The Effect of Credit Ratings on Credit Default Swap Spreads and Credit Spreads

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During recent years, the market for credit derivatives has grown almost exponentially, and it is today the fastest-growing market for derivative products. Credit derivatives are privately negotiated derivative instruments with payoffs that are linked to a credit-sensitive asset or an index and hence to the creditworthiness of a given reference entity—that is, a corporation or sovereign entity. In contrast to standard interest rate derivatives, credit derivatives allow isolation of firm-specific credit risk from the overall market risk.

Credit derivatives are designed as hedging instruments. For example, an investor who is exposed to credit risk in some reference entity may therefore seek to protect himself by buying protection from a third party who is willing to acquire exposure in the reference entity. In effect, the credit derivatives market has become a trading market, and trades in credit derivatives are taken to be proxies for trades in actual loans or bonds of the reference entity. Therefore, credit derivative trades have become tools to replicate a funded cash bond or cash loan of a reference entity, without all the inflexibilities, lack of availability, and regulatory and geographical barriers.

The most common type of credit derivative is the credit default swap (CDS).[1] A CDS is an insurance contract that provides insurance for the holder against losses caused by the occurrence of default on a bond issued by a corporation or sovereign entity, also referred to as the reference entity. In the event of default by the reference entity, the protection seller pays a certain amount to the protection buyer. The default payment is structured to replace the loss that a typical lender would incur upon default of the reference entity. In exchange the protection buyer makes periodic payments to the protection seller, until the reference entity defaults or until maturity of the contract. From a theoretical point of view, a combined position in a CDS and a defaultable coupon-bearing bond issued by the same reference entity should trade close to the price of a default-free coupon-bearing bond. As a result, the CDS spread should be approximately equal to the credit spread over the risk-free rate.

CDSs enable corporations to trade off the default risk associated with one or several reference entities in an efficient, cost-effective way. It is of paramount importance that financial institutions and policymakers have a clear understanding of the use of credit derivatives and their intended consequences such that the credit derivatives market and the CDS market in particular do not transmit additional systemic risk into the financial market. Our study is an attempt to understand the underlying nature of the CDS market.

In this article we focus on the pricing of CDS contracts from an empirical perspective. The article has two objectives. The first is to analyze the relationship between CDS spreads and credit spreads. The second is to examine how changes in credit ratings affect CDS and

corporate bond prices. We study the relationship between CDS spreads and credit spreads using principal component analysis and regression analysis and use an event study to examine how CDS spreads and credit spreads respond to reclassifications in credit ratings.

Existing studies that analyze the approximate equality between CDS spreads and credit spreads include those by Houweling and Vorst [2003], Blanco, Brennan, and Marsh [2003], and Hull, Predescu, and White [2004]. Houweling and Vorst [2003], compare CDS spreads to credit spreads graphically and find that the bond market and the CDS market deviate considerably. For A-rated reference entities, only small deviations are found, whereas large deviations are found for B-rated reference entities.

Blanco et al. [2003] perform a cross-sectional regression study of CDS prices, risky bond yields, and swap rates. Contrary to Houweling and Vorst [2003], they find that the bond market and the CDS market appear to price credit risk equally for most reference entities. Hull et al. [2004] regress the CDS spread on the credit spread, using both the Treasury rate and the swap rate as proxies for the risk-free rate. They find that the approximate relationship between CDS spreads and credit spreads does not hold with equality.

Longstaff, Mithal, and Neis [2004] use the information in CDSs to obtain measures of the size of the default and non-default components in corporate spreads using the CDS spread as a direct measure of the default component and indirectly using a reduced-form model to measure the size of the default component. They find that the majority of the corporate spread is due to default risk and that the result holds for all rating categories and is robust to the definition of the riskless curve.

Norden and Weber [2004] analyse the intertemporal co-movements of weekly and daily changes in CDS spreads, bond spreads, and stock returns by fitting a three-dimensional vector autoregressive model. They find that stock returns are negatively associated with CDS spreads and bond spreads and that bond spreads are the most, and stock returns the least, predictable.

Another line of empirical research on CDSs looks at the determinants of the CDS price. Virtually all studies in this portion of the literature are regression studies that use the CDS price or CDS spread as the dependent variable and independent variables such as the risk-free short rate, the yield of the reference obligation, the interest rate volatility, the time to maturity, the credit rating of the reference obligation, leverage, stock returns, index returns, and the historical and the implied volatility. Studies include Skinner and Townend [2002], Aunon-Nerin, Cossin, Hricko, and Huang [2002], Benkert [2004], and Abid and Naifar [2005]. Generally, these studies find that most of the variables have significant impact on the observed levels of CDS prices or spreads. Aunon-Nerin et al. [2002] and Abid and Naifar [2005] find that credit rating is the most important single source of information on credit risk overall. Benkert [2004] finds that implied volatility has a stronger effect than historical volatility and that both remain relevant in the presence of credit ratings, which contribute an equal amount of explanatory power. Aunon-Nerin et al. [2002] find behavioral differences between high- and low-rated underlyings, sovereign and corporate underlyings, and underlyings from different markets.

Our study of the relationship between CDS spreads and credit spreads falls into two parts. We first investigate whether CDSs and defaultable bonds price credit risk equally by applying principal component analysis to CDS spread and credit spread data. Furthermore, we take the approach of Hull et al. [2004] and regress CDS spreads on credit spreads. Our findings suggest that the CDS spreads and credit spreads are highly related but not equal on average and that CDSs and defaultable bonds price credit risk differently.

Second, we investigate which factors contribute to the pricing of CDSs. In particular, we incorporate into the regression analysis various proxies for credit risk, such as credit rating, maturity and amount of issue of the reference obligation, the default-free short rate, the slope of the default-free yield curve, and industry and time dummies. We find that credit rating, short rate, slope, and most industry and time dummies add significant information.

As argued in the existing literature and supported in this article, credit rating is an important factor in the pricing of credit risk. It is therefore interesting to investigate how the financial markets react to changes in credit rating. In effect, we find it natural to study how CDS spreads and credit spreads react to changes in credit rating, as the first part of the article reveals significant differences between the CDS market and the corporate bond market. Therefore, we conduct an event study using both CDS spreads and credit spreads.

To our knowledge, the only similar study on CDS spreads is a study by Hull et al. [2004], who explore the relationship between CDS spreads and rating announcements (downgrades/upgrades, review for downgrades/upgrades, and outlooks). They find that all three types of announcements are anticipated by the CDS

market and that reviews for downgrades contain significant information, whereas downgrades and negative outlooks do not.

Although event studies of CDSs are very few, many studies have considered the reaction of bond prices to changes in credit rating. Early studies include Grier and Katz [1976] and Katz [1974], who base their studies on monthly changes in bond yields and bond prices, respectively. They find some anticipation of changes in credit rating in the industrial bond market. Wansley, Glascock, and Clauretie [1992] use a data set of weekly bond prices and find strong negative effects of downgrades, but not of upgrades, on bond returns during the period just before and just after the announcement. This asymmetric effect is confirmed by Hand, Holthausen, and Leftwich [1992], who use daily data and find negative excess bond and stock returns for downgrades, but weaker positive returns for upgrades. Hite and Warga [1997] find the strongest price reaction among downgrades to and within non-investment-grade classes. Furthermore, returns exhibit a positive reaction to upgrades from non-investment grade to investment grade. Other upgrades have weak effects. Steiner and Heinke [2001] use Eurobond data and find that announcements for downgrades and negative watch listings induce significant abnormal returns on the announcement day and the following trading days. Upgrades and positive watch listings do not cause any significant price changes.

Our study differs from the existing studies in that we look at both the CDS market and the bond market. We place emphasis on the difference between the two markets' reactions to changes in credit rating. As has been found by other studies we find that changes in credit rating are anticipated by both markets. Furthermore, we discover evidence of lagged effects of changes in credit rating and differences between investment-grade issues. We find that the size of the change in credit rating matters in both the CDS market and the corporate bond market. We also find asymmetric effects in both markets as downgrades have a larger impact than upgrades. This supports the literature on corporate bonds but is in contrast to the findings of Hull et al. [2004]. Interestingly, our results suggest that the CDS market reacts faster and more significantly to changes in credit rating than the bond market.

CREDIT DEFAULT SWAPS

In its basic form, a CDS, or in short a *default swap*, contract is an over-the-counter contract between two parties in which one of the parties, the protection buyer, wishes to buy insurance against the possible default on a bond issued by a third party. The bond issuer is called the *reference entity*, and the bond itself the *reference obligation*. The reference entity could be a corporation or a sovereign issuer.

The two parties agree to enter into a contract terminating at the time of default by the reference entity or at maturity, whichever comes first. In the event of default by the reference entity, a CDS can be settled with a *cash settlement*, in which case the buyer keeps the underlying but is compensated by the seller for the loss incurred by the credit event, or with a *physical settlement*, in which case the buyer delivers the reference obligation to the seller and in return receives the full notional amount. The cash settlement amount is either the difference between the notional and market value of the reference issue or a predetermined fraction of the notional amount. Furthermore, a CDS may include a delivery option similar to that found in Treasury notes and bond futures contracts.

In exchange the protection buyer agrees to pay an annuity premium to the protection seller until the time of default by the reference entity or maturity of the contract, whichever comes first. If default occurs between premium payments, the protection buyer must pay to the protection seller the part of the premium that has accrued since the most recent CDS premium payment. At origination a standard CDS contract does not involve exchange of cash flows (ignoring dealer margins and transaction costs) and therefore has a market value of zero. Hence, the annuity premium, for which the market value of the CDS is zero, is determined at origination. This premium, which is typically quoted in basis points per $100 notional amount of the reference obligation, is called the market *credit default swap spread* or *credit default swap premium*.

