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

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Abstract

This paper empirically investigates the relationship between credit spreads and credit default swap spreads, and how these spreads react to changes in credit ratings. Our analysis deals the time period 2000 to 2002 and covers 72 corporations which span a wide range of industries and credit ratings. Our findings suggest that credit spreads and credit default swap spreads are not equal on average, but highly related, and that this relationship is more pronounced for non-investment grade corporations. In addition, we discover that credit rating and macroeconomic factors such as the default-free short rate and the slope of the default-free yield curve add significant information to the difference between credit spreads and credit default swap spreads. Furthermore, we find clear empirical evidence that credit spreads and credit default swap spreads react to changes in credit ratings, in particular to downgrades. We also find evidence of anticipated and lagged effects of changes in credit rating in addition to differences between investment grade. Interestingly, our findings show that the CDS market reacts faster and more significantly to changes in credit ratings than the bond market.

JEL Classification: G13; G14;

Keywords: Credit Risk, Credit Default Swaps, Credit Rating, Principal Component Analysis, Event Study.

1 Introduction

During recent years, the market for credit derivatives has grown almost exponentially. Credit derivatives are contingent claims with payoffs that are linked to the creditworthiness of a given corporation or sovereign entity. The purpose of the instruments is to allow for trade of the risks associated with certain debt-related events.

The most popular and common type of credit derivative is the credit default swap (CDS). A CDS is a contract which 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. A CDS can be settled with a cash settlement or a physical settlement. 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.

In this paper we focus on the pricing of CDS contracts from an empirical perspective. The paper has two objectives. The first is to empirically analyze the relationship between CDS spreads and credit spreads. The second is to examine how changes in credit ratings effect CDS and corporate bond prices. We study the relationship between CDS spreads and credit spreads by 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 which analyze the approximate equality between CDS spreads and credit spreads include studies by Houweling & Vorst (2003), Blanco, Brennan & Marsh (2003) and Hull, Predescu & White (2004). Houweling & Vorst (2003) compare CDS spreads to credit spreads graphically and find that the bond market and the CDS market deviate considerably, although the outcome of their analysis varies with credit rating. In effect, for A-rated reference entities only small deviations from the approximate relationship are found on average. However, for B-rated reference entities large deviations between the two are found.

Blanco et al. (2003) perform a cross sectional regression study of CDS prices, risky bond yields and swap rates, using a small cross-section data set consisting of both US and European firms. Contrary to Houweling & Vorst (2003), they find that the bond market and the CDS markets 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.

Another line of empirical research on the CDSs looks at the determinants of the CDS price. Virtually all studies in this part of the literature are regression studies which use the CDS price or CDS spread as the dependent variable. Studies include Skinner & Townend (2002), Aunon-Nerin, Cossin, Hricko & Huang (2002) and Benkert (2004). Skinner & Townend (2002) use arguments from option pricing theory and suggest that the CDS price should be highly dependent on the risk-free short rate, the yield of the reference obligation, the interest rate volatility, the time to maturity and the payable amount of the reference obligation in the event of default. They find that four of these variables contain significant information, namely the risk-free rate, yield, volatility and time to maturity.

Benkert (2004) conducts a regression analysis using CDS panel data, incorporating variables such as credit rating, liquidity, leverage, historical volatility and implied volatility. He 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) conduct studies on CDS transaction data by regressing CDS premiums on various proxies for credit risk such as credit rating, risk-free short rate, slope of the default-free yield curve, time to maturity, stock prices, historical volatility, leverage and index returns. They find that most of the variables predicted by credit risk pricing theories have significant impact on the observed levels of CDS prices, but that credit rating is the most important single source of information on credit risk overall. Furthermore, behavioral differences between high and low rated underlyings, sovereign and corporate underlyings and underlyings from different markets are found.

Our study of the relationship between CDS spreads and credit spreads falls in 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 onto 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.

Secondly, we investigate which factors contribute to the difference in the pricing of CDSs and corporate bonds. In particular, we incorporate 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, industry and time dummies, into the regression analysis to investigate which variables explain the difference between CDS spreads and credit spreads. We find that credit rating, short rate, slope and most industry and time dummies add significant information to the difference in the spreads.

We point out that the regression study presented in this paper differs from previous regression studies of the CDS in that we try to explain which factors determine the difference in CDS spreads and credit spreads, rather than try to explain which factors determine the CDS price itself.

As argued in the existing literature and supported in this paper, credit rating is the most important single 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 paper reveal 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 (down/upgrades, review for down/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.

