Final Thesis

CDS Model and Market Spreads Amid the Financial Crisis

Dominik Jaretzke, Maastricht University

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Abstract

I calculate CDS spreads for 106 North-American obligors using an advanced version of the CreditGrades model that incorporates implied equity volatilities. I estimate spreads over a period from 2004 to mid-2009, which makes this the first study that explicitly investigates the period of the financial crisis. I examine the relationship between empirical market spreads and model spreads and test for the correlation of the spreads. In a next step, I investigate the deviation of market and model spreads according to the obligors' credit rating class and different time periods. I run panel regressions with several macro-economic and firm-specific factors in order to identify factors that influence market and model spreads. Finally, the sources of the gap between market and model spreads are determined.

I find that market and model spreads are highly correlated and that the model prices and tracks CDS spreads reasonable well. However, I also detect a consistent underestimation of spreads during the period up to mid-2007 for investment grade obligors, suggesting the inclusion of jump risk to increase short-term spreads. The model performs very well during the crisis, a result attributable to the inclusion of implied equity volatilities. Finally, important factors are missing in structural modelss. In particular, the public debt level, real housing prices, industrial production, the risk-free rate, equity volatilities, the volatility skew, CDS liquidity, and company returns should be included in future advancements of the model.

[1] I thank Drs. Daniel Hann, PhD Candidate at Maastricht University, for useful ideas and comments and his extensive support as a supervisor while I have been writing my final thesis.

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I. Introduction

The credit derivatives market has been characterized by tremendous growth over the last decade and has become six times as large as the equity derivatives market. The market peaked in 2007 when it reached a size of $60 trillion. Credit derivatives are used by financial institutions to transfer credit risk. In particular, a credit default swap (CDS) is a privately traded contracts used to insure against a borrower defaulting on debt or to speculate on their credit quality. The notional amount of the contracts is usually $10 million. CDS spreads are quoted in basis points per annum of the contract's notional amount. For example, a CDS spread of 450 bps for five-year Southwest Airlines debt means that default insurance for a notional amount of $10 million costs $450,000 p.a. This premium is usually paid quarterly on fixed dates, i.e. $112,500 per quarter. While the period up to 2007 has seen comparably low spreads for investment grade obligors and non-investment grade or high-yield obligors, spreads sky-rocketed during the current financial crisis based on uncertainty and the fear of many company bankruptcies.

An extensive body of academic research, which tries to explain the determinants of CDS spreads, has evolved since understanding the determinants of credit spreads is important for financial analysts, traders, and economic policy makers (Alexander & Kaeck, 2008). In doing so, academics usually turn to the theoretical determinants used by structural models, which can be used to estimate theoretical spreads. Structural models have been introduced in the 1970s, with Merton's model (1974) being the most popular and known. These models use firm fundamentals such as equity value, the leverage ratio, and asset volatility to estimate fundamentally-based fair spreads. A main assumption of structural models is that both equity and debt can be regarded as different contingent claims on the company's assets and the value of these claims is similar to option contracts. Therefore, structural models consider default if the value of a company's assets falls below a certain threshold associated with the company's liabilities. The main advantage of structural models is that they are based on sound economic arguments and that default is modeled in terms of firm fundamentals. Several advancements have been introduced over time and in 2002 a group of investment banks have introduced the CreditGrades model. This model is easy to implement and quickly became the industry standard.

Theoretical determinants of CDS spreads can be sub-divided into fundamental and macro-economic factors. Skinner & Townend (2002) suggest five factors that should explain CDS spreads and find that the risk-free rate, yield, volatility, and time to maturity are significant while the payable amount of the reference obligation in the event of default is insignificant. Benkert (2004) finds that option-implied volatility is a more important factor in explaining variation in CDS spreads than historical volatility. Later research (Cremers et al., 2006 & 2007) confirms these findings and additionally show that including the implied volatility skew as determinant of market spreads to proxy for potential jump risk premiums in equity is important. Zhang et al. (2009) find that volatility risk and jump risk are important determinants of CDS spreads. It is now conventional wisdom that implied volatilities are superior to historical volatilities in explaining CDS spreads. Liquidity was a long observed but unidentified factor in determining CDS spreads though. Studies by Tang & Yang (2007) and Bongaerts et al. (2007) show that liquidity in the CDS market has a substantial impact on CDS spreads after controlling for firm-specific and market factors. Credit ratings are negatively related to CDS spreads. Thus, a downgrade of a firm's credit rating is associated with an increase in its CDS spread. Aunon-Nerin et al. (2002) find that a firm's credit rating provides important information for credit spreads. They also note that ratings have strong non-linearity, threshold effects and work better for lower than higher graded companies. Finally, in a recent study Das et al. (2009) show that accounting information has a potentially important role to play in predicting distress. Important accounting information, for example, are firm size, ROA, interest coverage, sales growth, book leverage, or retained earnings. Besides fundamental factors, macro-economic factors can provide additional information to explain variations in credit spreads. Collin-Dufresne et al. (2001), Schaefer & Strebulaev (2004), Amato (2005), Longstaff et al. (2005), Avramov et al. (2007), and Imbierowicz (2009) show that pure economic factors such as unemployment rate, inflation, industrial production, and indicators for expectations of future economic prospects (such as consumer confidence, business confidence, and market sentiment) provide important additional information in explaining credit spreads. Finally, Tang & Yan (2008) e.g. show that average credit spreads are decreasing in GDP growth rate, but increasing in GDP growth volatility. Moreover, the authors show that spreads are negatively related to market sentiment, i.e. spreads are lower when investor sentiment is high and vice versa.