Credit events that typically trigger a CDS include bankruptcy, failure to make a principal or interest payment, repudiation/moratorium, obligation acceleration, obligation default, or restructuring.

The maturity of a CDS contract is negotioable and is not necessarily the same as the maturity of the reference entity. Maturities from a few months up to 10 years or more are possible; however, most CDSs are quoted for a benchmark time-to-maturity of 5 years. Typical payment terms are quarterly or semiannually.

The risk between the protection buyer and protection seller is called the *counterparty risk* and has only little impact on the valuation and hedging of a CDS for most practical cases. Hence, we do not deal with counterparty

EXHIBIT 1
Payoff of the Portfolio

t	Defaultable Bond	CDS	Default-free Bond	Portfolio
0	$-\bar{C}(0,T_K;\bar{c})$	0	$C(0,T_K;\bar{c}-z)$	$C(0,T_K;\bar{c}-z)-\bar{C}(0,T_K;\bar{c})$
T_k	$\bar{c}$	$-z$	$-\bar{c}+z$	0
T_K	$1+\bar{c}$	$-z$	$-1-\bar{c}+z$	0
τ	π	$1-\pi$	$-C(\tau,T_K)$	$1-C(\tau,T_K)$

Payoff of the portfolio consisting of a defaultable coupon bearing bond, a CDS on this bond and a default-free coupon bearing bond. The time of default is given by τ.

risk in this article. Lando [2000] and Hull and White [2001] examine CDSs in the presence of counterparty risk.

Relationship Between CDS Spreads and Credit Spreads

A combined position of a CDS with a defaultable coupon-bearing bond issued by the same reference entity should trade close to the price of a default-free coupon-bearing bond, assuming that the CDS and the defaultable bond price default risk equally. Basically, an investor who invests in a portfolio consisting of a position in a defaultable coupon-paying bond and a CDS on this bond eliminates most of the risks associated with default. In effect, the portfolio itself can be viewed as a synthetic default-free coupon-bearing bond.

Let $\bar{y}$ denote the yield to maturity on the defaultable bond and z the CDS spread. The investor's net annual return is then approximately equal to $\bar{y} - z$. The relationship

$$z = \bar{y} - y \tag{1}$$

where y is the yield to maturity on the default-free bond should therefore hold approximately.[2] However, Equation (1) is only an approximative relationship, as the hedge is less than perfect. This can easily be seen by comparing payoffs. We consider a portfolio consisting of

- one defaultable coupon-bearing bond $\bar{C}$ with fixed coupon $\bar{c}$, recovery rate π, and payment dates $T_0, T_1 \ldots, T_K$
- one CDS on this bond with CDS rate z and maturity T_K
- a short position in a default-free coupon-bearing bond C with coupon $\bar{c} - z$ and payment dates $T_0, T_1 \ldots, T_K$. We hold the default-free bond until time of default and sell it afterwards.

The payoff of the portfolio is given in Exhibit 1. We notice that the payoff of the portfolio is zero in the case of no default. As a result, if the payoff of the portfolio at default is also zero, the initial prices of the two bonds should be the same, as we could otherwise make a risk-free profit.

However, the payoff of the portfolio is not zero at default. In the event of default, the payoff from the position in the defaultable bond and the CDS is the notional value of the defaultable bond, whereas the value of the default-free bond will in general be different from the bond's notional value. The value of the default-free bond will depend on the dynamics of the term structure of default-free interest rates and time left to maturity.

There are a number of assumptions and approximations underlying this arbitrage argument, including ability to short sell, absence of counterparty risk and delivery options in the CDS, absence of tax effects, short-selling costs, and the like. Furthermore, differences in the definition of a credit event in two contracts is ignored.

THE DATA

CDS data have been obtained from JP Morgan Chase. Like Houweling and Vorst [2003], Blanco et al. [2003], Longstaff et al. [2004], Benkert [2004], and Hull et al. [2004], we use five-year CDS quotes, which are also the most commonly traded. To analyze the relationship between CDSs and defaultable bonds, we matched the CDS data to bond data from Bloomberg. We matched each quoted CDS in the data set to a quoted bond issued by the same reference entity. Ideally, we would match the CDS with a bond of the same maturity as the CDS. However, in practice, a corporate bond with exactly the same maturity as the CDS is only rarely available. We matched the CDS with the corporate bond with the maturity closest to that of the CDS. A similar matching process is applied by Houweling and Vorst [2003]. Houweling and Vorst [2003] also match by interpolating between two bonds to match exactly the maturity of the CDS.[3] However, the credit spreads obtained by matching the closest possible maturity resemble the credit spreads obtained by interpolation. We do not consider other matching methods.

In constructing the credit spreads, we use the Treasury curve as a proxy for the risk-free curve. Bond traders tend to regard the Treasury curve as the benchmark for the risk-free curve, whereas derivative traders tend to use the swap curve, as they consider Libor/swap rates to correspond closely to their opportunity cost of capital. The choice of the risk-free curve for CDS pricing has been analyzed by Hull et al. [2004], among others. They find that the benchmark risk-free rate used by the CDS market is between the Treasury rate and the swap rate. This partly supports the findings of Houweling and Vorst [2003] that using government curves results in an overestimation of credit risk. Our use of the Treasure curve is conditioned by data availability.

From this, we obtain a sample of 72 firms covering the period January 2000 through December 2002, although not every firm is represented throughout the entire period. We exclude all bonds containing special features, such as embedded options and sinking funds, from our sample. Furthermore, we collect various characteristics of each corporate bond from Bloomberg. Hence, for each corporate bond observation, we collect the Standard and Poor's credit rating of the bond, the maturity, and the amount of issue.

In the following, we use the CDS spread measured in basis points as a measure of the overall cost of a CDS transaction following Houweling and Vorst [2003], Skinner and Townend [2002], Aunon-Nerin et al. [2002], Blanco et al. [2003], Longstaff et al. [2004], and others. The credit spread, on the other hand, is defined as the bond yield minus a maturity-matched risk-free rate. In the remainder of this section we present a brief description of the data.

Corporations and Industry

Exhibit 2 presents the reference entities in the data set, along with the CDS spread, the credit spread, standard deviations, and average credit rating over the sample period. Our sample covers large corporations such as Wal-Mart and Walt Disney, with relatively low average CDS spreads of 64 and 21 basis points and an average credit spread of 96 and 56 basis points, respectively. In comparison, corporations in economically sensitive industries, such as United Airlines and Lucent Technologies, have average CDS spreads of 2,807 and 3,956 basis points and average credit spreads of 1,236 and 1,225 basis points, respectively. Furthermore, we notice that the average CDS spread of Southern California Edison is 266 basis points,

