Internet Appendix

Corporate Credit Risk Premia

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A. CDS Data

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 market value is determined in a special auction. Before the Big Bang, a popular alternative settlement mechanism was for the buyer of protection to submit to the seller of protection debt instruments of the named firm, of the total notional amount specified in the default-swap contract, and to receive in return a cash payment equal to that notional amount, less the fraction of the default-swap premium that had accrued (on a time-proportional basis) since the last regular premium payment date.[1] By either settlement approach, the buyer of protection benefits from an effective "cheapest to deliver" option, meaning an option to receive a CDS default settlement payment that is based on particular bonds that are likely to be the cheapest bonds to deliver in settlement of the auction, among all eligible bonds of the defaulted issuer.

For the purpose of settlement of default swaps, 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. The coverage of default swaps for out-of-bankruptcy restructuring has varied somewhat. Banks, especially European banks, generally prefer to include restructuring as a covered default event, given the relatively greater exposure of bank loans (versus traded bonds) to restructuring risk. 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.

Coverage of restructuring also increases the potential value of the cheapest to deliver option, given that bonds of the same seniority are not necessarily of the same market value in a restructuring. Our CDS data apply to senior unsecured debt instruments. For a given level of seniority, there is less recovery-value heterogeneity if the event of default is bankruptcy or failure to pay, for these events

[1]Starting with the defaults of Collins-Aikman, Northwest Airlines, Delta Airlines and Delphi in 2005, the market has used auctions for cash settlement of CDS for cases involving major defaults, in order to avoid settlement disruptions caused by a shortage of transferable debt instruments of the underlying name, relative to the number and sizes of required settlement trades.

normally trigger bankruptcy claims or cross-acceleration covenants, respectively, that cause debt of equal seniority to get pari passu (equal proportional) recovery. Restructuring is associated with higher default recovery, on average. If restructuring is included as a contractually covered credit event, then there is also the potential for significant heterogeneity at default in the market values of the various debt instruments of the obligor, as fractions of their respective principals, especially when there is significant heterogeneity with respect to maturity. Restructuring therefore increases the value to the buyer of protection of the cheapest-to-deliver option. Without, at this stage, data bearing on the heterogeneity of market values of the pool of deliverable obligations for each default swap, we are in effect treating the cheapest-to-deliver option value as a constant that is absorbed into the estimated mean fractional loss given default, LGD, to the seller of protection in the event of default.

The impact of the cheapest-to-deliver option is mitigated by ISDA contractual standards that restrict the types of deliverable debt instruments, especially with respect to maturity. While there was a different standard for European firms ("modified-modified") versus U.S. firms ("modified") prior to the Big Bang Protocol, the standard CDS contract now excludes restructuring as a default event. Because our data are for U.S. firms, we rely on CDS quotes for modified restructuring in the main part of the paper. We repeat our analysis for CDS without restructuring in Internet Appendix H.

Ignoring the effect of the cheapest-to-deliver option, the CDS rate is, in frictionless markets, a close approximation of the par-coupon credit spread of the same maturity as the default swap.[2] To the extent that CDS rates differ from bond credit spreads, Blanco, Brennan, and Marsh (2005) indicate that CDS rates tend to reflect somewhat fresher information.

B. 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. Roughly speaking, the distance to default is the number of standard deviations

[2]This follows from arbitrage reasoning shown by Duffie (1999).

of annual asset growth by which the firm's expected assets at a given maturity exceed a measure of book liabilities. The liability measure is, in the current implementation of the EDF model, the firm's short-term book liabilities plus one half of its long-term book liabilities. Estimates of current assets and the current standard deviation of asset growth ("volatility") are calibrated from historical observations of the firm's equity-market capitalization and of the liability measure. The calibration, explained for example in Vassalou and Xing (2004), is based on the model of Black and Scholes (1973) and Merton (1974), by which the price of a firm's equity may be viewed as the price of an option on assets struck at the level of liabilities. Crosbie and Bohn (2003) and Kealhofer (2003) provide more details on the model and the fitting procedures for distance to default and EDF. Bharath and Shumway (2008) show that the fitting procedure is relatively robust.

A common industry measure of default likelihood is the average historical default frequency of firms with the same credit rating as the target firm. This measure is often used, for example, in implementations of the CreditMetrics approach (www.msci.com), and is convenient given the usual practice by financial-services firms of tracking credit quality by internal credit ratings based on the approach of the major rating agencies such as Moody's and Standard and Poor's. The rating agencies, however, do not claim that their ratings are intended to be a measure of default probability, and they acknowledge a tendency to adjust ratings only gradually to new information, a tendency strongly apparent in the empirical analysis of Nickell, Perraudin, and Varotto (2000), Bahar and Nagpal (2001), Kavvathas (2001), and Lando and Skødeberg (2002), among others. Korablev and Dwyer (2007) report that the Moody's Analytics EDF measure has an out-of-sample accuracy ratio of 0.88 for the period 2001-2006, as opposed to an accuracy ratio of 0.75 for ratings-based default prediction.

During our sample period, the incidence of defaults is not especially surprising relative to the EDF-predicted number of defaults. Korablev and Dwyer (2007) estimate that the model that produces Moody's Analytics EDFs would have placed a probability of 52.0% on the event that there would have been as few or fewer defaults in 2002 by firms in their sample than the actual number of defaults. Similarly, the p-values for 2003, 2004, 2005 and 2006 are 21.3%, 51.4%, 74.5% and 45.1%, respectively. A low p-value is observed only for 2003, when, according to Korablev and Dwyer (2007), EDFs predicted "too many" defaults. Crossen, Qu, and Zhang (2011) also argue that the EDF model performs consistently over time and in different credit cycles. They provide accuracy ratios for EDFs, ranging from 81.5% to 93.9% between 2002 and 2006, and from 82.9% to 87.6% between 2007 and 2009. In any case, we are not aware that marginal investors in corporate debt had access to better default probability estimates than those widely supplied to the market in the form of EDFs.[3]

[3] The Moody's Analytics EDF measure covers over 41,000 publicly traded firms, and is extensively used in the financial services industry. For example, from information provided to us by Moody's Analytics, 40 of the world's 50 largest financial institutions are subscribers.

C. Additional Tables and Figures

Table C.1: **Variation in one-year and ten-year credit risk premia explained by expected losses** The table reports the results of the panel data regression (5), for one-year (left panel) and ten-year (right panel) CDS and expected loss data. The coefficients β^i and β_m capture firm and month fixed effects (FEs). The numbering of the model specifications reflects that of Table 5 in the main text. CDS rates 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 include the 892,362 firm-date pairs (left panel) and 918,929 pairs (right panel) used in later regressions that include additional covariates and hence impose greater demands on data availability. They cover 466 public U.S. firms, over 2002-2015.

	I	I(F)	I(FM)	I	I(F)	I(FM)
		1-year			10-years	
Constant	2.119	3.294	4.009	2.817	5.627	5.511
	(0.030)	(0.067)	(0.059)	(0.028)	(0.070)	(0.050)
log(ExpL)	-0.427	-0.233	-0.589	-0.447	-0.763	-0.685
	(0.007)	(0.014)	(0.005)	(0.005)	(0.011)	(0.008)
Firm FE	No	Yes	Yes	No	Yes	Yes
Month FE	No	No	Yes	No	No	Yes
R^2	0.329	0.597	0.809	0.275	0.569	0.801
RMSE	0.965	0.748	0.516	0.687	0.530	0.360

Table C.2: **Sources of variation in short- and long-term credit risk premia** The table reports results for the panel data regression (6) when CDS rates and EDF-based expected losses are measured at the one-year or ten-year maturity horizon. 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 Baa 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. For the one-year maturity, the data cover 462 public U.S. firms, over 2002-2015. For the ten-year maturity, the data cover 466 firms.

	1yr	10yrs		1yr	10yrs
Constant	15.065	7.206	Trsy rate	-0.129	-0.218
	(0.440)	(0.199)		(0.010)	(0.004)
log(ExpL)	-0.937	-1.044	log(CSENT)	-2.477	-0.311
	(0.007)	(0.014)		(0.104)	(0.051)
$\log(\text{IV}_{atm})$	1.030	0.593	1/CDS notional	1.968	0.187
	(0.036)	(0.017)		(0.068)	(0.067)
$\log(\text{IV}_{otm}/\text{IV}_{atm})$	1.166	0.516	Trsy rate $\times D_{HY}$	0.166	0.097
	(0.061)	(0.038)		(0.007)	(0.003)
Recent upgrade	-0.149	-0.066	1/CDS notional $\times D_{HY}$	0.774	0.044
	(0.010)	(0.006)		(0.097)	(0.066)
Recent downgrade	0.154	0.105	Refined ratings dummies	Yes	Yes
	(0.010)	(0.008)	Sector dummies	Yes	Yes
Recent upgr HY to IG	0.003	0.019	R^2	0.747	0.789
	(0.039)	(0.020)	RMSE	0.592	0.371
Recent dngr IG to HY	0.019	0.009			
	(0.030)	(0.016)			
$\log(\text{ExpL})^2$	0.020	0.014			
	(0.001)	(0.002)			
$\log(\text{IV}_{atm}) \times D_{HY}$	0.157	0.033			
	(0.024)	(0.012)			
$\log(\text{IV}_{otm}/\text{IV}_{atm}) \times D_{HY}$	-0.497	-0.358			
	(0.085)	(0.054)			

Table C.3: **Descriptive statistics for alternative PD measures** The table reports median five-year PD estimates for EDF-based (EDF), RMI-based (RMI), ratings-based (Rtg), refined-ratings-based (Rtg_r), scaled refined-ratings-based (Rtg_s) and combined (PD_c) PDs. PDs are reported as annualized rates in basis points. The data cover 467 public U.S. firms, over 2002-2015.

	EDF	RMI	Rtg	Rtg_r	Rtg_s	PD_c		EDF	RMI	Rtg	Rtg_r	Rtg_s	PD_c
			All							By sector			
	35	23	40	40	22	43	BM	30	23	41	42	25	39
			By year				CG	26	23	44	45	32	45
2002	38	30	31	31	36	35	CS	37	22	42	43	27	45
2003	46	35	36	36	28	42	Egy	22	25	40	40	23	33
2004	43	21	44	44	24	49	Fin	89	39	24	24	13	59
2005	39	19	43	43	22	47	Hlth	23	13	29	29	17	35
2006	34	22	42	42	20	45	Ind	26	21	40	40	23	33
2007	30	23	38	38	20	41	Tech	60	22	24	24	15	45
2008	36	28	38	38	27	45	Tele	45	26	56	60	37	78
2009	44	51	37	37	31	49	Utl	13	17	43	44	28	32
2010	41	36	41	41	26	48				By rating			
2011	35	21	42	42	26	46	Aaa	8	7	2	2	1	5
2012	33	24	40	40	22	41	Aa	12	9	6	6	4	9
2013	32	14	40	40	20	41	A	21	15	14	15	9	19
2014	29	11	37	37	18	39	Baa	31	21	41	41	25	41
2015	27	11	35	35	18	37	Ba	63	35	157	159	95	124
							B	141	58	548	548	294	351
							Caa	314	102	1,273	1,290	648	757
							Ca-C	449	132	1,845	1,845	948	1,133

Table C.4: **Descriptive statistics for expected losses and credit risk premia for alternative PD measures** The table reports median five-year expected losses (ExpL) and median premium-to-expected-loss ratios (Prem/ExpL). The underlying PD measures are EDF-based (EDF), RMI-based (RMI), ratings-based (Rtg), refined-ratings-based (Rtg_r), scaled refined-ratings-based (Rtg_s) or combined (PD_c) PDs. Expected loss rates are reported in basis points of notional. The data cover 467 public U.S. firms, over 2002-2015.

