. This is consistent with investors shunning the safer, lower-yielding instruments in favor of debt instruments with higher returns. We find similar evidence about IG debt relative to weaker credits when we employ the Greenwood and Hanson (2013) variable that measures issuer quality to refine our reaching-for-yield proxy.

The ZLB period is exceptionally challenging for financial intermediaries that mainly invest in safer fixed income assets because their revenues drop much more than their expenses. While money market mutual funds are not involved in the CDS market, their difficulties in covering fixed operating expenses are shared by pension funds, insurers and banks that do trade CDS. We use the difference between short-term Treasury rates and money fund expenses to proxy for changes in the supply of CDS market capital. We find that the reduction in suppliers of risky capital contributes to the higher credit risk premia in the ZLB period.

Regulation also appears to be a factor in the post-GFC period. The Volcker Rule is a potential impediment to CDS trading and we find that its implementation in 2014 is associated with higher required premia on CDS. Similarly, the higher capital required to trade CDS once derivatives are required to be traded with central counterparties also appears to raise the required premia for investors in the CDS market. Related to these findings, the relationship between bank capital and risk premia is positive, as it is for insurers too.

In sum, while the long period of low interest rates after the financial crisis led to a lower cost of borrowing for U.S. corporations, the higher credit risk premia that accompanied the ultra-low rates did not. Thus, if it were possible to lower risk premia while also lowering expected losses and Treasury rates, the ZLB policy might be a more effective tool in future recoveries.

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A. Conditioning Variables

This appendix provides summary statistics on the variables that are included in the benchmark credit risk premia model and details on the sources of data used to test the hypotheses related to the residuals.

A.1 Variables used in the benchmark model

Refined ratings, as was described earlier in the text, are associated with firms based on Moody's rating and adjusted for watchlist and outlook status. Recent upgrade/downgrade indicator variables are one if the firm's alphanumeric rating has been upgraded/downgraded in the past six months, and zero otherwise. Implied volatility is calculated from equity options and is measured in nominal terms.

We measure consumer confidence with the University of Michigan Consumer Sentiment index. Composite depth is a proxy for the market liquidity of the firm's CDS and is measured by the number of CDS quotes provided to Markit for a given firm on a given date. The market total CDS notional outstanding is sourced from ISDA and BIS, and is measured in trillions of U.S. dollars, adjusted for double-counting.

A.2 Ambiguity measures

Data on macroeconomic forecasts are obtained from the Blue Chip Financial Forecasts, which are monthly forecasts of GDP and interest rates for five quarters ahead. The Blue Chip forecast data include individual forecaster estimates as well as the consensus forecast. The number of forecasters surveyed is typically in the range of 45 to 50 economists. Following Shi (2017), we use the one-quarter ahead forecasts of GDP and the Fed Funds rate in the months of January, April, and October to calculate quarterly time series of the dispersion of analysts' forecasts. The dispersion is calculated as the difference in the 90th and 10th percentiles of individual forecasts.

The VoV ambiguity measure is constructed following the method in Agarwal, Arisoy, and Naik (2017). However, rather than calculating the VoV just for the VIX, we calculate the volatility of the volatility of the firm's equity to create a firm VoV variable.

A.3 ISS prediction

The ISS variable is measured following the method in Greenwood and Hanson (2013), using one-year RMI PDs to measure issuer quality.

A.4 Expense ratio—revenue pressure

We use the average expense ratio of MMMFs as a measure of the pressure on financial intermediaries that invest in safe fixed income assets. We obtain MMMF expenses from the Investment Company Institute (ICI). The ICI reports average expenses on an annual basis. Following Chodorow-Reich (2014), we compare the average expense ratio of the MMMFs to the yield on the one-month Treasury bill. To obtain the average T-bill yield for the calendar year, we average the monthly rates reported by the St. Louis Federal Reserve's FRED database.

A.5 Capital ratio for life insurance companies

The American Council of Life Insurers (ACLI) reports insurance capital on a yearly basis. We obtain data from 2002 to 2016 on the capital surplus ratio excluding valuation allowances from the 2016 ACLI factbook. Because the 2017 ratio is not available, we assume the 2017 ratio is the same as the 2016 capital ratio.

A.6 Capital ratio for banks

Bank equity to asset ratios are obtained from the FDIC, which reports ratios for all banks and for the following categories: (1) over $250 billion (b.) in assets; (2) assets of $10 b. to $250 b.; (3) $1 b. to 10 b. and (4) under $1 billion. We use the second largest category of banks because it is less subject to small sample issues but still represents the banks that are the most likely to engage in CDS transactions.

A.7 CDS market structure

Aldasoro and Ehlers (2018) show evidence on changes in counterparty relationships in the CDS market, noting that in 2010 CDS are required to trade on exchanges. They obtain data from the BIS, which reports data on counterparties in the CDS market on a semi-annual basis beginning in 2004. Since the CCP market share is zero in 2004 and continues to be zero until 2010, we assume it is zero in 2002 and 2003 as well.

A.8 Descriptive statistics

Table A.1 provides descriptive statistics for the variables described in this appendix. For variables that exhibit substantial skewness, such as the volatility measures, RMI-based expected losses, consumer sentiment, the volume of defaulted debt and CDS composite depth, we also provide descriptive statistics for skewness-reducing variable transformations.