EXHIBIT 2
Average Credit and CDS Spreads by Firm

Corporation	Sector	Obs	Rating	Credit Spread	CDS Spread	α	β
Abitibi-Consolidated Inc	BM	456	BBB	297 (68)	207 (88)	-143*	1.18*
AK Steel	BM	186	BB	379 (69)	337 (79)	36	0.80*
Albertsons	Retail	473	BBB	216 (39)	81 (19)	34*	0.21*
Alcoa	BM	392	A	79 (17)	40 (11)	29*	0.15*
American Standard	CG	278	BB	250 (41)	222 (67)	-131*	1.41*
Apple Computer	Tech	537	BB	410 (94)	261 (34)	193*	0.17*
Argosy Gaming	Leis	319	B	399 (77)	311 (75)	101*	0.53*
Arrow Electronics	Tech	427	BBB	433 (99)	310 (99)	167*	0.33*
AT and T Corp	Tele	251	A	98 (42)	53 (40)	-36*	0.91*
Avon Products Inc	Retail	456	A	94 (38)	32 (7)	24*	0.09*
BellSouth Corp	Tele	371	AA	191 (26)	36 (16)	81*	-0.23*
Boeing Co	Def	693	A	135 (29)	45 (29)	-25*	0.52*
Calpine Corp	Power	542	BB	1031 (1080)	1314 (1532)	-78*	1.35*
Caterpillar Inc	CG	557	A	134 (34)	47 (14)	56*	-0.07*
Charter Comm	Media	544	B	895 (787)	1004 (956)	-28	1.15*
Chesapeake Energy	Energy	184	B	355 (64)	287 (25)	199*	0.25*
Clear Channel	Media	646	BBB	224 (51)	173 (93)	-163*	1.50*
CMS Energy	Energy	212	BB	269 (16)	257 (55)	-382*	2.37*
Comcast Cable	Media	393	BBB	263 (201)	257 (165)	52*	0.79*
Computer Science Corp	Tech	303	A	177 (26)	90 (33)	-19	0.62*
Cox Comm	Media	696	BBB	189 (126)	160 (117)	1	0.84*
Daimler Chrysler	Auto	696	A	149 (47)	101 (54)	-4	0.71*
Danaher	CG	363	A	153 (28)	59 (15)	19*	0.26*
Deere	CG	651	A	162 (31)	55 (19)	100*	-0.28*
Delphi Auto Systems	Auto	553	BBB	180 (43)	127 (50)	26*	0.56*
Dillards Inc	Retail	625	BB	522 (165)	474 (228)	-142*	1.18*
Dominion Resources	Power	106	BBB	117 (15)	70 (10)	65*	0.04*
Dow Chemical	BM	693	A	105 (29)	61 (44)	-46*	1.02
Duke Cap Corp	Power	646	A	185 (74)	119 (125)	-153*	1.47*
Eastman Kodak	Retail	97	A	90 (10)	26 (2)	18*	0.09*
Echoster DBS	Media	556	B	475 (134)	458 (137)	-1	0.97*
El Paso Corp	Energy	325	BBB	167 (22)	183 (69)	368*	1.10*
Federated Dept Stores	Retail	198	BBB	137 (42)	102 (35)	28*	0.54*
General Motors Corp	Auto	693	A	206 (63)	122 (104)	-187*	1.50*
Hasbro Inc	Retail	251	BB	466 (87)	323 (65)	368*	-0.10*
Hewlett Packard	Tech.	456	A	133 (40)	90 (31)	29*	0.46*
IBM Corp	Tech	693	A	115 (21)	43 (18)	0.3	0.37*
Ingersoll-Rand Co	CG	193	A	209 (21)	65 (23)	36*	0.14*
International Paper	BM	638	BBB	144 (28)	87 (19)	104*	-0.12*
ITT Corp	Leis	456	BBB	237 (56)	234 (142)	637*	-1.69*
Lear Corp	Auto	206	BB	367 (92)	262 (51)	130*	0.36*
Lockheed Martin Corp	Def	696	BBB	143 (48)	74 (13)	55*	0.14*
Lucent Technologies	Tele	383	B	1239 (813)	1230 (669)	306*	0.75*
Mandalay Bay	Leis	283	BB	454 (107)	453 (143)	45	0.90
May Dept	Retail	440	A	164 (19)	56 (19)	-17*	0.44*
MGM Mirage Inc	Leis	407	BB	296 (61)	242 (74)	-30*	0.92*
Motorola	Tech	436	BBB	331 (112)	274 (97)	24*	0.76*
Nabors Industries	Energy	460	A	124 (23)	83 (23)	29*	0.44*
Nextel Comm	Tele	579	B	1031 (401)	935 (450)	-167*	1.07*
Nordstrom Inc	Retail	456	BBB	235 (48)	117 (38)	25*	0.39*
Northwest Airlines	Air	287	B	1329 (730)	1484 (927)	-158*	1.24*
Park Place Enter. Corp	Leis	475	BBB	313 (101)	209 (58)	54*	0.50*
Phillip Morris Cos	Retail	636	A	141 (63)	106 (38)	89*	0.12*
Pride	Energy	456	BB	344 (79)	385 (53)	234*	0.44*
Rohm and Haas	BM	553	A	136 (28)	49 (10)	22*	0.20*
Saks Inc	Retail	387	BB	554 (174)	543 (188)	63*	0.87*
Six Flags	Leis	95	B	429 (103)	364 (198)	117	0.57*
Sony Corp	Retail	384	A	70 (13)	22 (7)	29*	-0.10*
Southern California Edison	Power	522	B	266 (101)	567 (309)	354*	0.80
Sprint	Tele	456	BBB	401 (232)	391 (370)	-207*	1.50*
Station Casinos Inc	Leis	255	B	461 (108)	283 (75)	30*	0.55*
Sun Microsystems	Tech	427	BBB	262 (131)	151 (91)	22*	0.49*
Target Corp	Retail	541	A	120 (29)	37 (11)	53*	-0.14*
TXU Corp	Power	154	BBB	156 (26)	91 (10)	48*	0.28*
Unisys Corp	Tech	319	BB	373 (88)	407 (97)	124*	0.76*
United Airlines	Air	302	CCC	2807 (2720)	3955 (3275)	1500*	0.88*
Viacom Inc	Media	694	A	118 (27)	65 (20)	46*	0.16*
Visteon	Auto	540	BBB	242 (74)	198 (82)	17	0.75*
Wal-Mart Stores Inc	Retail	362	AA	64 (14)	21 (7)	7*	0.22*
Walt Disney	Media	696	A	96 (24)	56 (40)	-48*	1.07
Weatherford International	Energy	455	BBB	153 (22)	85 (33)	52*	0.21*
Weyerhaeuser	BM	228	A	131 (36)	76 (22)	58*	0.14*

This table presents for each firm the mean and the standard deviation of the credit spread and the CDS spread in basis points. Rating is the average S&P rating, Obs is the number of observations and the sectors to which the firms belong are: Air=Airline, Auto=Automobile, BM=Basic Material, CG=Capital Goods, Def=Defence, Leis=Leisure, Tech=Technology, Tele=Telecom. We estimate the regression $CDS_{it} = \alpha_i + \beta_i \cdot Spreadit + \varepsilon_{it}$. Regression coefficients are presented. An asterisk (*) indicates significance at a 5 % level for the null hypotheses $\alpha_i = 0$ and $\beta_i = 1$, respectively.

and the average credit spread is 567 basis points, reflecting the California energy crisis.

From Exhibit 2, we see that CDS spreads and credit spreads are of the same magnitude on average and tend to be good proxies for each other, although imperfect. Equality between the two is widely assumed among practitioners. To some extent, research by Skinner and Townend [2002] and Blanco et al. [2003] supports the practitioners' view, whereas that by Hull et al. [2004] and Longstaff et al. [2004] does not. To test formally whether the approximative relationship between the CDS spread (*CDS*) and the credit spread (*Spread*) holds with equality, we consider the following regression

$$CDS_{it} = \alpha_i + \beta_i \cdot Spread_{it} + \varepsilon_{it} \qquad (2)$$

where ε_{it} is an error term. We test the null hypotheses $\alpha_i = 0$ and $\beta_i = 1$ for each firm i. Exhibit 2 shows the estimated α and β. Significance at a 5% level is marked with an asterisk (*). For almost all reference entities, we find that the CDS and the credit spread do not price default risk equally and are not equivalent on average.

Exhibit 3 presents the distribution of CDS spreads, credit spreads, and average credit rating by industry. The figures illustrate that corporations concentrated in economically sensitive industries, such as the airlines, have extreme spreads. Industries that tend to have relatively low spreads are automobiles, basic materials, capital goods, and defence. This may stem from the transparency associated with mature highly capital-intensive industries relative to the new labour-intensive industries of the information-based economy. On the other hand, technology had low spreads in 2000 but tended to have higher spreads during 2001 through 2002. Industries that experienced financial distress in 2002, such as power and telecom, had significantly higher spreads. Ironically, the airline industry would have been classified as a low-spread industry prior to 2001. In general, the CDS spread of each industry mimics the pattern of the credit spread, as expected, but not uniformly. Clearly, the industry concentration of a reference entity may matter, and we control for it in our further analysis.

EXHIBIT 3
Average Credit Spread and CDS Spread by Sector and by Year

Sector	Year	Obs.	Ratings	Credit Spread	Std.	CDS Spread	Std.
Airlines	2001	124	B	982	167	1447	235
	2002	465	CCC	2381	2324	3099	2973
Automobile	2000	700	A	188	85	86	94
	2001	1056	BBB	217	77	141	71
	2002	932	BBB	206	87	189	78
Basic Material	2000	492	A	142	37	48	24
	2001	1439	A	158	92	92	89
	2002	1215	BBB	172	110	99	132
Capital Goods	2000	280	A	196	13	40	13
	2001	828	A	167	36	61	41
	2002	987	BBB	163	62	101	80
Defense	2000	461	A	170	35	51	31
	2001	462	BBB	135	24	60	27
	2002	466	BBB	113	37	67	19
Energy	2000	289	BB	294	88	233	85
	2001	1069	BBB	208	80	199	114
	2002	734	BBB	209	125	190	157
Leisure	2000	89	BBB	210	20	140	23
	2001	914	BB	357	124	258	172
	2002	1287	BB	347	113	304	85
Media	2000	1051	BBB	191	120	121	140
	2001	1545	BBB	226	150	201	167
	2002	1629	BBB	448	578	472	684
Power	2000	318	BBB	211	57	98	101
	2001	953	BB	235	128	324	311
	2002	699	BB	804	1033	1098	1418
Retail	2000	1122	A	201	198	122	223
	2001	2411	BBB	244	187	157	191
	2002	1773	BBB	231	184	185	201
Technology	2000	302	A	193	139	90	115
	2001	1432	BBB	254	127	178	122
	2002	1864	BBB	297	160	217	140
Telecom	2000	459	BBB	233	188	120	149
	2001	854	BBB	511	373	410	405
	2002	727	BB	1110	729	1117	643

This table presents the average credit spread, the average CDS spread and credit rating by sector and by year. The credit rating is the yearly average of the Standard and Poor's long-term-debt rating for each sector. Credit spreads, CDS spreads and their standard deviations are given in basis points. Obs. is the number of observations in each subsample.

Credit Ratings

Rating assignments by large public rating agencies such as Moody's and Standard and Poor's have a significant influence on the market. Market participants place a great deal of trust in the credit ratings provided by the agencies, and the majority of institutional investors are restricted to investments in certain rating classes. As such, credit ratings are the most widely observed and commonly used measure for credit quality of specific debt issues or the issuing entity.

