NBER WORKING PAPER SERIES

CORPORATE CREDIT RISK PREMIA

Antje Berndt
Rohan Douglas
Darrell Duffie
Mark Ferguson

Working Paper 24213
http://www.nber.org/papers/w24213

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2018

Berndt is a Professor of Finance at the Research School of Finance, Actuarial Studies and Statistics, Australian National University. Douglas is the founder and CEO of Quantifi, Inc. Duffie is the Dean Witter Distinguished Professor of Finance at the Graduate School of Business, Stanford University. Duffie is also a research associate of the National Bureau of Economic Research and a member of the board of directors of Moody's Corporation. Ferguson is an independent quantitative finance contractor. We are grateful to Alex Edmans (editor) and Francis Longstaff (referee) for helpful comments and suggestions. We thank Moody's Analytics for access to EDF data; Jeff Bohn, Richard Cantor, Ashish Das, Jim Herrity, David Kreisman, Albert Metz and Roger Stein for answering data-related questions; and Moody's Investor Services for a research grant to Antje Berndt that partially supported her work. We thank seminar participants at numerous universities and conferences. We are also grateful to Yacine Ait-Sahalia, Franklin Allen, Gene Fama and Mitchell Petersen for useful discussions, to Jeremy Graveline, Gustavo Manso, Sergey Lobanov, Leandro Saita, and Wei Yang for research assistance, and to Linda Bethel and Sandra Berg for technical assistance. This paper is a comprehensive revision of our previous work, entitled "Measuring Default Risk Premia from Default Swap Rates and EDFs." The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed a financial relationship of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w24213.ack

Corporate Credit Risk Premia
Antje Berndt, Rohan Douglas, Darrell Duffie, and Mark Ferguson
NBER Working Paper No. 24213
January 2018
JEL No. G12,G13,G22,G24

ABSTRACT

We measure credit risk premia - prices for bearing corporate default risk in excess of expected default losses - using Markit CDS and Moody's Analytics EDF data. We find dramatic variation over time in credit risk premia, with peaks in 2002, during the global financial crisis of 2008-09, and in the second half of 2011. Even after normalizing these premia by expected default losses, median credit risk premia fluctuate over time by more than a factor of ten. Credit risk premia comove with macroeconomic indicators, even after controlling for variation in expected default losses, with higher premia per unit of expected loss during times of market-wide distress. Countercyclical variation of premia-to-expected-loss ratios is more pronounced for investment-grade issuers than for high-yield issuers.

Antje Berndt
Research School of Finance,
Actuarial Studies and Statistics
Australian National University
Canberra
Australia
antje.berndt @anu.edu.au

Rohan Douglas
Quantifi LLC
rdouglas@quantifisolutions.com

Darrell Duffie
Graduate School of Business
Stanford University
Stanford, CA 94305-7298
and NBER
duffie@stanford.edu

Mark Ferguson
Independent Quantitative Finance Consultant
mefergus@gmail.com

An online appendix is available at http://www.nber.org/data-appendix/w24213

1. Introduction

We estimate the level and time variation of corporate credit risk premia, which are the prices for bearing corporate default risk, in excess of expected default losses. For each firm, we use credit default swap (CDS) rates to measure the total price for bearing default risk. We define the associated credit risk premium as the difference between the CDS rate and the expected rate of loss to protection sellers. This premium compensates sellers of default protection for the riskiness of their losses. Credit risk premia are magnified by the countercyclicality of default-timing risk and proportional losses in the event of default. Credit risk premia are also increased by market illiquidity.

Figure 1 shows the daily time series of median five-year CDS rates and estimates of their expected loss components. Our data cover all public U.S. firms for which there are observable Markit CDS rates and firm-specific default probabilities, as estimated by the Moody's Analytics EDF measure. This sample is comprised of almost 1.2 million matched CDS-EDF pairs, and covers more than 500 firms over the period from 2002 to 2015.

We find dramatic variation over time in credit risk premia, with peaks in 2002, during the 2008-09 global financial crisis (GFC), and during the second half of 2011. (The last half of 2011 included a component of the European sovereign debt crisis and also the U.S. government's "debt-ceiling" crisis.) Daily median premia-to-expected-loss ratios fluctuate between a low of 0.75 in March 2005 and a high of 9.7 in January 2009. In other words, the median net compensation for bearing corporate default risk (above and beyond expected losses), per unit of expected loss, ranges over time by more than a factor of ten.

In addition to temporal variation, there are substantial cross-sectional differences in credit risk premia. Median premia increase from less than 10 basis points of bond principal per year for Aaa firms to more than 700 basis points for Ca-C firms. Per unit of expected losses, median premia exhibit a tent shape across the rating spectrum, increasing from 1.4 for Aaa firms to 4.0 for Ba firms before decreasing again to 2.1 for Ca-C firms. Across sectors, median premia-to-expected-loss ratios are highest for utilities at 8.5, and lowest for financial firms at 0.64.

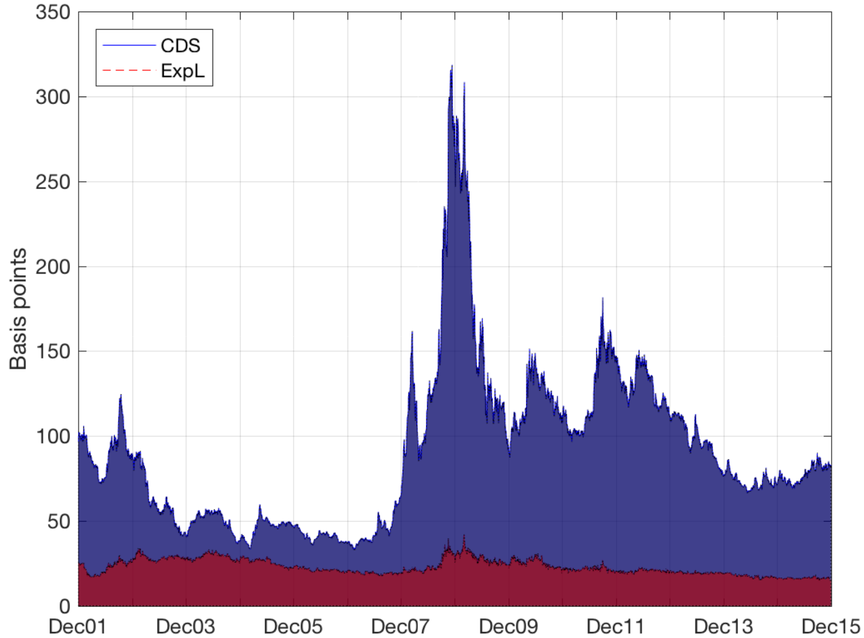

Figure 1: **Median CDS rates and expected default losses** The figure shows the daily times series of median five-year CDS rates (CDS) and median five-year expected losses (ExpL). Only days on which matched CDS-expected-loss pairs are available for 50 or more firms are shown. The data include about 1.2 million firm-date pairs for 505 public U.S. firms and cover the period from 2002 to 2015.

We investigate the extent to which variation in credit risk premia, across firms and over time, can be explained by variation in firm-specific and macroeconomic variables. Standard asset-pricing concepts (for instance, Cochrane, 2001) imply that in the absence of market frictions, and under weak technical conditions, there exists a stochastic discount factor (SDF) process with the property that the credit risk premium for short-term CDS contracts is approximately equal to the conditional covariance between default losses and the SDF. For longer-term CDS contracts, the risk premium is a slightly more complicated function of conditional covariances between default losses or default indicators in future periods and the SDF (Berndt, 2015).

These covariances with the SDF are difficult to quantify directly. Theory provides little guidance on the "correct" specification of the SDF. Moreover, estimation is hampered by the relative rarity of corporate defaults. As predictors of credit risk premia, we exploit variables that help explain (i) future default losses or default events, by including expected loss rates, credit ratings, and implied volatilities; (ii) future changes in the SDF, by incorporating business-cycle indicators; or (iiii) conditional covariances between the two, for which we include business-cycle indicators interacted[1] with credit ratings. We also examine the explanatory role of proxies for CDS market liquidity.

As an alternative perspective on credit risk premia, we also focus on the ratio of the total CDS rate to the expected rate of default loss. Not only are these CDS-to-expected-loss ratios more incisive than un-normalized risk premia for the purpose of cross-sectional comparisons, these ratios also have the technical advantage of always being positive, and hence of having a well defined logarithm. We show that a sizable fraction of the cross-sectional and temporal variation of CDS-to-expected-loss ratios—26% in a log-linear setting—is explained by variation in the underlying expected loss rates. A 10% proportional increase in the expected loss rate is associated with a 5.4% proportional increase in the corresponding CDS rate, implying that CDS-to-expected-loss ratios (and hence premium-to-expected-loss ratios) tend to decrease as expected losses increase. The one-standard-deviation confidence band for a given CDS-to-expected-loss ratio, however, is wide, at 44% to 226% of the fitted ratio. We show that much of this noise can be eliminated by controlling for firm fixed effects and time fixed effects.

We investigate the extent to which these firm and time fixed effects in credit risk premia can alternatively be captured by observable firm characteristics and macroeconomic indicators. To do so, we build a predictive model for CDS-to-expected-loss ratios that is based on log-linear panel-data regressions. We argue that a fairly small set of predictor variables, consisting of refined credit ratings and sector dummies, equity-option-implied volatilities, proxies for investor-clientele effects, interest rates, consumer sentiment, and a CDS market liquidity measure, achieves nearly the same goodness of fit as that obtained by using firm and time fixed effects. Indeed, together with expected default losses, these variables capture 82% of the variation in premia, just shy of the 84% explained by the fixed-effects model.

For a given firm, a refined credit rating from Moody's can be defined by raising the firm's

[1]Hilscher and Wilson (2017) argue that credit ratings are strongly related to the systematic risk priced in the CDS market.

alphanumeric credit rating by one notch (for example from Ba2 to Ba1) if the firm is on "positive outlook" and by two notches if it is on "upgrade watch."[2] Symmetric but opposite adjustments are made to refined ratings for firms with a negative outlook or on downgrade watch, respectively. We show that refined ratings are important predictors of cross-sectional variation in credit spreads, in that higher refined ratings are associated with significantly lower CDS rates, even after controlling for EDF-based expected losses. In that sense, refined ratings supply a significant amount of information about relative credit quality across firms.

We show that both the level and "smirk" of option-implied volatility have significant positive relationships with CDS rates, even after controlling for expected losses and refined ratings. The level effect is consistent with volatility risk being priced, in which case credit risk premia should be higher for more firms whose equity volatilities are higher. The smirk is measured as the ratio of out-of-the-money to at-the-money put-implied volatilities. This suggests that the volatility smirk contains information about the cost of insuring against sudden large increases in firm default risk, which is not surprising given the role of negative jump risk in individual-firm option smirks, as found by, for example, Van Buskirk (2009).

We also find a strong negative relationship between credit risk premia and interest rates, and between credit risk premia and consumer sentiment. The countercyclicality of credit risk premia tends to be more pronounced for investment-grade firms than for high-yield firms. This is consistent with the notion that during times of market-wide distress, the supply of risk capital is reduced across the spectrum of bonds in a manner that does not fully discriminate for credit quality, resulting in a price for bearing default risk, per unit of default risk to be borne, that is disproportionately higher for high-quality debt.

In supporting work, we allow for a range of alternative assumptions that affect our estimators for a firm's probability of default (PD) and expected loss given default (LGD). While our results

[2]These are designations are published by Moody's Investor Services, which supplied our ratings data. One of the authors of this study has been a member of the board of directors of Moody's Corporation since October 2008. These notch refinements compensate somewhat for the fact that credit ratings tend to be stable over time relative to statistical estimates of default probabilities such as Moody's EDF measures, which we exploit in this study.

are robust to alternative LGD specifications, we highlight the importance of the choice of PD estimators when quantifying the level and variation of credit risk premia. We also compare our main results for the benchmark five-year maturity to results for longer and shorter maturities.

Our work extends prior empirical research on default risk premia. Fisher (1959) took a simple regression approach to explaining yield spreads on corporate debt in terms of various credit-quality and liquidity related variables. Fons (1987) gave the earliest empirical analysis, to our knowledge, of the relationship between expected default losses and credit spreads. Driessen (2005) estimated the relationship between actual and risk-neutral default probabilities, using U.S. corporate bond price data and assuming that conditional default probabilities are equal to average historical default frequencies by credit rating. Kavvathas (2001) and others have shown, however, that for a given firm at a given time, the historical default frequency of firms of the same rating is a stale and coarse-grained estimator of conditional default probability. At the same time, Kurbat and Korbalev (2002), Kealhofer (2003) and Bohn, Arora, and Korbalev (2005) argue that the Moody's Analytics EDF provides significantly more power to discriminate among the default probabilities of firms. We therefore use EDFs as our primary measure of default probabilities. We quantify how measured credit risk premia vary with alternative PD measures.

Blanco, Brennan, and Marsh (2005) show that CDS rates represent somewhat fresher price information than do bond yield spreads. This may be due to the fact that default swaps are "unfunded exposures," in the language of dealers, meaning that in order to execute a trade, neither cash nor the underlying bonds need to be immediately sourced and exchanged. Default swap rates are therefore less likely to be affected by market illiquidity than are bond yield spreads. The extent of this difference in liquidity is explored in Longstaff, Mithal, and Neis (2005).

While trading frictions in the CDS market seem less severe than those in the underlying bond market, Bühler and Trapp (2009) find evidence of spillover effects from bond illiquidity to CDS prices. They argue that, everything else the same, CDS rates increase as the underlying corporate bonds become more illiquid and, as a result, expected loss given default becomes larger. Ambrose, Cai, and Helwege (2012), Ellul, Jotikasthira, and Lundblad (2012) and Chen, Lookman, Schürhoff, and Seppi (2014) analyze the effects of price pressure in corporate bond markets associated with rating downgrades, particularly those associated with transitions between investment-grade (IG) and high-yield (HY) ratings. This IG-HY segmentation effect may also spill over from bond to CDS trading. A number of other studies, including Tang and Yan (2008), Chen, Fabozzi, and Sverdlove (2010), Bongaerts, de Jong, and Driessen (2011), Chen, Cheng, and Wu (2013), Junge and Trolle (2015) and Arakelyan and Serrano (2016), focus on the CDS market itself and document significant liquidity effects.

Delianedis and Geske (1998), Delianedis, Geske, and Corzo (1998), Bohn (2000) and Huang and Huang (2012) use structural approaches to estimating the relationship between actual and risk-neutral default probabilities, generally assuming that the Black-Scholes-Merton model applies to the asset value process, and assuming constant volatility. Eom, Helwege, and Huang (2004) have found that these structural models tend to fit the data rather poorly, and typically underestimate credit spreads, especially for shorter maturity bonds. Chen, Collin-Dufresne, and Goldstein (2009) show an improvement in fit by incorporating an assumption of counter-cyclical default boundaries. Our study does not rely on structural modeling, except insofar as EDFs depend in part on the Black-Scholes-Merton model. Our estimates of credit risk premia arise directly from observed data and simple econometric specifications.