	ExpL						Prem/ExpL					
	EDF	RMI	Rtg	Rtg_r	Rtg_s	PD_c	EDF	RMI	Rtg	Rtg_r	Rtg_s	PD_c
All												
	21	13	23	23	13	25	2.99	6.14	2.22	2.13	4.42	2.02
By year												
2002	22	17	17	17	21	20	3.54	4.67	5.69	5.69	4.08	3.71
2003	27	20	22	22	16	24	1.86	2.42	2.13	2.11	3.31	1.60
2004	26	13	26	26	14	29	1.30	3.83	1.04	0.89	2.49	0.78
2005	22	11	25	25	13	27	1.35	4.25	0.92	0.92	2.69	0.77
2006	19	13	24	24	12	26	1.31	2.82	0.72	0.70	2.56	0.59
2007	18	13	22	22	11	24	1.48	2.97	0.97	0.95	2.74	0.84
2008	21	17	23	23	16	27	5.20	7.83	4.34	3.93	6.14	3.80
2009	27	31	22	22	19	29	4.77	4.09	4.68	4.18	6.81	3.94
2010	24	21	24	24	15	28	3.64	5.61	3.30	3.14	6.06	2.96
2011	21	12	25	25	16	27	4.56	9.21	3.62	3.54	6.14	3.34
2012	20	15	23	23	13	24	5.11	8.78	3.84	3.81	7.56	3.63
2013	19	8	23	23	12	24	4.01	11.66	2.57	2.49	5.99	2.56
2014	17	6	22	22	11	23	3.20	11.86	1.75	1.66	4.38	1.90
2015	16	7	21	21	11	22	3.87	11.40	1.93	1.86	4.47	2.11
By sector												
BM	18	13	24	24	15	23	3.63	5.97	2.30	2.12	4.41	2.40
CG	16	13	26	26	18	26	3.92	7.93	1.74	1.65	3.50	2.20
CS	22	13	25	25	16	26	3.00	6.69	1.55	1.52	3.43	1.78
Egy	13	14	23	23	14	19	4.44	5.72	2.72	2.62	5.17	3.01
Fin	51	23	14	14	8	34	0.67	3.39	4.74	4.61	8.85	1.33
Health	13	8	18	17	10	21	2.77	6.09	1.78	1.74	3.86	1.72
Ind	15	12	24	23	14	20	3.17	5.71	1.80	1.75	3.69	1.96
Tech	35	13	14	15	9	26	1.06	6.83	3.14	3.00	6.12	1.56
Tele	27	15	33	35	22	46	3.33	9.29	2.43	1.80	3.93	2.27
Utl	8	10	25	25	17	18	9.09	7.67	1.50	1.46	3.29	2.77
By rating												
Aaa	5	4	1	1	1	3	1.90	3.24	15.82	15.37	28.51	3.67
Aa	7	5	3	3	2	5	2.12	4.00	7.29	6.62	11.70	2.81
A	12	9	8	9	5	11	2.04	4.10	3.59	3.47	6.77	2.38
Baa	18	12	24	24	15	24	3.19	5.91	2.35	2.23	4.50	2.40
Ba	37	21	90	93	55	71	4.14	8.82	0.70	0.74	2.07	1.48
B	80	34	296	297	165	197	3.29	9.48	0.09	0.11	1.03	0.66
Caa	198	66	693	731	383	453	2.56	9.35	-0.13	-0.12	0.68	0.42
Ca-C	291	104	1,219	1,218	652	797	3.80	12.90	0.40	0.42	1.41	1.22

Table C.5: **Sources of variation in credit risk premia for alternative PD measures** The table reports detailed results for the panel data regression (6), after replacing the dependent variable by the logarithm of five-year CDS rates. Results are shown for specification IX in Table 7, and for the alternative PD measures listed in Table 8. 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.

	EDF	RMI	Rtg	Rtg_r	Rtg_s	PD_c
Constant	9.908	9.171	9.242	9.206	8.483	9.928
	(0.194)	(0.195)	(0.193)	(0.200)	(0.205)	(0.204)
log(ExpL)	-0.099	-0.044	0.124	0.068	0.171	-0.174
	(0.009)	(0.007)	(0.016)	(0.020)	(0.021)	(0.013)
$\log(IV_{atm})$	0.680	0.668	0.825	0.837	0.807	0.671
	(0.020)	(0.020)	(0.017)	(0.016)	(0.016)	(0.019)
$\log(IV_{otm}/IV_{atm})$	0.679	0.667	0.705	0.690	0.669	0.640
	(0.041)	(0.038)	(0.039)	(0.038)	(0.038)	(0.039)
Recent upgrade	-0.096	-0.093	-0.109	-0.107	-0.107	-0.094
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)
Recent downgrade	0.129	0.091	0.137	0.130	0.128	0.124
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)
Recent upgr HY to IG	0.039	0.028	0.020	0.021	0.021	0.033
	(0.027)	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)
Recent dngr IG to HY	0.032	0.023	0.028	0.037	0.034	0.043
	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.016)
$\log(\text{ExpL})^2$	0.036	0.031	-0.009	0.022	0.006	0.074
	(0.001)	(0.001)	(0.002)	(0.005)	(0.004)	(0.002)
$\log(IV_{atm}) \times D_{HY}$	-0.059	0.001	0.050	0.018	0.007	-0.021
	(0.015)	(0.014)	(0.013)	(0.013)	(0.014)	(0.015)
$\log(IV_{otm}/IV_{atm}) \times D_{HY}$	-0.568	-0.487	-0.449	-0.404	-0.426	-0.461
	(0.058)	(0.053)	(0.059)	(0.054)	(0.054)	(0.055)
Trsy rate	-0.216	-0.230	-0.217	-0.216	-0.213	-0.218
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
log(CSENT)	-0.997	-0.837	-0.866	-0.884	-0.737	-1.030
	(0.048)	(0.047)	(0.048)	(0.049)	(0.048)	(0.050)
1/CDS notional	0.627	0.588	0.593	0.583	0.378	0.617
	(0.047)	(0.050)	(0.047)	(0.049)	(0.059)	(0.050)
Trsy rate $\times D_{HY}$	0.094	0.104	0.101	0.096	0.096	0.091
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
1/CDS notl $\times D_{HY}$	0.137	0.266	0.292	0.191	0.207	0.037
	(0.055)	(0.057)	(0.060)	(0.054)	(0.063)	(0.051)
Refined ratings	Yes	Yes	Yes	Yes	Yes	Yes
Sectors	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.836	0.836	0.828	0.828	0.829	0.838
RMSE	0.412	0.412	0.422	0.421	0.420	0.409

Table C.6: **Descriptive statistics for alternative LGD measures** The table reports median estimates for historical (Hist), trailing (Trlg) and ratings-based LGD. Ratings-based LGD statistics are shown by IG/HY status one year prior to default (Rtg (1y)) and five years prior to default (Rtg (5y)). The data cover 467 public U.S. firms, over 2002-2015.

	Hist	Trlg	Rtg (1y)	Rtg (5y)		Hist	Trlg	Rtg (1y)	Rtg (5y)
		All					By sector		
	0.63	0.55	0.58	0.57	BM	0.63	0.55	0.57	0.56
		By year			CG	0.63	0.55	0.58	0.57
2002	0.63	0.65	0.49	0.49	CS	0.63	0.55	0.58	0.57
2003	0.63	0.66	0.51	0.51	Egy	0.63	0.55	0.58	0.57
2004	0.64	0.59	0.56	0.59	Fin	0.63	0.55	0.57	0.56
2005	0.64	0.50	0.56	0.58	Hlth	0.63	0.55	0.57	0.56
2006	0.64	0.45	0.54	0.56	Ind	0.63	0.55	0.58	0.56
2007	0.62	0.42	0.54	0.55	Tech	0.63	0.55	0.58	0.57
2008	0.63	0.49	0.55	0.55	Tele	0.63	0.55	0.59	0.58
2009	0.64	0.66	0.60	0.58	Utl	0.63	0.55	0.58	0.57
2010	0.63	0.62	0.61	0.57			By rating		
2011	0.63	0.51	0.61	0.58	Aaa	0.63	0.55	0.56	0.55
2012	0.63	0.60	0.61	0.58	Aa	0.63	0.55	0.55	0.55
2013	0.63	0.57	0.62	0.58	A	0.63	0.55	0.56	0.55
2014	0.63	0.56	0.62	0.57	Baa	0.63	0.55	0.63	0.60
2015	0.63	0.57	0.61	0.57	Ba	0.63	0.55	0.63	0.60
					B	0.63	0.55	0.57	0.56
					Caa	0.63	0.61	0.63	0.60
					Ca-C	0.63	0.56	0.63	0.60

Table C.7: **Regression results for alternative LGD measures** 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 in the main text. Expected loss rates are computed as in Section 3, after replacing benchmark LGD estimates by the alternative LGD measures described in Table D.1. 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.

	Constant			**Historical**		
	I	I(FM)	IX	I	I(FM)	IX
Constant	2.723	4.323	9.921	2.716	4.322	9.912
	(0.027)	(0.048)	(0.194)	(0.027)	(0.048)	(0.194)
log(ExpL)	0.556	0.539	-0.114	0.556	0.539	-0.113
	(0.003)	(0.007)	(0.009)	(0.003)	(0.007)	(0.009)
Firm FE	No	Yes	No	No	Yes	No
Month FE	No	Yes	No	No	Yes	No
Controls	No	No	Yes	No	No	Yes
R^2	0.351	0.856	0.836	0.351	0.856	0.836
RMSE	0.819	0.386	0.412	0.819	0.386	0.412

	Trailing			**Ratings-based**		
	I	I(FM)	IX	I	I(FM)	IX
Constant	2.752	4.375	9.834	2.761	4.298	9.892
	(0.029)	(0.048)	(0.192)	(0.027)	(0.049)	(0.195)
log(ExpL)	0.571	0.539	-0.076	0.562	0.539	-0.072
	(0.004)	(0.007)	(0.009)	(0.003)	(0.006)	(0.009)
Firm FE	No	Yes	No	No	Yes	No
Month FE	No	Yes	No	No	Yes	No
Controls	No	No	Yes	No	No	Yes
R^2	0.379	0.856	0.835	0.373	0.858	0.835
RMSE	0.801	0.386	0.413	0.805	0.383	0.413