While event studies of CDS are very few, many studies have considered the reaction of bond prices to changes in credit rating. Early studies include Grier & 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 & 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 & Leftwich (1992), who use daily data and find negative excess bond and stock returns for downgrades, but weaker positive returns for upgrades.

Hite & 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 & Heinke (2001) use Eurobond data and find that announcements for downgrades and negative watchlistings induce significant abnormal returns on the announcement day and the following trading days. Upgrades and positive watchlistings 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 found elsewhere in the literature, 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 has 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.

The remainder of the paper is organized as follows. Section 2 provides a brief introduction to CDSs. In particular, we give a formal argument for the approximative relationship between the CDS spread and the credit spread. Section 3 summarizes the data used throughout the paper. In section 4 we present the results of the principal component analysis on CDS spreads and credit spreads. The results of the regression analysis, investigating which factors determine the difference between CDS spreads and credit spreads, are presented in section 5. Section 6 presents the results of the event study examining the relationship between CDSs, corporate bonds and reclassifications in credit rating. Section 7 concludes.

2 Credit Default Swaps

In its basic form a *credit default swap* (CDS) or in short a *default swap* contract is an OTC 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 would either be the difference between the notional and market value of the reference issue or a predetermined fraction of the notional amount. Furthermore, a CDS could 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 has therefore 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 e.g. bankruptcy, failure to make a principal or interest payment, repudiation/moratorium, obligation acceleration, obligation default or restructuring.

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

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 risk in this paper. Lando (2000) and Hull & White (2001) examine CDSs in the presence of counterparty risk.

2.1 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 both 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.[1] 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 table 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.

[1] The relation between CDS spreads and bonds spreads holds exactly for floating rate notes instead of coupon-bearing bonds, see e.g. Duffie (1999).

Table 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.

There is 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 similar. Furthermore, differences between the definition of a credit event in two contracts is ignored.

3 The Data

CDS data has been obtained from the Federal Reserve Board.[2] The Federal Reserve Board maintains a data set of CDS quotes for every major sector of the economy. Like Houweling & Vorst (2003), Blanco et al. (2003), Longstaff, Mithal & Neis (2004), Benkert (2004) and Hull et al. (2004), we use five-year CDS quotes. 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 has been applied by Houweling & Vorst (2003). Houweling & Vorst (2003) also match CDSs to bonds 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 zero curve as the benchmark for the risk-free zero curve, whereas derivative traders tend to use the swap zero curve, as they consider Libor/swap rates to correspond

[2] This data was collected while the first author was on leave at the Federal Reserve Board. The Federal Reserve Board maintains data set of daily closing mid-market CDS quotes, and the authors produced the CDS spreads from the reports.

[3] Studies by Blanco et al. (2003) have also used this approach. Hull et al. (2004), Longstaff et al. (2004) match by regression.

closely to their opportunity cost of capital. The choice of the risk-free curve for CDS pricing has been analyzed e.g. by Hull et al. (2004). 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 & Vorst (2003) that using government curves result in an overestimation of credit risk. Our use of the treasure curve is due to data availability.

From this data matching, we obtain a sample of 72 firms for the period January 2000 through December 2002, although each firm is not represented throughout the entire sample. We exclude all bonds that contain special features, such as embedded options, sinking funds, etc. 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 the 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 & Vorst (2003), Skinner & Townend (2002), Aunon-Nerin et al. (2002), Blanco et al. (2003), Longstaff et al. (2004) etc. 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.

3.1 Corporations and Industry

Table 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 2807 and 3956 basis points and average credit spreads of 1236 and 1225 basis points, respectively. Furthermore, we notice that the average CDS spread of Southern California Edison is 266 basis points and the average credit spread is 567 basis points, reflecting the California energy crisis.

From table 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. Assuming equality between the two is widely used among practitioners. To some extent, research by Skinner & Townend (2002) and Blanco et al. (2003) supports the practitioners' view, while Hull et al. (2004) and Longstaff et al. (2004) do 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 regressing

$$CDS_{it} = \alpha_i + \beta_i \cdot Spread_{it} + \varepsilon_{it}, \tag{2}$$

where ε_{it} is an error term. We test the null hypotheses $\alpha_i = 0$ and $\beta_i = 1$ for each firm i. Table 2 shows the estimated α and β's. 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.