Moody's rate their bonds as Aaa, Aa, A, Baa, Ba, B, or Caa, dividing all but the Aaa rating into subcategories, such as Aa1, Aa2, and Aa3. Correspondingly, Standard and Poor's rate their bonds as AAA, AA, A, BBB, BB, B, or CCC, dividing all but the AAA bonds into subcategories such as AA+, AA, and AA-. Bonds rated Aaa by Moody's and AAA by Standard and Poor's are considered to have almost no risk of defaulting in the near future,

EXHIBIT 4

Average Credit Spread and CDS Spread by Credit Rating and by Year

Credit Rating	Year	Obs.	Credit Spread	Std.	CDS Spread	Std.
AA	2000	344	119	70	20	8
	2001	524	131	55	44	20
	2002	29	143	21	40	14
A	2000	2945	145	57	41	33
	2001	4811	141	61	66	48
	2002	4070	125	54	81	62
BBB	2000	1532	222	155	139	185
	2001	4591	221	102	147	105
	2002	4225	261	166	230	182
BB	2000	339	320	94	259	64
	2001	1865	452	199	430	245
	2002	2439	399	161	403	213
B	2000	403	448	91	370	83
	2001	1058	581	280	568	360
	2002	1717	1147	893	1241	1160
CCC	2001	38	196	39	437	133
	2002	194	1517	1277	2784	3214
CC	2002	77	6881	1774	7287	1667
C	2001	174	305	30	880	103
Investment Grade Issues	2000	4821	167	109	71	117
	2001	9926	178	91	103	89
	2002	8324	194	141	157	156
	Total	23071	181	115	115	127
Non-Investment Grade Issues	2000	742	389	112	319	92
	2001	3135	484	237	501	304
	2002	4427	851	1117	952	1445
	Total	8304	671	851	726	1100
Full Sample		31375	311	498	277	636

This table presents the average credit spread and the average CDS spread by credit rating and by year. Credit spreads, CDS spreads and their standard deviations are given in basis points. Obs. is the number of observations in each subsample.

whereas credit ratings below Baa3 and BBB−, respectively, are referred to as below investment grade or non-investment grade.

When rating agencies announce changes in credit rating, they quite often refer to a corporation rather than the individual bonds issued by the corporation. We will do the same. Naturally, it would be rare to actually find a corporation issuing bonds of different credit ratings, and hence a credit rating is viewed as a description of the creditworthiness of the bond issuers, rather than a description of the quality of the bond itself.

Exhibit 4 presents CDS spreads and credit spreads for each rating class by year for 2000 through 2002. The data include a wide range of credit ratings, spanning from AA-rated down to C-rated firms, although most observations are in the A, BBB, and BB rating classes.

As expected, there are significant differences across credit ratings. The average CDS spread is 277 basis points, and the average credit spread is 311 basis points, for the entire sample. Taking the average of all investment-grade issues, the average CDS spread is 115 basis points, and the average credit spread is 181 basis points. For non-investment-grade issues, they are 726 and 671 basis points, respectively.

Both the CDS spread and the credit spread show a clear upward trend across rating classes as we move from a CDS spread of 20 basis points and a credit spread of 119 basis points in the AA rating class in 2000 to 448 and 370 basis points, respectively, in the B rating class for 2000. Similar patterns are seen for 2001 and 2002.

DIFFERENCES BETWEEN CREDIT SPREADS AND CDS SPREADS

The initial data analysis suggests that credit spreads and CDS spreads are good proxies for each other but not equal on average. As a result, we wish to analyze further how CDS spreads and credit spreads differ. In this section, we employ a principal component analysis to investigate whether fundamental differences exist between the way that CDSs and defaultable bonds price credit risk.

In essence, the idea of principal component analysis is to reduce the dimensionality of the data description by looking for standard linear combinations of the original variables that can be used to summarize the data, losing in the process as little information as possible. In other words, we seek the linear combination that has maximal variance. Early articles applying principal component analysis or factor analysis in yield curve analysis include those by Litterman and Scheinkman [1991] and Steeley [1990].

We estimate the principal components of both CDS spreads and credit spreads. Exhibit 5 shows the percentages and cumulative percentages of variance explained by the first 10 principal components for both credit spreads and CDS spreads. The first principal component explains 76% of total variance for CDS spreads and 69% for credit spreads. The second principal component explains 14% for CDS spreads and 15% for credit spreads. If we look at the cumulative percentage of the variance explained, the first two principal components explain a little more than 90% for CDS spreads, whereas we would have to include five principal components to obtain the same degree of explanation for credit spreads.

The results clearly suggest that there are differences between the way that corporate bonds and CDSs price credit risk. In the following section we look further into this matter.

DETERMINANTS OF CREDIT SPREADS AND CDS SPREADS

Our previous findings suggest that CDS spreads and credit spreads are related, although not equal on average, and that CDSs and corporate bonds price credit risk differently, as reflected in the CDS spreads and the credit spreads. Similarly to the previous literature, we seek to find which factors determine the CDS spread. We refer the reader to the opening section of this article for a review of empirical studies that have documented the key determinants of CDS price levels.

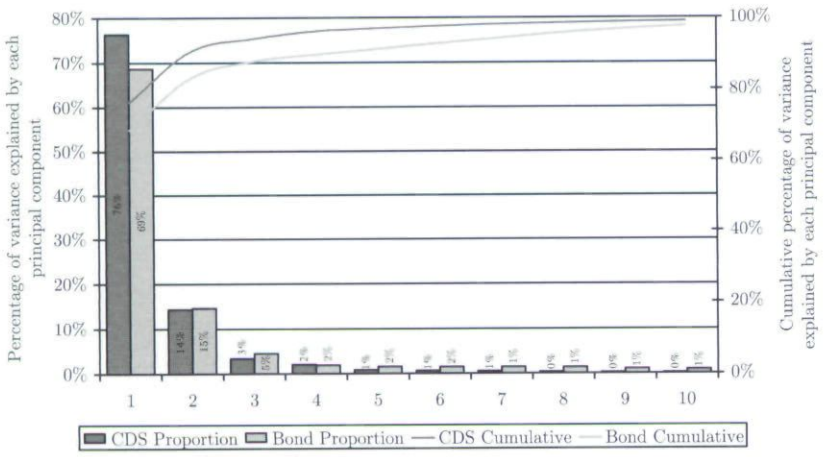
We propose that a linear regression model fits the data well. The motivation for this linear specification is the work by Duffie and Liu [2001], who, by analyzing the relationship between fixed-rate and floating-rate spreads in a reduced-form model setup, document how the floating-fixed spread is linear in the issuer's credit spread, the slope of the yield curve, and the level of the yield curve. Therefore, we use the credit spread, risk-free short rate, and slope of the default-free yield curve as explanatory variables in our regression. Furthermore, we test for the significance of credit rating, maturity, and amount of issue of the corporate bond. We add industry- and time-specific dummy variables to test for market segmentation. To sum up, we suggest the regression model

$$\begin{aligned} CDS_t &= \alpha_t + \beta_1 \cdot Spread_t + \beta_2 \cdot Short_t + \beta_3 \cdot Slope_t \\ &\quad + \beta_4 \cdot DRating_t + \beta_5 \cdot LSize_t + \beta_6 \cdot LMaturity_t \\ &\quad + \sum_{j=1}^{11} \gamma_j \cdot Industry_{j,t} + \sum_{j=1}^{3} \delta_j \cdot Year_{j,t} + \varepsilon_t \end{aligned} \tag{3}$$

where ε_t is an error term. *CDS* refers to the CDS spread, *Spread* is the credit spread of the reference entity, *Short* is the risk-free short rate, *Slope* is the slope of the default-free yield curve, *LSize* is the log of the amount of issue of the reference obligation, *LMaturity* is the log of the maturity of the reference obligation, $Industry_j$ is a dummy variable indicating to which industry the reference entity belongs, and $Year_j$ is a dummy variable indicating to which year the observation belongs. *DRating* is an ordinal dummy variable translating the credit rating of the reference entity to a numerical scale ranging from 1 to 24, 1 being the highest rating classification and 24 the lowest. We refer the reader to the appendix for a full description of all variables used in the analysis.

Using model-independent estimates, Longstaff et al. [2004] find that the CDS spread explains on average 49% of the credit spread for AAA- and AA-rated bonds, 51% for A-rated bonds, 56% for BBB-rated bonds, and 71% for below-investment-grade bonds. Accordingly, we expect the credit spread to be positively related to the CDS spread and the CDS spread to be positively related to credit rating. Furthermore, we expect the risk-free short rate and the slope of the default-free yield curve to have a negative relationship with the CDS spread. As discussed in Skinner and Townend [2002], rising short rates make the future value of any payments decline, implying that the value of the swap declines and the CDS spread falls accordingly. The slope of the yield curve can be seen as an indicator of economic activity, as a steeper term structure of interest rates is associated with an improvement of the business climate, whereas a flatter term structure is associated with a decrease in the economic activity. Therefore, we expect that a rising slope of the yield curve should lead to lower CDS spreads as economic activity increases.

EXHIBIT 5
Principal Components Analysis



The figure shows the percentage and the cumulative percentage of the variance explained by the first 10 principal components for both credit and CDS spreads.