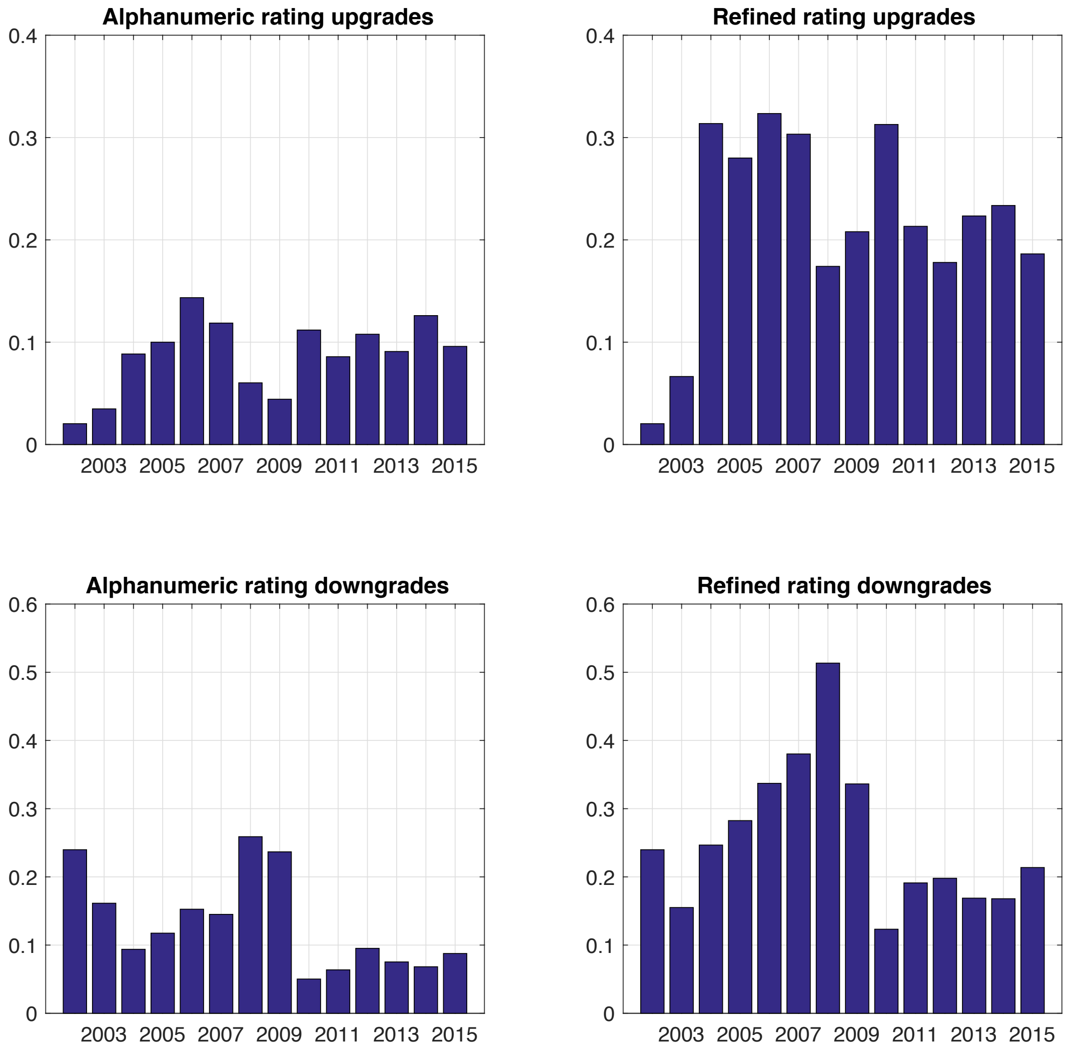

Figure C.1: **Rating upgrades and downgrades** The figure shows the average annual number of rating upgrades (top panel) and rating downgrades (bottom panel) per firm. The left panel is based on Moody's alphanumeric rating. The right panel is based on the refined rating. The data include the 497 firms in our sample with alphanumeric and refined rating data, over 2002-2015.

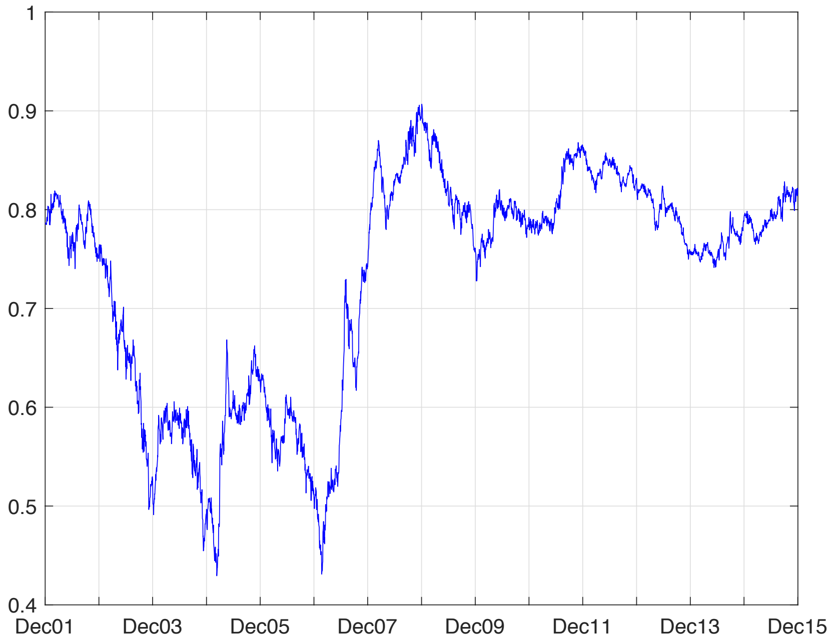

Figure C.2: **Median ratios of credit risk premia to CDS rates** The figure shows the median premium-to-CDS ratio. Only days on which premia are available for 50 or more firms are shown. The data cover 505 public U.S. firms, over 2002-2015.

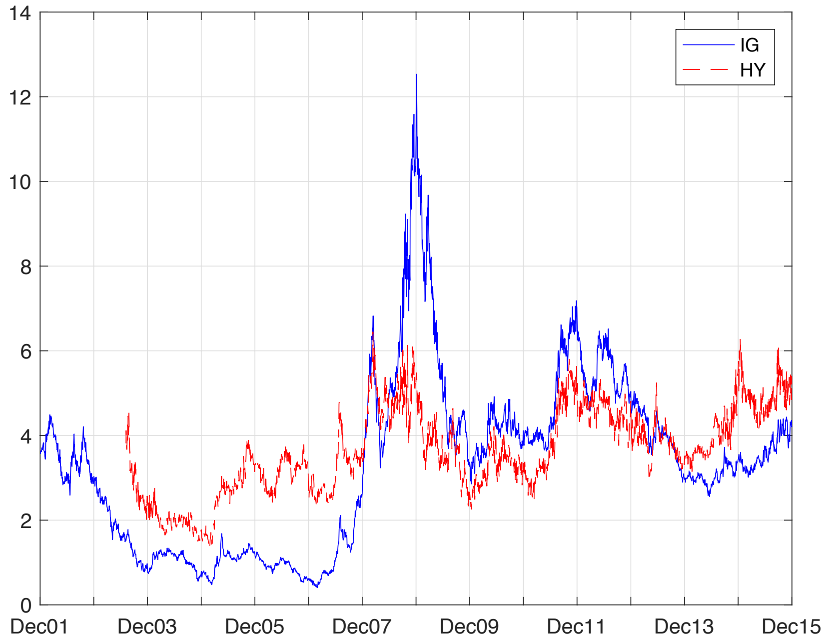

Figure C.3: **Median credit risk premia: Investment grade versus high yield** The figure shows the daily times series of median premium-to-expected-loss ratios for investment-grade firms and for high-yield firms. For each rating status, only days on which premia are available for 50 or more firms are shown. The data cover 505 public U.S. firms, over 2002-2015.

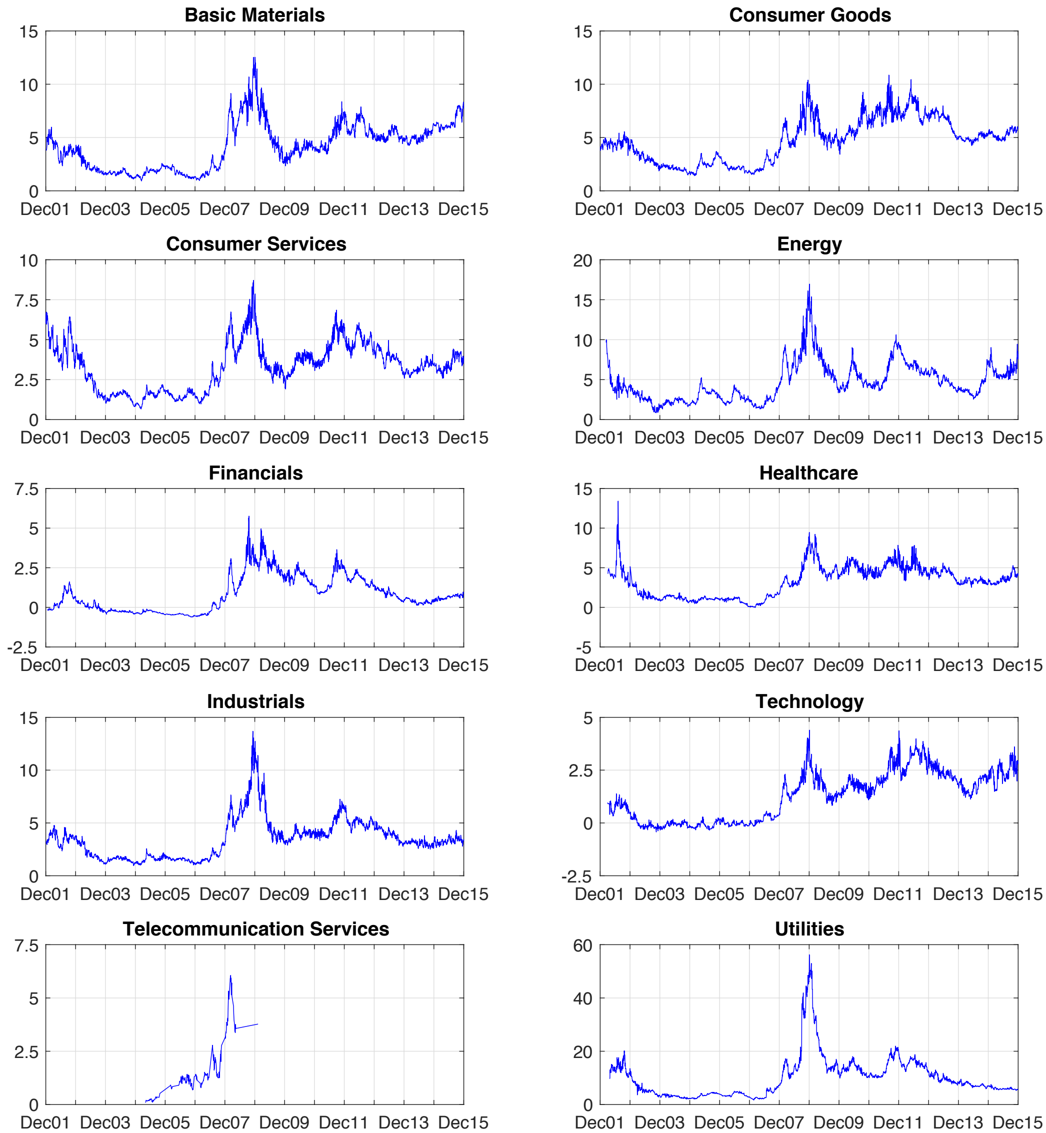

Figure C.4: **Median credit risk premia by sector** The figure shows the daily times series of median premium-to-expected-loss ratios for various sectors. For each sector, only days on which premia are available for ten or more firms are shown. The data cover 505 public U.S. firms, over 2002-2015.

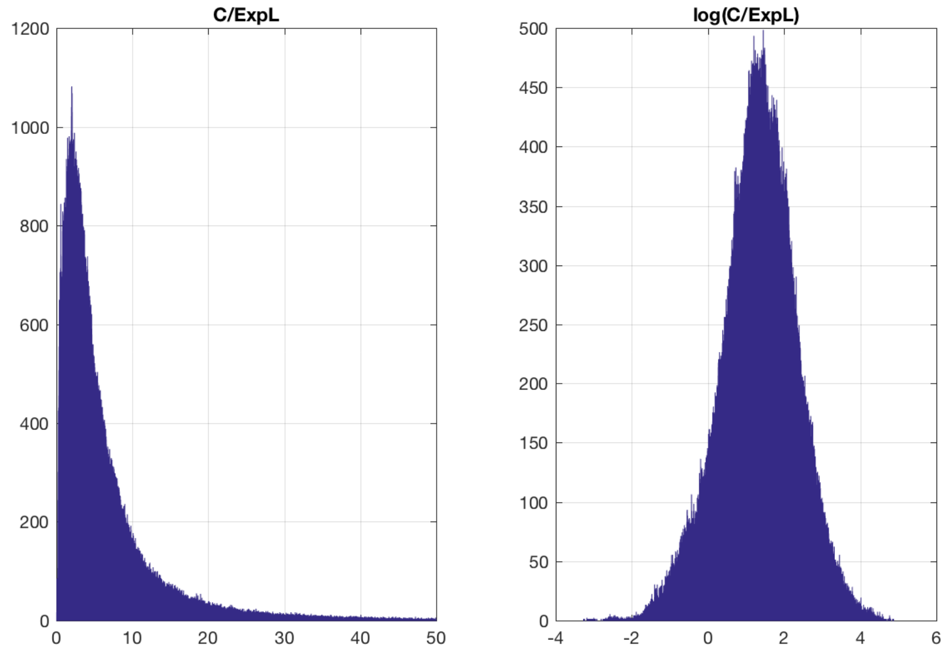

Figure C.5: **Unconditional distribution of credit risk premia** The left panel shows the histogram of the ratio of CDS rate to expected default loss rate, and the right panel shows the histogram of the logarithm of CDS-rate-to-expected-loss ratios. The data cover 505 public U.S. firms, over 2002-2015.