Table 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 which tend to have relatively low spreads, are automobiles, basic materials, capital goods and defense. This may stem from the transparency associated with mature highly capital intensive industries relative to the new labor intensive industries of the information based economy. On the other hand, technology had low spreads in the year 2000, but tended to have higher spreads over the 2001 through 2002 time period. Industries which experienced financial distress in the year 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 the year 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.

3.2 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 by Aaa, Aa, A, Baa, Ba, B and Caa, dividing all but the Aaa rating in to subcategories such as Aa1, Aa2 and Aa3. Correspondingly, Standard and Poor's rate their bonds by AAA, AA, A, BB, BB, B and CCC, dividing all but the AAA 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, 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 credit worthiness of the bond issuers, rather than a description of the quality of the bond itself.

Table 4 presents CDS spreads and credit spreads for each rating class by year for the 2000 through 2002 time period. The data include a wide range of credit ratings, spanning from AA rated down to C rated firms, although we have most observations 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, while 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 the year 2000 to 448 and 370 basis points, respectively, in the B rating class for the year 2000. Similar patterns are seen for the years 2001 and 2002.

Evidently, credit rating is a highly important determinant in the pricing of CDSs and corporate bonds, in that higher rated firms are compensated for their credit profile relative to lower rated firms.

4 Differences in Credit Spreads and CDS Spreads

The initial data analysis of section 3.1 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 in which way 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.

Basically, 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 which has maximal variance. Early papers applying principal component analysis or factor analysis in yield curve analysis include Litterman & Scheinkman (1991) and Steeley (1990).

We estimate the principal components of both CDS spreads and credit spreads. Figure 1 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 should 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.

5 Determinants of Credit Spreads and CDS Spreads

Our findings in sections 3 and 4 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. We wish to investigate further how the spreads differ, and in particular, we wish to investigate whether common factors exist which add significant information to the explanation of the differences between CDS spreads and credit spreads. We emphasize that we seek to find variables which explain the differences of CDS spreads and credit spreads, rather than just explain which factors determine the CDS spread alone. We refer to the introduction for a review of empirical studies which 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 & Liu (2001), who, by analyzing the relationship between fixed-rate and floating rate spreads in a reduced form model setup, document that 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

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

where ε_t is an error term. For comparison purposes, we estimate the regression model with credit spread as the dependent variable, as well,

$$\begin{aligned} Spread_t = {} & \alpha_t + \beta_1 \cdot CDS_t + \beta_2 \cdot Short_t + \beta_3 \cdot Slope_t \\ & + \beta_4 \cdot DRating_t + \beta_5 \cdot LSize_t + \beta_6 \cdot LMaturity_t \\ & + \sum_{j=1}^{11} \gamma_j \cdot Industry_{j,t} + \sum_{j=1}^{3} \delta_j \cdot Year_{j,t} + \varepsilon_t. \end{aligned} \tag{4}$$

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 to section A in 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 percent of the credit spread for AAA and AA rated bonds, 51 percent for A-rated bonds, 56 percent for BBB rated bond and 71 percent for below-investment grade bonds. Accordingly, we expect the credit spread to be positively related to the CDS spread, and both the spreads 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 credit spread and the CDS spread. As discussed in Skinner & 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, while 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 and credit spreads, as economic activity increases.

5.1 Empirical Results

Table 5 shows the estimation results of our regression model given by (3), using the CDS spread as the dependent variable. We present regression coefficients and their t-statistics. Variables which are not statistically significant at the 5 percent level are removed from the analysis. Prior research (for example 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 which are rated as investment grade and non-investment grade, to test the effect of differences in credit rating quality.[4]

For all estimations we report the adjusted R-squared and an F-test for whether the coefficients are jointly equal to zero. All estimations appear well specified with significant F-test. In addition, 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] Furthermore, we notice that 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 the view that credit ratings

[4] Bonds rated BB and below by Standard and Poor's are classified as non-investment grade.

[5] All results reported throughout the paper 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.

are the most important single 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 of the investment grade subsample to the non-investment grade, we discover some clear differences. Firstly, 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, we notice that the credit spread has no impact on the two subsamples in a similar manner. It appears that the credit spread has a much higher loading on the CDS spread for non-investment grade relative to investment grade, perhaps suggesting that market practitioners rely much 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 compares to what has been found by other researchers, e.g. 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 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 (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 one, if the reference entity is rated AA, A, BBB, BB or B, respectively, and zero otherwise. We leave out dummies for credit ratings below B. Figure 2 shows the regression coefficients and their standard deviations. We see a clear increasing pattern in the estimates which confirm our expectations of market prices being more sensitive to credit rating for low investment grade issues.