EXHIBIT 6
Determinants of the CDS Spread

	Full Sample		Investment Grade Issues		Non-Investment Grade Issues	
Variables	Coef.	T-Value	Coef.	T-Value	Coef.	T-Value
Intercept	-57.7	3.18*	41.94	7.51*	-232.02	2.84*
Spread	1.02	249.86*	0.84	178.18*	1.00	115.84*
DRating	8.29	13.88*	5.49	16.52*	35.89	10.08*
Short	-17.65	4.54*	-17.47	16.13*	-72.3	5.97*
Slope	-10.97	2.85*	-9.33	8.64*	-53.3	3.74*
Airline	631.14	48.10*			659.74	23.88*
Automobile	30.78	5.08*	-19.63	8.27*	93.83	2.33*
Basic Material	31.26	5.47*	-30.16	12.81*	80.97	2.05*
Capital Goods			-65.14	26.47*	94.17	2.60*
Defense	21.71	2.76*	-44.51	16.62*		
Energy	52.74	7.77*	-12.21	4.38*	163.09	6.44*
Leisure	-23.59	3.57*	-15.50	5.43*		
Media	56.38	10.66*	-6.22	2.58*	125.86	5.58*
Power	194.05	28.11*	-27.91	9.92*	429.72	18.46*
Retail	25.97	5.38*	-29.04	13.41*	97.14	3.91*
Technology			-40.09	17.74*	87.29	3.32*
D2000	-26.45	2.53*	-13.70	4.82*		
D2001	-28.27	5.69*	-22.68	16.19*	-29.89	2.47*
Adjusted R^2	0.82		0.76		0.79	
F-Value	9709		4497		2136	

This table presents the determinants of the CDS spread. The dependent variable is the CDS spread measured in basis points in all OLS regressions. The explanatory variables used are the credit spread, the risk-free short rate, the slope of the default free yield curve, the credit rating, the maturity and the amount of issue of the corporate bond. Furthermore, we add industry and time specific dummy variables to test for market segmentation. We estimate separate regressions for reference entities which are rated as investment grade and non-investment grade, to test the effect of differences in credit rating quality. Investment grade issues span credit ratings BBB or higher, while Non-Investment grade issues span credit ratings below BBB. DRating is an ordinal dummy variable indicating the long term debt rating of the firm by Standard and Poor's. AA =1, A = 2, etc. Slope is the slope of the default-free term structure measured as the difference between the ten year US Treasury bond and the three month US Treasury bill. Short is the three month US Treasury Bill. Variables, which are not statistically significant at the 5 percent level, are removed from the analysis. See section A in the appendix for a definition of each variable.

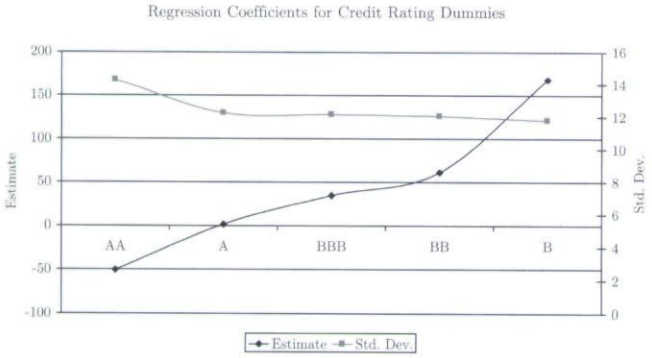
Empirical Results

Exhibit 6 shows the regression coefficients and their t-statistics for the regression model given by Equation (3). Variables that are not statistically significant at the 5% level are removed from the analysis. Prior research (e.g., Longstaff et al. [2004]; and Blanco et al. [2003]) suggests that pricing effects may differ for bonds based on their credit quality. Hence, we estimate separate regressions for reference entities that are rated as investment grade and non-investment grade to test the effect of differences in credit rating quality.[4] We present the adjusted R-squared and an F-test for whether the coefficients are jointly equal to zero for all estimations. All estimations appear well specified with significant F-test. The adjusted R-squared is 0.82 for the full sample model, 0.76 for investment grade, and 0.79 for non-investment grade.

As expected, the credit spread (*Spread*) is a highly significant explanatory variable in the three regressions, with positive regression coefficients.[5] The explanatory variables *LMaturity* and *LSize* are eliminated from all regression studies, which is not surprising, as all CDSs used in the study have similar notional values and a maturity of five years. The explanatory variables *DRating*, *Short*, and *Slope* are significant in all three regression models, and the estimated coefficients are of the predicted sign. In particular, the variable *DRating* is highly significant, confirming that credit ratings are a very important source of information on the credit quality of a borrower. What is particularly interesting is that most of the industry dummy variables—*Automobile, Basic Material, Energy, Media, Power*, and *Retail*—are significant in all three regression models. This suggests that the impact of these industry dummies is not captured in the credit ratings and that the CDS market may be segmented along industry type. Furthermore, we find that the *Year* dummies are significant in all cases except the 2000 dummy for the non-investment-grade subsample.

When comparing results for the investment-grade subsample to those for the non-investment-grade subsample, we discover some clear differences. First, non-investment-grade issues appear to be more sensitive to the macroeconomic factors. This is indicated by the regression coefficients for the variables *Short* and *Slope*, which are significantly more negative for investment-grade than non-investment-grade issues. This supports the results of Blanco et al. [2003], who found that systematic market-wide variables play a key role in CDS pricing. Furthermore, it appears that the credit spread has a much higher loading on the CDS spread for non-investment grade than for investment grade, suggesting that market practitioners rely more on the credit spread for non-investment-grade issues when pricing the CDS. Finally, the ordinal credit rating dummy is more significant for the non-investment-grade issues, suggesting that credit rating affects low investment-grade issues more than it affects high investment-grade issues. This is comparable to what has been found by other researchers, including

EXHIBIT 7
Regression Coefficients for Credit Rating Dummies



The figure shows regression coefficients and standard deviations of the credit rating dummies for the rating classes AA, A, BBB, BB, and B. The model estimated is the regression model given by Equation (3), replacing the variable *D Rating* with a set of dummy variables taking the value 1 if the reference entity is rated AA, A, BBB, BB, or B, and 0 otherwise. Dummies for credit ratings below B are left out.

Aunon-Nerin et al. [2002], who find similar differences between high- and low-rated entities.

Naturally, using an ordinal dummy variable to measure the credit rating of the reference entity implies that credit rating has the same impact on the analysis for both high and low investment-grade issues. However, as is suggested by the difference in the regression results for investment-grade and non-investment-grade issues and supported by existing empirical literature, credit rating has a larger impact on prices for low investment-grade issues than for high investment-grade issues. To test for this, we estimate the regression model given by Equation (3) replacing the variable *DRating* with a set of dummy variables indicating the credit rating of the reference entity. In particular, we add dummy variables taking the value 1 if the reference entity is rated AA, A, BBB, BB, or B, and 0 otherwise. We leave out dummies for credit ratings below B. Exhibit 7 shows the regression coefficients and their standard deviations. We see a clear increasing pattern in the estimates, which confirms our expectation that market prices will be more sensitive to credit rating for low investment-grade issues.

To draw a conclusion based on our results on the determinants of the CDS spreads, we find that the risk-free short rate and the slope of the default-free yield curve have significant influence on the CDS spread, suggesting that aggregate macroeconomic factors play a role in the CDS market. Furthermore, we find a highly significant dependence of the credit spreads on the CDS spread. As credit spreads widen, so do the CDS spreads. We also find that credit rating is a highly significant determinant of the CDS spread. As the credit rating of the issue declines, the CDS spread responds accordingly and the cost of capital increases, as indicated by the positive regression coefficient. We find clear evidence that low-rated issues are more sensitive to credit rating than high-rated issues. In addition, the majority of the industry-specific dummies are statistically significant, suggesting that the impact of these variables is not captured in the credit ratings and that the market may be segmented along industry types.

CREDIT SPREADS, CDS SPREADS, AND CHANGES IN CREDIT RATING

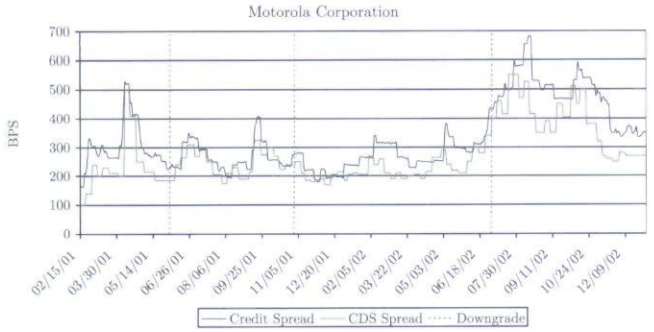
As found in the literature and supported in this article, credit ratings are the most important single source of information on credit risk overall. It is therefore natural to examine how prices of corporate bonds and CDS contracts issued by the same reference entity respond to changes in credit rating. Therefore, we examine in this section whether a change in credit rating of a particular bond is immediately reflected in its price. We include the CDS contract in our study for comparison, as the previous analysis has suggested significant differences between the CDS market and the corporate bond market.

The data include both downgrades and upgrades: a total of 59 downgrades and 11 upgrades divided over 41 firms. A downgrade (upgrade) in credit rating should theoretically cause credit spreads and CDS spreads to jump up (down).

In Exhibit 8, we illustrate the effect of a downgrade on the CDS spread and the credit spread for Motorola Corporation over a period of two years. During this period three downgrades are seen: from A to A-, to BBB+, and finally to BBB.

The first downgrade, on June 1, 2001, does not have a clear effect on the credit spread. However, the CDS spread shows an increase of approximately 50 basis points a few days later. At the date of the second downgrade, October 31, 2001, we see an upward jump in the credit spread of approximately 40 basis points some days before, but no clear change of the CDS spread is seen. At the date of the third downgrade, July 1, 2002, we see a clear upward trend in the credit spread and the CDS spread both before and after the downgrade. One reason that changes in credit rating have little effect on the spreads is that often the market anticipates the reclassifications and has therefore already made corrections in the prices.

EXHIBIT 8
Motorola Corporation



The figure illustrates the effect of a downgrade on the CDS spread and the credit spread. The figure shows the CDS spread and the credit spread of Motorola Corporation measured in basis points during the period from February 15, 2001, to December 31, 2002. During this period three downgrades are observed. The timing of the three downgrades is marked with dotted lines.