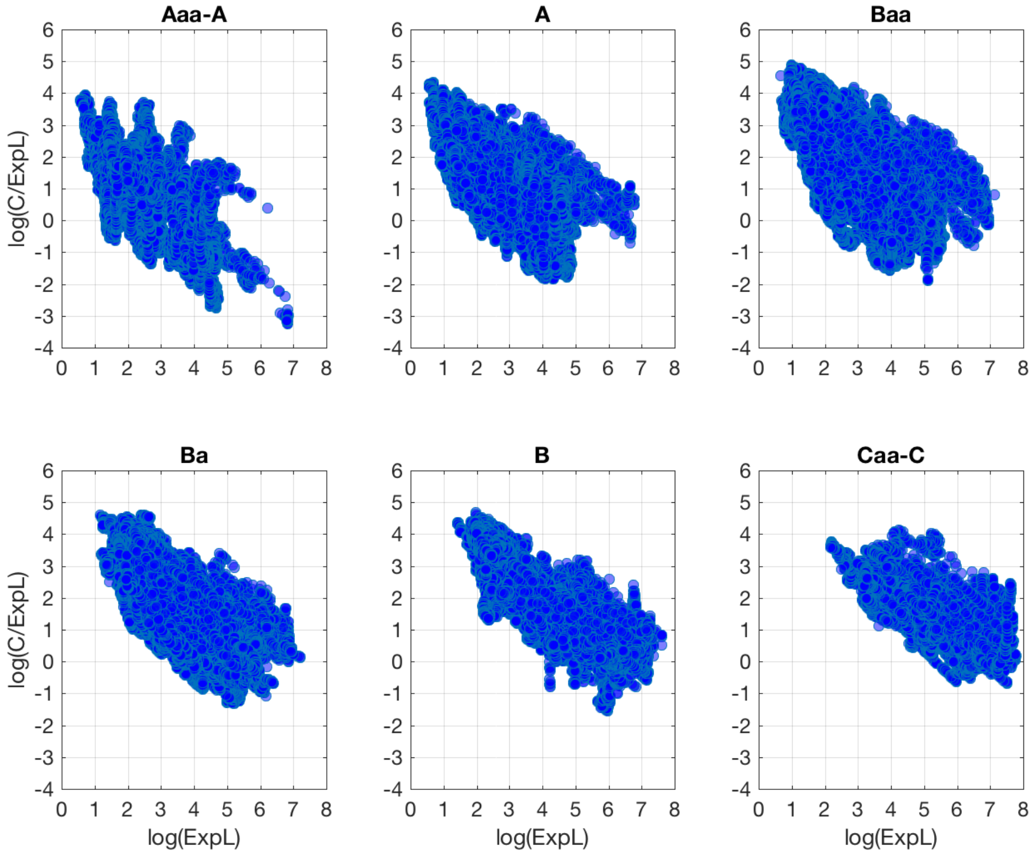

Figure C.6: **CDS-to-expected-loss ratios versus expected losses by rating** This figure shows the scatter plot of expected losses and CDS-to-expected-loss ratios, logarithmic, by Moody's refined letter rating. The data cover 467 public U.S. firms, over 2002-2015.

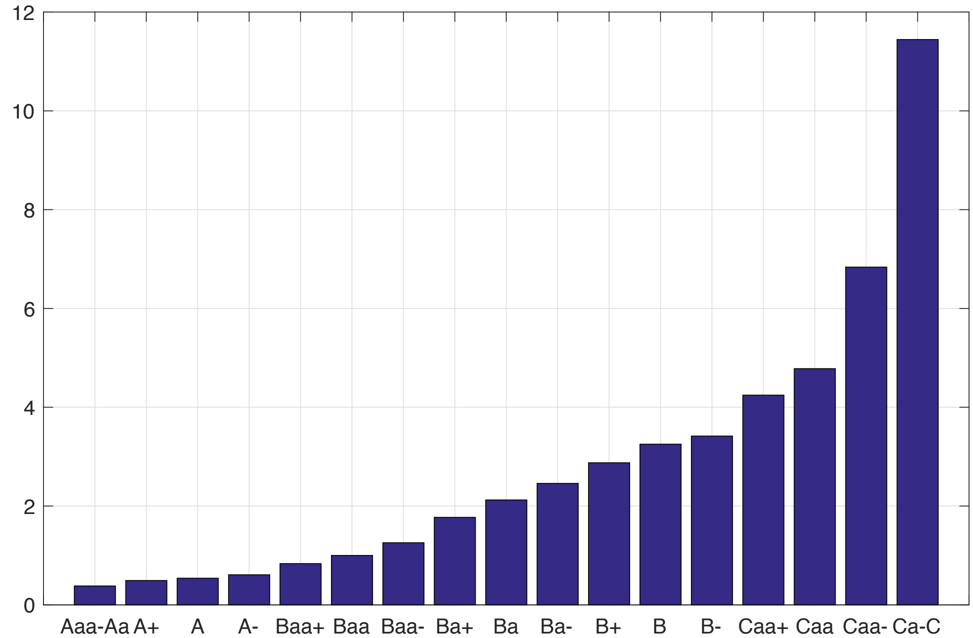

Figure C.7: **Refined ratings multipliers** The figure shows the multipliers for the refined ratings dummies in specification II in Table 6, $\exp(\beta_{Rtg})$. Refined ratings are alpha-numeric ratings adjusted for watchlist and outlook status.

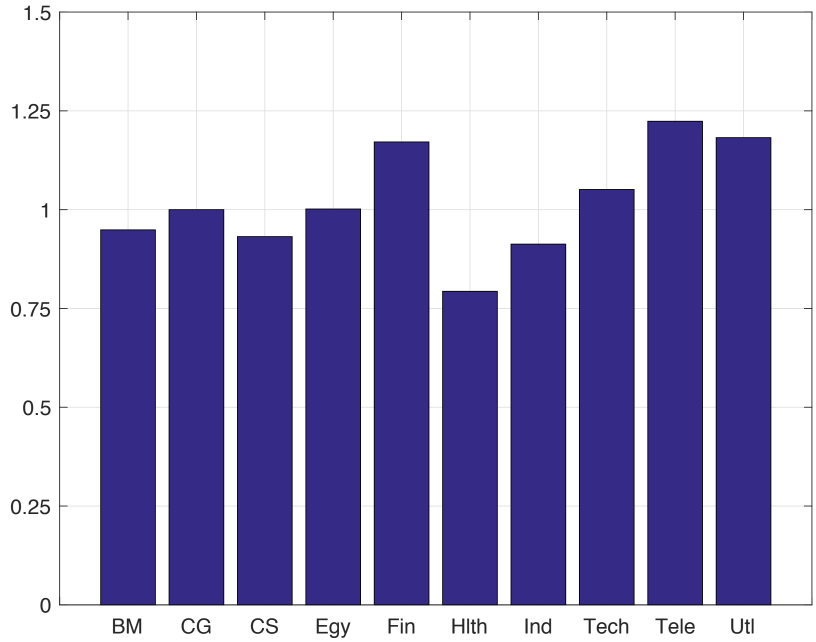

Figure C.8: **Sector multipliers** The figure shows the multipliers for the sector dummies in specification IV in Table 6, $\exp(\beta_{Sec})$.

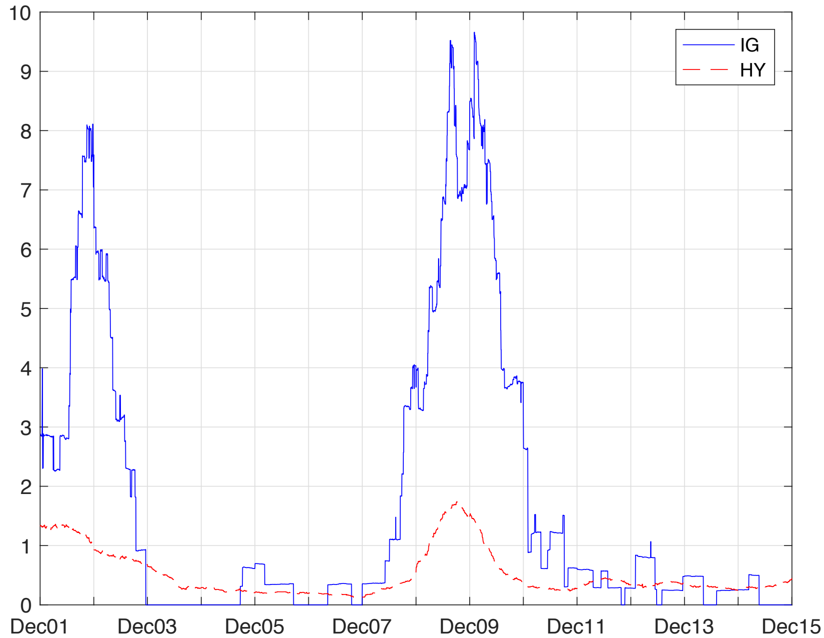

Figure C.9: **Ex-post frailty ratios** The figure shows the daily time series of the ex-post frailty ratio for IG firms and for HY firms. For IG firms, this ratio is computed as the observed number of defaults over the past twelve months among all firms with an IG rating at the beginning of the year divided by the number of defaults predicted across all IG-rated firms at the beginning of the same year, using PDs based on refined ratings. For HY firms, the frailty ratio is computed in a similar fashion. The data include all rated firms in Moody's Default & Recovery Database, except those with a Moody's industry code of "Sovereign & Public Finance" or "Unassigned." Only days on which data are available for 50 or more IG firms and 30 or more HY firms are shown.