To conclude 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 ahighly 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.

Table 6 shows the estimation results of the regression model given by (4), using *Spread* as the dependent variable. Similarly to the previous analysis, we estimate separate regressions for investment grade and non-investment grade issues. All estimations appear well specified, with significant F-tests. The adjusted R-squares are 0.82 for the full sample model, 0.76 for investment grade and 0.79 for non-investment grade. Variables $LSize$ and $LMaturity$ are statistically insignificant, whereas the variables CDS, $DRating$, $Short$ and $Slope$ are significant, and coefficients are of the predicted sign in all regressions. Furthermore, we find that the majority of the industry dummies are significant for all regressions.

Comparing tables 5 and 6, we find that the credit spread appears to react more to market-wide variables than the CDS spread, as indicated by the estimated regression coefficients for the $Short$ and $Slope$ variables. This finding is consistent with the results of Blanco et al. (2003). On the other hand, the CDS spread seems to react more to changes in the credit rating than the credit spread, as we shift from investment grade to non-investment grade issues. In particular, the estimated regression coefficient for $DRating$ changes from 12.86 to 16.28 for the credit spread, which is less than three basis points, while the coefficient on $DRating$ changes from 5.49 to 35.9 for the CDS, which is more than thirty basis points. This suggests that bond market participants rely less on the information contained in the credit ratings than credit default swap market participants.

6 Credit spreads, CDS Spreads and Changes in Credit Rating

As found in the literature and supported in this paper, 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 reasons, as the previous analysis has suggested significant differences between the CDS market and the corporate bond market.

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

In figure 3, we illustrate the effect of a downgrade on the CDS spread and the credit spread. The figure shows observations of the credit spread and the CDS spread for Motorola Corporation over a period of two years. During this time period a total of three downgrades is seen: from A downto A-, downto BBB+ and finally downto BBB.

The first downgrade, which happens on June 1st, 2001, does not have a clear effect on the credit spread. However, the CDS spread shows an increase of about 50 bps a few days later. At the date of the second downgrade, October 31st, 2001, we see an upward jump in the credit spread of about 40 bps some days before, but no clear change of the CDS spread is seen. At the date of the third downgrade, July 1st, 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.

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*, basically testing if the level of the spread changes around the time a change in credit rating occurs, by comparing it to what it was before the change in credit rating took place. The model will allow 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 (down/upgrades, review for down/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, but 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, which has been calculated for each overall rating category. The analysis is done 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.

6.1 Model Setup

We define an *event* as a change in credit rating and the *event date* as the day where a change in credit rating occurs. The time 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

[6] A standard reference to event studies is Campell, Lo & MacKinlay (1997, chapter 4).

windows before and after the event date, as done by Larraín, Reisen & 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 studies we conduct in the following, 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 $s_t^m = [s_{1t}^m, \ldots, s_{Nt}^m]$ 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

$$\widehat{Z}_i^m = \sum_{t \in L_2} \hat{\epsilon}_{it}^m, \qquad m = CDS, Credit \tag{5}$$

with sample variance $\left(\hat{\sigma}_i^m\right)^2 = \sum_{t,s \in L_2} \hat{V}_{i,ts}^m$, 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

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

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

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 by the following test statistic

$$J = \frac{\overline{Z}^m}{\widehat{\overline{\sigma}}^m}, \tag{6}$$

which is asymptotically standard normally distributed under the null hypothesis.

[7] As event studies are often applied to stock returns, the sum in equation (5) is usually referred to as the cumulative abnormal return (CAR) elsewhere in the literature.

6.2 Empirical Results

The results of the event study are shown in figure 4 and table 7. 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 figure 4 we graph the cumulative excess spreads averaged across all upgrades and all downgrades across time for the time interval [-30,15], and in table 7 we present test statistics for four different choices of event window. The event windows used in the study are: a three day 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 each, and a 14 day 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 figure 4 we see first of all that cumulative excess spreads are positive for downgrades and negative for upgrades as expected. Secondly, 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, which are not reported in the paper, 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, figure 4 suggests that changes in credit rating have a larger impact on the CDS spread than on the credit spread, and that the change in CDS spread is more concentrated around the event date than the change in credit spread.

Table 7 reports the test (6) for each choice of event window and for all downgrades, all upgrades and for groups of initial credit rating 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 8 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 not rejected for all choices of event window in the case of CDS spreads, but is accepted in the case of credit spreads. This implies that for B-rated investment grade issues a downgrade in credit rating does not have significant impact on CDS spreads.