Table A.1: **Descriptive statistics for conditioning variables** The table reports descriptive statistics for the control variables in the panel regression (8). Volatilities are measured in nominal terms, interest rates in percent, and CDS notional in trillions of U.S. dollars.

	Mean	SD	5%	25%	50%	75%	95%
				Raw data			
IV_{atm}	0.32	0.18	0.16	0.21	0.27	0.37	0.65
IV_{otm}/IV_{atm}	1.17	0.20	1.04	1.11	1.15	1.20	1.33
IV_{atm}^{SPX}	0.18	0.07	0.11	0.13	0.16	0.21	0.32
$IV_{otm}^{SPX}/IV_{atm}^{SPX}$	1.29	0.07	1.18	1.24	1.29	1.33	1.43
CSENT	82.41	11.36	60.10	74.20	84.60	91.90	96.90
Composite depth	7.5	4.1	3.0	5.0	7.0	9.0	15.0
CDS notional	22.9	15.3	2.2	11.8	21.0	30.4	54.6
Fed funds rate	1.52	1.78	0.08	0.14	0.79	2.28	5.25
5-year Treasury rate	2.61	1.27	0.81	1.57	2.34	3.70	4.71
Slope	1.1	0.9	-0.7	0.6	1.3	1.7	2.4
FF range	0.14	0.10	0.00	0.10	0.10	0.20	0.30
Firm VoV	0.19	0.16	0.07	0.11	0.16	0.22	0.41
MM-MF	1.01	1.52	-0.23	-0.11	0.58	1.16	4.26
CCP	0.07	0.09	0.00	0.00	0.00	0.11	0.30
Insurance capital ratio	8.9	0.4	8.1	8.6	8.9	9.2	9.5
Bank capital ratio	9.3	1.1	7.4	8.4	9.7	10.3	10.6
				Transformed data			
$\log(IV_{atm})$	-1.24	0.44	-1.84	-1.55	-1.29	-0.99	-0.44
$\log(IV_{otm}/IV_{atm})$	0.15	0.10	0.04	0.10	0.14	0.18	0.28
$\log(IV_{atm}^{SPX})$	-1.79	0.35	-2.24	-2.06	-1.85	-1.56	-1.15
$\log(IV_{otm}^{SPX}/IV_{atm}^{SPX})$	0.25	0.06	0.17	0.22	0.25	0.29	0.35
$\log$ CSENT	4.40	0.15	4.10	4.31	4.44	4.52	4.57
1/CDS notional	0.11	0.17	0.02	0.03	0.05	0.08	0.46

B. Additional Tables and Figures

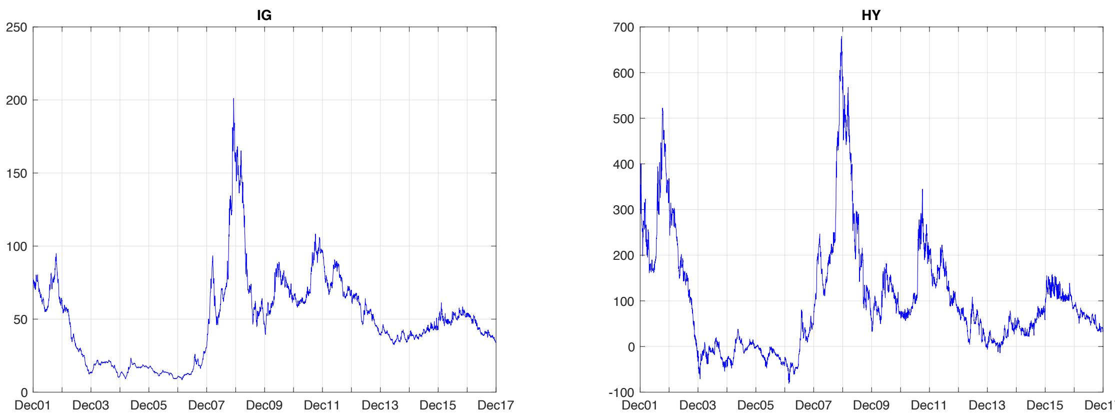

Figure B.1: **Median ratings-based credit risk premia** The left panel of the figure shows the daily times series of the median premium-to-expected-loss ratio, $\mathrm{RP}_t/\mathrm{EL}_t$ for IG firms. EL is computed using refined-ratings-based PDs. Only days on which premia are available for 50 or more IG firms are shown. The right panel shows the daily median across HY firms. Only days on which premia are available for 10 or more HY firms are shown.