To examine empirically whether a change in credit rating has an immediate effect on the credit spread and the CDS spread, we apply an event study analysis.[6] In particular, we employ a *constant mean model*, essentially testing whether the level of the spread changes around the time of a change in credit rating by comparing it with the spread before the change in credit rating. The model allowss us to examine whether a structural break in the spreads occurs around the time a change in credit rating occurs.

A similar study on CDS spreads has been conducted by Hull et al. [2004], who explore the relationship between CDS spreads and rating announcements (downgrades/upgrades, review for downgrades/upgrades, and outlooks). They find that all three types of announcements are anticipated by the CDS market and that reviews for downgrades contain significant information, whereas downgrades and negative outlooks do not. The starting point for their study is adjusted CDS spread observations, subtracting from each spread observation an index of CDS spreads calculated for each overall rating category. The analysis is carried out on adjusted spread changes over intervals $[n_1, n_2]$. The adjusted spread changes are calculated as the adjusted spread for day n_1 subtracted from the adjusted spread for day n_2.

Model Setup

We define an *event* as a change in credit rating and the *event date* as the day a change in credit rating occurs. The period over which we measure the effect of the event on the CDS spread and the credit spread is referred to as the *event window*, L_2. Usually the event window consists of the event day and perhaps also the day(s) before and/or after the event. To test for the anticipation of a change in credit rating, we use different lengths of event windows before and after the event date, as done by Larraín, Reisen, and Maltzan [1997] and Hull et al. [2004].

To measure the behavior of the CDS spread and the credit spread prior to the change in credit rating, we use a sample of observations prior to the event window as a reference sample. We refer to this set of observations as the *estimation window*, L_1.

For all the following studies, we collect the estimation window sample such that the estimation window is the same for each event regardless of the choice of event window. We do this to compare results for each choice of event window. Our construction ensures that every event window spans only one event and all observations in each estimation window are from the same rating class.

Given a sample of N events we assume that the vectors of spreads $s_t^m = [s_{1t}^m, \cdots, s_{Nt}^m]$ are independently, multivariate normally distributed for all t and for $m = CDS, Credit$. We estimate the following equation over the estimation window

$$s_{it}^m = \mu_i^m + \varepsilon_{it}^m, \qquad t \in L_1, m = CDS, Credit$$

for each event i, where μ_i^m is the mean of the spread taken over L_1 and ϵ_{it}^m is a normally distributed disturbance term with zero mean. Let $\hat{\mu}_i^m$ be the sample mean of s_t^m over the estimation window L_1. We can estimate the *excess spread* as

$$\hat{\epsilon}_{it}^m = s_{it}^m - \hat{\mu}_i^m, \qquad t \in L_2, m = CDS, Credit$$

over the event window for each event i. We define the *cumulative excess spread* for each event i as the sum of the residuals

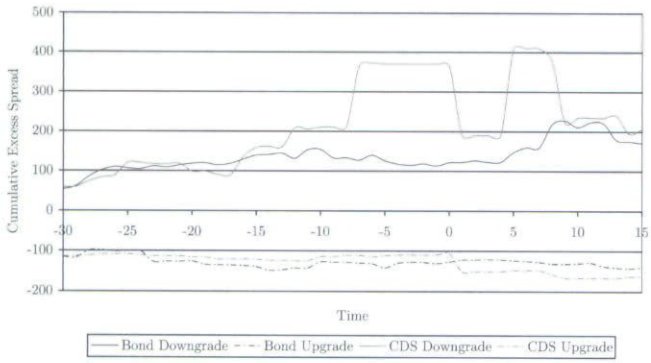
$$\hat{Z}_i^m = \sum_{t \in L_2} \hat{\epsilon}_{it}^m, \qquad m = CDS, Credit \tag{4}$$

with sample variance $(\hat{\sigma}_i^m)^2 = \sum_{t,s \in L_2} \hat{V}_{i,ts}^m$ where $\hat{V}_i^m$ is the covariance matrix of the excess spreads.[7] By assumption there is no correlation between the excess spreads across firms and across time, implying that we can aggregate the cumulative excess spreads over a subsample Γ of n events:

$$\overline{Z}^m(\Gamma) = \frac{1}{n} \sum_{i \in \Gamma} \hat{Z}_i^m$$

$$(\hat{\sigma}^m)^2(\Gamma) = \frac{1}{n^2} \sum_{i \in \Gamma} (\hat{\sigma}_i^m)^2$$

EXHIBIT 9
Cumulative Excess Spreads



Plot of cumulative excess spreads averaged across all downgrades and upgrades across time for the time interval spanning from 30 days before the event to 15 days after the event.

EXHIBIT 10
Event Study Results

Credit Spreads - Downgrades					
		Time Interval			
Rating	Events	[-30,-16]	[-15,-1]	[-1,1]	[1,15]
AA/A	18	13.3809*	17.0804*	5.1570*	8.4942*
BBB	11	2.9429*	5.6278*	2.0632*	2.7730*
BB/B/CCC	12	13.1173*	16.4409*	7.7985*	25.3769*
All	41	14.3206*	19.6619*	8.6495*	25.3576*
Credit Spreads - Upgrades					
		Time Interval			
Rating	Events	[-30,-16]	[-15,-1]	[-1,1]	[1,15]
All	8	-1.0826	-1.2492	-0.5787	-1.1921
CDS Spreads - Downgrades					
		Time Interval			
Rating	Events	[-30,-16]	[-15,-1]	[-1,1]	[1,15]
AA/A	18	21.7424*	23.7017*	12.7213*	32.1560*
BBB	11	1.2549	1.3113	0.2716	-0.1013
BB/B/CCC	12	8.7149*	28.0974*	16.2265*	27.7016*
All	41	10.3215*	28.9184*	16.4812*	28.7629*
CDS Spreads -Upgrades					
		Time Interval			
Rating	Events	[-30,-16]	[-15,-1]	[-1,1]	[1,15]
All	8	-1.6058	-1.6456	-0.8549	-2.2256*

This table shows the results of event studies with four different choices of event window for both credit spreads and CDS spreads. The time interval $[-30,-16]$ is from 30 business days before the event to 16 business days before the event. The other time intervals are defined similarly. All studies are done with an observation window of 75 observations ending 31 business days prior to the event date. We test the null hypothesis that changes in credit rating have no impact on the excess CDS spread and the excess credit spread, respectively. The test statistics are shown for both upgrades and downgrades. For downgrades the test statistics grouped by the initial credit rating are also shown. An asterisk (*) indicates significance at a 5 percent level. Rejection of the null hypothesis implies that a change in credit rating has significant impact on the spreads.

Γ could be all upward changes in credit ratings, all changes for one reference entity, or similar. We test the null hypothesis H_0 that the given events have no impact on excess spreads using the following test statistic:

$$J = \frac{\overline{Z}^m}{\hat{\sigma}^m} \tag{5}$$

which is asymptotically standard normally distributed under the null hypothesis.

Empirical Results

The results of the event study are shown in Exhibits 9 and 10. In the following we will refer to the event date as day 0 and to the time interval spanning the period from 30 days before the event to 15 days before the event as $[-30,-15]$.

In Exhibit 9 we graph the cumulative excess spreads averaged across all upgrades and all downgrades across time for the time interval $[-30,15]$, and in Exhibit 10 we present test statistics for four different choices of event window. The event windows used in the study are a 3 days event window $[-1,1]$ around the event date, two 14 days event windows $[-30,-16]$ and $[-15,-1]$ including 14 business days before the event date, and a 14 days event window [1,15] including the days after the event date.

For all studies we use an estimation window of 75 observations ending 31 business days before the event date. We do this in order to ensure that the estimation window is the same for all studies. With this specification of estimation window and event window, we find a total of 41 downgrades and 8 upgrades.

From Exhibit 9 we see first of all that cumulative excess spreads are positive for downgrades and negative for upgrades, as expected. Second, we notice that the absolute value of the cumulative excess spreads is much larger for upgrades than for downgrades and that cumulative excess CDS spreads and cumulative excess credit spreads exhibit some similarities for both upgrades and downgrades. However, the behavior across time and between contracts differs.

For downgrades, the cumulative excess credit spread is generally increasing, whereas the cumulative excess CDS spread peaks just before and just after the event date. A sharp decline in cumulative excess CDS spread is seen just after the event date. Studies not reported in this article, show that these extreme fluctuations of the cumulative

excess CDS spreads are limited to CCC-rated issues only. For other rating classes, the fluctuation of the cumulative excess CDS spread resembles that of the cumulative excess credit spread. The cumulative excess credit spread is more or less constant across time for upgrades, whereas the cumulative excess CDS spread is slightly decreasing for upgrades. To conclude, Exhibit 9 suggests that changes in credit rating have a larger impact on the CDS spread than on the credit spread and that the change in the CDS spread is more concentrated around the event date than the change in the credit spread.

Exhibit 10 reports the test in Equation (5) for each choice of event window for all downgrades, for all upgrades, and for groups of initial credit ratings for downgrades (the credit rating before the downgrade). Significance at a 5% level is marked with an asterisk. We group credit ratings into A-rated investment-grade issues (AA/A), B-rated investment-grade issues (BBB) and non-investment-grade issues (BB/B/CCC). We do not report test statistics for the upgrades by credit rating, as we have only eight upgrade events in our sample.

The test statistics for all downgrades show a rejection of the null hypothesis for all choices of event window for both CDS spreads and credit spreads, which implies that downgrades have significant impact on the spreads. From the test statistics grouped into rating classes, we notice first of all that the test statistics for the B-rated investment-grade issues are smaller than those for the A-rated investment-grade issues and the non-investment-grade issues, for both the CDS spread and the credit spread. Furthermore, for the B-rated investment-grade issues the null hypothesis is accepted for all choices of event window in the case of CDS spreads, but is rejected in the case of credit spreads. This implies that for B-rated investment-grade issues a downgrade in credit rating does not have a significant impact on CDS spreads.