Generally, 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. An 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 conclusions made in existing empirical literature 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 windows, 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 up- and downgrades, especially since the test statistics for upgrades reported in table 7 are summed over credit ratings spanning from A to C rated corporations.

6.2.1 Determinants of Changes in Credit Spreads and CDS Spreads

The event study test statistics presented in table 7 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.

As we expect that a downgrade of two credit ratings has a more significant impact on CDS spreads and credit spreads than a downgrade of one credit rating, we analyze the significance of the number of changes in credit rating further in the following. 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 in section 6.2 as our dependent variables in the regression.[8] To analyze if the outcome of the regression varies over time, we use the four different choices of event windows from section 6.2 for four different regression studies.

The explanatory variables used in the regression are variables which we expect to have an influence on the outcome of the events. In effect, to further address if 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 tables 8, 9, 10 and 11, 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 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 by how many rating classes 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 to the downgrade observations.

As mentioned before, we include a set of dummy variables in the regression, indicating 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.

[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.

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.

Secondly, we notice that, especially for the credit spread models, the signs of the regression coefficients are similar across event windows and models, e.g. we note that the *intercept* is negative for all models studied except 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 in the final model for all choices of event windows in the case of credit spreads. However, in the case of CDS spreads the *upgrade* dummy is only eliminated in the final model for one event window. This is in agreement with our findings of section 6.2, where we found that an upgrade has a larger effect on CDS spreads than on credit spreads. Still, 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 depend 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 in 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 in 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 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.

7 Conclusion

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

Our study suggests that there are 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 which suggests that the CDS market and the bond market are segmented along industry type, as we find that the industry type, to which the reference entity belongs, contains significant information on CDS spreads and credit 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 and bond 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, compared to the bond market.

As expected, we find that the number 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.

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A Description of Variables

Below is listed a description of the variables which we use throughout the paper.

CDS	is the credit default swap measured in basis points.
Spread	is the credit spread measured in basis points and defined as the difference between 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 three month US Treasury bill.
Slope	is the slope of the default-free term structure of interest rates, measured as the difference between the ten year US Treasury bond and the three month US 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.
Defence	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.
Telecom	is a dummy variable coded 1, if the firm is classified in the telecom industry, 0 otherwise.
$D2000$	is a dummy variable coded 1, if the observation is in year 2000, 0 otherwise.
$D2001$	is a dummy variable coded 1, if the observation is in year 2001, 0 otherwise.
$D2002$	is a dummy variable coded 1, if the observation is in year 2002, 0 otherwise.

Table 2: Average Credit and CDS Spreads by Firm

Corporation	Sector	Obs	Rat-ing	Credit Spread	CDS Spread	α	β
Abitibi-Consolidated Inc	Basic Mat.	456	BBB	297 (68)	207 (88)	-143*	1.18*
AK Steel	Basic Mat.	186	BB	379 (69)	337 (79)	36	0.80*
Albertsons	Retail	473	BBB	216 (39)	81 (19)	34*	0.21*
Alcoa	Basic Mat.	392	A	79 (17)	40 (11)	29*	0.15*
American Standard	Cap. Goods	278	BB	250 (41)	222 (67)	-131*	1.41*
Apple Computer	Tech.	537	BB	410 (94)	261 (34)	193*	0.17*
Argosy Gaming	Leisure	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	Telecom	251	A	98 (42)	53 (40)	-36*	0.91*
Avon Products Inc	Retail	456	A	94 (38)	32 (7)	24*	0.09*
BellSouth Corp	Telecom	371	AA	191 (26)	36 (16)	81*	-0.23*
Boeing Co	Defense	693	A	135 (29)	45 (29)	-25*	0.52*
Calpine Corp	Power	542	BB	1031 (1080)	1314 (1532)	-78*	1.35*
Caterpillar Inc	Cap. Goods	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	Automobile	696	A	149 (47)	101 (54)	-4	0.71*
Danaher	Cap. Goods	363	A	153 (28)	59 (15)	19*	0.26*
Deere	Cap. Goods	651	A	162 (31)	55 (19)	100*	-0.28*
Delphi Auto Systems	Automobile	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	Basic Mat.	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	Automobile	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*

This table presents the average credit spread and CDS spread for each firm. Credit spreads and CDS spreads are given in basis points, and their standard deviations are given in parentheses. Credit rating is the average of the Standard and Poor's long-term-debt rating. Obs is the number of observations. To test whether the CDS spread and the credit spread price default risk equally on average, we estimate equation 2. The regression coefficients are presented, and an asterisk (*) indicates significance at a 5 percent level for the null hypotheses, that is $\alpha_i = 0$ and $\beta_i = 1$, respectively.