The remainder of the paper is structured as follows. Section 2 describes the data and sample construction. Section 3 explains our calculation of expected default loss rates. Section 4 quantifies the cross-sectional and temporal variation in credit risk premia. Section 5 analyzes the extent to which variation in credit risk premia is explained by variation in expected losses. Section 6 presents panel regressions that point to significant comovement of credit risk premia with refined credit ratings, equity-option-implied volatility, and a range of macroeconomic indicators, even after controlling for expected losses. Section 7 extends our analysis to alternative measures of expected default loss. Section 8 concludes.

2. Data Sources and Sample Construction

This section describes our data sources for default swap rates and conditional default probabilities.

2.1 Markit CDS Data

A credit default swap (CDS) is a derivative contract designed to transfer credit risk. With minor exceptions, a CDS is economically equivalent to a bond insurance contract. The buyer of protection makes periodic (usually quarterly) "insurance" payments until the expiration of the contract or until a contractually defined credit event, whichever is earlier. The annualized rate of payment, per unit of covered bond principal, is called the CDS rate. Beginning with the Big Bang Protocol of April 2009, CDS rates were standardized to 100 basis points for investment-grade debt and 500 basis points for high-yield debt. Since this change, each CDS trade is negotiated with an "upfront" payment (positive or negative), as additional compensation for the protection seller.

Our CDS rate observations, obtained from Markit Partners, are "at-market," meaning that they represent bids or offers of the default-swap rates at which a buyer or seller of protection is proposing to enter into new default swap contracts without an up-front payment. Assuming no upfront and zero dealer margins, the at-market CDS rate is, in theory, that for which the net market value of the contract is zero. For CDS with standardized annual running payment rates of 100 and 500 basis points, the bid and ask CDS rate data are as provided by Markit. A quoted CDS rate is converted to an upfront payment using a standard industry formula. The rates provided by Markit are composite CDS quotes, in that they are computed based on bid and ask quotes obtained from two or more anonymous CDS dealers. We assume that the composite CDS rate is the rate at which the market value of the default swap is indeed zero.

For our CDS data the stipulated credit event is default by a named firm. If the credit event occurs before the expiration of the CDS, the buyer of protection receives from the seller of protection the difference between the face value and the market value of the underlying debt.

The contractual definition of default normally allows for bankruptcy, a material failure by the obligor to make payments on its debt, or a restructuring of the debt that is materially adverse to the interests of creditors. This is the same definition of default used for purposes of the Moody's Analytics EDF estimator of default probability.

The coverage of default swaps for out-of-bankruptcy restructuring has varied somewhat. ISDA, the industry coordinator of standardized default-swap contracts, has arranged a number of consensus contractual definitions of default and coverage in the event of default. All of our CDS data are for U.S. firms, with a consensus contractual definition known as "modified restructuring." The contractual definition of default affects the measured credit risk premia, of course, because a wider definition of default implies a higher default probability and more recovery-value heterogeneity.[3] We repeat our analysis for CDS without restructuring in the internet appendix.

Our CDS data apply to senior unsecured debt instruments. We vary expected loss given default (LGD) estimates across firms and time using Markit estimates. In Section 7 we show that our findings are qualitatively robust to alternative LGD assumptions. Additional details regarding our CDS data, including a description of the settlement mechanism and the cheapest-to-deliver option available to the buyer of protection, are provided in Internet Appendix A.

2.2 Moody's Analytics EDF Data

Moody's Analytics provides current firm-by-firm estimates of annualized conditional probabilities of default over time horizons that include the benchmark horizons of one and five years. For a given firm and time horizon, this "EDF" estimate of default probability is fit non-parametrically from the historical default frequency of other firms that had the same estimated "distance to default" as the target firm. The distance to default of a given firm is effectively a leverage measure adjusted for current market asset volatility (see Internet Appendix B for details). Duffie, Saita, and Wang (2007), Bharath and Shumway (2008), and Duffie et al.

[3]While the probability of a CDS trigger event occurring increases when out-of-bankruptcy restructurings are covered, Berndt, Jarrow, and Kang (2007) document that the likelihood of a restructuring event is substantially smaller than that of a bankruptcy or missed payment.

(2009) show that although distance to default is a sufficient explanatory variable for conditional default probabilities in the theoretical models of Black and Scholes (1973), Merton (1974), Fischer, Heinkel, and Zechner (1989), and Leland and Toft (1996), among others, some incremental predictive power can be obtained by including additional firm-specific and macroeconomic explanatory variables. Consistent with this, we will show that, controlling for EDFs, CDS rates are also explained in part by refined credit ratings.

While one could criticize the EDF measure as an estimator of the "true" conditional default probability, it has some merits relative to other available approaches to estimating conditional default probabilities. First, the Moody's Analytics EDF is readily available for essentially all public U.S. companies, and for a large fraction of foreign public firms. Second, EDFs are fitted non-parametrically to the distance to default, and are therefore somewhat robust to model misspecification. While the measured distance to default (DD) is itself based on a theoretical option-pricing model, the function that maps DD to EDF is consistently estimated in a stationary setting, even if the underlying theoretical relationship between DD and default probability does not apply. That is, conditional on only the distance to default, the measured EDF is equal to the "true" DD-conditional default probability as the number of observations goes to infinity, under typical mixing and other technical conditions for non-parametric qualitative-response estimation. Details on the out-of-sample predictive power of EDFs are provided in Internet Appendix B.

2.3 Refined Credit Ratings

We collect data on Moody's alphanumeric senior unsecured issuer ratings. For the purpose of obtaining refined credit ratings, continuous 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. We will show that refined ratings exhibit substantially more time-series variation than raw alphanumeric ratings, and that they have more explanatory power for credit risk premia than unrefined ratings.

2.4 Sample Construction

We identify all public U.S. firms that can be matched unambiguously across Markit, Moody's Analytics, Compustat and CRSP databases. We restrict Markit data to senior unsecured debt and CDS based on modified restructuring. We use CDS quotes for which Markit rates the quality of the quote as BB or higher, and for which a default recovery rate estimate is available. If a quote-quality rating is not available, we require a composite level of "CcyGrp," "DocAdj" or "Entity Tier." Although Markit CDS data go back as far as 2001, after cleaning the data we find few 2001 observations. We therefore restrict our sample for estimation purposes to the period of 2002 to 2015.

We exclude firms with less than one year of matched CDS-EDF data, and remove any extreme "needles" in the CDS and EDF time series for a given firm that cannot be explained by market-wide or firm-specific events. This leaves us with 505 unique firms—as identified by their Compustat identifiers called "gvkey"—from ten industry sectors, and with 1,189,330 matched daily CDS-EDF pairs. The number of CDS quote contributors ranges from three to 33 in our sample, with a median composite depth of seven.

2.5 Descriptive Statistics

The range of credit qualities of the firms in our data may be judged from Table 1, which shows, for each credit rating, the number of firms in our study with that median Moody's senior unsecured issuer rating during the sample period. The table indicates a concentration of firms 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.

Figure 2 shows time series of median five-year CDS and EDF rates. Median CDS rates are substantially higher following WorldCom's default in July 2002, during the 2008-09 financial crisis, and during the latter half of 2011 (when there were severe concerns about European peripheral sovereign debt and faltering negotiations over the U.S. government debt ceiling).

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 505 public U.S. firms and cover the period from 2002 to 2015. Rating data are available for 497 of the 505 firms in our sample.

	Aaa	Aa	A	Baa	Ba	B	Caa	Ca-C	NR	All
Basic Materials	0	0	8	17	7	3	0	0	0	35
Consumer Goods	0	4	12	31	18	10	3	0	1	79
Consumer Services	0	1	9	29	14	14	5	1	2	75
Energy	1	1	6	22	9	6	0	1	0	46
Financials	1	9	20	41	4	5	0	0	1	81
Healthcare	1	0	13	12	6	2	1	0	2	37
Industrials	1	3	17	30	14	6	3	0	0	74
Technology	1	0	10	10	3	4	0	0	1	29
Telecommunications Services	0	0	2	4	2	2	1	0	0	11
Utilities	0	0	2	26	4	5	0	0	1	38
All	5	18	99	222	81	57	13	2	8	505

While median EDFs also exhibit local peaks at these times, temporal variation in CDS rates tends to be much more than proportionately impacted.

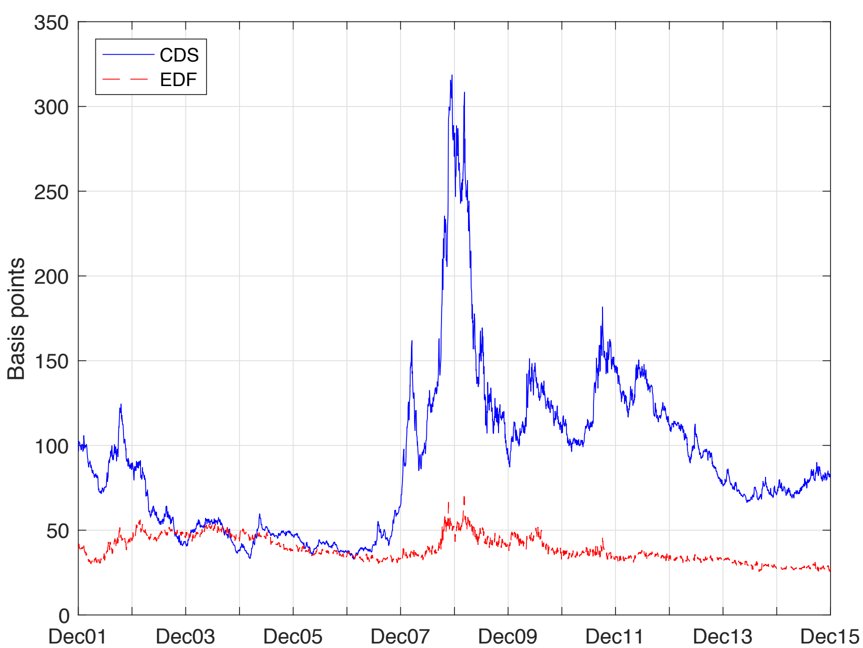

Figure 2: **Median five-year CDS rates and EDFs** The figure shows the daily times series of median five-year CDS rates and median five-year EDF rates. Only those days on which matched CDS-EDF pairs are available for 50 or more firms are shown. The data cover 505 public U.S. firms, over 2002-2015.

Table 2 reports summary statistics for CDS rates, EDFs and Markit estimates of recovery rates, by year, sector and credit rating. This table reveals cross-sectional differences in the relationship between CDS rates and EDFs. Financial firms and, to some extent, technology firms stand out in that median EDFs are higher relative to median credit spreads than is the case for other sectors. This suggests that financial and technology firms may have relatively lower credit risk premia. While these cross-sector differences in median credit risk premia are confirmed in Section 4, our panel regression analysis in Section 6 reveals that much of these differences can be explained by differences in credit quality across sectors.

Table 2: **Descriptive statistics for CDS rates, EDFs and recovery rates** The table reports median five-year CDS rates and EDFs, as well as Markit estimates of recovery rates (Rec). CDS rates and EDFs are reported as annualized rates, in basis points. The data cover 505 public U.S. firms, over 2002-2015.

	CDS	EDF	Rec		CDS	EDF	Rec
		All				By sector	
	83	38	0.40	BM	87	31	0.40
		By year		CG	94	28	0.40
2002	88	39	0.42	CS	98	40	0.40
2003	60	48	0.41	Egy	95	23	0.40
2004	49	49	0.39	Fin	84	88	0.40
2005	46	44	0.39	Hlth	53	25	0.40
2006	41	37	0.40	Ind	68	27	0.40
2007	44	33	0.40	Tech	85	70	0.40
2008	134	40	0.40	Tele	124	62	0.40
2009	156	47	0.40	Utl	73	13	0.40
2010	120	43	0.40			By rating	
2011	121	37	0.40	Aaa	22	14	0.40
2012	129	35	0.40	Aa	28	14	0.40
2013	98	33	0.40	A	42	20	0.40
2014	73	30	0.40	Baa	80	33	0.40
2015	77	28	0.40	Ba	185	66	0.40
				B	343	143	0.40
				Caa	692	375	0.35
				Ca-C	1,430	738	0.31

While recovery rate estimates tend to be close to 40%, we observe a notable decrease in estimated recovery rates as credit quality decreases.

Figure 3 highlights that refined credit ratings exhibit substantially more time-series variation than raw alphanumeric ratings. The average annual frequency of refined rating changes per firm fluctuates between a low of 0.22 in 2002 and a high of 0.69 in 2008. By comparison, the average annual frequency of alphanumeric rating changes per firm ranges from 0.15 to only 0.32.

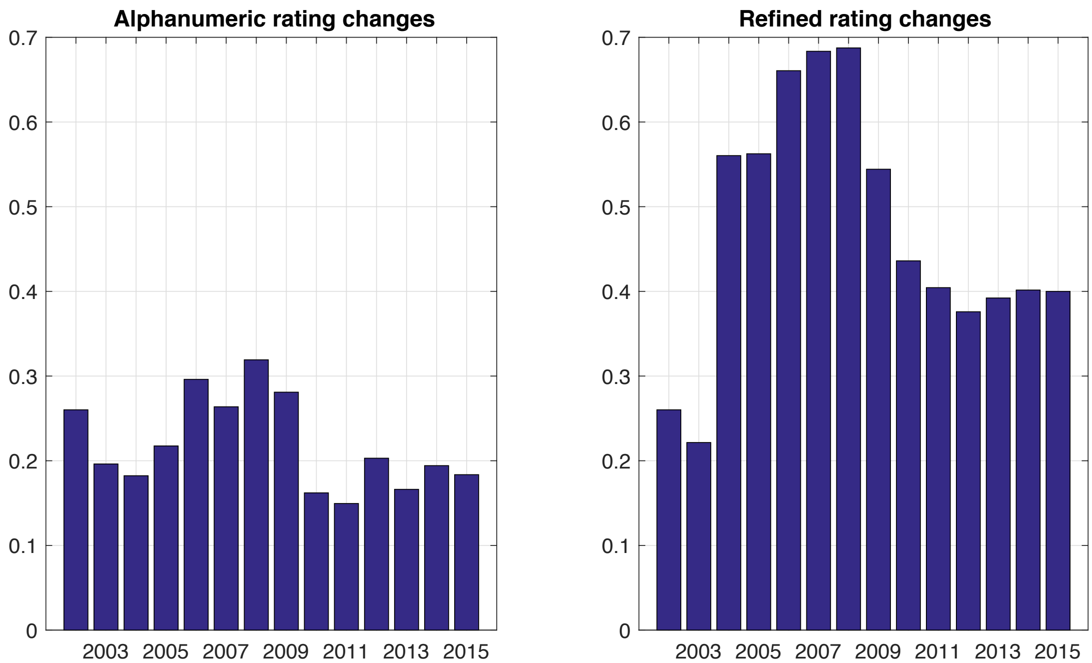

Figure 3: **Rating changes** The figure shows the average annual number of rating changes per firm. The left panel is based on Moody's unadjusted alphanumeric rating. The right panel is based on the refined rating. The data include the 497 firms in our sample with alphanumeric and refined rating data, over 2002-2015.