Research on the pricing and tracking ability of structural models is still very limited though, which is a major motivation of my study. While there have been some studies (Bedendo et al., 2008; Imbierowicz, 2009) that estimate spreads with the help of structural models, there is no up-to-date study that makes use of the new findings from prior research. Therefore, this study estimates spreads with the help of an advanced version of the CreditGrades model, which uses implied equity volatilities. I test for the model's performance by comparing the estimated spreads to empirical observed market spreads. In particular, I estimate spreads for 107 North-American investment grade and high-yield grade obligors and compare these spreads with market spreads over a time period ranging from January 2004 to August 2009. This makes this study to the most extensive one to date. Moreover, there is no study to date that explicitly researches any model's performance during the financial crisis, which is another major motivation of this study. In a next step I try to determine the sources of the deviation (or gap) between market and model spreads. I provide important insights into what factors are important determinants of the gap and, in turn, of market and model spreads. I further investigate whether there are differences in sub-periods or among credit rating classes.

The contribution of this study is three-fold. First, the study is the first study that explicitly examines the pricing and tracking ability of a structural model during the financial crisis. I do provide new insight into the pricing performance of the model during the crisis period and extend Imbierowicz' (2009) results by using option-implied volatilities. Second, the study provides a comprehensive survey of all identified factors to date, which are missing in structural models. Furthermore, most of these factors are used as control variables in order to determine the sources of the gap between market and model spreads. Thus, the study provides important insights into the significance of factors, especially in light of the underlying credit rating class as well as different sub-periods. Third and finally, the study provides an up-to-date view to practitioners of how the most advanced structural model performs in pricing CDS spreads, especially during a crisis period.

The remainder of this paper is organized as follows. Section II provides an introduction to credit default swaps. Section III reviews the current body of research on structural models, determinants of CDS spreads, the pricing ability of structural models, and the application of these models in trading exercises. Section IV presents the chosen model while Section V provides an overview of my dataset. Section VI outlines the empirical results starting with an analysis of market and model spreads. Afterwards, determinants of the gap are analyzed using panel regression analysis, followed by a discussion of the results. Finally, Section VII concludes the study and summarizes the main findings, outlines the study's contribution, presents important limitations, and gives suggestions for future research.

II. Credit Default Swaps

This section provides an overview of what credit default swaps are, how they are priced, and the overall credit derivatives market. In general, credit derivatives, which were first introduced during the early 1990s, are privately held, negotiable, bilateral contracts whose payoff is conditional on the occurrence of a credit event. A credit event, in turn, is usually characterized with respect to an asset's or reference entity's bankruptcy, failure to pay, obligation default, obligation acceleration, repudiation/moratorium, restructuring, ratings downgrade below a certain threshold[2], and changes in the credit spread[3] (Schönbucher, 2003). Credit derivatives are mainly used by banks, hedge funds, insurance companies, and large corporations to transfer and repackage credit risk (Das, 2005). Other purposes of credit derivatives are speculation, hedging, and diversifying to taxation issues (Tavakoli, 2001).

While constrained and less liquid in the beginning, the introduction of new products (and in particular credit default swaps in the latter part of the 1990s) has triggered a tremendous growth in the credit derivatives market. In fact, the credit derivatives market surpassed the equity derivates market in the beginning 2003, while it surpassed the equity derivatives market by factor six in the end of 2007. The growth since the beginning of the century can also be explained with the fact that "credit remained one of the major components of business risk for which no tailored risk-management products existed" (J.P. Morgan, 1999, p. 7). Therefore, "fixed income derivatives introduced the ability to manage duration, convexity, and callability independently of bond positions; credit derivatives complete the process by allowing the independent management of default or credit spread risk".

A) Definition

A credit default swap is a privately traded contract used to insure against a borrower defaulting on debt or to speculate on their credit quality. Thus, a CDS is a means of transferring credit risk between counterparties. The protection buyer (from now on "buyer" for simplicity) pays the protection seller (from now on "seller" for simplicity) a periodic premium to insure against a credit event by a reference entity until maturity of the contract or the credit event, whatever happens first. The periodic fee is often paid quarterly and the typical maturity of the most liquid contracts is five years, with four maturity dates: 20th

[2] Only for ratings-triggered credit derivatives
[3] Only for credit spread-triggered credit derivatives

March, 20th June, 20th September, and 20th December. “This standardization of maturities has increased the liquidity of CDS contracts and as a result has attracted more participants” (Merrill Lynch, 2006, p. 12). The notional amount of the contracts is usually \$10 million. Moreover, CDS spreads are quoted in basis points per annum of the contract’s notional amount. For example, a CDS spread of 380 bps for five-year General Motors debt means that default insurance for a notional amount of \$10 million costs \$380,000 p.a. This premium is paid quarterly, i.e. \$95,000 per quarter.