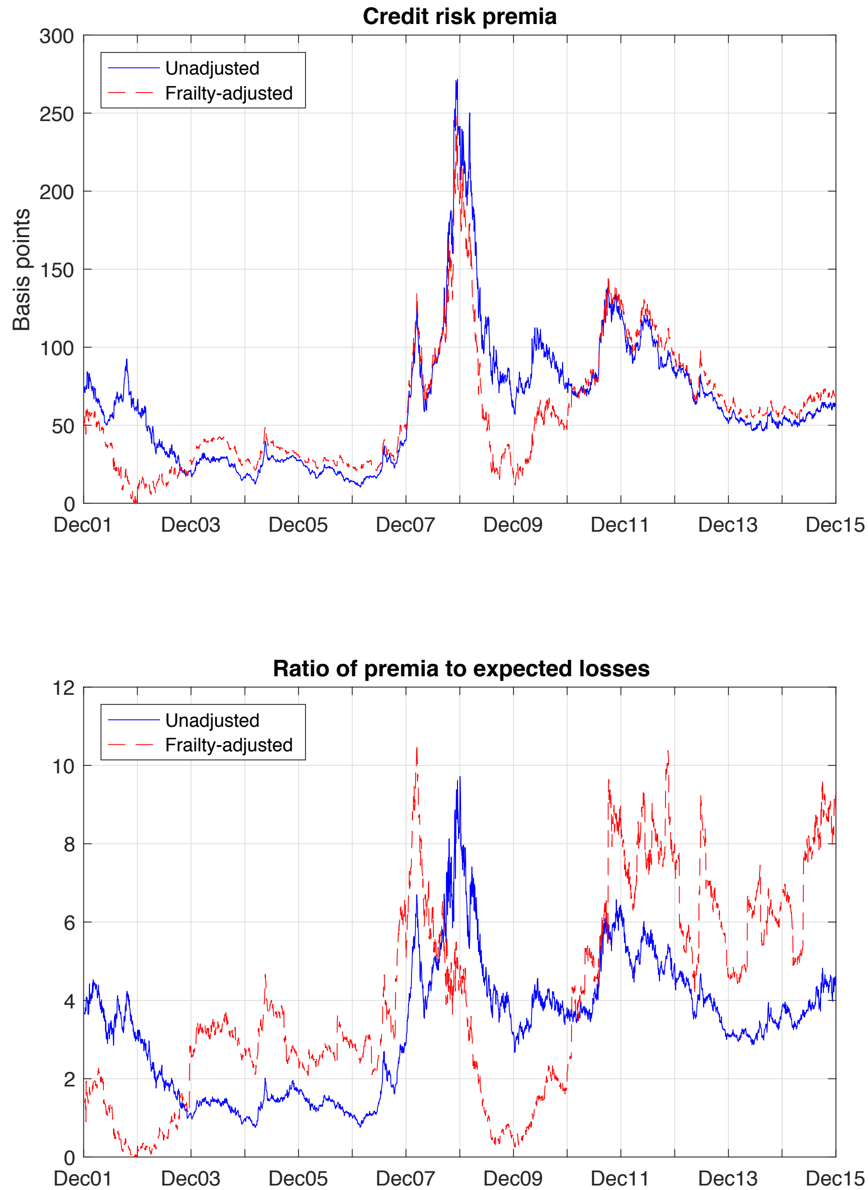

Figure C.10: **Median frailty-adjusted credit risk premia** The top panel of the figure shows the daily times series of the median frailty-adjusted credit risk premium component of five-year CDS rates in basis points. The bottom panel shows the corresponding median premium-to-expected-loss-rate ratios. For firm i, frailty-adjusted credit risk premia are computed as the difference between observed CDS rates and frailty-adjusted expected loss rates $\mathrm{ExpL}_t^i(1+\mathrm{FR^i}_t)/2$. Here, $\mathrm{FR^i}_t$ denotes the time-t ex-post frailty ratio for IG (HY) firms in Figure C.9 if firm i has IG (HY) status at time t. "Unadjusted" refers to credit risk premia estimates based on unadjusted expected loss rates ExpL_t. We use the benchmark expected losses computed in Section 3 of the main text to measure ExpL_t. Only days on which data are available for 50 or more firms are shown. The data cover 505 public U.S. firms, over 2002-2015.

D. Alternative Loss Given Default Measures

In addition to Markit-based estimates of loss given default, we consider four alternative specifications. These include (i) an assumption of constant LGD, (ii) historical LGD estimates, (iii) trailing LGD estimates and (iv) ratings-based LGD estimates. The latter take into account the timing of default. Details on the definition of these alternative LGD measures, and on how they are sourced, are provided in Table D.1.

Table D.1: **Loss given default measures** The table lists various loss given default measures. Column one shows our notation for the LGD measure, column two the source of the data and column three the definition of $E_t(L^i_{t+k\Delta,\Delta})$. "Moody's" refers to aggregate recovery rate statistics reported in Moody's annual "Corporate Default and Recovery Rates" studies (see, for example, Moody's Investors Service (2016)). For 2002, ratings-based LGD is observed only for the one-year horizon. We assume it is the same for all horizons. For 2003, there are no ratings-based estimates and we set LGD equal to the 2002 values. For 2005, historical LGD is unavailable and set equal to the 2004 value.

LGD measure	Source	Definition of $E_t(L^i_{t+k\Delta,\Delta})$
Benchmark	Markit	L^i_t, where $1 - L^i_t$ is the recovery rate reported for firm i on date t
Alternatives		
Constant	Moody's	0.624, which is one minus the issuer-weighted average recovery rate measured by post-default trading prices for senior unsecured corporate bonds between 1983 and 2015
Historical	Moody's	L_t, where $1 - L_t$ is the issuer-weighted average recovery rate for senior unsecured bonds between 1982 and the beginning of year t
Trailing	Moody's	L_t, where $1 - L_t$ is the issuer-weighted average recovery rate for senior unsecured bonds reported for the previous year
Ratings-based	Moody's	$E_t(L^i_{t+k\Delta,\Delta}) = L^{IG/HY(i,t)}_{t,1}$ for $k = 0, .., \frac{1-\Delta}{\Delta}$, $E_t(L^i_{t+k\Delta,\Delta}) = L^{IG/HY(i,t)}_{t,2}$ for $k = \frac{1}{\Delta}, .., \frac{2-\Delta}{\Delta}$, and so on, where $1 - L^{IG/HY}_{t,y}$ is the average issuer-weighted recovery rate for senior unsecured bonds between 1982 and the beginning of year t for firms of IG/HY status y years prior to default

E. The Specification and Fitting of Term Structures of Default Probabilities

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. This flexibility is useful, given the changes in the EDF term structure over time observed in Figure E.1.

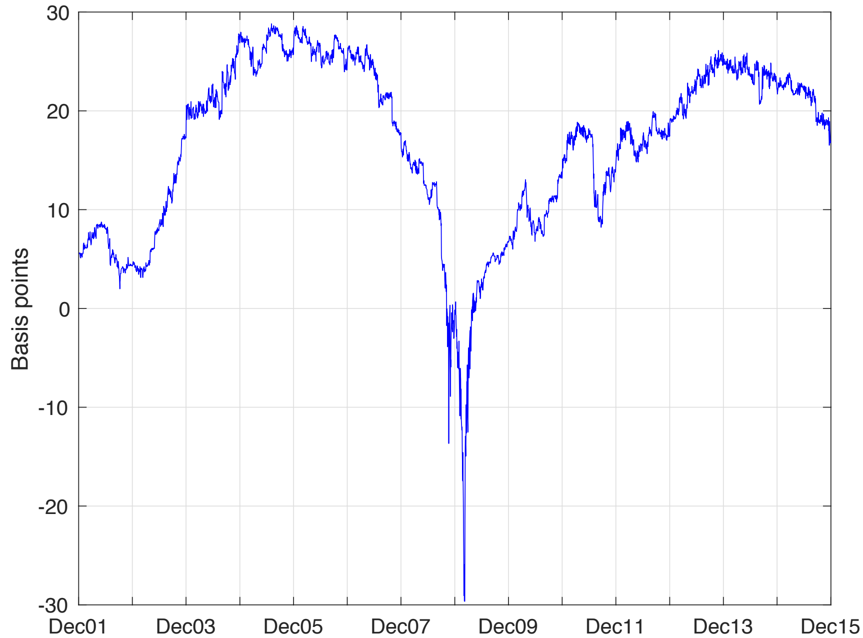

Figure E.1: **Median EDF term structure** The figure shows the daily median difference between five-year and one-year EDFs. The data cover 505 public U.S. firms, over 2002-2015.

The Nelson-Siegel-Svensson model, adapted to the term structure of conditional default probabilities, proposes that

$$E_t(D_{t,T}) \quad = \quad 1 - e^{-f_t(T-t)(T-t)}, \tag{E.1}$$

where the date-t annualized spot default hazard rate $f_t(m)$ for maturity m is

$$f_t(m) \quad = \quad \beta_{0,t} + \beta_{1,t}\frac{1-e^{-\theta_1 m}}{\theta_1 m} + \beta_{2,t}\left(\frac{1-e^{-\theta_1 m}}{\theta_1 m} - e^{-\theta_1 m}\right) + \beta_{3,t}\left(\frac{1-e^{-\theta_2 m}}{\theta_2 m} - e^{-\theta_2 m}\right), \tag{E.2}$$

for parameters

$$\Theta \quad = \quad (\beta_0, \beta_1, \beta_2, \beta_3, \theta_1, \theta_2).$$

The special case of $\beta_{3,t} = 0$ corresponds to the original Nelson and Siegel (1987) model specification. The parameter vector Θ is allowed to vary with the firm and across time.[4]

[4]Variation of Θ across time is not necessarily consistent with the martingale condition associated with dynamic term structures. The martingale issue is addressed by Filipović (1999). Given the sparseness of our data, a more sophisticated

In what follows, we consider a particular date t but drop the subscript t to simplify notation. The term structure parameters in Θ have economic interpretations that are useful for our calibration exercise. First, $\lim_{m\to\infty} f(m) = \beta_0$ and $\lim_{m\to 0} f(m) = \beta_0 + \beta_1$, meaning that β_0 and β_1 can be calibrated to the long-term level and the slope of the term structure of default probabilities. Second, β_2 and β_3 allow two humps in the term structure, with θ_1 and θ_2 determining the positions of the respective humps.

For a given firm and date, we estimate the parameter vector Θ by requiring model-implied one-year and five-year default probabilities to match their EDF counterparts. To facilitate a robust estimation of longer-term forward default rates, we augment our data with the ten-year refined-ratings-based PD estimates described in Internet Appendix I. Ten years is the longest horizon for which an alternative PD measure is available throughout the sample period. We require model-implied ten-year default probabilities to match refined-ratings-based PDs.[5] Summary statistics for the one-year and five-year EDFs and ten-year refined-ratings-based PDs are reported in Table E.1.

Table E.1: **Nelson-Siegel-Svensson model calibration** The first three columns show median annualized one-year, five-year and ten-year PDs in basis points. The one-year and five-year PDs are measured as one-year and five-year EDFs. The ten-year PDs are measured as the refined-ratings-based PD estimates described in Internet Appendix I. The next four columns report median parameter estimates for the Nelson-Siegel-Svensson model in Equation (E.2), when calibrated to one-year, five-year and ten-year PDs on a firm and date basis. The hump location parameters are preset to $\theta_1 = 0.3587$ and $\theta_2 = 0.1793$, and the reported β estimates are in basis points. The last column shows the percentage of firm-date pairs for which the beginning of the term structure has an inverted hump shape. The first row reports medians across firms and over time, and the remaining rows report similar statistics by rating category. The data cover 505 public U.S. firms, over 2002-2015.

	1yr PD	5yr PD	10yr PD	β_0	β_1	β_2	β_3	Inv hump
All	14	38	56	56	-35	-113	119	0.59
Aaa-Aa	4	14	17	17	-15	-22	32	0.34
A	6	20	26	26	-22	-44	58	0.42
Baa	11	33	52	52	-35	-106	111	0.58
Ba	28	66	142	143	-60	-354	337	0.79
B	74	143	434	443	-100	-1,622	1,155	0.89
Caa	362	375	916	961	-111	-5,912	4,586	0.96
Ca-C	1,167	738	1,406	1,515	651	-9,109	5,842	1.00

We chose the extended Nelson-Siegel framework over the original specification that sets $\beta_3 = 0$ to allow for two humps in the term structure of default hazard rates rather than just one. Why is

term-structure model that avoids this problem is unlikely to offer much improvement.

[5]For 37,679 of the 1,189,330 firm-date pairs in our sample, refined ratings are unavailable. If, for a given firm and date, a refined rating is not available, we first regress refined ratings on one-year EDFs using all available data for that date, and then use that fitted relationship to fill in the missing refined rating.

this flexibility important? Consider a scenario in which, for a given firm and date, the five-year EDF is lower than the one-year EDF and the ten-year annualized ratings-based PD, as tends to be the case for the lowest-rated firms in Table E.1. If $\beta_3 = 0$, the data suggest a term structure of default probabilities with an inverted hump at a medium horizon. At the long end of the term structure, default rates would continue to rise past the ten-year PD estimate, perhaps significantly so. Allowing for two humps enables us to constrain long-term default probabilities, even in the case of an inverted hump at medium horizons. In particular, for each firm and date we impose the over-identifying restriction that the long-term level parameter β_0 is equal to the ten-year refined-ratings-based PD.