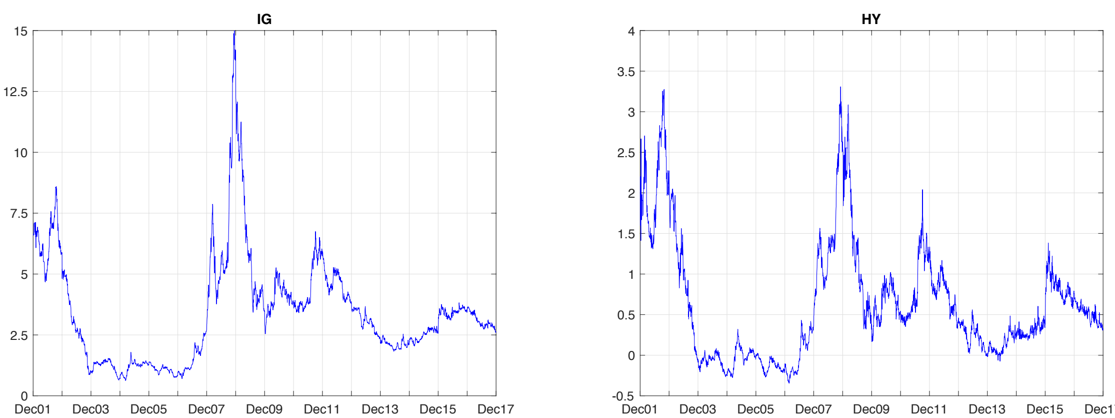

Figure B.2: **Median ratings-based credit risk premia per unit of expected loss** The left panel of the figure shows the daily times series of the median premium-to-expected-loss ratio, $\mathrm{RP}_t/\mathrm{EL}_t$ for IG firms. EL is computed using refined-ratings-based PDs. Only days on which premia are available for 50 or more IG firms are shown. The right panel shows the daily median across HY firms. Only days on which premia are available for 10 or more HY firms are shown.

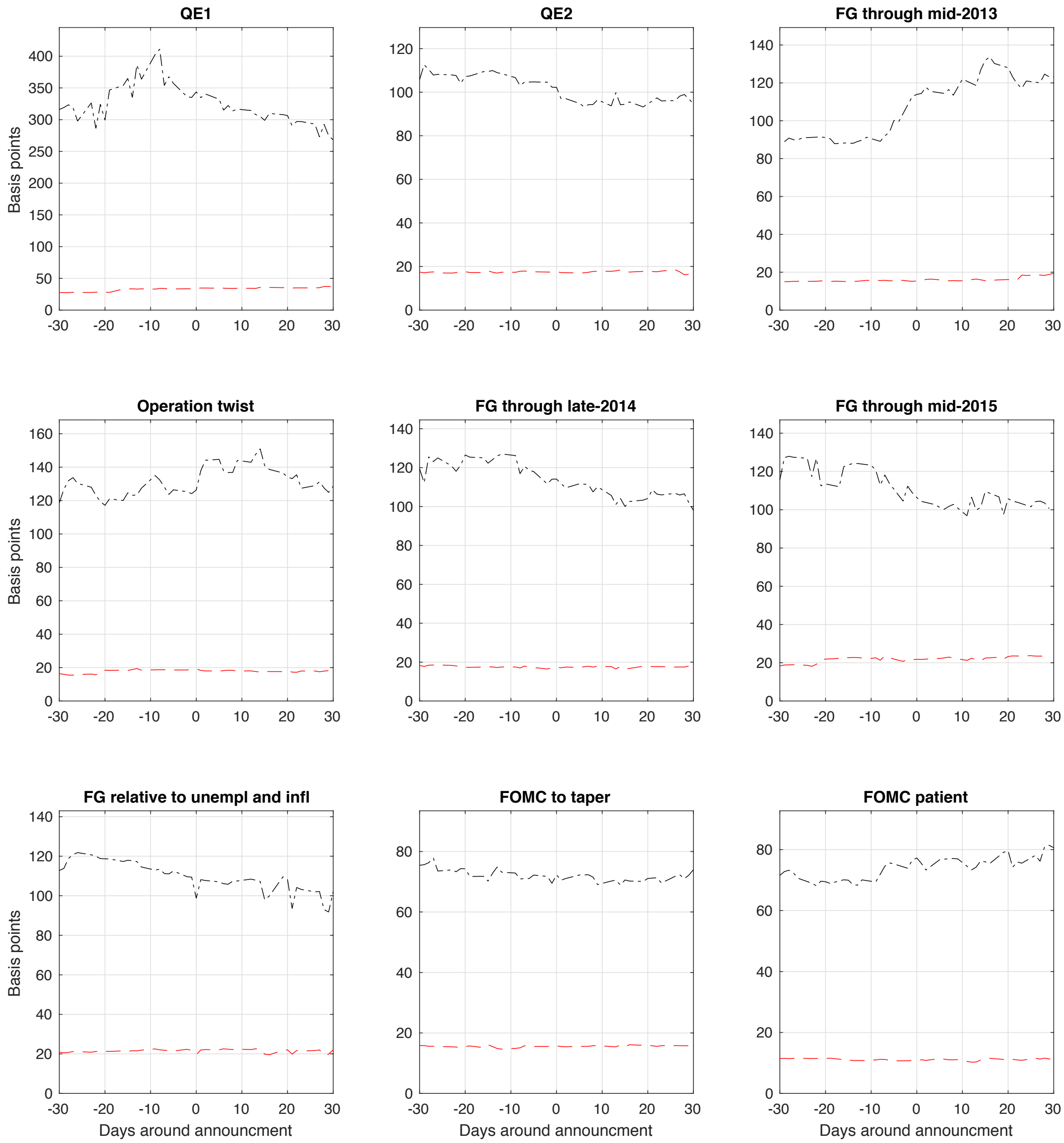

Figure B.3: **Announcement effects on expected losses and credit risk premia** The figure shows the daily average five-year expected loss rate (red dashed line) and the daily average five-year credit risk premium (black dash-dot line) around major unconventional monetary policy announcements, across Baa2 rated firms. EL is computed using RMI PDs.