Figure C.1 in Internet Appendix C reveals that rating downgrades tend to outweigh rating upgrades, especially in 2002-03 and 2008-09, which are both periods of credit stress.

3. Estimating Expected Default Loss Rates

For a given firm, let C_t denote the time-t at-market CDS rate. In the absence of market frictions, and under purely technical regularity conditions (it suffices that there is a finite number of states of the world), 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 at-market CDS rate satisfies

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

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.[4] The at-market CDS rate C_t equates the market values of the two legs.

We ignore the CDS counterparty risk on CDS rates because, as shown by Arora, Gandhi, and Longstaff (2012) and Du et al. (2016), these tend to be tiny in practice, given standard collateralization and netting agreements.

If investors were risk-neutral, M_t would be be deterministic and the resulting CDS rate, denoted ExpL_t, would solve the equation

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

where $d_{t,y}$ is the price at time t of a default-free zero-coupon bond with y years to maturity. Solving,

$$\mathrm{ExpL}_t \;=\; \frac{\sum_{k=0}^{K-1} d_{t,(k+1)\Delta}\, E_t\left(L_{t+k\Delta,\Delta} D_{t+k\Delta,\Delta}\right)}{\Delta \sum_{k=0}^{K-1} d_{t,(k+1)\Delta}\, E_t\left(1 - D_{t+k\Delta,\Delta}\right)}. \tag{3}$$

The "credit risk premium," denoted Prem_t, is defined to be the difference between the observed CDS rate C_t and the hypothetical CDS rate ExpL_t that would apply in the absence of risk aversion. Our main object of concern is the decomposition

$$C_t \;=\; \mathrm{ExpL}_t + \mathrm{Prem}_t. \tag{4}$$

[4] We take the simple view that defaults, should they occur, occur at the end of a payment period. This allows us to abstract from accrued interest computations.

By this construction, any liquidity-related effects in CDS pricing are also absorbed into Prem_t.

We assume for simplicity that the expected loss given default and the default indicator are conditionally independent, so that $E_t\left(L_{t+k\Delta,\Delta}D_{t+k\Delta,\Delta}\right) = E_t\left(L_{t+k\Delta,\Delta}\right)E_t\left(D_{t+k\Delta,\Delta}\right)$. In the main part of the paper, we set $L_t \equiv E_t(L_{t+k\Delta,\Delta})$ equal to one minus the time-t Markit recovery rate estimate for the given firm. An alternative LGD specification that allows $E_t(L_{t+k\Delta,\Delta})$ to change with the forecasting horizon k is proposed in Internet Appendix D.

For a flat and relatively low term structure of default probabilities, ExpL_t is a close approximation of the annualized expected rate of loss to the protection seller, and we will henceforth refer to ExpL_t as "the expected loss rate." We do not, however, impose a flat term structure of default probabilities. As a result, computing the weighted expected loss rate ExpL_t in Equation (3) involves computing expected default frequencies at different horizons. In particular,

$$E_t\left(D_{t+k\Delta,\Delta}\right) \;=\; E_t\left(D_{t,(k+1)\Delta}\right) - E_t\left(D_{t,k\Delta}\right).$$

Moody's Analytics estimates of $E_t(D_{t,T})$ are available for a maturity T of one year or five years. To estimate the term structure of PDs at other maturities, we adapt the methodology of Nelson and Siegel (1987), originally developed to fit term structures of risk-free interest rates, along with the extension suggested by Svensson (1994). Unlike reduced-form single-factor term structure models commonly used to describe default arrival, the Nelson-Siegel-Svensson framework is flexible enough to fit both one-year and five-year EDFs for a given firm on a given date.[5] This flexibility is useful, given the changes in the EDF term structure over time observed in Figure E.1 in the internet appendix.

Details regarding the specification and our fitting of PDs with the Nelson-Siegel-Svensson model are provided in Internet Appendix E. Figure 4 shows the fitted term structures of default probabilities out to ten years, at the median across firms and time, for each given credit rating.

[5] In a prior version of this paper, we estimated the Black-Karasinski model for actual default intensities using one-year EDFs. While the model-implied five-year EDFs matched their observed counterparts reasonably well for the 2002-2004 period, fitting errors at the five-year maturity became more substantial once we extended the sample period to 2015.

For high-yield firms, the short end of the term structure generally exhibits an inverted hump. For investment-grade firms, the term structure is generally upward sloping, with a steeper slope at medium maturities and a more shallow slope at short and long maturities. In Section 7 we perform robustness checks by using a simple interpolation between observed default probabilities, instead of using the Nelson-Siegel-Svensson fit.

Summary statistics for expected losses are provided in Table 3. The median expected loss component of five-year CDS rates, across firms and over time, is 22 basis points. The median ratio of expected loss to CDS rate ranges from 0.16 in 2008 and 2012 to 0.44 in 2004, with an overall median of 0.26.[6] Across sectors, the ratio of expected loss to CDS rate tends to be highest for financial firms—the median ratio across firms in this sector and over time is 0.61—and lowest for utilities, with a median ratio of 0.11. Across the rating spectrum, the median ratio of expected loss to CDS rate has an inverted tent shape, in that this ratio decreases as credit quality declines from 0.41 for Aaa firms to 0.20 for Ba firms, and then increases again to 0.32 as credit quality declines past Ba.

4. Level and Variation of Credit Risk Premia

This section quantifies the cross-sectional and temporal variation of credit risk premia.

4.1 Level and Cross-Sectional Variation of Credit Risk Premia

Summary estimates of credit risk premia, Prem_t, are described in Table 3. These are shown in basis points of covered debt principal per year. We also show these credit risk premia as a fraction of CDS rates, and also as a multiple of the expected weighted default loss rate, ExpL_t. The median credit risk premium, across firms and over time, is 58 basis points of notional per year. There is substantial variation in credit risk premia across firms. Median premia increase from less than 10 basis points for Aaa firms to more than 700 basis points for Ca-C firms. As a multiple of the expected loss rate, median premia increase from 1.4 for Aaa firms to 4.0 for Ba

[6] Median expected-loss-to-CDS ratios are computed as one minus the median ratios of premium to CDS rate, with the latter being reported in the fourth column of Table 3.

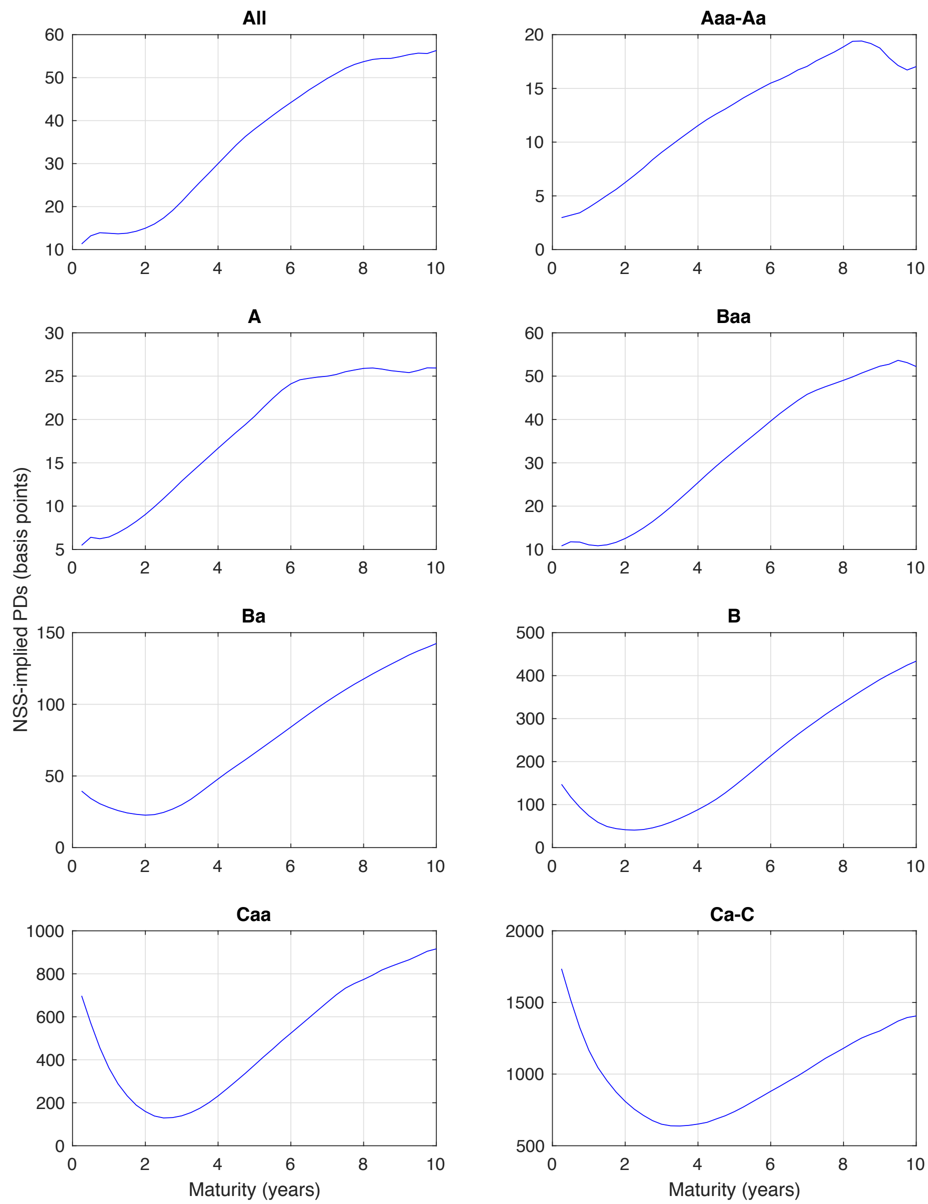

Figure 4: **Nelson-Siegel-Svensson fitted term structure of default probabilities** The figure shows the term structure of default probabilities out to ten years, measured in basis points per year. The top left plot shows, for every maturity, the median PD across firms and over time. The remaining plots show the median PD by letter rating. The data cover 505 public U.S. firms over 2002-2015.

firms, before decreasing again to 2.1 for Ca-C firms. The median ratio of premium to expected loss is highest for utilities at 8.5, and lowest for financial firms at 0.6.

By definition, for a given issuer at a given time, the ratio of the CDS rate to the expected loss rate exceeds the corresponding premium-to-expected-loss ratio by one. The CDS-to-expected-

Table 3: **Descriptive statistics for expected losses and credit risk premia** The table reports median five-year CDS rates, expected losses (ExpL) and credit risk premia (Prem) in basis points, median premium-to-CDS ratios (Prem/CDS) and median premium-to-expected-loss ratios (Prem/ExpL). The data cover 505 public U.S. firms, over 2002-2015.

	CDS	ExpL	Prem	$\frac{\text{Prem}}{\text{CDS}}$	$\frac{\text{Prem}}{\text{ExpL}}$		CDS	ExpL	Prem	$\frac{\text{Prem}}{\text{CDS}}$	$\frac{\text{Prem}}{\text{ExpL}}$
			All					By sector			
ExpL	83	22	58	0.74	2.92	BM	87	18	66	0.78	3.63
			By year			CG	94	16	72	0.80	3.97
2002	88	23	65	0.78	3.63	CS	98	24	69	0.75	3.00
2003	60	28	35	0.65	1.84	Egy	95	14	77	0.81	4.37
2004	49	29	24	0.56	1.27	Fin	84	51	32	0.39	0.64
2005	46	25	25	0.58	1.36	Hlth	53	14	37	0.73	2.71
2006	41	21	20	0.57	1.34	Ind	68	15	48	0.76	3.09
2007	44	19	23	0.61	1.54	Tech	85	41	39	0.50	0.99
2008	134	23	105	0.84	5.17	Tele	124	36	79	0.70	2.36
2009	156	28	119	0.83	4.72	Utl	73	8	65	0.89	8.48
2010	120	25	86	0.79	3.68			By rating			
2011	121	22	89	0.82	4.56	Aaa	22	8	9	0.59	1.43
2012	129	21	99	0.84	5.16	Aa	28	8	13	0.65	1.83
2013	98	19	70	0.80	4.01	A	42	12	26	0.68	2.11
2014	73	18	52	0.76	3.22	Baa	80	19	57	0.76	3.12
2015	77	16	57	0.80	3.88	Ba	185	38	143	0.80	4.01
						B	343	79	242	0.77	3.37
						Caa	692	220	459	0.71	2.49
						Ca-C	1,430	431	738	0.68	2.12

loss ratio, at the sample median across firms and over time, is 3.9. In the absence of market frictions, CDS rates are approximately equal to corresponding par bond yield spreads (Duffie, 1999). Thus, CDS-to-expected-loss ratios are close proxies for yield-spread-to-expected-loss ratios. Descriptive statistics for the ratio of average corporate bond yield spreads to average expected loss rates have been provided by Huang and Huang (2012), Driessen (2005) and Giesecke et al. (2011), among others. These authors use historical default frequencies to compute average expected losses rates and report yield-spread-to-expected-loss ratios between 1.1 and 2.6.[7]

Our estimates are thus somewhat higher than those reported in prior work. Some of this

[7]Giesecke et al. (2011) compute a ratio of average yield spreads to estimated average actual credit losses of 2.0 for the 1866-2008 period. Driessen (2005) uses a reduced-form modeling approach and reports a ratio of risk-neutral to actual default intensities of 1.8 for AA-rated firms, 2.6 for A-rated firms and 2.4 for BBB-rated firms, for the 1991-2000 period. Using the structural model of Leland and Toft (1996), and bond price data for 1973-1993, Huang and Huang (2012) calibrate model parameters that determine actual and risk-neutral default probabilities. Our calculation of the associated estimated ratios of annualized risk-neutral to actual five-year default probabilities ranges from 1.8 for Aa-rated firm to 1.1 for B-rated firms.

difference is based on the fact that we compute expected loss rates based on EDFs rather than on rating-based PDs. In Section 7 we show that median CDS-to-expected-loss ratios decrease from 3.9 to 3.2 when EDFs are replaced by rating-based PDs. As a further source of difference from the prior literature, we report the sample median of ratios for specific firms and dates, rather than the ratio of sample-average CDS rates to sample-average expected loss rates. For rating-based PDs, changing the computation from the median ratio to the ratio of averages further lowers the reported ratio from 3.2 to 2.2, which is in line with the prior literature.

4.2 Temporal Variation of Credit Risk Premia

The daily time series of median credit risk premia is displayed in Figure 5. Annual summary statistics are provided in Table 3. We observe dramatic changes over time in the price of default insurance, even after controlling for changes in expected default protection losses. Annual median premia (CDS rate net of expected loss due to default) were 65 basis points in 2002, then dropped almost 50% to 35 basis points in 2003. These premia stayed below 30 basis points between 2004 and 2007, before sharply increasing to over 100 basis points during the 2008-09 financial crisis. For the first three years following the crisis, median premia remained fairly high—between 85 and 100 basis points—before declining to lower levels. They amounted to 70, 52 and 57 basis points in 2013, 2014 and 2015, respectively. Notably, throughout the entire 2010-15 post-crisis period, median premia remained far above their pre-crisis levels.