In the Nelson-Siegel-Svensson framework, θ_1 and θ_2 determine the maturities m_1^* and m_2^* at which the loadings on the curvature factors β_2 and β_3 achieve their respective maxima.[6] Following standard practice going back to Nelson and Siegel (1987), we fix θ_1 and θ_2 at pre-specified values. Given the range of maturities for which we observe PD estimates, we choose $\theta_1 = 0.3587$ to maximize the loading on β_2 at $m_1^* = 5$ years and $\theta_2 = 0.1793$ to maximize the loading on β_3 at $m_2^* = 10$ years. Fixing θ_1 and θ_2, and calibrating β_0 to long-term PDs, allows us compute the values of β_1, β_2, and β_3 by solving a system of three linear equations.

Table E.1 reports summary statistics for our parameter estimates. Not surprisingly, the long-term level parameter β_0 tends to increase as credit quality worsens. Except for the lowest rated firms, β_1 tends to be negative, meaning that the short end of the credit term structure, $\beta_0 + \beta_1$, tends to be lower than the long end, β_0, and that the slope tends to be positive. For firms rated Ca or C, the slope is negative, in line with the high short-term default probabilities reported in the first column of the table.

Table E.1 also reveals that for high-yield firms, the short end of the term structure generally exhibits an inverted hump. This is confirmed in Figure 4 in the main text, which shows the fitted term structure of default probabilities out to ten years. The PDs of high-yield firms tend to be lowest between two and four years of maturity. For firms rated Ba or B, observed one-year, five-year and ten-year default rates are generally increasing in maturity, and the inverted hump in the fitted term structure is relatively flat. For firms rated Caa, one-year and five-year default rates tend to be of similar value and the model fits a more pronounced inverted hump to capture the steep increase between five-year and ten-year PDs.

[6] These loadings are $(1 - e^{-\theta_1 m_1^*})/(\theta_1 m_1^*) - e^{-\theta_1 m_1^*}$ and $(1 - e^{-\theta_2 m_2^*})/(\theta_2 m_2^*) - e^{-\theta_2 m_2^*}$, respectively.

For firms rated Ca or C, observed one-year default rates are often substantially higher than five-year rates, which in turn are somewhat lower than ten-year rates, resulting in an inverted hump shape with the lowest PDs observed at medium maturities. For investment-grade firms, on the other hand, the term structure is generally upward sloping. The slope tends to be steeper at medium maturities and more shallow at short and long maturities.

F. Conditioning Variables

In this appendix, we provide details on the conditioning variables used in Sections 6 and 7 of the main text.

F.1 Options data

We use OptionMetrics' Standardized Options data to obtain firm-specific implied volatilities (IV) for put options of a given maturity. OptionMetrics computes the interpolated volatility surface for each firm on each day, using a methodology based on a kernel smoothing algorithm. The data include information for standardized puts at Deltas of -0.80 through -0.20. We refer to puts with a Delta of -0.2 as out of the money (OTM), and to puts with a Delta of -0.5 as at the money (ATM). IV data are available for standardized options with horizons of 30, 60, 91, 152, 182, 273, 365 and 730 days. A preliminary analysis identified the 91-day horizon as the preferred horizon for predicting credit risk premia. We also obtain market-wide implied volatilities (MV) for standardized 91-day put options on the S&P500 index.

A closely related and commonly used barometer of aggregate equity-market volatility is the Chicago Board Options Exchange (CBOE) volatility index, VIX, which is available from the CBOE website. The VIX index is based on real-time prices of options on the S&P 500 index and is designed to reflect investors' consensus view of 30-day expected stock-market volatility. The sample correlation between VIX and 30-day ATM MV exceeds 99%.

F.2 Treasury rates

Interest rate data are obtained from the Federal Reserve Board's website, and are based on the calibration technique described in Gurkaynak, Sack, and Wright (2007). We use the five-year rate as a measure of the level of the Treasury yield curve, and the difference between the five-year and one-year rates as a measure of the slope.

F.3 Consumer sentiment

We measure consumer sentiment using the University of Michigan Consumer Sentiment index, CSENT. CSENT is a leading economic indicator that gauges consumers' economic expectations. It leads the business cycle because consumer expectations can indicate future consumer spending. Leduc (2010) and Milani (2013), for example, argue that sentiments not only react to movements in economic fundamentals but are themselves an independent cause of economic fluctuations.

The sentiment index for a given reference month is released at the end of that month. To avoid a look-ahead bias, for any given day we use the CSENT value reported at the end of the previous month.

F.4 Unemployment rate

We collect data on the seasonally adjusted civilian unemployment rate, UNRATE. The data are disseminated by the U.S. Bureau of Labor Statistics as part of the Employment Situation report and are available from the Federal Reserve Economic Data (FRED) website. The unemployment rate represents the number of unemployed as a percentage of the labor force. The labor force is defined as people sixteen years of age and older, who currently reside in one of the 50 U.S. states or the District of Columbia, who do not reside in institutions and who are not on active duty in the Armed Forces.

The Employment Situation report is typically released on the third Friday after the conclusion of the reference week, i.e., the week which includes the 12th of the reference month. This often, but not always, coincides with the first Friday of the month following the reference month. For any given day, we use the UNRATE value reported for the previous month.

F.5 Consumption growth

We measure annualized consumption growth at quarterly frequency. Growth rates are based on real personal consumption expenditures per capita for nondurable goods and services. Personal consumption expenditures per capita are reported as seasonally adjusted annual rates, separately for nondurable goods and for services. They are converted from nominal to real by dividing the expenditures in dollars by their respective chain-type price indices.

The data are disseminated by the U.S. Bureau of Economic Analysis and can be downloaded from FRED. Advance estimates for a reference quarter are generally available one month after the end of that quarter. For a given day, we use the last available value except for days in April, July, October and January when we use the value for the second-to-last quarter.

F.6 Leading index

The Leading Index for the U.S., USSLIND, is disseminated by the Federal Reserve Board of Philadelphia and can be downloaded from FRED. It is available at a monthly frequency, with seasonal adjustment. The Leading Index predicts the six-month growth rate of the U.S. Coincident Index. The Coincident Index combines four indicators—non-farm payroll employment, average hours worked in manufacturing by production workers, the unemployment rate, and real wage and salary disbursements—to summarize current economic conditions in a single statistic.[7]

The index is usually released one month after the reference month.[8] For any given day, we therefore use the value reported for the second-to-last month.

F.7 Business cycle indicator

We use a dummy variable called NBER that is turned on during NBER recessions and off otherwise.

F.8 Volume of defaulted debt

We obtain monthly data on the volume of U.S. defaulted debt from Moody's Analytics. We compute the Defaulted Debt variable as the average U.S. defaulted debt volume in billions of dollars over the past twelve months.

F.9 Bond trading volume

The Securities Industry and Financial Markets Association (SIFMA) disseminates data on the average daily trading volume for U.S. corporate bonds. Between 2002 and 2004, the data are sourced from the Financial Industry Regulatory Authority Fact Book (FINRA Fact Book) and reported on an annual basis. For any given date, we use the value for the previous year. As a result, there are no

[7] The trend of the index is set equal to the trend of the gross domestic product (GDP), so the long-term growth of the index matches the long-term growth in GDP. For details, see www.phil.frb.org/research-and-data/regional-economy/indexes.

[8] From time to time, the lag exceeds one month. For a sample release schedule, see www.philadelphiafed.org/research-and-data/regional-economy/indexes/leading/schedule.

observations for 2002 dates. To facilitate computations over the full sample period, we take the simple view that average daily bond trading volume in 2001 was similar to that in 2002. Since 2005, the data are sourced from FINRA TRACE and reported on a monthly basis. For a given date, we use the value for the previous month. The data include all publicly traded bonds, and are also available by IG/HY status. Bond trading volume can be used as a proxy for bond-market liquidity (Beau (2016)).

F.10 CDS notional

CDS notional outstanding is reported twice a year, in billions of U.S. dollars and adjusted for double-counting. Until June 2010, we use data from the bi-annual ISDA Market Survey (see www.isda.org/statistics/pdf/ISDA-Market-Survey-historical-data.pdf). ISDA stopped disseminating these survey data after June 2010. From December 2010 onwards, we use the Bank of International Settlement data, specifically Table D10.1 titled "OTC, credit default swaps, by type of position." For a given day, the variable CDS notional is set equal to the value reported at the end of the previous six-month period.

F.11 CDS composite depth

For every composite five-year CDS quote that we observe, Markit reports the composite depth, that is, number of sources that contributed to the composite. In our sample, the composite depth ranges from two to 33, with a median of seven. A number of papers have used the composite depth as a proxy for CDS liquidity. See, for example, Pu (2009), Massa and Zhang (2012), Slive, Witmer, and Woodman (2012), Junge and Trolle (2015) and Arakelyan and Serrano (2016).

F.12 Descriptive statistics

Table F.1 provides descriptive statistics for the variables described in this appendix. These statistics are used in Sections 6 and 7 of the main text and in Internet Appendix H to assess the economic significance of the association between credit risk premia and conditioning variables. For variables that exhibit substantial skewness, such as the volatility measures, RMI-based expected losses, consumer sentiment, the volume of defaulted debt and CDS composite depth, we also provide descriptive statistics for skewness-reducing variable transformations.

Table F.1: **Descriptive statistics for conditioning variables** The table reports descriptive statistics for the control variables in the panel regression (6). Volatilities are measured in nominal terms, interest rates, unemployment and consumption growth in percent, defaulted debt and average daily bond trading volume in billions of U.S. dollars, and CDS notional in trillions of U.S. dollars. The data cover 467 public U.S. firms, over 2002-2015.

	Mean	SD	5%	25%	50%	75%	95%
			Raw data				
IV_{atm}	0.32	0.17	0.16	0.22	0.28	0.37	0.63
IV_{otm}/IV_{atm}	1.17	0.21	1.05	1.11	1.15	1.20	1.31
MV_{atm}	0.18	0.07	0.11	0.13	0.16	0.22	0.33
MV_{otm}/MV_{atm}	1.28	0.06	1.18	1.24	1.28	1.32	1.37
VIX	0.20	0.09	0.11	0.14	0.17	0.23	0.38
Trsy rate	2.59	1.29	0.78	1.56	2.39	3.69	4.71
Trsy slope	1.03	0.73	-0.33	0.53	1.15	1.59	2.08
CSENT	80.3	11.1	59.8	72.9	81.8	89.7	95.9
UNRATE	6.64	1.77	4.50	5.10	6.00	8.20	9.80
Consumption growth	0.86	1.43	-2.58	-0.13	0.93	1.93	2.86
USSLIND	1.00	0.94	-1.18	0.65	1.35	1.61	1.86
Defaulted debt	3.84	4.97	0.46	1.20	2.09	3.65	15.79
Bond trading volume	16.0	3.1	11.1	13.8	15.7	17.9	21.1
IG bond trading volume	10.9	2.2	7.3	9.3	11.1	12.3	14.3
HY bond trading volume	5.0	1.2	3.6	4.3	4.7	5.7	7.5
CDS notional	25.1	15.0	2.2	14.6	26.0	31.2	54.6
CDS composite depth	8	4	3	5	7	9	16
			Transformed data				
$\log(IV_{atm})$	-1.23	0.42	-1.84	-1.53	-1.28	-0.99	-0.47
$\log(IV_{otm}/IV_{atm})$	0.15	0.10	0.05	0.10	0.14	0.18	0.27
$\log(MV_{atm})$	-1.76	0.34	-2.19	-2.03	-1.81	-1.53	-1.11
$\log(MV_{otm}/MV_{atm})$	0.25	0.05	0.17	0.21	0.25	0.28	0.32
log(VIX)	-1.70	0.38	-2.17	-1.99	-1.77	-1.48	-0.96
log(CSENT)	4.38	0.14	4.09	4.29	4.40	4.50	4.56
log(Defaulted debt)	0.76	1.04	-0.78	0.19	0.74	1.29	2.76
log(CDS composite depth)	1.92	0.49	1.10	1.61	1.95	2.20	2.77
1/CDS notional	0.10	0.17	0.02	0.03	0.04	0.07	0.46

G. The Term Structure of Credit Risk Premia

The evolution over time of the term structure of credit risk premia is displayed in Figure G.1. The figure shows the daily time series of median differences between five-year and one-year premia, and between ten-year and one-year premia. We observe that the term structure was relatively flat prior to the Great Recession. The term structure 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.