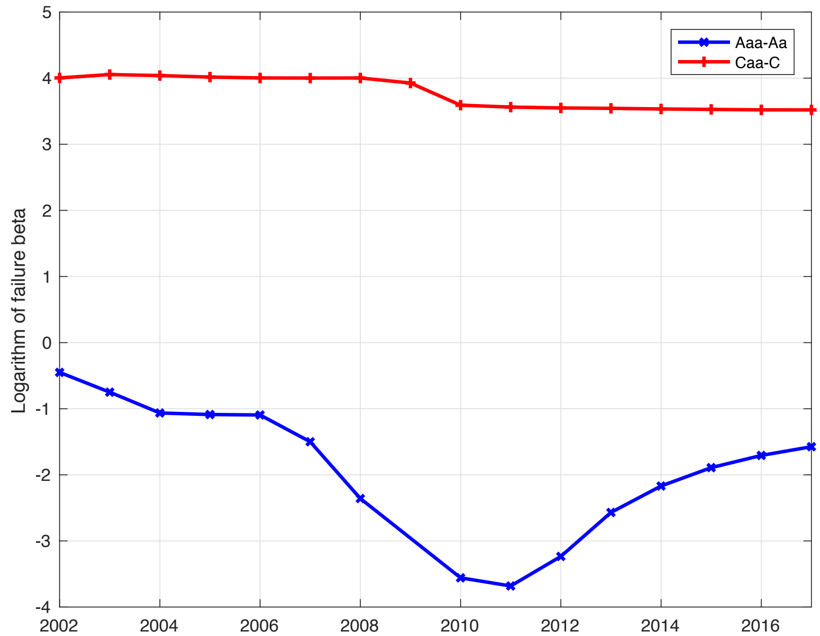

Figure B.4: **Failure beta for Aaa–Aa and Caa–C rated firms** The figure shows the time series of failure betas for Aaa–Aa and Caa–C rated firms. For a given year, failure betas are estimated according to Equation (6) using data until the end of the previous year for firms that are covered by both the NUS RMI database and the Moody's DRD database. For Aaa–Aa rated firms, the 2009 failure beta estimate is slightly negative and omitted from the plot.

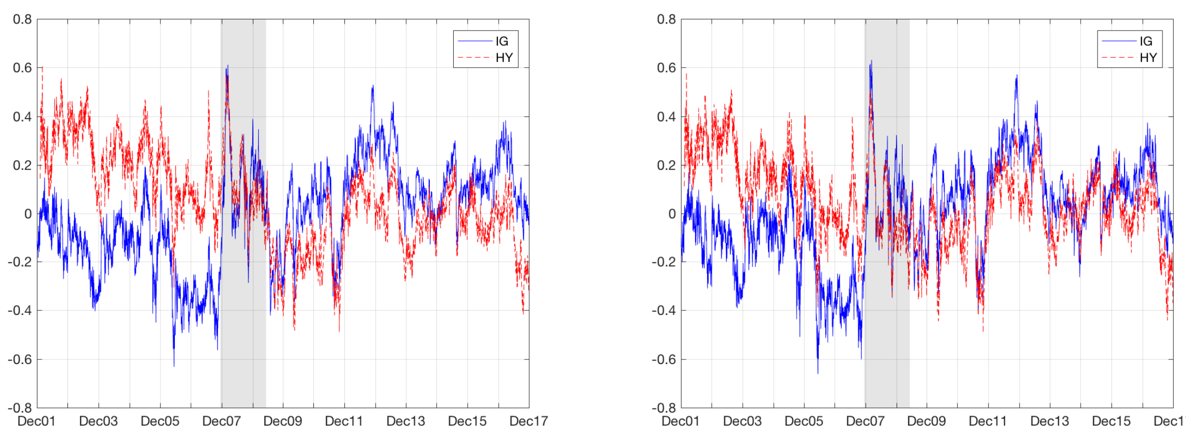

Figure B.5: **Residuals by credit status** The left figure shows the daily time series of median residuals in the benchmark regression reported in column 1 of Table 3. EL is measured using RMI PDs. The right figure shows the residuals in column 1 of Table B.1. The shaded area indicates the NBER recession period from December 2007 to June 2009.