The test statistics for CDS spreads are larger than those for credit spreads for all choices of event window for A-rated investment-grade issues and non-investment-grade issues except for the $[-30,-16]$ event window for non-investment-grade issues. This suggests that a change in credit rating has a larger impact on CDS spreads than on credit spreads for non-investment-grade issues, and especially for A-rated investment-grade issues. The test statistics also indicate that this pattern is particularly visible around the event date. This suggests that CDS markets are more liquid than corporate bond markets, in that the new information is reflected more rapidly in CDS prices than in corporate bond prices.

The fact that the test statistics for A-rated investment-grade issues are larger than those for B-rated investment-grade issues implies that a downgrade has a larger impact on spreads for the A-rated than for the B-rated investment-grade issues. One interpretation of this could be that a downgrade hurts A-rated issues more than it hurts B-rated investment-grade issues, as A-rated issues are considered to be of reliable high quality, whereas BBB-rated issues are already rated close to non-investment grade.

However, it is interesting that the test statistics for the non-investment-grade issues are larger than those for the B-rated investment-grade issues, as the non-investment-grade issues are already considered vulnerable to default to some extent. Our findings support the existing empirical literature in suggesting that spreads are more sensitive to changes in credit rating for low-rated issues.

Overall, we can conclude that there is clear empirical evidence that credit spreads and CDS spreads change around the time of the event date in the case of downgrades. However, this change does not happen only at the event date itself, but also before and after the event, especially for credit spreads. This could indicate that the change in credit rating is expected in some cases or that the reaction to changes in credit rating does not happen immediately.

On the other hand, the test statistics for upgrades fail to reject the null hypothesis for all choices of event window except for the event window $[1,15]$ for CDS spreads. This suggests that upgrades in credit rating do not have a significant impact on the credit spreads before, at, and after the event date. However, during the period we analyze, there are significantly more downgrades than upgrades, so we must be careful when drawing conclusions from the analysis with respect to comparing upgrades and downgrades, especially since the test statistics for upgrades reported in Exhibit 10 are summed over credit ratings spanning from A- to C-rated corporations.

Determinants of Changes in Credit Spreads and CDS Spreads

The event study test statistics presented in Exhibit 10 include both upgrades and downgrades by more than one credit rating. Although a downgrade of one credit rating is by far the most common event, our sample of events includes downgrades by one, two, and three rating classes and upgrades by one, two, and six rating classes.

EXHIBIT 11

Regression Results for the Event Window [−30,−16]

	Model 1		Model 2		Model 3	
	Estimate	Std.	Estimate	Std.	Estimate	Std.
Credit Spreads						
Intercept	-9.3245*	4.07	-11.1572*	0.46		
Upgrade	-1.8734	3.72				
Shift size	2.0019*	0.07	1.9951*	0.08		
AA	8.4524	4.01	10.2918*	0.39		
A	12.0497*	3.95	13.8968*	0.32		
BBB	27.6202*	4.13	28.9606*	1.67		
BB	27.6996*	3.52	29.2754*	0.86		
B	78.8106*	5.70	80.3390*	4.86		
CCC	45.7458*	4.01	47.5853*	0.39		
R^2	0.2497		0.2495			
Adj. R^2	0.0957		0.1181			
CDS spreads						
Intercept	-2.5700	2.57	-1.4573	1.12		
Upgrade	-7.2735*	2.37	-7.4531*	2.13	-7.6779*	1.96
Shift size	1.6406*	0.05	1.6259*	0.04	1.5982*	0.03
AA	1.9428	2.54				
A	5.2254*	2.50	4.1439*	1.10	2.7451*	0.16
BBB	22.1160*	2.59	21.0669*	1.42	19.6990*	0.97
BB	26.7056*	2.27	25.6417*	1.01	24.2600*	0.67
B	66.4572*	4.01	65.3917*	3.94	64.0041*	4.20
CCC	43.3960*	2.54	42.2981*	1.11	40.8684*	0.03
R^2	0.2906		0.2906		0.2905	
Adj. R^2	0.1451		0.1665		0.1867	

This table presents a regression analysis of the determinants of the changes in credit spreads and CDS spreads. The dependent regression variable is the absolute value of the cumulative excess credit spread and the cumulative excess CDS spread, respectively, and the explanatory variables are variables which we expect to have an influence on the outcome of the events. In particular, the variables AA, A, BBB, BB, B and CCC are dummy variables indicating the credit rating of the firm before the downgrade/upgrade. Shift size indicates how many rating classes the upgrade/downgrade spans, and Upgrade is a dummy variable indicating whether the event is an upgrade or a downgrade. We present OLS estimates, their standard deviation and t-statistics. The cumulative excess spreads are estimated for the [−30,−16] event window, and the observation window includes 75 observations ending 30 business days prior to the event date. An asterisk (*) indicates significance at a 5 percent level. We eliminate the explanatory variable with the smallest, insignificant t-statistic from the model, until we reach a model where all variables are significant at a 5 percent level.

As we expect a downgrade of two credit ratings to have a more significant impact on CDS spreads and credit spreads than a downgrade of one credit rating, we analyze the significance of the size of changes in credit rating further. To investigate the association between initial credit rating, credit rating after the event date, and cumulative excess spreads, we regress cumulative excess spreads on characteristics of interest. To ease the interpretation of results, we use absolute values of the cumulative excess spreads estimated previously as our dependent variables in the regression.[8] To analyze whether the outcome of the regression varies over time, we use the four different choices of event window used in the previous section for four different regression studies.

The explanatory variables used in the regression are variables that we expect to have an influence on the outcome of the events. In effect, to further address the issue of whether initial credit rating has an impact on the credit spread and the CDS spread, we use a set of dummy variables to indicate the initial credit rating and a set of dummy variables to indicate whether the event observation is an upgrade or a downgrade. Furthermore, we use a numeric variable to indicate by how many rating classes the reference entity is upgraded/downgraded.

The results for the event windows [−30,−16], [−15,−1], [−1,1], and [1,15] are given in Exhibits 11, 12, 13, and 14 respectively. We present the OLS estimates and their standard deviations. An asterisk indicates significance at a 5% level. For each choice of event window, we continue to eliminate the explanatory variable with the smallest insignificant t-statistic from the model until we reach a model where all variables are significant at a 5% level.

The explanatory regression variable *shift size* is a measure for the number of rating classes by which the reference entity is upgraded/downgraded at the event date. We use the absolute value. In other words, the variable takes the value 1 if the firm is downgraded or upgraded by one rating class at the event date, and 0 otherwise. We do this as we have only a few upgrade observations compared with the number of downgrade observations.

As mentioned before, we include a set of dummy variables in the regression to indicate the initial credit rating. The explanatory regression variable *AA* is a dummy variable which takes the value 1 if the firm was AA-rated before the downgrade/upgrade, and 0 otherwise. The variables *A, BBB, BB, B,* and *CCC* are defined similarly. Furthermore, we include the dummy variable *upgrade* in the regression analysis. The variable takes the value 1 if the event is an upgrade, and 0 if it is a downgrade.

From the tables we notice first of all that we have the same number of eliminations of explanatory variables for CDS spreads and credit spreads for the event windows [−15,−1] and [−1,1], whereas we need more eliminations for CDS spreads for the [−30,−16] window and for credit spreads for the [1,15] window.

Second, we notice that especially for the credit spread models, the signs of the regression coefficients are similar across event windows and models. For example, we note that the *intercept* is negative for all models studied except

EXHIBIT 12

Regression Results for the Event Window [−15,−1]

	Model 1		Model 2	
	Estimate	Std.	Estimate	Std.
Credit Spread				
Intercept	-7.0814	4.01	-8.8359*	0.43
Upgrade	-1.7935	3.68		
Shift size	2.9842*	0.06	2.9777*	0.07
AA	5.6044	3.95	7.3655*	0.36
A	8.8210*	3.89	10.5893*	0.30
BBB	28.0162*	3.99	29.2995*	1.63
BB	17.5896*	3.44	19.0981*	0.64
B	85.1338*	5.97	86.5970*	5.29
CCC	128.5634*	3.95	130.3244*	0.36
R^2	0.3515		0.3514	
Adj. R^2	0.2185		0.2379	
CDS spread				
Intercept	-2.1549	2.60		
Upgrade	-7.4846*	2.39	-7.8256*	1.99
Shift size	1.6066*	0.05	1.5727*	0.04
AA	5.0618	2.56	2.9408*	0.04
A	5.1920*	2.53	3.1089*	0.17
BBB	21.3515*	2.62	19.3237*	1.00
BB	22.0265*	2.38	19.9736*	0.97
B	75.3587*	3.77	73.3002*	3.73
CCC	969.0150*	2.56	966.8940*	0.04
R^2	0.9589		0.9589	
Adj. R^2	0.9504		0.9517	

See notes to Exhibit 11.