Per unit of expected default loss, annual median credit risk premia were lowest at 1.3 in 2004 and highest at 5.2 in 2008. Their temporal pattern is similar to that for premia measured in basis points, mainly because the variation in credit spreads far outweighs that of expected losses. (The time series of median premia, measured as a fraction of CDS rates, is shown in Figure C.2 in the internet appendix.)

In Table 4, we report the sample correlation between median credit risk premia and various macroeconomic variables. The latter are described in detail in Internet Appendix F. For premia measured in basis points of notional debt per year, the comovement is most pronounced for

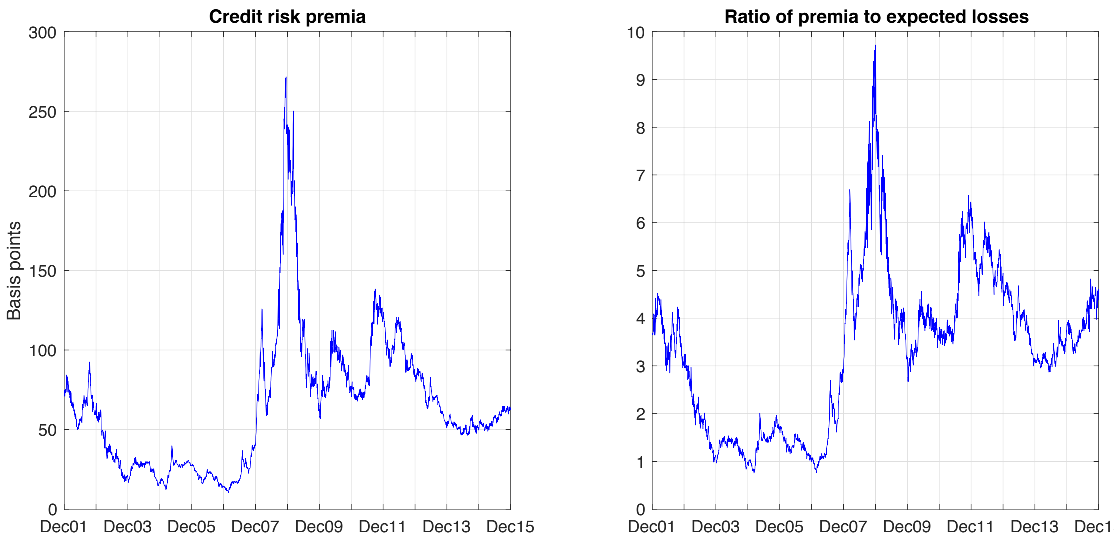

Figure 5: **Median credit risk premia** The left panel of the figure shows the daily times series of the median credit risk premium component of five-year CDS rates in basis points. The right panel shows the median premium-to-expected-loss ratio, $\mathrm{Prem_t}/\mathrm{ExpL}_t$. Only days on which premia are available for 50 or more firms are shown. The data cover 505 public U.S. firms, over 2002-2015.

measures of aggregate stock-market volatility, consumer sentiment and consumption growth. The sample correlation between each of these macro time series and median credit risk premia has an absolute magnitude in excess of 70%.[8] For premium-to-expected-loss ratios, the macro variables whose correlation with median credit risk premia are largest in magnitude are consumer sentiment and the five-year Treasury yield. In each case, the sample correlation is close to or below –70%.

Table 4 reveals that the extent to which credit risk premia change over time and co-move with macro fundamentals depends on the credit quality of the underlying firm. When measured in basis points of notional, premia tend to be more volatile for lower credit quality firms. But when expressed as a multiple of expected loss rates, premia generally exhibit more variation over time for higher credit quality firms. Indeed, daily median premium-to-expected-loss ratios are twice as volatile for investment-grade firms as for high-yield firms, as visualized in Figure C.3 in

[8]The statistics in Table 4 are computed using daily data. If a macro variable is observed only once a month or quarter, for any given day we use the last available observation. Details are provided in Internet Appendix F. We note that the square of a correlation reported in the table is equal to the R^2 of the regression of median risk premia on the associated macro variable. This statistic therefore measures the fraction of the variation in median premia that can be explained by variation in the macro variable.

Table 4: **Comovement between credit risk premia and macroeconomic variables** The table reports the standard deviation of daily median credit risk premia (column 1) and the correlation between daily median premia and various macroeconomic variables (columns 2 through 12). The macro variables include market-wide implied volatilities for standardized 91-day at-the-money and out-of-the-money put options on the S&P500 index ($\mathrm{MV}_{\mathrm{atm}}$ and $\mathrm{MV}_{\mathrm{otm}}$), aggregate stock market volatility as measured by the VIX index (VIX), the five-year Treasury rate (Trsy rate), the difference between five-year and one-year Treasury rates (Trsy slope), the University of Michigan Consumer Sentiment Index (CSENT), the unemployment rate (UNRATE), consumption growth (Cons growth), the leading index for the U.S. (USSLIND), a dummy variable that is one during NBER recessions and zero otherwise (NBER), the average monthly volume of defaulted U.S debt over the past twelve months (Dfltd debt), and CDS notional outstanding (CDS notional). The macro variables, and how they are sourced, are described in detail in Internet Appendix F. The standard deviations and correlations are reported for median premia computed across all firms (row 1), investment-grade firms (row 2) and high-yield firms (row 3). Only days on which premia are available for 50 or more firms are used in the respective calculations. The data cover 505 public U.S. firms, over 2002-2015.

	SD	$\mathrm{MV}_{\mathrm{atm}}$	$\frac{\mathrm{MV}_{\mathrm{otm}}}{\mathrm{MV}_{\mathrm{atm}}}$	VIX	Trsy rate	Trsy slope	CSENT	UN-RATE	Cons growth	USS-LIND	NBER	Dfltd debt	CDS not'l
							Prem						
All	42	0.78	-0.04	0.74	-0.57	0.25	-0.76	0.58	-0.71	-0.53	0.55	0.52	0.48
IG	31	0.77	-0.03	0.74	-0.58	0.29	-0.75	0.61	-0.68	-0.50	0.51	0.50	0.45
HY	104	0.89	-0.21	0.84	-0.48	0.30	-0.78	0.56	-0.78	-0.67	0.61	0.63	0.56
							Prem/ExpL						
All	1.64	0.65	0.09	0.61	-0.68	0.25	-0.71	0.54	-0.66	-0.38	0.50	0.39	0.50
IG	2.04	0.69	0.05	0.65	-0.66	0.26	-0.74	0.58	-0.69	-0.45	0.53	0.45	0.50
HY	1.01	0.38	0.27	0.37	-0.58	-0.01	-0.44	0.14	-0.39	-0.11	0.34	0.10	0.48

the internet appendix. For IG firms, median premium-to-expected-loss ratios move closely with consumer sentiment, Treasury rates, aggregate stock-market volatility and consumption growth. For HY firms, however, there is a much smaller correlation between credit risk premium ratios and these macro fundamentals.

Our observations are consistent with the notion that during times of market-wide distress, increases in credit spreads outpace increases in expected default losses. The disproportionate increase in the price of default insurance is more pronounced for firms of higher credit quality.

Lastly, Figure C.4 in the internet appendix displays the time series of daily median premium-to-expected-loss ratios for each sector. These ratios tend to be most volatile for utilities (with a standard deviation of 7.8) and least volatile for financials and technology firms (each having a standard deviation of 1.1). In Section 6, we investigate in more detail the extent to which variation in premia, across firms and over time, is associated with variation in firm-specific and macroeconomic variables.

Internet Appendix G characterizes the term structure of credit risk premia, over time, by industry and by credit rating. The term structure was relatively flat prior to the financial crisis of 2008-09, and steepened in the post-crisis years. Between 2010 and 2013, median differences between five-year and one-year premia were particularly wide, often in excess of 50 basis points. In what follows, we develop a predictive model for cross-sectional and temporal variation in five-year credit risk premia. Corresponding results for one-year and ten-year premia are provided in the internet appendix.

5. The Fraction of Variation in Credit Risk Premia Explained by Expected Default Losses

This section investigates the extent to which variation in credit risk premia can be explained by variation in expected default losses. In light of Equation (4), this is equivalent to quantifying the sensitivity of credit spreads to expected losses. While Figure 6 shows the expected positive relationship between five-year CDS rates and five-year expected loss rates, the dispersion in observed CDS rates is large at each level of expected loss, and becomes larger as the expected loss rate increases.

In order to obtain a tighter link between credit spreads and expected losses and to mitigate the effect of heteroskedasticity, we explore this relationship in log-log space. That is, we relate the logarithm of CDS rates to the logarithm of expected loss rates. The sample distribution of the logarithm of CDS-to-expected loss ratios exhibits much less skewness and is more suited to linear modeling than that of the raw ratios. (See Figure C.5 in the internet appendix.) Figure 7 reveals a strong positive relationship between $\log(C_t^i)$ and $\log(\mathrm{ExpL}_t^i)$.

At the five-year maturity, regressing the logarithm of the CDS rate on the logarithm of the expected loss rate produces a highly significant regression[9] coefficient of 0.555. The CDS rate

[9]This regression analysis is based on a somewhat smaller sample of 1,003,488 firm-date pairs that covers 467 firms. These data later enter regressions that include additional covariates, and hence impose greater demands on data availability.

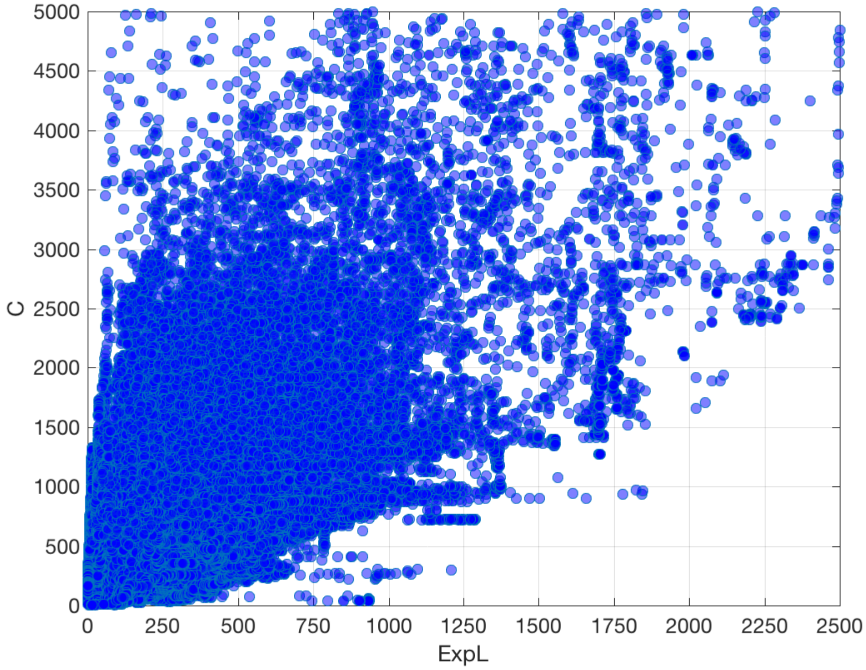

Figure 6: **CDS rates versus expected default loss rates** This figure shows the scatter plot of five-year expected loss rates and five-year CDS rates, both measured in basis points of notional. The data cover 505 public U.S. firms, over 2002-2015.

is estimated to increase proportionately by approximately $\exp(0.555 \times \log(1.1)) - 1 = 5.4\%$ for each 10% proportional increase in the expected loss rate. This fitted relationship implies that credit spreads, per unit of expected losses, are decreasing in expected losses.

Consider the linear regression model

$$\log\left(\frac{C_t^i}{\mathrm{ExpL}_t^i}\right) \quad = \quad \beta_0 + \beta_1 \log(\mathrm{ExpL}_t^i) + \sum_{\text{firm } i} \beta^i D^i(i,t) + \sum_{\text{month } m} \beta_m D_m(i,t) + \epsilon_t^i, \qquad (5)$$

where i identifies the firm, t is the date, β_0 and β_1 are scalars, D^i is a dummy variable that is one for firm i and zero otherwise, D_m is a dummy variable that is one for month m and zero otherwise, and ϵ_t^i is a random disturbance term. The coefficients β^i and β_m capture firm and month fixed effects. Detailed results are reported in Table 5.

Without fixed effects, the OLS estimate for β_1 in Equation (5) is –0.445. A 10% proportional increase in the expected loss rate is thus associated with a proportional decrease of

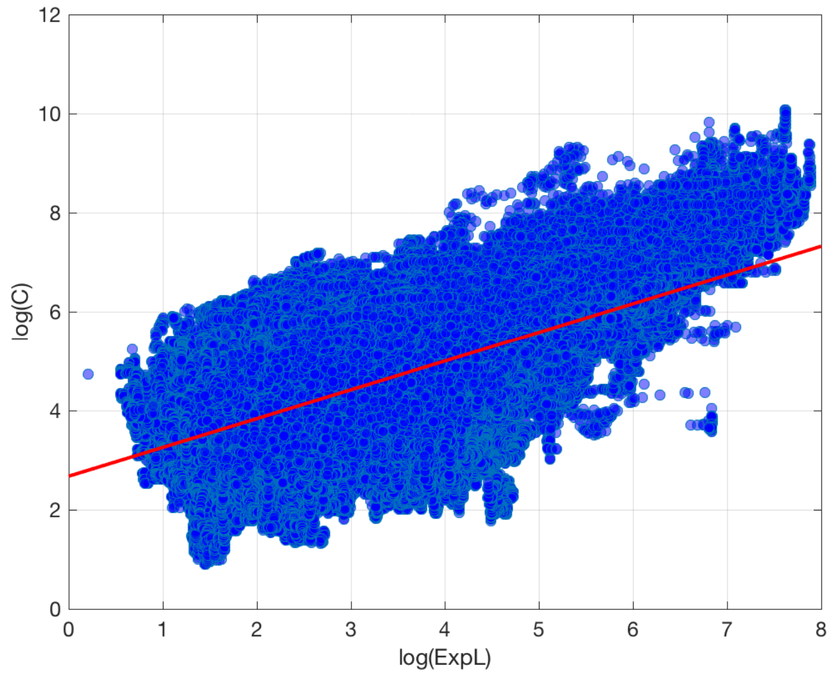

Figure 7: **CDS rates versus expected default loss rates, logarithmic** This figure shows the scatter plot of five-year expected loss rates and five-year CDS rates, logarithmic, and the associated OLS fitted relationship. The data cover 505 public U.S. firms, over 2002-2015.

Table 5: **Variation in credit risk premia explained by variation in expected loss rates** The table reports the results of the panel data regression (5). The coefficients β^i and β_m capture firm and month fixed effects (FEs). Credit spreads and expected losses are measured in basis points. Driscoll-Kraay standard errors that are robust to heteroskedasticity, autocorrelation and cross-sectional dependence are reported in parentheses. The data cover 467 public U.S. firms, over 2002-2015.