Table B.1: **Changes in systematic default risk exposure** The table reports the results of the panel data regression (8). In the first column, expected losses EL are measured using RMI PDs, in the second column they are measured using refined-ratings-based PDs. IV_{atm} and IV_{otm} are the firm-level standardized 91-day put-implied volatilities at a Delta of –50% and –20%. IV_{atm} and IV_{otm} denote similar volatilities for the aggregate stock market. Refined ratings dummies identify the firm- and date-specific Moody's rating, adjusted for watchlist and outlook status. Recent upgrade/downgrade dummies are one if the firm's alphanumeric rating has been upgraded/downgraded in the past six months, and zero otherwise. CSENT is the University of Michigan Consumer Sentiment index. We also control for the number of CDS quotes provided to Markit for a given firm on a given date. The market total CDS notional outstanding is sourced from ISDA and BIS, and is measured in trillions of U.S. dollars, adjusted for double-counting. The failure beta is estimated using Equation (6). For a given year, only data available until the end of the previous year are used the estimation of (6). In the third column, we force the coefficient on log(EL) to be –1 by regressing $\log(C)$ on all other predictor variables. Credit spreads and expected losses are measured in basis points of notional, and implied volatility is measured in nominal terms. The benchmark refined rating category is Baa2 and the benchmark sector is Consumer Goods. Driscoll-Kraay standard errors that are robust to heteroskedasticity, autocorrelation and cross-sectional dependence are reported in parentheses. The data cover 522 public U.S. firms and nearly 1.3 million firm-date observations. The sample period is 2002–2017.

	RMI	Rtg	
Constant	10.158	9.785	10.510
	(0.316)	(0.308)	(0.316)
log(EL)	-0.941	-0.764	-1.000
	(0.003)	(0.019)	
$\log(\mathrm{IV}_{atm})$	0.726	0.853	0.836
	(0.019)	(0.018)	(0.018)
$\log(\mathrm{IV}_{otm}/\mathrm{IV}_{atm})$	0.801	0.804	0.809
	(0.038)	(0.037)	(0.038)
Recent upgrade	-0.046	-0.048	-0.051
	(0.005)	(0.005)	(0.005)
Recent downgrade	0.132	0.131	0.141
	(0.007)	(0.007)	(0.007)
Recent upgr HY to IG	-0.037	-0.039	-0.040
	(0.015)	(0.015)	(0.015)
Recent dngr IG to HY	0.086	0.080	0.080
	(0.017)	(0.018)	(0.018)
$\log(\mathrm{IV}^{SPX}_{atm})$	0.194	0.152	0.150
	(0.038)	(0.039)	(0.038)
$\log(\mathrm{IV}^{SPX}_{otm}/\mathrm{IV}^{SPX}_{atm})$	2.775	2.838	2.725
	(0.155)	(0.162)	(0.155)
log(CSENT)	-1.238	-1.281	-1.273
	(0.084)	(0.085)	(0.084)
Nbr of CDS quotes	-0.012	-0.009	-0.010
	(0.001)	(0.001)	(0.001)
1/CDS notional	0.424	0.454	0.460
	(0.047)	(0.047)	(0.046)
Failure beta	0.106	0.086	0.107
	(0.008)	(0.008)	(0.008)
Rating dummies	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes
R^2	0.833	0.728	0.797
RMSE	0.462	0.462	0.465

Table B.2: **Ambiguity aversion** The table reports the results of the panel data regression (8). In the first column, expected losses EL are measured using RMI PDs, in the second column they are measured using refined-ratings-based PDs. IV_{atm} and IV_{otm} are the firm-level standardized 91-day put-implied volatilities at a Delta of –50% and –20%. IV_{atm} and IV_{otm} denote similar volatilities for the aggregate stock market. Refined ratings dummies identify the firm- and date-specific Moody's rating, adjusted for watchlist and outlook status. Recent upgrade/downgrade dummies are one if the firm's alphanumeric rating has been upgraded/downgraded in the past six months, and zero otherwise. CSENT is the University of Michigan Consumer Sentiment index. We also control for the number of CDS quotes provided to Markit for a given firm on a given date. The market total CDS notional outstanding is sourced from ISDA and BIS, and is measured in trillions of U.S. dollars, adjusted for double-counting. FF range is the interdecile range of interest rate forecasts from the Blue Chips Financial Forecasts. Firm VoV is computed using Equation (10). Credit spreads and expected losses are measured in basis points of notional, and implied volatility is measured in nominal terms. The benchmark refined rating category is Baa2 and the benchmark sector is Consumer Goods. Driscoll-Kraay standard errors that are robust to heteroskedasticity, autocorrelation and cross-sectional dependence are reported in parentheses. The data cover 522 public U.S. firms and nearly 1.3 million firm-date observations. The sample period is 2002–2017.