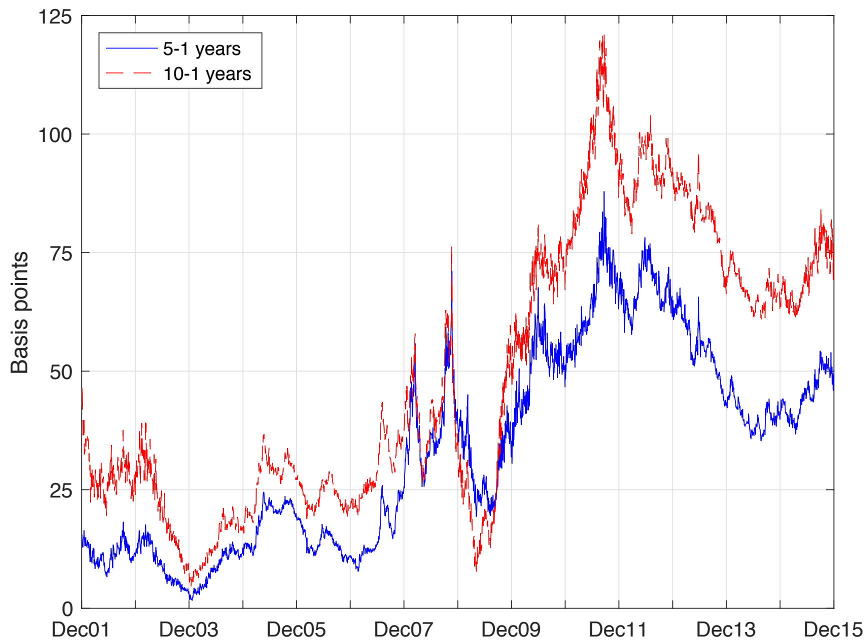

Figure G.1: **Term structure of credit risk premia** The figure shows the daily times series of median differences, in basis points of notional, between five-year and one-year credit risk premia (solid line), and between ten-year and one-year credit risk premia (dashed line). Only days on which data are available for 50 or more firms are shown. The data cover 505 public U.S. firms, over 2002-2015.

Do cross-maturity changes in premia go hand in hand with changes in expected losses? Figure G.2 shows that the ratio of premia to expected default loss rates tended to be the same across maturities between 2005 and 2007. Prior to 2003, however, long-term premium-to-expected-loss ratios were significantly higher than their short- and medium-term analogues. Post-crisis, on the other hand, the term structure of ratios of premia to expected losses has been hump-shaped, with five-year premia per unit of risk higher than their one-year and ten-year counterparts.

Table G.1 reports additional summary statistics for ratios of premium to expected loss, by industry

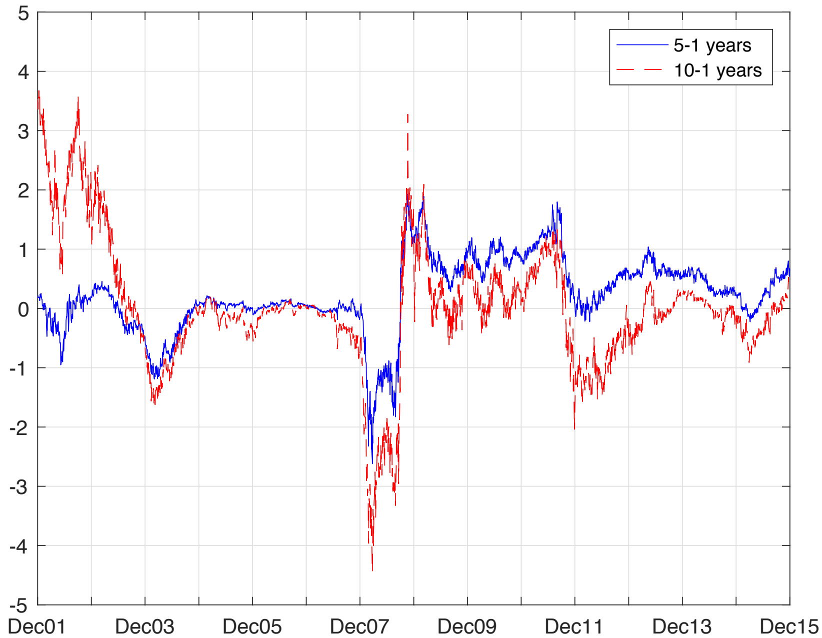

Figure G.2: **Term structure of credit risk premia to expected loss ratios** The figure shows the daily times series of median differences between five-year and one-year credit risk premia to expected loss ratios (solid line) and between ten-year and one-year premia to expected loss ratios (dashed line). Only days on which data are available for 50 or more firms are shown. The data cover 505 public U.S. firms, over 2002-2015.

and credit rating. The term structure of credit risk premia, per unit of expected loss, has a median across firms that tends to be upward-sloping for financials and technology firms, and downward-sloping for utilities. For firms in the remaining sectors, this term structure tends to be hump-shaped. The highest rated firms often exhibit an inverted-hump-shaped term structure, whereas medium and low rated firms tend to have a hump-shaped term structure.

The relationship between credit rating and the term structure of the ratio of credit risk premium to expected default loss rate is explored in more detail in Table G.2. An inverted-hump-shaped term structure is observed for highly rated firms for every year in our sample. This effect is particularly pronounced in 2009.

Table G.1: **Descriptive statistics for term structure of credit risk premium to expected loss ratios** The table reports median statistics for premium-to-expected-loss ratios, Prem/ExpL, by year, sector and letter rating. For each panel, the first three columns are for maturities of one, five, and ten years. The last three columns show the difference between five-year and one-year ratios, the difference between ten-year and one-year ratios, and the curvature defined as five-year ratios minus the average of one-year and ten-year ratios. The data cover 505 public U.S. firms, over 2002-2015.

	1	5	10	5-1	10-1	curv		1	5	10	5-1	10-1	curv
			All							By sector			
	2.43	2.92	2.58	0.16	-0.11	0.06	BM	2.84	3.63	2.91	0.50	-0.29	0.42
			By year				CG	3.94	3.97	3.04	0.21	-0.76	0.29
2002	3.54	3.63	5.07	-0.04	2.22	-1.36	CS	2.09	3.00	2.34	0.52	0.11	0.35
2003	1.60	1.84	2.16	-0.05	0.25	-0.52	Egy	3.77	4.37	3.56	0.30	-0.79	0.26
2004	1.57	1.27	0.92	-0.45	-0.68	-0.26	Fin	0.25	0.64	0.82	0.09	0.23	-0.07
2005	1.20	1.36	1.04	0.08	-0.10	0.00	Hlth	2.23	2.71	2.08	0.04	-0.06	-0.02
2006	1.07	1.34	1.00	0.06	-0.03	0.00	Ind	2.96	3.09	2.61	0.00	-0.59	0.01
2007	1.47	1.54	1.38	0.00	-0.17	-0.02	Tech	0.37	0.99	1.49	0.31	0.76	-0.16
2008	5.70	5.17	4.31	-0.58	-1.68	-0.42	Tele	1.45	2.36	2.49	0.60	0.41	0.20
2009	3.14	4.72	4.19	0.86	0.38	0.61	Utl	8.58	8.48	4.80	-0.78	-3.61	0.53
2010	2.45	3.68	3.52	0.88	0.26	0.73				By rating			
2011	3.17	4.56	4.25	1.04	0.56	0.65	Aaa	1.65	1.43	1.72	-0.69	-0.47	-0.60
2012	4.56	5.16	4.28	0.28	-0.87	0.25	Aa	2.39	1.83	2.75	-0.34	-0.08	-0.61
2013	3.02	4.01	3.37	0.65	-0.01	0.56	A	2.25	2.11	2.71	-0.06	-0.04	-0.19
2014	2.69	3.22	2.75	0.40	0.06	0.31	Baa	2.71	3.12	2.88	0.22	-0.20	0.12
2015	3.37	3.88	3.13	0.23	-0.23	0.30	Ba	2.98	4.01	2.52	0.76	-0.51	0.76
							B	1.67	3.37	1.75	1.34	0.13	1.21
							Caa	0.64	2.49	1.24	1.44	0.62	1.12
							Ca-C	0.65	2.12	1.61	1.17	0.69	0.95

Table G.2: **Term structure of credit risk premia by year and rating** The table reports median differences between five-year and one-year (top panel) and ten-year and one-year (middle panel) premium-to-expected-loss ratios, by year and letter rating. The bottom panel shows median differences between five-year and the average of one-year and ten-year premium-to-expected-loss ratios. The data cover 505 public U.S. firms, over 2002-2015.

	Aaa	Aa	A	Baa	Ba	B	Caa	Ca-C	All
Difference between 5- and 1-year Prem/ExpL									
2002	0.15	0.00	-0.28	-0.07	0.94	1.28	0.57	0.81	-0.04
2003	0.23	0.04	-0.10	-0.25	-0.36	0.76	-4.57	0.98	-0.05
2004	0.05	-0.30	-0.53	-0.63	-0.78	0.33	2.06	1.20	-0.45
2005	0.06	-0.05	0.04	0.17	-0.23	-0.07	2.89	-0.18	0.08
2006	0.00	-0.07	0.01	0.12	0.36	0.96	1.25	0.00	0.06
2007	-0.42	-0.23	-0.07	0.02	0.44	0.89	0.87	2.12	0.00
2008	-2.85	-1.24	-1.10	-1.35	0.56	1.51	1.29	1.40	-0.58
2009	-12.71	-5.73	0.31	0.71	1.76	2.24	0.90	1.55	0.86
2010	-5.55	-1.79	0.37	0.75	1.56	2.06	1.19	2.20	0.88
2011	-3.37	-1.20	0.62	1.01	1.90	2.16	2.20	1.93	1.04
2012	-4.03	-4.05	-0.50	0.29	1.57	2.07	1.80	0.57	0.28
2013	-2.34	-0.75	0.10	0.66	1.82	1.85	1.93	-4.57	0.65
2014	-2.57	-0.79	-0.01	0.45	1.07	1.11	1.70	2.06	0.40
2015	-2.18	-1.49	-0.56	0.40	1.13	1.26	1.46	2.89	0.23
All	-0.69	-0.34	-0.06	0.22	0.76	1.34	1.17	1.17	0.16
Difference between 10-year and 1-year Prem/ExpL									
2002	6.24	3.83	3.09	0.86	-1.82	1.25	0.12	0.49	2.22
2003	4.28	2.24	1.20	-0.34	-2.60	-0.10	-17.70	0.52	0.25
2004	0.36	-0.17	-0.40	-0.96	-1.78	-0.70	3.46	0.37	-0.68
2005	0.18	0.10	0.11	-0.12	-1.41	-1.25	1.35	-1.39	-0.10
2006	0.00	-0.02	0.10	-0.08	-0.66	-0.66	0.45	0.00	-0.03
2007	-0.37	-0.30	-0.06	-0.22	-0.10	-0.35	0.48	-1.90	-0.17
2008	-3.21	-0.16	-0.94	-3.38	-1.49	-0.08	0.62	0.90	-1.68
2009	-11.76	-0.73	1.84	-0.10	-0.05	0.34	-0.18	1.52	0.38
2010	-11.14	-3.94	0.78	0.00	0.09	0.43	0.00	1.23	0.26
2011	-4.86	-1.43	0.50	0.71	0.38	0.70	0.59	0.74	0.56
2012	-5.10	-5.24	-1.43	-0.81	-1.07	0.48	0.89	0.12	-0.87
2013	-2.05	-0.84	-0.39	0.03	0.15	0.74	0.61	-17.70	-0.01
2014	-1.48	-0.30	-0.30	0.15	-0.02	0.47	0.92	3.46	0.06
2015	-2.09	-0.72	-0.88	-0.03	-0.14	0.51	0.56	1.35	-0.23
All	-0.47	-0.08	-0.04	-0.20	-0.51	0.13	0.69	0.69	-0.11
Difference between 5-year and average of 1- and 10-year Prem/ExpL									
2002	-2.89	-2.11	-2.00	-0.79	1.19	0.58	0.37	0.55	-1.36
2003	-1.81	-1.67	-0.95	-0.30	0.30	0.75	0.32	0.72	-0.52
2004	-0.14	-0.25	-0.47	-0.28	-0.13	0.67	0.33	1.58	-0.26
2005	-0.05	-0.17	-0.08	0.10	0.01	0.34	1.82	0.09	0.00
2006	-0.07	-0.08	-0.05	0.06	0.42	1.16	1.09	0.00	0.00
2007	-0.26	-0.14	-0.07	-0.01	0.35	0.93	0.58	2.79	-0.02
2008	-0.94	-2.72	-1.35	-0.52	0.73	1.49	0.97	0.85	-0.42
2009	-8.31	-6.01	-0.87	0.58	1.68	1.92	1.03	0.84	0.61
2010	-3.90	-1.15	-0.23	0.62	1.57	2.11	1.16	1.55	0.73
2011	-1.13	-0.94	0.04	0.55	1.97	1.99	1.80	1.63	0.65
2012	-1.58	-1.18	-0.15	0.22	1.70	1.77	1.32	0.37	0.25
2013	-1.39	-0.41	0.12	0.60	1.54	1.43	1.62	0.32	0.56
2014	-1.24	-0.64	0.02	0.33	0.96	0.70	1.25	0.33	0.31
2015	-1.87	-0.98	-0.10	0.40	0.99	1.05	1.34	1.82	0.30
All	-0.60	-0.61	-0.19	0.12	0.76	1.21	0.95	0.95	0.06