	I	I(F)	I(FM)
Constant	2.746	3.294	4.236
	(0.027)	(0.067)	(0.049)
log(ExpL)	-0.445	-0.353	-0.463
	(0.003)	(0.010)	(0.007)
Firm FE	No	Yes	Yes
Month FE	No	No	Yes
R^2	0.261	0.619	0.836
RMSE	0.817	0.587	0.386

$1 - \exp(-0.445 \times \log(1.1)) = 4.2\%$ in the ratio of CDS rate to expected loss rate. The root mean squared error (RMSE) for this fitted relationship is 0.817. An assumption of normally distributed disturbances implies a one-standard-deviation confidence band for a given CDS-to-expected-loss ratio of between $\exp(-0.817) = 44\%$ and $\exp(0.817) = 226\%$, as a multiple of the fitted ratio. While the CDS data are noisy in this sense, the relationship between the logarithm of the CDS-rate-to-expected-loss-rate ratio and the expected loss rate is highly significant. Variation in expected loss rates, on its own, explains a sizable fraction—an R^2 of about 26%—of variation in this log ratio.

Table 5 reveals that the inclusion of firm and month fixed effects in Equation (5) results in a substantially higher R^2 (84% with fixed effects, compared to 26% without) and in a much lower root mean squared error (0.39 with fixed effects, compared to 0.82 without). The left panel in Figure 8 and Figure C.6 in the internet appendix reveal that lower rated firms tend to have higher credit spreads, even after conditioning on expected losses. This may be due to differences in the degree of systematic risk across credit quality or to clientele effects that restrict the set of investors that supply default protection for risky firms.

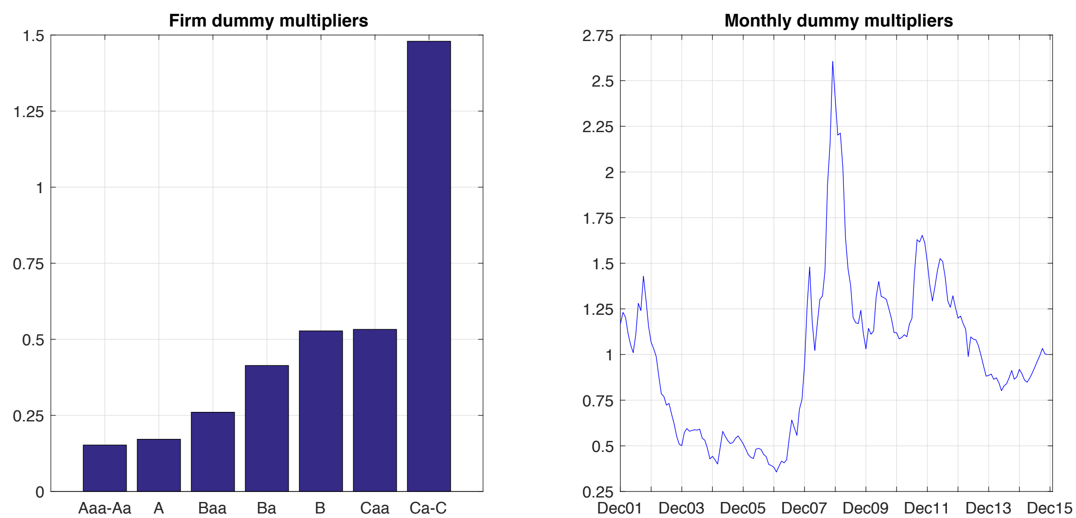

Figure 8: **Firm and month dummy multipliers** The left panel shows the median firm dummy multiplier in regression (5), $\exp(\beta^i)$, by refined letter rating. The right panel displays the time series of monthly dummy multipliers, $\exp(\beta_m)$. The data cover 467 public U.S. firms, over 2002-2015.

The right panel in Figure 8 shows that, after controlling for the level of default risk, there is substantial time variation in investors' compensation for bearing corporate default risk. We observe markedly higher credit spreads per unit of expected loss in 2002, during the 2008-09 financial crisis and in late 2011, a period covering concerns over peripheral European sovereign debt and also the U.S. government debt ceiling crisis.

Table C.1 in the internet appendix provides similar findings across the maturity spectrum. In the next section, we investigate the extent to which firm and time fixed effects are captured by observable firm characteristics and macroeconomic variables.

6. Predicting Credit Risk Premia

In order to isolate firm characteristics and time-series variables that may be responsible for the important firm and time fixed effects that we discovered in Equation (5), we estimate a panel-data regression model in which $\sum_{\text{firm } i} \beta^i D^i$ and $\sum_{\text{month } m} \beta_m D_m$ are replaced by controls of the form $X_t^i \beta_X'$ and $Y_t \beta_Y'$. Specifically,

$$\log\left(\frac{C_t^i}{\text{ExpL}_t^i}\right) = \beta_0 + \beta_1 \log(\text{ExpL}_t^i) + X_t^i \beta_X' + Y_t \beta_Y' + \varepsilon_t^i. \tag{6}$$

Here, X_t^i and Y_t are vectors of firm-specific and macroeconomic predictors, respectively, β_X and β_Y are coefficient vectors to be estimated, and ε_t^i is a random disturbance. The predictor variables that we consider in the regression analysis are described in detail in Internet Appendix F.

6.1 Firm-Specific Predictors

Here, we explore firm-specific predictors of credit risk premia. Our findings are summarized in Table 6. Specification I is the benchmark model of the previous section, which assumes that $\beta_X = 0$ and $\beta_Y = 0$. Specification II is motivated by our findings in Figures 8 and C.6, and includes dummies for the alphanumeric rating, as adjusted for watchlist and outlook status, in the vector X_t^i of firm-specific predictor variables. Table 6 reports that these refined ratings dummies are highly statistically significant and have large explanatory power for credit spreads, even after controlling for expected loss rates. Indeed, adding refined ratings dummies increases the R^2 from 26% to 58%, and lowers the residual standard error from 0.82 to 0.62. Comparing these results with those for the model with firm fixed effects in Table 5, we find that refined ratings dummies have nearly as much explanatory power as firm fixed effects.

Table 6: **Firm-specific sources of variation in credit risk premia** The table reports the results of the panel data regression (6). Here, IV_{atm} and IV_{otm} are the standardized 91-day put-implied volatilities at a Delta of –50% and –20%. 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. 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 467 public U.S. firms, over 2002-2015.

	I	II	III	IV	V	VI
Constant	2.746	3.600	5.086	5.260	5.257	5.884
	(0.027)	(0.020)	(0.041)	(0.044)	(0.044)	(0.045)
log(ExpL)	–0.445	–0.737	–0.899	–0.937	–0.939	–1.399
	(0.003)	(0.005)	(0.005)	(0.007)	(0.007)	(0.014)
$\log(\text{IV}_{atm})$			0.985	1.030	1.025	1.045
			(0.029)	(0.030)	(0.030)	(0.030)
$\log(\text{IV}_{otm}/\text{IV}_{atm})$			1.722	1.614	1.610	1.888
			(0.078)	(0.076)	(0.076)	(0.092)
Recent upgrade					–0.098	–0.099
					(0.008)	(0.009)
Recent downgrade					0.105	0.111
					(0.009)	(0.009)
Recent upgrade from HY to IG					–0.068	–0.022
					(0.030)	(0.031)
Recent downgrade from IG to HY					0.049	0.055
					(0.018)	(0.018)
$\log(\text{ExpL})^2$						0.073
						(0.002)
$\log(\text{IV}_{atm}) \times D_{HY}$						–0.265
						(0.012)
$\log(\text{IV}_{otm}/\text{IV}_{atm}) \times D_{HY}$						–1.278
						(0.075)
Refined ratings dummies	No	Yes	Yes	Yes	Yes	Yes
Sector dummies	No	No	No	Yes	Yes	Yes
R^2	0.261	0.576	0.698	0.710	0.711	0.723
RMSE	0.817	0.619	0.522	0.512	0.511	0.500

The regression coefficient estimates for the refined ratings dummies follow the pattern displayed in Figure C.7 in the internet appendix. They are higher for lower rated debt. For example, at a given expected loss, investor compensation per unit of risk is estimated to be 46% lower for A than Baa firms, and 112% higher for Ba than Baa firms. In that sense, refined ratings are important predictors of cross-sectional variation in credit spreads.

Our findings are consistent with permanent ratings-based investor clientele effects. While many investors would consider buying an investment-grade (IG) bond, a more restricted set of investors are open to buying high-yield (HY) bonds, often because of agency-based asset management mandates. What we have in mind, in addition to portfolio holdings regulations and risk-based capital requirements for financial institutions, are supply and demand effects associated with different types of investors. Less sophisticated investors may not trust their information as much as investment professionals who specialize in distressed debt. Less sophisticated investors, in this sense, may also know less about managing distressed debt positions, in particular through a restructuring. As a result, less sophisticated investors are likely to prefer higher-rated bonds over a lower-rated bonds, controlling for a given price per unit of default risk, and are more likely to provide IG-restricted investment mandates to their asset managers, such as mutual funds.

Specification III goes further by including firm-specific implied-volatility measures as predictor variables. Although our expected-loss measure includes the impact of equity volatility through distance to default, it could suffer from functional misspecification and noise. Hence an additional direct measure of expected future equity volatility such as a firm's at-the-money put-implied volatility, IV_{atm}, may help control for solvency risk. Furthermore, under the natural presumption that there is a price for bearing market-value volatility above and beyond that implied by default risk, we would expect credit risk premia to be higher for more volatile firms after controlling for expected losses.

In addition to the level of implied volatility (IV), we also control for the smirk of the IV surface. The smirk is measured as the ratio of out-of-the-money (OTM) to at-the-money (ATM) put-implied volatilities, $\mathrm{IV}_{otm}/\mathrm{IV}_{atm}$. The idea here is that the volatility smirk may contain information about the cost of insuring against sudden large increases in a firm's default risk. Table 6 shows that adding the log of a firm's IV and the log of the smirk of the IV surface to the regression model increases the R^2 from 58% to 70%, and lowers the residual standard error from 0.62 to 0.52.

The loadings on IV and the IV smirk are both positive and highly statistically significant.

An increase in the level of the IV surface from 30% to 45%, for example, is associated with[10] an increase in the CDS-rate-to-expected-loss-rate ratio of $\exp(0.985 \times \log(1.5)) - 1 = 49.1\%$. An increase in the volatility smirk of 10% is associated with an estimated increase in the ratio of CDS rate to expected loss rate of about $\exp(1.722 \times \log(1.10)) - 1 = 17.8\%$.

Specification IV adds sector fixed effects. With this, the regression R^2 increases from 70% to 71%, and the residual standard error decreases from 0.52 to 0.51. The estimated sector loadings are shown in Figure C.8. Using Consumer Goods as the benchmark sector and holding everything else the same, financial, technology, telecommunications and utility firms tend to command higher credit risk premia per unit of expected loss, whereas healthcare companies tend to command lower prices for bearing default risk.

Specification V further augments the set of conditioning variables with dummy variables for recent upgrades, downgrades and changes in the IG/HY status. While there are only minor improvements in the goodness of fit, we find evidence of statistically significant ratings momentum effects. We find that CDS rates of firms whose alphanumeric rating has been downgraded in the past six months tend to be $\exp(0.105) - 1 = 11.1\%$ higher than those of firms that, although otherwise similar, did not experience a recent change in rating. This proportional increase is even more pronounced, at $\exp(0.105 + 0.049) - 1 = 16.7\%$, for firms that were downgraded from IG to HY status. These temporary price pressure effects are in addition to the permanent ratings-based clientele effects discussed earlier. Their presence points to inefficiencies in the re-allocation of corporate bonds that are sold by restricted to unrestricted investors when firms fall out of IG status.[11] A recent upgrade, on the other hand, tends to be associated with $\exp(-0.098) - 1 = -9.3\%$ proportionately lower credit spreads. The tightening of spreads is particularly pronounced for upgrades from HY to IG status, with spreads expected to change

[10] According to Table F.1 in the internet appendix, the average value of $\log(\text{IV}_{atm})$ is –1.23, which corresponds to an ATM IV of about 30%. The standard deviation of $\log(\text{IV}_{atm})$ is 0.42, which roughly translates into a 50% change in IV_{atm}. The standard deviation of $\log(\text{IV}_{otm}/\text{IV}_{atm})$ is 0.10, which roughly translates into a 10% change in $\text{IV}_{otm}/\text{IV}_{atm}$.

[11] Ambrose, Cai, and Helwege (2012), Ellul, Jotikasthira, and Lundblad (2012) and Chen et al. (2014), among others, also analyze price pressure effects in corporate bond markets associated with rating downgrades from IG to HY.

proportionally by $\exp(-(0.098 + 0.068)) - 1 = -15.3\%$.

The most elaborate model in Table 6, Specification VI, allows for second-order terms of expected losses and interactions of the volatility surface variables with high-yield ratings status. These additional variables increase the R^2 from 71% to 72%, and lower the residual standard error from 0.51 to 0.50. We find that the log-log relationship between the CDS-rate-to-expected-loss-rate ratio and the expected loss rate exhibits some degree of convexity. Specifically, the sensitivity of the logarithm of C/ExpL to the logarithm of ExpL decreases as the expected loss rate increases. While a 10% increase in the expected loss rate from 10 to 11 basis points of notional is associated with a 9.6% decrease in C/ExpL, a 10% increase in the expected loss rate from 100 to 110 basis points is associated with only a 6.7% decrease in C/ExpL. The sensitivity of credit risk premia to the implied volatility surface also decreases as credit quality deteriorates.

Taking these effects together, the credit risk premia of riskier firms tend to be less sensitive to changes in firm-specific default risk and volatility controls. This is consistent with the evidence in Figure C.3 in the internet appendix, which shows that CDS-to-expected-loss ratios tend to exhibit more (counter-cyclical) time-series variation for investment-grade firms than for high-yield firms.

6.2 Macroeconomic Predictors

Figure 9 displays the time series of average regression residuals for the most elaborate model in Table 6, Specification VI. While the fit is reasonably close, it tends to underestimate CDS rates between 2003 and 2007. The model overestimates CDS rates in 2002 and between 2008 and 2015. We now explore the extent to which this unexplained common co-movement can be explained by comovement of credit spreads with macroeconomic variables.