EXHIBIT 13

Regression Results for the Event Window [−1,−1]

	Model 1		Model 2		Model 3		Model 4	
	Estimate	Std.	Estimate	Std.	Estimate	Std.	Estimate	Std.
Credit Spread								
Intercept	-0.6867	0.78	-0.3823	0.34				
Upgrade	1.0133	0.72	0.9642	0.65	0.9052	0.59		
Shift size	0.1940*	0.01	0.1900*	0.01	0.1827*	0.01	0.2030*	0.01
AA	0.5315	0.77						
A	1.5630*	0.76	1.2671*	0.33	0.9002*	0.04	0.8572*	0.04
BBB	5.1791*	0.81	4.8921*	0.41	4.5332*	0.19	4.7530*	0.27
BB	3.4480*	0.67	3.1569*	0.26	2.7944*	0.12	2.8919*	0.09
B	14.1542*	1.00	13.8627*	0.79	13.4986*	0.76	13.6258*	0.74
CCC	47.3404*	0.77	47.0400*	0.34	46.6649*	0.01	46.6447*	0.01
R^2	0.5801		0.5801		0.5800		0.5790	
Adj. R^2	0.4940		0.5066		0.5186		0.5289	
CDS Spread								
Intercept	1.3090*	0.51	0.8533*	0.23	0.4748*	0.04	0.4068*	0.04
Upgrade	-0.9010	0.47	-0.8274	0.42				
Shift size	0.5403*	0.01	0.5463*	0.01	0.5363*	0.01	0.5369*	0.01
AA	-0.7958	0.50						
A	-0.9171	0.50	-0.4742*	0.22	-0.0743	0.04		
BBB	2.7166*	0.53	3.1463*	0.30	3.3149*	0.24	3.3822*	0.24
BB	2.7935*	0.47	3.2293*	0.25	3.5054*	0.20	3.5723*	0.20
B	11.4733*	0.62	11.9097*	0.52	12.1621*	0.52	12.2293*	0.53
CCC	265.7506*	0.50	266.2004*	0.22	266.5889*	0.03	266.6562*	0.03
R^2	0.9835		0.9835		0.9835		0.9835*	
Adj. R^2	0.9802		0.9806		0.9811		0.9815*	

See notes to Exhibit 11.

EXHIBIT 14

Regression Results for the Event Window [1,15]

	Model 1		Model 2		Model 3	
	Estimate	Std.	Estimate	Std.	Estimate	Std.
Credit Spread						
Intercept	0.6779	3.57				
Upgrade	2.3579	3.27	2.4652	2.70		
Shift size	1.3072*	0.06	1.3179*	0.04	1.3733*	0.07
AA	-1.5835	3.52	-0.9162*	0.04	-0.9716*	0.07
A	2.7388	3.46	3.3942*	0.16	3.2768*	0.20
BBB	20.3175*	3.73	20.9554*	0.86	21.5537*	1.25
BB	24.3112*	3.08	24.9570*	0.85	25.2221*	0.75
B	58.2868*	4.08	58.9345*	2.34	59.2807*	2.33
CCC	485.0080*	3.52	485.6753*	0.04	485.6199*	0.07
R^2	0.8863		0.8863		0.8862	
Adj. R^2	0.8630		0.8664		0.8695	
CDS Spread						
Intercept	32.9715*	2.31				
Upgrade	-5.8111*	2.13				
Shift size	4.8649*	0.05				
AA	-32.6530*	2.27				
A	-33.6878*	2.24				
BBB	-15.5837*	2.43				
BB	-15.2502*	2.14				
B	20.5603*	2.54				
CCC	967.6302*	2.27				
R^2	0.9800					
Adj. R^2	0.9758					

See notes to Exhibit 11.

for the first model with the [1,15] event window, where the intercept is also highly insignificant. In the case of the CDS spreads, the intercept is positive in the models where it is significant.

The *upgrade* dummy variable is highly insignificant and is eliminated from the final model for all choices of event window in the case of credit spreads. However, in the case of CDS spreads the *upgrade* dummy is eliminated from the final model for only one event window. This is in agreement with our previous finding that an upgrade has a larger effect on CDS spreads than on credit spreads. Nevertheless, whether an upgrade is more likely to have immediate impact on the CDS spread than a downgrade is difficult to conclude from our findings, as the outcome of the regression analysis depends on the fact that the data set includes significantly more downgrades than upgrades.

We notice that the regression coefficients for the credit rating dummy variables are positive and decreasing for the majority of the studies, that is, low for high rating classes and high for lower rating classes. Furthermore, all credit rating dummies are significant for the final model for most of the

regressions. The *AA* dummy is eliminated from the final model for the three day event window [−1,1] for both the CDS spread and the credit spread and for the event window [−30,−16] for the CDS spread. The *A* dummy is eliminated from the final model for the three day event window [−1,1] for the CDS spread. Overall, our findings suggest that a rating reclassification affects the lower credit rating classes more than the higher classes for both the CDSs and the corporate bonds. The regression coefficients for the variable *shift size* are positive and highly significant for all studies, implying that the size of change in credit ratings matters.

We conclude that there is empirical evidence that a credit rating reclassification has a larger effect on the credit spread and the CDS spread for lower-rated corporations than for higher-rated corporations. Similarly, we find that the number of classes by which the credit rating of the reference entity is changed has a significant impact on both the credit spread and the CDS spread around the event date. Furthermore, we find that downgrades have a significant impact on both CDS spreads and credit spreads, whereas upgrades seem to have a significant impact on CDS spreads only.

CONCLUSION

This article is a contribution to the relatively scarce empirical literature on the pricing of CDSs. It addresses the relationship between CDSs and defaultable bonds, using cross-sectional data covering 72 corporations spanning a wide range of industries and credit ratings. The analysis covers the time period 2000–2002.

Our study suggests fundamental differences in the way CDSs and corporate bonds price credit risk. Generally, we find that the CDS spread and the credit spread are highly related but not equal on average. As credit spreads widen, so do the CDS spreads, and conversely. Furthermore, we find that the relationship between CDS spreads and credit spreads is stronger for non-investment-grade corporations.

We find that credit rating is a significant determinant of both CDS spreads and credit spreads for investment-grade issues and especially for non-investment-grade issues. In addition, we find evidence to suggest that the CDS market is segmented along industry type as we find that the industry type to which the reference entity belongs contains significant information on CDS spreads. This information is not captured in the credit rating of the reference entity. Furthermore, we suggest that aggregate macroeconomic factors influence the CDS market, as we find significant information in the risk-free short rate and the slope of the default-free yield curve. Particularly, non-investment-grade reference entities appear to be sensitive to macroeconomic factors.

In addition, we examine how prices of corporate bonds and CDS contracts issued by the same reference entity respond to changes in credit rating. We find that both credit spreads and CDS spreads change around the time of a downgrade in credit rating. However, we did not find clear evidence that an upgrade in credit rating has an effect on the spreads, particularly in the case of credit spreads.

Furthermore, our findings suggest that the changes in credit ratings are anticipated by both the bond market and the CDS market. We also find evidence of lagged effects. However, our results indicate that the CDS market reacts faster and more significantly to changes in credit ratings than the bond market.

As expected, we find that the number of classes by which the credit rating of the reference entity is reclassified is reflected in both credit spreads and CDS spreads. A change of two rating classes has a higher effect on the spreads than a change of one rating class. We also find some empirical evidence that a change in credit rating has a larger effect on the credit spread and CDS spread for lower-rated corporations than for higher-rated corporations.

APPENDIX
Description of Variables

CDS	is the credit default swap measured in basis points.
Spread	is the credit spread measured in basis points and defined as the yield on the reference bond less the risk-free interest rate of the same maturity.
LSize	is the log of the amount of the issue.
LMaturity	is the log of the maturity.
Short	is the default-free short rate measured by the 3 month U.S. Treasury bill.
Slope	is the slope of the default-free term structure of interest rates, measured as the difference between the 10 year U.S. Treasury bond and the 3 month U.S. Treasury bill.
DRating	is an ordinal dummy variable indicating the long-term debt rating of the reference bond by S&P's. AA = 1, A = 2, etc.
Airline	is a dummy variable coded 1 if the firm is classified in the airline industry, 0 otherwise.

Automobile	is a dummy variable coded 1 if the firm is classified in the automobile industry, 0 otherwise.
Basic Material	is a dummy variable coded 1 if the firm is classified in the basic material industry, 0 otherwise.
Capital Goods	is a dummy variable coded 1 if the firm is classified in the capital goods industry, 0 otherwise.
Defense	is a dummy variable coded 1 if the firm is classified in the defense industry, 0 otherwise.
Energy	is a dummy variable coded 1 if the firm is classified in the energy industry, 0 otherwise.
Leisure	is a dummy variable coded 1 if the firm is classified in the leisure industry, 0 otherwise.
Media	is a dummy variable coded 1 if the firm is classified in the media industry, 0 otherwise.
Power	is a dummy variable coded 1 if the firm is classified in the power industry, 0 otherwise.
Retail	is a dummy variable coded 1 if the firm is classified in the retail industry, 0 otherwise.
Technology	is a dummy variable coded 1 if the firm is classified in the technology industry, 0 otherwise.
DRating	is an ordinal dummy variable indicating the long-term debt rating of the reference bond by S&P's. AA = 1, A = 2, etc.
Airline	is a dummy variable coded 1 if the firm is classified in the airline industry, 0 otherwise.

[5]All results reported in this article use two-tailed tests. We follow this more conservative approach even though we specify directional hypotheses for some of our variables that would permit us to use one-tailed tests.

[6]A standard reference for event studies is Campell, Lo, and MacKinlay [1997, chap. 4].

[7]As event studies are often applied to stock returns, the sum in Equation (4) is usually referred to as the *cumulative abnormal return* (CAR) elsewhere in the literature.

[8]We remark that most of our excess CDS spreads are positive, as we have significantly more downgrades than upgrades in our event sample. As a result, taking the absolute value of all CDS spreads does not change the outcome of the cross-sectional analysis greatly.

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