	RMI	Rtg		RMI	Rtg
Constant	9.886	9.381	Constant	10.222	9.758
	(0.357)	(0.360)		(0.334)	(0.322)
log(EL)	-0.936	-0.715	log(EL)	-0.940	-0.734
	(0.003)	(0.018)		(0.003)	(0.019)
$\log(IV_{atm})$	0.710	0.848	$\log(IV_{atm})$	0.726	0.856
	(0.019)	(0.018)		(0.019)	(0.017)
$\log(IV_{otm}/IV_{atm})$	0.813	0.810	$\log(IV_{otm}/IV_{atm})$	0.779	0.780
	(0.039)	(0.038)		(0.040)	(0.039)
Recent upgrade	-0.035	-0.039	Recent upgrade	-0.036	-0.039
	(0.004)	(0.004)		(0.004)	(0.004)
Recent downgrade	0.122	0.121	Recent downgrade	0.122	0.121
	(0.007)	(0.007)		(0.007)	(0.007)
Recent upgr HY to IG	-0.055	-0.054	Recent upgr HY to IG	-0.054	-0.052
	(0.014)	(0.015)		(0.015)	(0.015)
Recent dngr IG to HY	0.107	0.096	Recent dngr IG to HY	0.105	0.095
	(0.017)	(0.017)		(0.017)	(0.018)
$\log(IV^{SPX}_{atm})$	0.220	0.175	$\log(IV^{SPX}_{atm})$	0.184	0.143
	(0.039)	(0.040)		(0.040)	(0.041)
$\log(IV^{SPX}_{otm}/IV^{SPX}_{atm})$	3.121	3.124	$\log(IV^{SPX}_{otm}/IV^{SPX}_{atm})$	3.111	3.113
	(0.159)	(0.163)		(0.161)	(0.166)
log(CSENT)	-1.214	-1.252	log(CSENT)	-1.291	-1.327
	(0.092)	(0.093)		(0.089)	(0.089)
Nbr of CDS quotes	-0.014	-0.011	Nbr of CDS quotes	-0.014	-0.010
	(0.001)	(0.001)		(0.002)	(0.001)
1/CDS notional	0.516	0.523	1/CDS notional	0.541	0.547
	(0.045)	(0.044)		(0.048)	(0.047)
FF range	0.391	0.395	Firm VoV	0.136	0.126
	(0.097)	(0.097)		(0.022)	(0.023)
Refined rating dummies	Yes	Yes	Rating rating dummies	Yes	Yes
Sector dummies	Yes	Yes	Sector dummies	Yes	Yes
R^2	0.832	0.731	R^2	0.831	0.729
RMSE	0.463	0.463	RMSE	0.464	0.464

Table B.3: **Reaching for yield** The table reports the results from regressing the residuals in Table B.1 on a HY dummy, a IG dummy interacted with a reaching for yield (RFY) proxy, and a HY dummy interacted with RFY. The RFY proxy is the post-GFC period (column1), the ZLB period (column 2), or the years at the zero lower bond where ISS exceeded its trailing three-year average (column 3). In the left panel, EL is based on RMI PDs. In the right panel, EL is based on refined-ratings-based PDs. Driscoll-Kraay standard errors that are robust to heteroskedasticity, autocorrelation and cross-sectional dependence are reported in parentheses. The data cover 522 public U.S. firms and nearly 1.3 million firm-date observations. The sample period is 2002–2017.

	RMI-based EL			Refined-ratings-based EL		
	post-GFC	ZLB	ISS/ZLB	post-GFC	ZLB	ISS/ZLB
Constant	-0.100	-0.064	-0.050	-0.095	-0.059	-0.047
	(0.015)	(0.014)	(0.012)	(0.014)	(0.014)	(0.012)
HY	0.140	0.097	0.060	0.115	0.087	0.052
	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)
RFY $\times$ IG	0.200	0.153	0.166	0.191	0.142	0.155
	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)	(0.190)
RFY $\times$ HY	-0.075	-0.073	-0.033	-0.037	-0.061	-0.016
	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)
R^2	0.037	0.022	0.020	0.032	0.018	0.018
RMSE	0.453	0.457	0.457	0.455	0.458	0.458

Table B.4: **MMMF operating costs** The table reports the results of the panel data regression (8). In the first column, expected losses EL are measured using RMI PDs, in the second column they are measured using refined-ratings-based PDs. IV_{atm} and IV_{otm} are the firm-level standardized 91-day put-implied volatilities at a Delta of –50% and –20%. IV_{atm} and IV_{otm} denote similar volatilities for the aggregate stock market. Refined ratings dummies identify the firm- and date-specific Moody's rating, adjusted for watchlist and outlook status. Recent upgrade/downgrade dummies are one if the firm's alphanumeric rating has been upgraded/downgraded in the past six months, and zero otherwise. CSENT is the University of Michigan Consumer Sentiment index. We also control for the number of CDS quotes provided to Markit for a given firm on a given date. The market total CDS notional outstanding is sourced from ISDA and BIS, and is measured in trillions of U.S. dollars, adjusted for double-counting. Credit spreads and expected losses are measured in basis points of notional, and implied volatility is measured in nominal terms. The benchmark refined rating category is Baa2 and the benchmark sector is Consumer Goods. Driscoll-Kraay standard errors that are robust to heteroskedasticity, autocorrelation and cross-sectional dependence are reported in parentheses. The data cover 522 public U.S. firms and nearly 1.3 million firm-date observations. The sample period is 2002-2017.