To this end, we augment the vector of conditioning variables in our basic regression model with macroeconomic variables. We focus on the five-year Treasury rate and the University of Michigan consumer sentiment index, as these exhibit the highest correlation with CDS-to-expected loss ratios in Table 4, and also include a proxy for CDS market liquidity.[12] Interest

[12] Additional macroeconomic controls are explored in Internet Appendix H. Adding market-wide equity volatil-

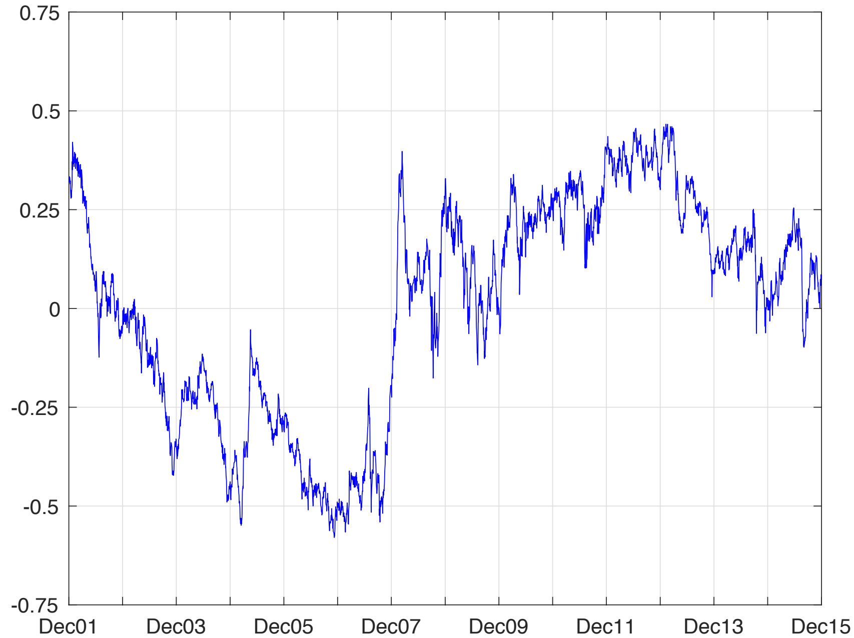

Figure 9: **Regression residuals after controlling for firm characteristics** This figure shows the daily time series of average residuals for Specification VI in Table 6. The data cover 467 public U.S. firms, over 2002-2015.

rates may be able to capture some of the unexplained variation in Figure 9 given that they were substantially higher prior to the Great Recession (when average regression residuals were lower) and lower afterwards (when average residuals were higher). A negative relationship between interest rates and credit spreads would also be consistent with the evidence in Duffee (1998, 1999), Collin-Dufresne, Goldstein, and Martin (2001), Campbell and Taksler (2003) and Avramov, Jostova, and Philipov (2007), among other research.

Indeed, we find that, all else the same, lower interest rates are associated with higher credit spreads. Specification VII in Table 7 includes all of the firm-specific controls in Table 6, as well as five-year Treasury rates. For this model, a marginal decrease in interest rates of one percentage point (in absolute interest rates) is associated with an increase in the ratio of CDS rate to expected loss rate of $\exp(-0.211 \times (-1)) = 23.5\%$. Controlling for interest rates improves the goodness of fit dramatically. It raises the R^2 from 72% to 79%, and lowers the residual standard

ity measures or the slope of the Treasury yield curve, for example, does not measurably improve the fit.

error from 0.50 to 0.43.[13]

Table 7: **Macroeconomic sources of variation in credit risk premia** The table reports additional results for the panel data regression (6). The numbering of the model specifications continues that of Table 6. Here, IV_{atm} and IV_{otm} are the standardized 91-day put-implied volatilities at a Delta of −50% and −20%. 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. Credit spreads and expected loss rates are measured in basis points of notional, interest rates are measured in percent, and implied volatility IV is measured in nominal terms. 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 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 467 public U.S. firms, over 2002-2015.

	VII	VIII	IX		VII	VIII	IX
Constant	6.123	9.926	9.916	Trsy rate	–0.211	–0.194	–0.216
	(0.028)	(0.192)	(0.194)		(0.005)	(0.004)	(0.004)
log(ExpL)	–1.210	–1.155	–1.104	log(CSENT)		–0.989	–0.998
	(0.008)	(0.008)	(0.009)			(0.047)	(0.048)
log(IV_{atm})	0.963	0.712	0.679	1/CDS notional		0.612	0.626
	(0.017)	(0.019)	(0.020)			(0.041)	(0.047)
log($\mathrm{IV}_{otm}/\mathrm{IV}_{atm}$)	0.944	0.745	0.678	Trsy rate $\times D_{HY}$			0.094
	(0.043)	(0.040)	(0.041)				(0.004)
Recent upgrade	–0.127	–0.104	–0.096	1/CDS notl $\times$ D_{HY}			0.148
	(0.007)	(0.007)	(0.006)				(0.055)
Recent downgrade	0.149	0.140	0.129	Refined ratings	Yes	Yes	Yes
	(0.009)	(0.009)	(0.008)	Sectors	Yes	Yes	Yes
Recent upgr HY to IG	0.033	0.033	0.040	R^2	0.794	0.809	0.812
	(0.028)	(0.027)	(0.027)	RMSE	0.431	0.416	0.412
Recent dngr IG to HY	0.091	0.098	0.032				
	(0.018)	(0.017)	(0.016)				
log(ExpL)^2	0.049	0.046	0.037				
	(0.001)	(0.001)	(0.001)				
log(IV_{atm}) $\times$ D_{HY}	–0.226	–0.230	–0.056				
	(0.012)	(0.012)	(0.015)				
log($\mathrm{IV}_{otm}/\mathrm{IV}_{atm}$) $\times$ D_{HY}	–0.729	–0.699	–0.566				
	(0.057)	(0.055)	(0.058)				

In Specification VIII in Table 7, we also control for the logarithm of the University of Michigan consumer sentiment index (CSENT) and the reciprocal of aggregate CDS notional outstanding.[14] The estimated coefficients for both variables are statistically and economically significant. The R^2 is raised from that of Specification VII, from 79% to 81%, and the residual

[13]Replacing interest rates with log interest rates in regression (6) results in a smaller R^2.

[14]Replacing the reciprocal of aggregate CDS notional outstanding by notional outstanding or the logarithm of notional outstanding yields a smaller R^2.

standard error is lowered from 0.43 to 0.42.

The consumer sentiment index is a leading economic indicator that may be used by investors to predict where the economy is headed. The higher the index the more optimistic consumers are about near-future economic conditions. We therefore anticipate a negative relationship between consumer sentiment and the price for default insurance. Consistent with this intuition, we find that a 15% increase in consumer sentiment, which is roughly consistent with a one-standard deviation increase in log(CSENT), is associated with a $\exp(-0.989 \log(1.15)) - 1 = -12.9\%$ proportional change (decrease) in CDS rates.

A marginal increase in aggregate CDS notional outstanding is associated with a decrease in CDS rates. For example, a one-standard-deviation increase in notional outstanding from 25 to 40 trillion is associated with a $\exp(0.612\,(1/40 - 1/25)) - 1 = -0.9\%$ decrease in spreads.

Motivated by the observation in Table 4 that the credit risk premia of high-yield firms tend to exhibit less comovement with macro fundamentals than those of investment-grade firms, Specification IX allows the loadings on the macroeconomic controls to depend on whether a firm is investment grade or high yield. We include these interaction terms for Treasury rates and CDS notional outstanding, only. The sample correlation of the interaction term for CSENT with that for ATM implied volatility and also that for Treasury rates is nearly 90% in absolute terms, implying that the loadings on these three interaction terms would be difficult to interpret.

We find that credit risk premia of HY firms are indeed less sensitive to the level of Treasury yields than those of IG firms. For total CDS notional outstanding, the difference in loadings is less pronounced, which is consistent with the evidence in Table 4. Both IG and HY firms tend to experience a decrease in CDS rates with increases in CDS notional outstanding.

The most elaborate model in Table 7, Specification IX, has an R^2 of 81% and a root mean squared error of 0.41. An assumption of normally distributed disturbances implies a one-standard-deviation confidence band for a ratio of CDS rate to expected loss rate covering the interval between $\exp(-0.41) = 66\%$ and $\exp(0.41) = 151\%$ of the fitted ratio. This error band is only slightly wider than that implied by the model with firm and month fixed effects in

Table 5.

Figure 10 shows multipliers for the refined ratings and sector dummies. The refined ratings multipliers are similar across the model specifications in Tables 6 and 7 for investment-grade firms. Even so, the inclusion of additional predictor variables in specifications III through IX—in particular the inclusion of implied volatility measures and the second-order term of expected losses—dampens the increase in ratings multipliers that we observed in Figure C.7 for Specification II. This is notable as credit quality drops from Ba to Ca-C. It suggests that the comparatively high proportional credit risk premia observed for lower rated firms often go hand in hand with much higher volatility or large expected default losses. In terms of the marginal cross-sector distribution of credit spreads, financials and telecommunication firms tend to command the highest ratio of credit risk premia to expected default losses. Healthcare firms have the lowest average credit risk premia in this sense.

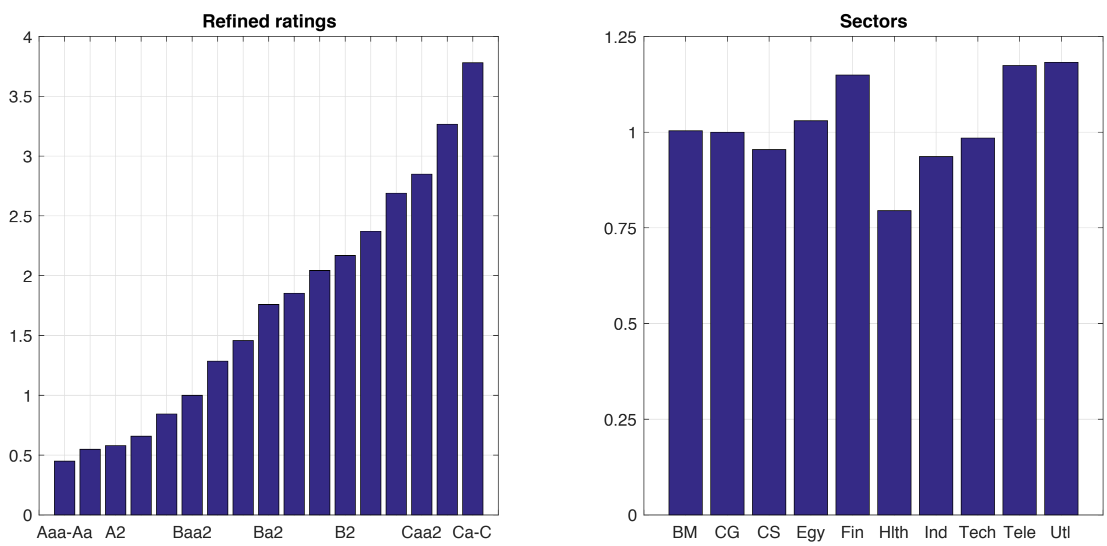

Figure 10: **Refined ratings and sector multipliers** The left panel shows multipliers for the refined ratings dummies $\exp(\beta_{Rtg})$ in specification IX of Table 7. Refined ratings are alpha-numeric ratings adjusted for watchlist and outlook status. The right panel shows the sector multipliers $\exp(\beta_{Sec})$ for the same regression model. The data cover 467 public U.S. firms, over 2002-2015.

Figure 11 displays the time series of average regression residuals for the most elaborate model in Table 7. Comparing the average residuals before and after controlling for macro variables, that is, comparing Figures 9 and 11, we find a substantial improvement in the goodness of fit. The overestimation of spreads between 2008 and 2015 is no longer apparent, and much of the underpricing between 2003 and 2007 has been corrected. This suggests that much of the previously unexplained comovement across firms in credit spreads is explained by time variation in macroeconomic variables that influence credit spreads.

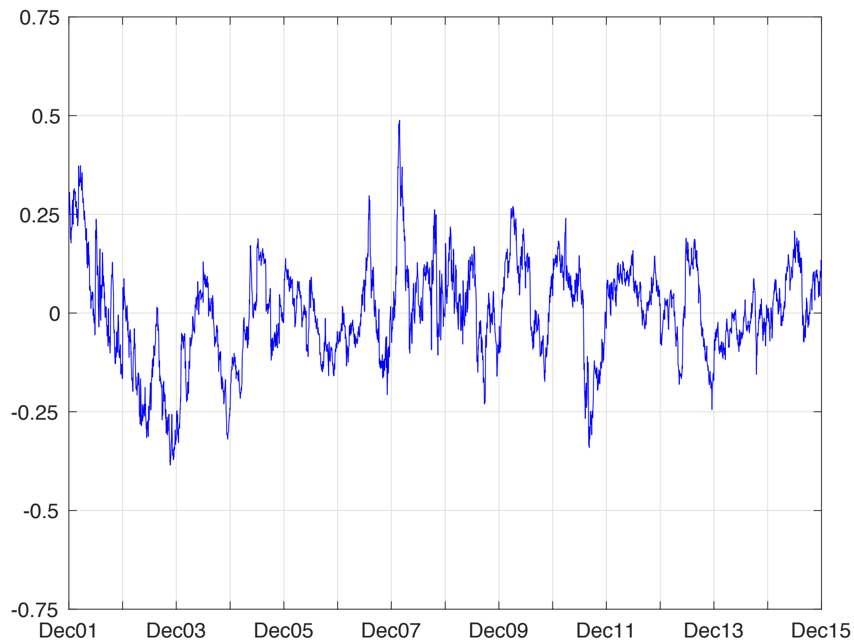

Figure 11: **Regression residuals after controlling for firm characteristics and macroeconomic variables** This figure shows the daily time series of average residuals for Specification IX in Table 7. The data cover 467 public U.S. firms, over 2002-2015.

In Internet Appendix H, we enlarge the vector of conditioning variables in the panel regression and show that further improvements in the goodness of fit are rather limited.

6.3 Economic Impact of Predictor Variables

Figure 12 shows the contribution of firm-specific variables to predicted credit risk premia, using Specification IX of Table 7. For this, we fix a specific date, December 31, 2003. On that date, the five-year Treasury rate was 3.25%, the consumer sentiment index (observed with a one-month lag) was 93.7, and the total outstanding CDS notional (last reported for June that year) was 2.7 trillion USD. For the benchmark scenario, we set the alphanumeric rating to Baa3. In order to select the remaining firm-specific variables, we first compute sample statistics for the December 31, 2003 subsample of firms with a Baa or Ba letter rating, that is, near the Baa3 benchmark. We then set the implied at-the-money and out-of-the-money volatilities to 25% and 30%, respectively, which are close to their respective sample means (and medians). We assume that the firm is part of the Consumer Goods sector, that its watchlist and outlook status are stable, and that it has not experienced any recent rating changes.

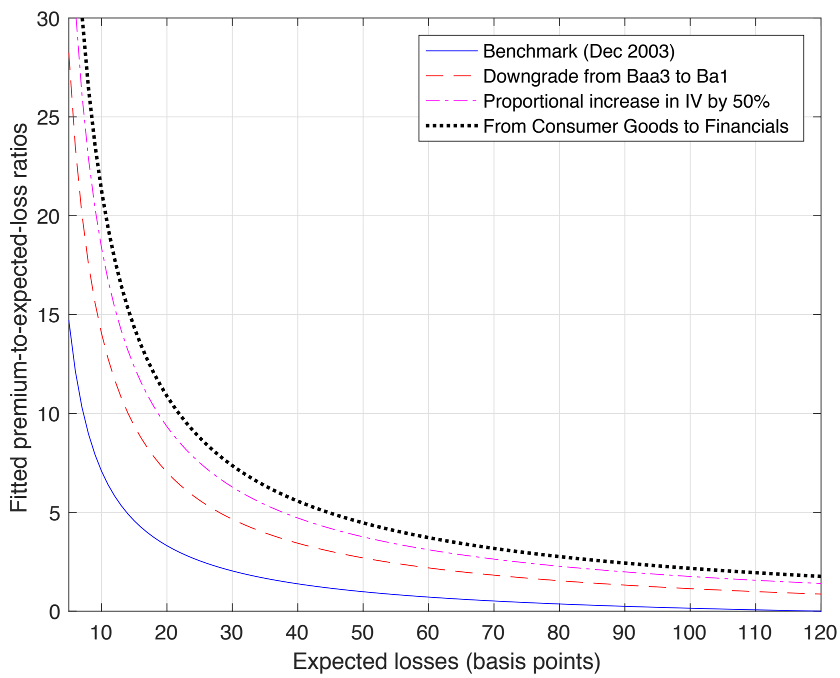

Figure 12: **Impact of firm-specific predictor variables** The figure shows fitted ratios of credit risk premium, Prem, to expected default loss rate, ExpL, as this ratio varies with the expected default loss rate, based on the estimated model for Specification IX in Table 7.