Table 2 continued: Average Credit and CDS Spreads by Firm

Corporation	Sector	Obs	Rat-ing	Credit Spread	CDS Spread	α	β
IBM Corp	Tech.	693	A	115 (21)	43 (18)	0.3	0.37*
Ingersoll-Rand Co	Cap. Goods	193	A	209 (21)	65 (23)	36*	0.14*
International Paper	Basic Mat.	638	BBB	144 (28)	87 (19)	104*	-0.12*
ITT Corp	Leisure	456	BBB	237 (56)	234 (142)	637*	-1.69*
Lear Corp	Automobile	206	BB	367 (92)	262 (51)	130*	0.36*
Lockheed Martin Corp	Defense	696	BBB	143 (48)	74 (13)	55*	0.14*
Lucent Technologies	Telecom	383	B	1239 (813)	1230 (669)	306*	0.75*
Mandalay Bay	Leisure	283	BB	454 (107)	453 (143)	45	0.9
May Dept	Retail	440	A	164 (19)	56 (19)	-17*	0.44*
MGM Mirage Inc	Leisure	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	Telecom	579	B	1031 (401)	935 (450)	-167*	1.07*
Nordstrom Inc	Retail	456	BBB	235 (48)	117 (38)	25*	0.39*
Northwest Airlines	Airlines	287	B	1329 (730)	1484 (927)	-158*	1.24*
Park Place Enter. Corp	Leisure	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	Basic Mat.	553	A	136 (28)	49 (10)	22*	0.20*
Saks Inc	Retail	387	BB	554 (174)	543 (188)	63*	0.87*
Six Flags	Leisure	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*	0.8
Sprint	Telecom	456	BBB	401 (232)	391 (370)	-207*	1.50*
Station Casinos Inc	Leisure	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	Airlines	302	CCC	2807 (2720)	3955 (3275)	1500*	0.88*
Viacom Inc	Media	694	A	118 (27)	65 (20)	46*	0.16*
Visteon	Automobile	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	Basic Mat.	228	A	131 (36)	76 (22)	58*	0.14*

This table presents the average credit spread and CDS spread for each firm. Credit spreads and CDS spreads are given in basis points, and their standard deviations are given in parentheses. Credit rating is the average of the Standard and Poor's long-term-debt rating. Obs is the number of observations. To test whether the CDS spread and the credit spread price default risk equally on average, we estimate equation 2. The regression coefficients are presented, and an asterisk (*) indicates significance at a 5 percent level for the null hypotheses, that is $\alpha_i = 0$ and $\beta_i = 1$, respectively.

Table 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 mean credit spread, the mean 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.

Table 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	2000	4821	167	109	71	117
Issues	2001	9926	178	91	103	89
	2002	8324	194	141	157	156
	Total	23071	181	115	115	127
Non-Investment	2000	742	389	112	319	92
Grade Issues	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 mean credit spread and the mean 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.

Table 5: Determinants of the Credit Default Swap 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 independent variable is the CDS spread measured in basis points in all OLS regressions. 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.

Table 6: Determinants of the Credit Spread

	Full Sample		Investment Grade Issues		Non-Investment Grade Issues	
Variables	Coef.	T-Value	Coef.	T-Value	Coef.	T-Value
Intercept	377.87	24.71*	92.23	19.61*	1082.88	17.14*
CDS	0.65	246.85*	0.69	184.79*	0.62	115.84*
DRating	14.97	31.53*	12.86	44.75*	16.28	5.78*
Short	-45.14	16.42*	-5.07	5.18*	-157.60	16.77*
Slope	-57.16	18.75*	-16.75	17.32*	-178.04	16.08*
Airline	-47.00	4.18*			-133.36	5.94*
Automobile	-133.42	20.90*	-41.94	26.26*	-185.20	5.86*
Basic Material	-140.64	22.55*	-47.88	31.28*	-246.49	7.94*
Capital Goods	-106.74	15.46*			-346.81	12.25*
Defense	-135.76	17.93*	-43.86	22.88*		
Energy	-184.23	27.35*	-71.53	35.82*	-298.86	15.16*
Leisure	-122.98	18.57*	-33.56	15.47*	-267.17	14.88*
Media	-155.18	26.70*	-71.12	45.25*	-228.91	12.99*
Power	-210.69	31.20*	-31.93	15.11*	-398.69	21.93*
Retail	-106.81	18.65*	-23.94	17.52*	-197.28	10.13*
Technology	-90.08	14.80*	6.78	4.46*	-225.74	10.97*
D2000	-43.28	8.22*	18.62	7.26*		
D2001			11.16	8.80*	-59.93	6.31*
Adjusted R^2	0.82		0.76		0.79	
F-Value	8717		4497		2046	

This table presents the determinants of the CDS spread. The independent variable is the credit spread measured in basis points in all OLS regressions. 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.