	RMI	Rtg		RMI	Rtg
Constant	8.710	8.505	Constant	8.783	8.716
	(0.267)	(0.280)		(0.269)	(0.277)
log(EL)	-0.947	-0.821	log(EL)	-0.949	-0.876
	(0.003)	(0.015)		(0.003)	(0.014)
$\log(\text{IV}_{atm})$	0.768	0.877	$\log(\text{IV}_{atm})$	0.778	0.880
	(0.017)	(0.015)		(0.017)	(0.015)
$\log(\text{IV}_{otm}/\text{IV}_{atm})$	0.683	0.686	$\log(\text{IV}_{otm}/\text{IV}_{atm})$	0.637	0.642
	(0.028)	(0.028)		(0.028)	(0.028)
Recent upgrade	-0.030	-0.034	Recent upgrade	-0.032	-0.035
	(0.004)	(0.004)		(0.004)	(0.004)
Recent downgrade	0.124	0.125	Recent downgrade	0.116	0.119
	(0.008)	(0.008)		(0.007)	(0.007)
Recent upgr HY to IG	-0.052	-0.052	Recent upgr HY to IG	-0.044	-0.044
	(0.013)	(0.014)		(0.013)	(0.014)
Recent dngr IG to HY	0.111	0.102	Recent dngr IG to HY	0.069	0.063
	(0.017)	(0.017)		(0.016)	(0.016)
$\log(\text{IV}^{SPX}_{atm})$	0.052	0.017	$\log(\text{IV}^{SPX}_{atm})$	0.048	0.013
	(0.026)	(0.027)		(0.027)	(0.027)
$\log(\text{IV}^{SPX}_{otm}/\text{IV}^{SPX}_{atm})$	1.549	1.575	$\log(\text{IV}^{SPX}_{otm}/\text{IV}^{SPX}_{atm})$	1.585	1.582
	(0.176)	(0.184)		(0.177)	(0.183)
log(CSENT)	-0.872	-0.914	log(CSENT)	-0.884	-0.918
	(0.071)	(0.074)		(0.072)	(0.074)
Nbr of CDS quotes	-0.004	-0.001	Nbr of CDS quotes	-0.002	0.000
	(0.001)	(0.001)		(0.001)	(0.001)
1/CDS notional	0.304	0.321	1/CDS notional	0.307	0.326
	(0.048)	(0.049)		(0.048)	(0.049)
MMMF operating costs	0.116	0.113	MMMF operating costs $\times 1_{\text{IG}}$	0.145	0.143
	(0.006)	(0.006)		(0.006)	(0.006)
			MMMF operating costs $\times 1_{\text{HY}}$	0.032	0.034
				(0.005)	(0.005)
Refined rating dummies	Yes	Yes	Refined rating dummies	Yes	Yes
Sector dummies	Yes	Yes	Sector dummies	Yes	Yes
R^2	0.845	0.749	R^2	0.849	0.755
RMSE	0.446	0.447	RMSE	0.439	0.441

Table B.5: **Regulation** The table reports the results of the panel data regression (8). In the first column, expected losses EL are measured using RMI PDs, in the second column they are measured using refined-ratings-based PDs. IV_{atm} and IV_{otm} are the firm-level standardized 91-day put-implied volatilities at a Delta of –50% and –20%. IV_{atm} and IV_{otm} denote similar volatilities for the aggregate stock market. Refined ratings dummies identify the firm- and date-specific Moody's rating, adjusted for watchlist and outlook status. Recent upgrade/downgrade dummies are one if the firm's alphanumeric rating has been upgraded/downgraded in the past six months, and zero otherwise. CSENT is the University of Michigan Consumer Sentiment index. We also control for the number of CDS quotes provided to Markit for a given firm on a given date. The market total CDS notional outstanding is sourced from ISDA and BIS, and is measured in trillions of U.S. dollars, adjusted for double-counting. Credit spreads and expected losses are measured in basis points of notional, and implied volatility is measured in nominal terms. The benchmark refined rating category is Baa2 and the benchmark sector is Consumer Goods. Driscoll-Kraay standard errors that are robust to heteroskedasticity, autocorrelation and cross-sectional dependence are reported in parentheses. The data cover 522 public U.S. firms and nearly 1.3 million firm-date observations. The sample period is 2002-2017.

	RMI	Rtg		RMI	Rtg
Constant	9.417	9.225	Constant	11.020	10.476
	(0.277)	(0.285)		(0.301)	(0.294)
log(EL)	-0.934	-0.771	log(EL)	-0.927	-0.688
	(0.003)	(0.016)		(0.003)	(0.015)
$\log(IV_{atm})$	0.743	0.876	$\log(IV_{atm})$	0.663	0.820
	(0.017)	(0.016)		(0.017)	(0.016)
$\log(IV_{otm}/IV_{atm})$	0.612	0.619	$\log(IV_{otm}/IV_{atm})$	0.670	0.670
	(0.026)	(0.026)		(0.031)	(0.031)
Recent upgrade	-0.045	-0.048	Recent upgrade	-0.032	-0.036
	(0.005)	(0.005)		(0.004)	(0.004)
Recent downgrade	0.127	0.127	Recent downgrade	0.123	0.121
	(0.007)	(0.007)		(0.007)	(0.007)
Recent upgr HY to IG	-0.049	-0.049	Recent upgr HY to IG	-0.068	-0.066
	(0.014)	(0.014)		(0.014)	(0.014)
Recent dngr IG to HY	0.097	0.088	Recent dngr IG to HY	0.111	0.097
	(0.016)	(0.016)		(0.017)	(0.017)
$\log(IV_{atm}^{SPX})$	0.257	0.204	$\log(IV_{atm}^{SPX})$	0.238	0.186
	(0.032)	(0.033)		(0.032)	(0.034)
$\log(IV_{otm}^{SPX}/IV_{atm}^{SPX})$	0.301	0.375	$\log(IV_{otm}^{SPX}/IV_{atm}^{SPX})$	0.038	0.083
	(0.215)	(0.222)		(0.237)	(0.239)
log(CSENT)	-0.968	-1.042	log(CSENT)	-1.332	-1.376
	(0.073)	(0.077)		(0.078)	(0.078)
Nbr of CDS quotes	-0.003	-0.001	Nbr of CDS quotes	-0.010	-0.006
	(0.001)	(0.001)		(0.001)	(0.001)
1/CDS notional	0.514	0.530	1/CDS notional	0.489	0.499
	(0.037)	(0.037)		(0.040)	(0.041)
Dodd-Frank Act	0.421	0.398	CCP market share	2.306	2.272
	(0.023)	(0.024)		(0.133)	(0.128)
Volcker Rule	0.082	0.098			
	(0.020)	(0.022)			
Refined rating dummies	Yes	Yes	Refined rating dummies	Yes	Yes
Sector dummies	Yes	Yes	Sector dummies	Yes	Yes
R^2	0.845	0.749	R^2	0.842	0.745
RMSE	0.445	0.446	RMSE	0.450	0.450