H. Robustness Checks

In this appendix, we enlarge the vector of conditioning variables in the panel data regression. We also repeat our empirical analysis after replacing the CDS quotes for modified restructuring that we use in the main part of the paper by CDS quotes without restructuring.

H.1 Augmented panel data regressions

Additional control variables for the panel data regression (6) are described in Internet Appendix F. They include aggregate equity-market volatility measures, the slope of the Treasury yield curve, alternative business cycle variables, proxies for aggregate bond market liquidity, and proxies for firm-specific CDS market liquidity. Table H.1 reports on the results and shows that the inclusion of these additional variables does not improve the goodness of fit in a meaningful way.

Table H.1: **Augmented panel data regressions** The table reports results for the panel data regression (6) when Specification IX in Table 7 is extended to include more controls. The additional controls are described in Internet Appendix F. Volatilities are measured in nominal terms, interest rates, unemployment and consumption growth in percent, and defaulted debt and average daily bond trading volume in billions of U.S. dollars. The data cover 467 public U.S. firms, over 2002-2015.

	R^2	RMSE
Specification IX	0.812	0.412
Specification IX + additional firm-specific variables		
log(CDS composite depth), log(CDS composite depth) $\times D_{HY}$	0.813	0.411
Specification IX + additional macroeconomic variables		
log(CSENT) $\times D_{HY}$	0.815	0.409
log(MV$_{atm}$), log(MV$_{otm}$/MV$_{atm}$), log(MV$_{atm}$) $\times D_{HY}$, log(MV$_{otm}$/MV$_{atm}$) $\times D_{HY}$	0.815	0.409
log(VIX), log(VIX) $\times D_{HY}$	0.814	0.410
Trsy slope, Trsy slope $\times D_{HY}$	0.814	0.410
UNRATE, UNRATE $\times D_{HY}$	0.816	0.408
Consumption growth, Consumption growth $\times D_{HY}$	0.814	0.410
USSLIND, USSLIND $\times D_{HY}$	0.813	0.411
log(Defaulted debt), log(Defaulted debt) $\times D_{HY}$	0.813	0.411
NBER, NBER $\times D_{HY}$	0.814	0.410
Bond trading volume, Bond trading volume $\times D_{HY}$	0.814	0.409
IG bond trading volume $\times(1 - D_{HY})$, HY bond trading volume $\times D_{HY}$	0.814	0.410

H.2 Comparing results for CDS quotes with and without restructuring

Table H.2 reports summary statistics for credit spreads and associated credit risk premia estimates, for CDS quotes with modified restructuring and CDS quotes without restructuring. The sample includes 996,326 firm-date pairs that cover 467 firms. It is slightly smaller than that of the 1,003,488 firm-date pairs used in Sections 5 and 6 of the main text because CDS quotes without restructuring are not always available.

Table H.2: **Descriptive statistics for CDS quotes with and without restructuring** The table reports the median difference between five-year CDS quotes for modified restructuring (M) and five-year CDS quotes without restructuring (X), as well as the median proportional difference between these quotes ((M-X)/M). The table also shows similar statistics for credit risk premia (Prem) and premium-to-expected-loss ratios (Prem/ExpL). Expected loss rates are computed as in Section 3. CDS rates and credit risk premia are reported as annualized rates in basis points. The data cover 467 public U.S. firms, over 2002-2015.

	CDS		Prem		Prem/ExpL			CDS		Prem		Prem/ExpL	
	M-X	$\frac{M-X}{M}$	M-X	$\frac{M-X}{M}$	M-X	$\frac{M-X}{M}$		M-X	$\frac{M-X}{M}$	M-X	$\frac{M-X}{M}$	M-X	$\frac{M-X}{M}$
			All							By sector			
	2	0.02	2	0.03	0.09	0.03	BM	2	0.03	2	0.03	0.12	0.03
			By year				CG	2	0.02	2	0.03	0.12	0.03
2002	5	0.06	5	0.08	0.26	0.08	CS	2	0.02	2	0.03	0.09	0.03
2003	3	0.06	3	0.08	0.16	0.08	Egy	2	0.03	2	0.03	0.14	0.03
2004	2	0.05	2	0.07	0.10	0.07	Fin	2	0.03	2	0.02	0.03	0.02
2005	2	0.05	2	0.06	0.09	0.06	Hlth	1	0.03	1	0.03	0.08	0.03
2006	2	0.05	2	0.06	0.10	0.06	Ind	2	0.03	2	0.03	0.10	0.03
2007	1	0.04	1	0.05	0.09	0.05	Tech	1	0.02	1	0.02	0.04	0.02
2008	4	0.04	4	0.04	0.20	0.04	Tele	3	0.02	3	0.03	0.10	0.03
2009	3	0.02	3	0.03	0.12	0.03	Utl	2	0.03	2	0.03	0.21	0.03
2010	1	0.02	1	0.02	0.06	0.02				By rating			
2011	1	0.01	1	0.02	0.05	0.02	Aaa	1	0.03	1	0.02	0.06	0.02
2012	2	0.02	2	0.02	0.10	0.02	Aa	1	0.04	1	0.02	0.08	0.02
2013	1	0.02	1	0.02	0.07	0.02	A	1	0.03	1	0.03	0.08	0.03
2014	1	0.02	1	0.02	0.05	0.02	Baa	2	0.02	2	0.03	0.10	0.03
2015	1	0.02	1	0.02	0.06	0.02	Ba	4	0.02	4	0.03	0.11	0.03
							B	6	0.02	6	0.03	0.08	0.03
							Caa	13	0.02	13	0.03	0.08	0.03
							Ca-C	23	0.02	23	0.02	0.05	0.02

CDS quotes without restructuring tend to be smaller than their counterparts for modified restructuring, consistent with the narrower definition of default when restructuring is excluded as a contractually covered credit event. The differences in the quotes, however, are generally small. At the median, CDS quotes with restructuring exceed those without restructuring by two basis points, or two percent of the quote with restructuring. For premium-to-expected-loss ratios, the median difference is 0.09, or 3% of the ratio with restructuring.[9]

We re-estimate the panel data regressions after replacing the CDS quotes for modified restructuring

[9] Moody's definition of default includes out-of-court debt restructuring. With regard to the definition of default, our benchmark measures of default probabilities and expected loss rates are therefore closer aligned with CDS quotes with restructuring than those without restructuring. While Markit reports estimates of recovery rates separately for CDS quotes with and without restructuring, we find that they are often the same. For over 90% of our firm-date observations, the ratio of LGD with restructuring to LGD without restructuring is between 0.98 and 1.01. Thus, we use the benchmark expected losses computed in Section 3 of the main text to report our findings.

by CDS quotes without restructuring. The results are shown in Table H.3.[10] They confirm that our findings in Sections 5 and 6 are robust to the specification of the restructuring clause.

Table H.3: **Regression results for CDS quotes with and without restructuring** The table reports results for the panel data regressions (5) and (6), for CDS quotes for modified restructuring and CDS quotes without restructuring. The numbering of the model specifications reflects that of Tables 5 and 7 in the main text. Expected loss rates are computed as in Section 3. 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.

	Modified restructuring			No restructuring		
	I	I(FM)	IX	I	I(FM)	IX
Constant	2.746	4.221	9.914	2.716	4.206	9.925
	(0.027)	(0.048)	(0.195)	(0.027)	(0.048)	(0.200)
log(ExpL)	-0.445	-0.461	-1.103	-0.445	-0.460	-1.103
	(0.003)	(0.007)	(0.009)	(0.003)	(0.007)	(0.009)
Firm FE	No	Yes	No	No	Yes	No
Month FE	No	Yes	No	No	Yes	No
Firm & macro vars	No	No	Yes	No	No	Yes
R^2	0.262	0.836	0.812	0.258	0.837	0.813
RMSE	0.816	0.385	0.411	0.822	0.385	0.412

I. Alternative Probability of Default Measures

In addition to Moody's Analytics EDF data, we collect probability of default estimates from two additional sources: the Risk Management Institute (RMI) at the National University of Singapore and Moody's Investor Service annual default studies.

RMI provides, on a monthly and firm-by-firm basis, conditional default probabilities for various horizons between one month and five years. The model and estimation methodology is based on Duan, Sun, and Wang (2012), and is an extension of the hazard-rate approach in Duffie, Saita, and Wang (2007) and Lando and Nielsen (2010). We match the firms in our sample to RMI PD data, by matching on firm-level cusip. (When no match was found that way, we match by hand.) On any given day, we assign each firm the RMI PDs reported for that firm at the end of the previous month.

Moody's disseminates annual default studies that report average cumulative issuer-weighted global default rates by alphanumeric senior unsecured issuer rating and maturity horizon, using data dating back to 1983. For example, Moody's 2016 annual default study reports global default rates based on

[10] The small differences between the results in Tables 5 and 7 and in Table H.3 are due to the reduction in sample size from 1,003,488 firm-date pairs in Sections 5 and 6 to 996,326 firm-date pairs in this appendix.

data from 1983 to 2015 (see Moody's Investors Service (2016)), Moody's 2015 study reports default rates based on data from 1983 to 2014 (see Moody's Investors Service (2015)), and so on. Starting with the 2005 study, default rates are available for maturities of one to twenty years. Prior to that, default rates are available only for maturities up to ten years.

To obtain ratings-based PD estimates, we set a firm's y-year PD estimate equal to the y-year default rate reported for the firm's alphanumeric rating category in the current year's annual default study. Similarly, we set a firm's refined-ratings-based y-year PD estimate equal to the y-year default rate reported for the firm's refined ratings category in the current year's annual default study. As a result, in any given year, a change in a firm's (refined-)ratings-based PD occurs only if the firm's (refined) rating changes.

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