The solid line in Figure 12 shows how, for the benchmark scenario, the fitted ratio of credit risk premium to expected loss rate changes as a function of the expected loss rate, displaying a convex relationship. The range of expected loss rates shown—from 5 to 120 basis points of notional per year—captures over 90% of the cross-sectional sub-sample distribution of expected loss rates. The mean (and median) of that distribution is close to 30 basis points, and the sample standard deviation is about 40 basis points. The fitted model predicts that an increase in the expected loss rate from 30 to 70 basis points, for example, is associated with a decrease in the premium-to-expected-loss-rate ratio from 2.0 to 0.5, which represents a decrease in the credit risk premium from 61 to 36 basis points of notional.

Holding the expected default loss rate constant, we recompute the fitted ratio of credit risk premium (Prem) to the expected default loss rate (ExpL) as the following consecutive changes occur: (i) the rating drops from Baa3 to Ba1, (ii) the implied volatility increases proportionately by 50% (roughly a one-standard-deviation increase), and (iii) the sector changes from Consumer Goods to Financials.[15] At an expected loss rate of 30 basis points, the downgrade from Baa3 to Ba1 results in a sizable increase in fitted premium-to-expected-loss-rate ratios, from 2.0 to 4.7. The increase in volatility leads to a further increase in the fitted ratio, from 4.7 to 6.3. Finally, the change in sectors means yet another increase, from 6.3 to 7.4. Although the relative increase in the fitted ratio, Prem/ExpL, resulting from the downgrade is higher for larger expected loss rates, the impact on the fitted ratio of an increase in implied volatility or a change in sector is not so sensitive to the level of the expected loss rate.

In the left plot of Figure 13, we hold the firm-specific variables at their benchmark levels, and shift the macro variables from their December 31, 2003 values to their December 31, 2008 values. By the latter date, the five-year Treasury rate had dropped to 1.56%, the consumer sentiment index had fallen to 55.3, and the total notional outstanding amount of CDS had expanded to 54.6 trillion USD. We observe that each of these variable changes has a sizable impact on predicted credit risk premia. At an expected default loss rate of 30 basis points, the decrease in interest rates is associated with an increase in the fitted premium-to-expected-loss-rate ratios from 2.0 to 3.4. The decrease in consumer sentiment results in a further increase in fitted premia from 3.4 to 6.4. The increase in CDS notional outstanding, however, brings fitted ratios back down, from 6.4 to 4.9.

In the right plot of the figure, we repeat the exercise for a new benchmark date, December 31, 2008, and examine the impact of shifting the macro variables to their levels five years later, on December 31, 2013. At the end of 2013, the Treasury rate was only slightly higher, at 1.76%,

[15] As the level of volatility changes, we hold the volatility skew constant. For HY firms, the degree of association between the volatility skew and credit risk premia is rather limited.

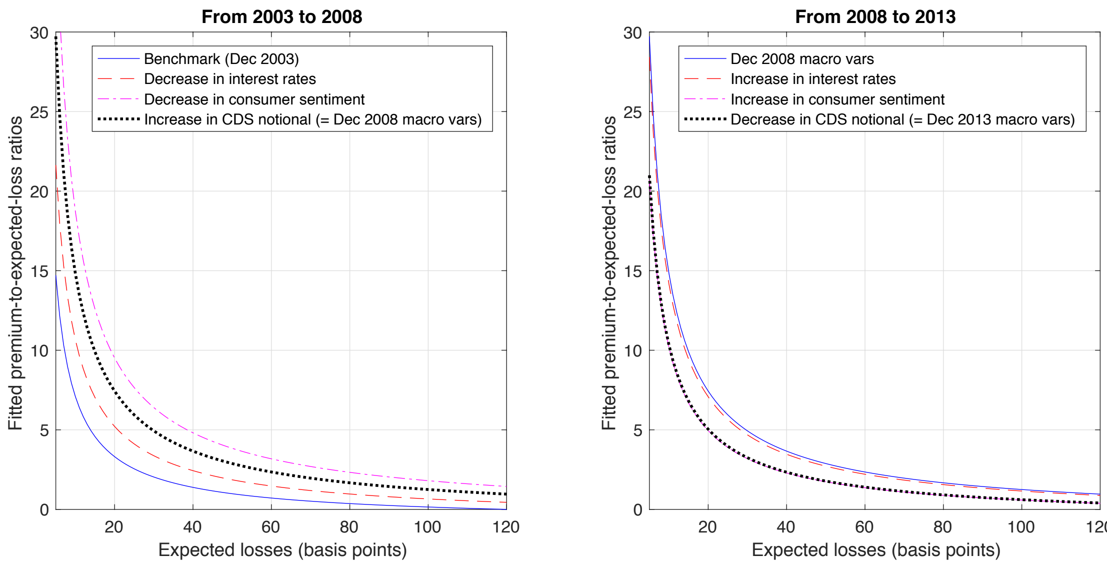

Figure 13: **Impact of macroeconomic predictor variables** The figure shows fitted Prem-to-ExpL ratios as a function of expected loss rates, using the results for Specification IX in Table 7. The left panel shows the changes in the fit as macro variables change from their December 31, 2003 to their December 31, 2008 values. The right panel shows the changes in the fit as macro variables change from their December 31, 2008 to their December 31, 2013 values.

than five years earlier. Between 2008 and 2013, consumer sentiment rose from 55.3 to 75.1, whereas CDS notional outstanding had shrunk from 54.6 to 24.3 trillion USD. In Figure 13, we find that the adjustment in predicted premia was mainly due to the increase in consumer sentiment.

6.4 Shorter and Longer Default Horizons

Table C.2 in the internet appendix reports the results for regression (6) when five-year CDS rates and expected losses are replaced by their one-year or ten-year counterparts. The results are qualitatively similar to those for the five-year default horizon. Short-term credit risk premia, however, are more closely aligned with firm-level implied volatilities, consumer sentiment, and total CDS notional outstanding than are long-term credit risk premia. These controls may have a relatively low degree of persistence in their impact on corporate default risk and pricing.

7. Alternative Measures of Expected Default Loss Rates

In this section, we decompose CDS rates into expected loss rates and credit risk premia using various alternative estimators of probability of default (PD) and loss given default (LGD).

7.1 Alternative Estimators of Probability of Default

So far, our estimates for expected loss rates and credit risk premia have been based on a Nelson-Siegel-Svensson term structure of default probabilities. This term structure was calibrated to one- and five-year EDFs and ten-year refined-ratings-based PDs (see Section 3). Internet Appendix I lists alternative sources for default-probability data and Table 8 describes the PD measures that we construct from these sources. These measures include (i) raw EDFs, (ii) PDs disseminated by the Risk Management Institute at the National University of Singapore (RMI PDs), (iii) ratings-based PDs that are equal to historical default rates for the firm's alphanumeric rating category, (iv) refined-ratings-based PDs that are matched to historical default rates based on the firm's alphanumeric rating adjusted for watchlist and outlook status, (v) refined-ratings-based PDs that are re-scaled so as to have the same cross-sectional mean on each date as that of the EDFs on that date, and (vi) combined PDs that are computed by averaging refined-ratings-based PDs with EDFs.

An important distinction between point-in-time PDs (such as EDFs and RMI PDs), which are updated frequently based on current information, and ratings-based PDs is that ratings tend to be updated more slowly.[16] This practice implies a reduction in the accuracy of the point-in-time translation of a rating to an implied default probability, and an increase in the stability of ratings and lower volatility of ratings-implied PDs, a somewhat desired property among users of ratings.

The appeal of scaled refined-ratings-based PDs is that they contain the same information about the relative credit quality across issuers as refined ratings, but that their variation over time, at least for average levels, tracks that of a point-in-time absolute measure of default risk.

[16]See, for example, Moody's Rating Policy and Approach which is available at www.moodys.com/Pages/amr002003.aspx.

Table 8: **Probability of default measures** The table lists various probability of default measures. Columns one and two show our notation for and the definition of the PD measures. Column three lists the maturity horizons for which these PDs are available.

PD measure	Definition of $E_t(D_{t,t+y})$	Maturities y
Benchmark	Nelson-Siegel-Svensson fitted PDs calibrated to 1- and 5-year EDFs and 10-year refined-ratings-based PDs (see Section 3)	Any
Alternatives		
EDFs	Cumulative y-year EDF (see Section 2)	1 and 5 years
RMI PDs	Cumulative y-year RMI PD (see Internet Appendix I)	3 and 6 months, 1, 2, 3 and 5 years
Ratings PDs	Historical cumulative y-year default rate for firm's alphanumeric rating category (see Internet Appendix I)	1, 2, 3, 4 and 5 years
Refined-ratings PDs	Historical cumulative y-year default rate for firm's refined rating category (see Internet Appendix I)	1, 2, 3, 4 and 5 years
Scaled refined-ratings PDs	Refined-ratings-based PDs scaled to have the same cross-sectional mean on date t as EDF-based PDs	1 and 5 years
Combined PDs	Average of EDF- and refined-ratings-based PDs	1 and 5 years

Averaging (rather than scaling) refined-ratings-based PDs with EDFs is another attempt to capture the cross-sectional ranking of firms provided by refined ratings with the time-series properties of EDFs in one combined PD measure.

For each alternative PD measure in Table 8, we use Equation (E.1) in the internet appendix to convert observed PDs into spot default hazard rates, and then linearly interpolate hazard rates across maturities.[17] This allows us to compute estimates of y-year default probabilities $E_t(D_{t,t+y})$ for any horizon y. Expected losses are calculated according to Equation (3), using Markit estimates of recovery rates as before.

Table C.3 in the internet appendix reports summary statistics for the various PD measures, and Table C.4 reports on the associated estimates of expected loss rates and credit risk premia. EDF-based estimates closely match those reported in Tables 2 and 3 for benchmark PDs.[18] RMI-based PDs and expected loss rates tend to be smaller than their EDF-based counterparts, especially between 2004 and 2005 and between 2013 and 2015. The differences between RMI-

[17]If the shortest observed horizon is one year, we assume that annualized spot default hazard rates for maturities of less than one year are equal to one-year hazard rates.

[18]Any differences between the EDF statistics in Tables 2 and C.3 are due to the sample underpinning the results in the latter table being somewhat smaller.

and EDF-based estimates are particularly pronounced for HY firms.

Ratings-based and refined-ratings-based PD and expected loss estimators tend to be lower than their EDF- and RMI-based counterparts for high-credit-quality firms, and substantially higher than these counterparts for low-credit-quality firms. For example, the median ratings-based expected loss rate for Caa-rated firms is 693 basis points, compared to 198 and 66 basis points for EDF-based and RMI-based expected loss rates. Scaled refined-ratings-based PDs have the same cross-sectional mean on each date as EDFs.[19] Since the cross-sectional average of EDFs is generally lower than its refined-ratings-based counterpart, scaled PDs tend to be lower than their unscaled counterparts. Combined PDs fall between EDFs and refined-ratings-based PDs. They tend to be higher (lower) than refined-ratings-based PDs for firms of high (low) credit quality.

Consistent with our estimates for expected default loss rates, the ratios of credit risk premia to expected loss rates tend to be largest for RMI-based PDs and smallest for (refined) ratings-based and for combined PDs.

We re-estimate the panel data regressions (5) and (6) for the alternative expected loss measures. The corresponding results are summarized in Table 9, and reported in more detail in Table C.5 in the internet appendix. To better facilitate comparisons across models, we replace log CDS-to-expected-loss-rate ratios with log CDS rates as the dependent variable. With this, the dependent variable is the same for all measures of expected loss rates. Despite the change in the left-hand-side variable, the information content of the panel data regressions is preserved. The only associated change in the estimated regression coefficients is that the coefficient for log(ExpL) increases by one if $\log(C)$ is used as the dependent variable instead of $\log(C/\text{ExpL})$.

The univariate model, Specification I, explains 36% and 35% of the variation in log CDS rates using, respectively, EDF- and RMI-based expected loss rates. Using ratings-based expected

[19] To be precise, for each date t and maturity horizon y, the scaled refined-ratings-based PD of a firm is computed by multiplying the refined-ratings-based estimate of $E_t(D_{t,t+y})$ for the firm with the ratio of the cross-sectional mean of EDF-based estimates of $E_t(D_{t,t+y})$ to the cross-sectional mean of refined-ratings-based estimates of $E_t(D_{t,t+y})$.

Table 9: **Variation in CDS rates explained by variation in expected loss rates** The table reports results for the panel data regressions (5) and (6), after replacing the dependent variable by the logarithm of five-year CDS rates. The numbering of the model specifications reflects that of Tables 5 and 7. Results are shown for the alternative PD measures listed in Table 8. Credit spreads and expected loss rates are measured in basis points of notional. Driscoll-Kraay standard errors that are robust to heteroskedasticity, autocorrelation and cross-sectional dependence are reported in parentheses. The data cover 467 public U.S. firms, over 2002-2015.