Table B.6: **Regulation—Capital ratios** The table reports the results of the panel data regression (8). In the first column, expected losses EL are measured using RMI PDs, in the second column they are measured using refined-ratings-based PDs. IV_{atm} and IV_{otm} are the firm-level standardized 91-day put-implied volatilities at a Delta of –50% and –20%. IV_{atm} and IV_{otm} denote similar volatilities for the aggregate stock market. Refined ratings dummies identify the firm- and date-specific Moody's rating, adjusted for watchlist and outlook status. Recent upgrade/downgrade dummies are one if the firm's alphanumeric rating has been upgraded/downgraded in the past six months, and zero otherwise. CSENT is the University of Michigan Consumer Sentiment index. We also control for the number of CDS quotes provided to Markit for a given firm on a given date. The market total CDS notional outstanding is sourced from ISDA and BIS, and is measured in trillions of U.S. dollars, adjusted for double-counting. Credit spreads and expected losses are measured in basis points of notional, and implied volatility is measured in nominal terms. The benchmark refined rating category is Baa2 and the benchmark sector is Consumer Goods. Driscoll-Kraay standard errors that are robust to heteroskedasticity, autocorrelation and cross-sectional dependence are reported in parentheses. The data cover 522 public U.S. firms and nearly 1.3 million firm-date observations. The sample period is 2002-2017.

	RMI	Rtg		RMI	Rtg
Constant	7.179	6.806	Constant	8.505	8.052
	(0.356)	(0.378)		(0.370)	(0.389)
log(EL)	-0.941	-0.755	log(EL)	-0.945	-0.751
	(0.003)	(0.017)		(0.003)	(0.019)
$\log(IV_{atm})$	0.749	0.874	$\log(IV_{atm})$	0.750	0.870
	(0.018)	(0.017)		(0.018)	(0.017)
$\log(IV_{otm}/IV_{atm})$	0.687	0.686	$\log(IV_{otm}/IV_{atm})$	0.777	0.774
	(0.030)	(0.030)		(0.038)	(0.037)
Recent upgrade	-0.050	-0.053	Recent upgrade	-0.041	-0.045
	(0.004)	(0.004)		(0.004)	(0.004)
Recent downgrade	0.119	0.118	Recent downgrade	0.113	0.111
	(0.008)	(0.008)		(0.007)	(0.008)
Recent upgr HY to IG	-0.020	-0.019	Recent upgr HY to IG	-0.030	-0.028
	(0.014)	(0.014)		(0.014)	(0.015)
Recent dngr IG to HY	0.104	0.094	Recent dngr IG to HY	0.103	0.093
	(0.017)	(0.017)		(0.017)	(0.018)
$\log(IV^{SPX}_{atm})$	0.252	0.210	$\log(IV^{SPX}_{atm})$	0.156	0.117
	(0.037)	(0.037)		(0.040)	(0.041)
$\log(IV^{SPX}_{otm}/IV^{SPX}_{atm})$	0.494	0.524	$\log(IV^{SPX}_{otm}/IV^{SPX}_{atm})$	1.840	1.834
	(0.205)	(0.206)		(0.199)	(0.201)
log(CSENT)	-0.842	-0.883	log(CSENT)	-1.373	-1.407
	(0.085)	(0.087)		(0.089)	(0.089)
Nbr of CDS quotes	-0.005	-0.002	Nbr of CDS quotes	-0.008	-0.005
	(0.001)	(0.001)		(0.001)	(0.001)
1/CDS notional	0.726	0.732	1/CDS notional	0.655	0.662
	(0.044)	(0.041)		(0.056)	(0.054)
Capital ratios (Banks)	0.197	0.195	Capital ratios (Insurance)	0.265	0.267
	(0.011)	(0.011)		(0.034)	(0.034)
Refined rating dummies	Yes	Yes	Refined rating dummies	Yes	Yes
Sector dummies	Yes	Yes	Sector dummies	Yes	Yes
R^2	0.842	0.746	R^2	0.835	0.734
RMSE	0.449	0.449	RMSE	0.460	0.459