Table 7: Event Study Results

Credit Spreads - Downgrades

Rating	Events	Time Interval [-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

Rating	Events	Time Interval [-30,-16]	[-15,-1]	[-1,1]	[1,15]
All	8	-1.0826	-1.2492	-0.5787	-1.1921

CDS Spreads - Downgrades

Rating	Events	Time Interval [-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

Rating	Events	Time Interval [-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. 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. 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.

Table 8: 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 shows OLS estimates, their standard deviation and t-statistics of regression specifications determining the performance of cumulative excess CDS spreads estimated for the [-30,-16] event window. An asterisk (*) indicates significance at a 5 percent level. The observation window for the event study includes 75 observations ending 30 business days prior to the event date. The independent 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. Upgrade is a dummy variable indicating whether the event is an upgrading or a downgrading.

Table 9: 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	

This table shows OLS estimates, their standard deviation and t-statistics of regression specifications determining the performance of cumulative excess CDS spreads estimated for the [-15,-1] event window. An asterisk (*) indicates significance at a 5 percent level. The observation window for the event study includes 75 observations ending 30 business days prior to the event date. The independent 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. Upgrade is a dummy variable indicating whether the event is an upgrading or a downgrading.

Table 10: 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*	

This table shows OLS estimates, their standard deviation and t-statistics of regression specifications determining the performance of cumulative excess CDS spreads estimated for the [-1,1] event window. An asterisk (*) indicates significance at a 5 percent level. The observation window for the event study includes 75 observations ending 30 business days prior to the event date. The independent 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. Upgrade is a dummy variable indicating whether the event is an upgrading or a downgrading.

Table 11: 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					

This table shows OLS estimates, their standard deviation and t-statistics of regression specifications determining the performance of cumulative excess CDS spreads estimated for the [1,15] event window. An asterisk (*) indicates significance at a 5 percent level. The observation window for the event study includes 75 observations ending 30 business days prior to the event date. The independent 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. Upgrade is a dummy variable indicating whether the event is an upgrading or a downgrading.

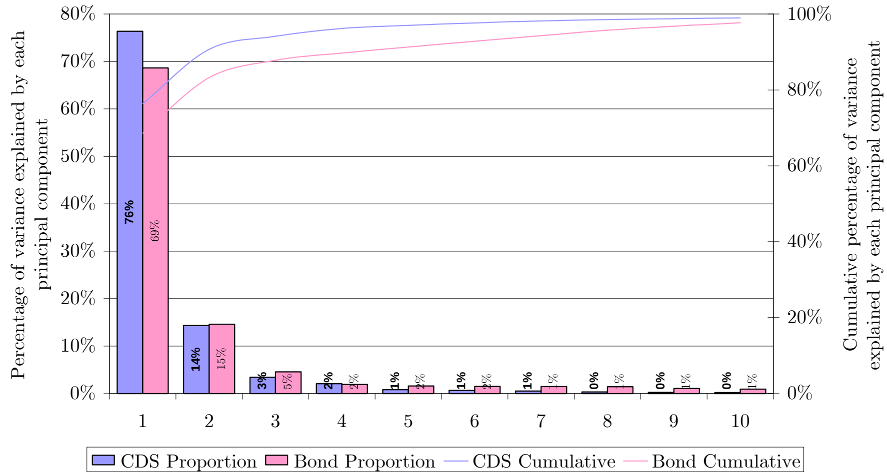

Figure 1: This figure shows the percentage and the cumulative percentage of the variance explained by the first 10 principal components for both credit and CDS spreads.