	EDFs			**RMI PDs**			**Ratings PDs**		
	I	I(FM)	IX	I	I(FM)	IX	I	I(FM)	IX
Constant	2.733	4.215	9.908	3.067	5.899	9.171	2.605	4.512	9.242
	(0.027)	(0.050)	(0.194)	(0.030)	(0.045)	(0.195)	(0.033)	(0.048)	(0.193)
log(ExpL)	0.558	0.535	–0.099	0.546	0.350	–0.044	0.567	0.413	0.124
	(0.003)	(0.007)	(0.009)	(0.009)	(0.006)	(0.007)	(0.004)	(0.007)	(0.016)
Firm FE	No	Yes	No	No	Yes	No	No	Yes	No
Month FE	No	Yes	No	No	Yes	No	No	Yes	No
Controls	No	No	Yes	No	No	Yes	No	No	Yes
R^2	0.359	0.857	0.836	0.354	0.841	0.836	0.534	0.848	0.828
RMSE	0.814	0.385	0.412	0.817	0.406	0.412	0.694	0.396	0.422

	Refined ratings PDs			**Scaled refined rtgs PDs**			**Combined PDs**		
	I	I(FM)	IX	I	I(FM)	IX	I	I(FM)	IX
Constant	2.562	4.364	9.206	2.791	4.618	8.483	2.042	3.287	9.928
	(0.031)	(0.040)	(0.200)	(0.026)	(0.038)	(0.205)	(0.034)	(0.040)	(0.204)
log(ExpL)	0.574	0.430	0.068	0.603	0.430	0.171	0.719	0.628	–0.174
	(0.003)	(0.005)	(0.020)	(0.004)	(0.005)	(0.021)	(0.004)	(0.005)	(0.013)
Firm FE	No	Yes	No	No	Yes	No	No	Yes	No
Month FE	No	Yes	No	No	Yes	No	No	Yes	No
Controls	No	No	Yes	No	No	Yes	No	No	Yes
R^2	0.558	0.860	0.828	0.616	0.861	0.829	0.593	0.877	0.838
RMSE	0.676	0.380	0.421	0.630	0.379	0.420	0.648	0.357	0.409

loss rates instead yields a substantially higher R^2: 53% for unadjusted ratings and 56% for ratings adjusted for watchlist and outlook status. If refined-ratings-based PDs are adjusted again by re-scaling them so as to have the same cross-sectional mean each date as EDFs, the R^2 increases from 56% to 62%. With over one million observations, this increase is rather significant. Alternatively, if we adjust refined-ratings-based PDs by averaging them with EDFs, the R^2 increases from 56% to 59%. This suggests that there is market-relevant default risk information in refined ratings that is not in EDFs, and vice versa.

The RMSE of the regression is the same for $\log(C/\text{ExpL})$ or $\log(C)$ as the dependent variable, and it can be compared across model specifications and expected loss measures in Tables 5-7 and 9. When benchmark or EDF-based expected loss rates are replaced by their scaled refined-ratings-based or combined-PD-based counterparts, the root-mean-squared prediction error is lowered from above 0.80 to below 0.65, which translates into an incremental reduction in RMSE in excess of 20%. Independent of the expected loss measure, however, the inclusion of firm and month fixed effects yields an RMSE of 0.41 or lower. Replacing firm and month fixed effects by the firm-specific and macroeconomic variables in Specification IX results in only slightly wider error bands.

Duffie et al. (2009) and Azizpour, Giesecke and Schwenkler (2017) find persistent variation in the average rate of realized corporate defaults, in excess of that predicted by observable variables. Among the additional sources of default clustering, they infer a significant latent influence on realized default probabilities, a macroeconomic process that they call "frailty." In principle, some portion of what we have measured as credit risk premia could arise from mis-specification of our measure ExpL_t of the expected default loss rate, which does not include such a latent frailty effect. To address this concern, we use Moody's Default & Recovery Database to compute the predicted number of defaults among all rated firms using refined-ratings-based PD estimates and compare this to the ex-post observed number of defaults. As shown in Figure C.9 in the internet appendix, we find that the ex-post observed number of defaults over the previous year exceeds the number of defaults predicted at the beginning of that year following times of significant market-wide distress, and that the number of realized defaults is lower than was predicted during non-crisis periods.

If market participants were indeed able to account for the role of latent factors that may cause future default rates to deviate from those predicted by EDFs, RMI PDs or ratings-based PDs, then our estimates of credit risk premia could potentially overestimate peak credit risk premia and underestimate trough risk premia, and perhaps overestimate time-series variation in credit risk premia.

We define the frailty ratio FR_t as the ratio of the observed number of defaults over the past twelve months among all rated firms to the number of defaults predicted at the beginning of the same year, using PDs based on refined ratings.[20] This ratio obviously involves a "look-ahead" effect that overstates the potential impact of frailty on the degree of variation over time in expected loss rates. In order to gauge the potential impact of latent factors on our estimates of credit risk premia, we therefore multiply expected loss rates ExpL_t with the factor $(1+\mathrm{FR}_t)/2$, meaning we compute frailty-adjusted expected loss rates as the equally weighted average of unadjusted expected loss rates ExpL_t and adjusted expected loss rates $\mathrm{FR}_t \times \mathrm{ExpL}_t$. We use this rough frailty adjustment to test whether our overall finding of large variation over time in credit risk premia survives after accounting for the potential impact of frailty.

Figure C.9, in combination with Figure 1, suggests that the frailty ratio FR_t tends to increase with the expected loss rate ExpL_t. As a consequence, the top panel of Figure C.10, shown in the internet appendix, shows that our estimates of credit risk premia for the period 2002-03 tend to be significantly lowered by the frailty adjustment. The same effect occurs from mid-2008 to 2010. Conversely, this rough adjustment for frailty tends to increase estimated credit risk premia at other times (when $\mathrm{FR}_t < 1$ but ExpL_t is relatively small).

The bottom panel of Figure C.10 shows median-firm ratios of credit risk premia to expected-loss rates, before and after adjusting expected loss rates. These median ratios are significantly reduced by the frailty adjustment in 2002-03 and from mid-2008 to 2010, and are significantly increased at most other times. Even after accounting for this potential frailty bias in our expected loss rates, there remains substantial time variation in credit risk premia relative to expected loss rates.

7.2 Alternative Estimators of Loss Given Default

We consider alternative estimates of loss given default, including (i) an assumption of constant LGD, (ii) historical LGD estimates based on issuer-weighted averages dating back to 1982, (iii) trailing LGD estimates based on the previous year's average recovery rate, and (iv)

[20] We compute FR_t separately for IG-rated firms and for HY-rated firms, allowing for potential differences across credit quality in the severity of the latent influence on realized default probabilities.

ratings-based LGD estimates. The latter take into account the timing of default. Details on the definition of these alternative LGD measures are provided in Internet Appendix D, and summary statistics are reported in Table C.6.

The median expected loss given default is 0.60 for the benchmark specification, 0.62 under the constant LGD assumption, 0.55 for historical LGD, 0.55 for trailing LGD, and 0.57 for ratings-based LGD and a five-year-ahead time of default. Compared to benchmark, constant and historical LGD estimates, trailing and ratings-based LGD estimates exhibit somewhat more temporal and cross-sectional variation. Overall, however, the various LGD estimates are fairly stable over time and across firms and default horizons.

We re-estimate the panel data regressions (5) and (6) for the alternative LGD specifications. The results are reported in Table C.7. The root mean squared errors remain nearly unchanged from those shown in Tables 5 and 7 for the benchmark model.

8. Concluding Remarks

We quantify the level and degree of variation in credit risk premia, measured as the rate of compensation for bearing default risk in excess of the expected rate of default loss. At each fixed level of expected default loss rate, we find dramatic variation in these risk premia over time, with peaks in 2002, during the 2008–09 global financial crisis (GFC), and in the second half of 2011. A potential explanation for the comparatively high credit risk premia in 2002, during the GFC, and in 2011, is that corporate debt and derivatives markets experienced significant reductions in risk-bearing capacity, relative to the amount of risk to be borne at these times, driving premia to comparatively high levels relative to the expected loss rates.

The slow decline in credit market premia following the peaks in 2002, 2008 and 2011 is consistent with frictions in the entry of new risk capital. Along the lines of the explanation suggested by Froot and O'Connell (1999) for time variation in catastrophe insurance risk premia, and by Duffie (2010) for asset markets more generally, capital moves into and out of the market for corporate credit in response to fluctuations in the price of risk, but not instantaneously.

Generally, when there are large losses or large increases in risk in a particular market segment, if capital does not move immediately out of other asset markets and into that segment, then risk premia would tend to adjust so as to match the demand for capital with the supply of capital that is available to the sector. Investors or asset managers with available capital take time to be found by intermediaries, to be convinced (perhaps being unfamiliar with the particular asset class) of the available risk premia, and to exit from the markets in which they are currently invested.

We document that the time variation in the ratio of credit risk premia to expected default loss rate is more pronounced for investment-grade firms than for high-yield firms. This is consistent with the notion that during times of market-wide distress, risk-bearing capacity is reduced across the credit quality spectrum, disproportionally increasing the price for bearing default risk, per unit of default risk to be borne, for high-quality debt.

References

Ambrose, B., Cai, K., and Helwege, J. (2012) Fallen angels and price pressure, *Journal of Fixed Income* **21**, 74–86.

Arakelyan, A. and Serrano, P. (2016) Liquidity in credit default swap markets, *Journal of Multinational Financial Management* **37–38**, 139–157.

Arora, N., Gandhi, P., and Longstaff, F. (2012) Counterparty credit risk and the credit default swap market, *Journal of Financial Economics* **103**, 280–293.

Avramov, D., Jostova, G., and Philipov, A. (2007) Understanding changes in corporate credit spreads, *Financial Analyst Journal* **63**, 90–105.

Azizpour, S., Giesecke, K., and Schwenkler, G. (2017) Exploring the sources of default clustering. Forthcoming, Journal of Financial Economics.

Berndt, A. (2015) A credit spread puzzle for reduced-form models, *Review of Asset Pricing Studies* **5**, 48–91.

Berndt, A., Jarrow, R., and Kang, C. (2007) Restructuring risk in credit default swaps: An empirical analysis, *Stochastic Processes and their Applications* **117**, 1724–1749.

Bharath, S. and Shumway, T. (2008) Forecasting default with the Merton distance-to-default model, *Review of Financial Studies* **21**, 1339–1369.

Black, F. and Scholes, M. (1973) The pricing of options and corporate liabilities, *Journal of Political Economy* **81**, 637–654.

Blanco, R., Brennan, S., and Marsh, I. (2005) An empirical analysis of the dynamic relationship between investment-grade bonds and credit default swaps, *Journal of Finance* **60**, 2255–2281.

Bohn, J. (2000) An empirical assessment of a simple contingent-claims model for the valuation of risky debt, *Journal of Risk Finance* **1**, 55–77.

Bohn, J., Arora, N., and Korbalev, I. (2005) Power and level validation of the EDF credit measure in the U.S. market. Working paper, Moody's KMV.

Bongaerts, D., de Jong, F., and Driessen, J. (2011) Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market, *Journal of Finance* **66**, 203–240.

Bühler, W. and Trapp, M. (2009) Time-varying credit risk and liquidity premia in bond and CDS markets. CFR working paper.

Campbell, J. and Taksler, G. (2003) Equity volatility and corporate bond yields, *Journal of Finance* **58**, 2321–2350.

Chen, L., and Collin-Dufresne, P., and Goldstein, R. (2009) On the relationship between credit spread puzzles and the equity premium puzzle, *Review of Financial Studies* **22**, 3367–3409.

Chen, R., Cheng, X., and Wu, L. (2013) Dynamic interactions between interest-rate and credit risk: Theory and evidence on the credit default swap term structure, *Review of Finance* **17**, 403–441.

Chen, R., Fabozzi, F., and Sverdlove, R. (2010) Corporate credit default swap liquidity and its implications for corporate bond spreads, *Journal of Fixed Income* **20**, 31–57.

Chen, Z., Lookman, A., Schürhoff, N., and Seppi, D. (2014) Rating-based investment practices and bond market segmentation, *Review of Asset Pricing Studies* **4**, 162–205.

Cochrane, J. (2001) Asset Pricing, *Princeton University Press.*

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

Delianedis, G. and Geske, R. (1998) Credit risk and risk-neutral default probabilities: Information about rating migrations and defaults. Working paper, University of California, Los Angeles.

Delianedis, G., Geske, R., and Corzo, T. (1998) Credit risk analysis with option models: Estimation and comparison of actual and risk-neutral default probabilities. Working paper, University of California, Los Angeles.

Driessen, J. (2005) Is default event risk priced in corporate bonds? *Review of Financial Studies* **18**, 165–195.

Du, W., Gadgil, S., Gordy, M., and Vega, C. (2016) Counterparty risk and counterparty choice in the credit default swap market. Working paper, Board of Governors of the Federal Reserve.

Duffee, G. (1998) The relation between Treasury yields and corporate bond yield spreads, *Journal of Finance* **53**, 2225–2241.

——— (1999) Estimating the price of default risk, *Review of Financial Studies* **12**, 197–226.

Duffie, D. (1999) Credit swap valuation, *Financial Analysts Journal* **55** (January-February), 55–87.

Duffie, D. (2010) Asset price dynamics with slow-moving capital, *Journal of Finance* **65**, 1238–1268.

Duffie, D., Eckner, A., Horel, G., and Saita, L. (2009) Frailty correlated default, *Journal of Finance* **64**, 2089–2123.

Duffie, D., Saita, L., and Wang, K. (2007) Multiperiod corporate default probabilities with stochastic covariates, *Journal of Financial Economics* **83**, 635–665.

Ellul, A., Jotikasthira, C., and Lundblad, C. (2012) Regulatory pressure and fire sales in the corporate bond market, *Journal of Financial Economics* **101**, 596–620.

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

Fischer, E., Heinkel, R., and Zechner, J. (1989) Optimal dynamic capital structure choice: Theory and tests, *Journal of Finance* **44**, 19–40.

Fisher, L. (1959) Determinants of the risk premium on corporate bonds, *Journal of Political Economy* **67**, 217–237.

Fons, J. (1987) The default premium and corporate bond experience. *Journal of Finance* **42**, 81–97.

Froot, K. and O'Connell, P. (1999) The pricing of U.S. catastrophe reinsurance, in *The Financing of Catastrophe Risk*, University of Chicago Press, 195–232.

Giesecke, K., Longstaff, F., Schaefer, S., and Strebulaev, I. (2011) Corporate bond default risk: A 150-year perspective, *Journal of Financial Economics* **102**, 233–250.

Hilscher, J. and Wilson, M. (2017) Credit ratings and credit risk: Is one measure enough?, *Management Science* **63**, 3414–3437.

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

Hull, J., Predescu, M., and White, A. (2004) The relationship between credit default swap spreads, bond yields, and credit rating announcements, *Journal of Banking & Finance* **28**, 2789–2811.

Junge, B. and Trolle, A. (2015) Liquidity risk in credit default swap markets. Working paper, EPFL and Swiss Finance Institute.

Kavvathas, D. (2001) Estimating credit rating transition probabilities for corporate bonds. Working paper, University of Chicago.

Kealhofer, S. (2003) Quantifying credit risk I: Default prediction, *Financial Analysts Journal* **59**, 30–44.

Kurbat, M. and Korbalev, I. (2002) Methodology for testing the level of the EDF credit measure. Moody's KMV report.

Leland, H. and Toft, K. (1996) Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads, *Journal of Finance* **51**, 987–1019.

Longstaff, F., Mithal, S., and Neis, E. (2005) Corporate yield spreads: Default risk or liquidity? New evidence from the default swap market, *Journal of Finance* **60**, 2213–2253.

Merton, R. (1974) On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* **29**, 449–470.

Nelson, R. and Siegel, F. (1987) Parsimonious modeling of yield curves, *Journal of Business* **60**, 473–489.

Svensson, L. (1994) Estimating and interpreting forward interest rates: Sweden 1992–1994. IMF working paper.

Tang, D. and Yan, H. (2008) Liquidity and credit default swap spreads. Working paper, University of Hong Kong.

Van Buskirk, A. (2009) Implied volatility skew and firm-level tail risk. Working paper, University of Chicago.