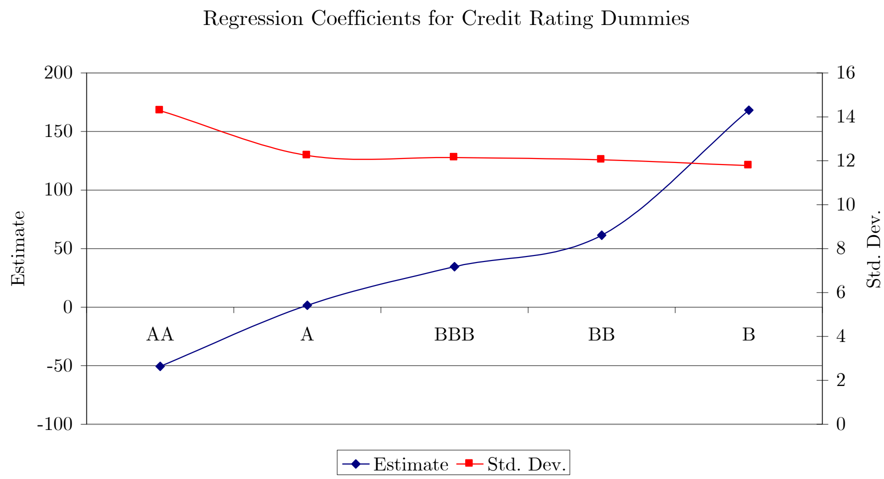

Figure 2: This figure shows regression coefficients and standard deviations of the credit rating dummies for the rating classes AA, A, BBB, BB and B. The model estimated is the regression model given by (3) replacing the variable *DRating* with a set of dummy variables taking the value one, if the reference entity is rated AA, A, BBB, BB or B, respectively, and zero otherwise. Dummies for credit ratings below B are left out.

Motorola Corporation

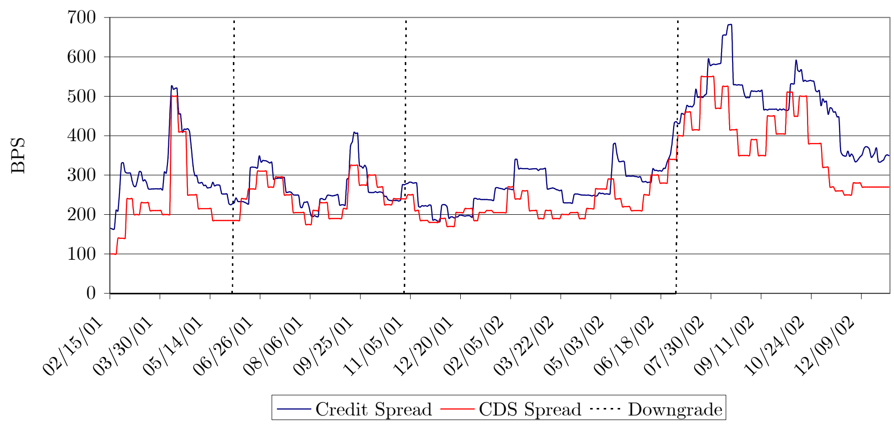

Figure 3: This figure shows the CDS and credit spread of Motorola Corporation during the period of February 15th, 2001 to December 31th, 2002. The timing of the three downgrades during this period are marked with a dotted line.

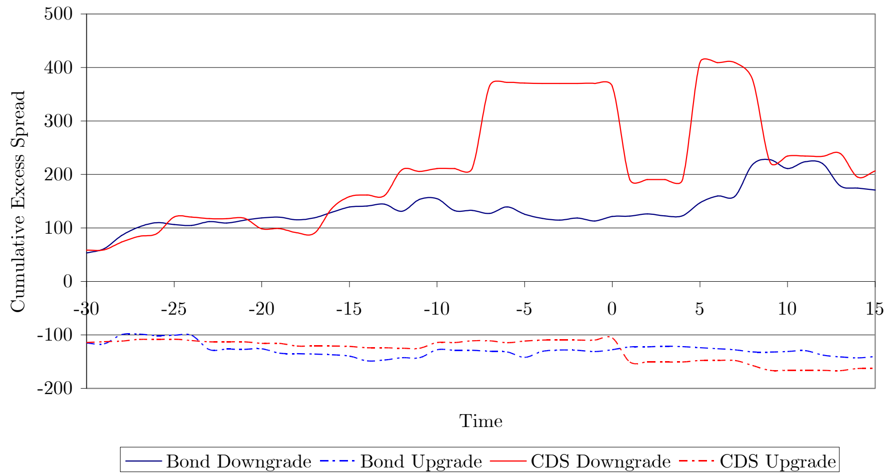

Figure 4: Plot of cumulative excess spreads for downgrades and upgrades.