Another important feature of CDSs is that the underlying reference entity has not to be owned by the protection buyer. Therefore, CDSs are often used for speculative purposes. Figure 1 (Merrill Lynch, 2006, p.12) shows the pre-credit event cash flows of a CDS contract while Figure 2 (Merrill Lynch, 2006, p. 12) shows the cash flows of a credit event.

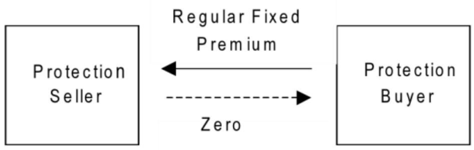


Figure 1 – Pre-Credit Event Cash Flows (Source: Merrill Lynch)

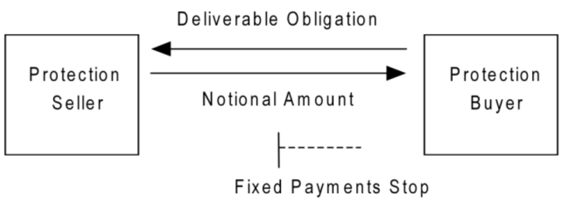


Figure 2 – Cash Flows from Credit Event (Physical Settlement) (Source: Merrill Lynch)

As can be seen in Figure 1, if there is no credit event the only cash flows flowing are the premium payments the buyer is obligated to pay to the seller. However, in the credit event (Figure 2) the seller is obligated to pay the notional amount of the contract to the buyer while the buyer has to deliver any qualifying debt instrument of the reference entity (Merrill Lynch, 2006, p. 11). Moreover, the buyer can stop paying the periodic fee, of course. This is an example of a physical settlement, which is explained in more detail in the next paragraph. What should be noticed in the credit event is that the claims on the reference entity are usually trading at a deep discount or can become completely worthless. However, there is a chance for the seller to recoup some money in case there is a recovery value. The seller’s net loss then amounts to the difference between the payment of the notional amount to the buyer and the recovery value of the bond plus the periodic payments received from the buyer. In this way the protection buyer "has effectively received credit protection on this price deterioration" by means of the CDS contract.

When it comes to the credit event this usually means the default of a company on the underlying entity, i.e. usually a corporate bond. The settlement of the contract can take different forms. Among the most common forms are the physical settlement and the cash settlement. Physical settlement, as indicated above, most often occurs in single-name CDSs. In this case, the buyer has to deliver any qualifying senior unsecured paper of the reference entity to the seller while the seller pays the notional amount in return. Additionally, all future payments of the buyer are terminated at this point. In a cash settlement, the seller pays the buyer the difference between the face value and the market value of the underlying. Cash settlements are most likely to occur when physical delivery is not possible, which happens when the obligor did not issue enough bonds. Also, cash settlements are the most common form when trading CDS indices and tranches.

B) Pricing

The value of a CDS is comprised of two components, namely the premium that is paid by the buyer and the credit protection. The present value of the CDS premium payment is given by

$$E^{Q}\left[c(0,T)\int_0^T\left(exp\left(-\int_0^s(r_u)du\right)1_{\{\tau>s\}}\right)ds\right], \tag{3.1}$$

where c(0,T) is the annual premium known as the CDS spread, T is the CDS contract's maturity, r is the risk-free interest rate, s is the bond's maturity and τ is the default time of the obligor. Assuming independence between the default time and the risk-free interest rate, Equation 3.1 can be written as

$$c(0,T)\int_0^T\left(P(0,s)q_0(s)\right)ds, \tag{3.2}$$

where P(0,s) is the price of a default-free zero-coupon bond with maturity s and $q_0(s)$ is the obligor's risk-neutral survival probability, $P(\tau > s)$, at $t = 0$.

Next, the present value of the credit protection is given by

$$E^Q\left[(1-R)exp\left(-\int_0^T (r_u)du\right)1_{\{\tau<T\}}\right], \qquad (3.3)$$

where R measures the recovery of the bond's market value as a percentage of par in the event of default. Making the assumption of independence between the default time and the risk-free interest rate as before and assuming a constant R, the expression can be written as

$$-(1-R)\int_0^T \left(P(0,s)q'_0(s)\right)ds, \qquad (3.4)$$

where $-q'_0(t) = -dq'_0(t)/dt$ is the probability density function of the default time. The CDS spread is determined by setting the value of the contract to zero, i.e. setting Equation 3.2 equal to Equation 3.4

$$0 = c(0,T)\int_0^T \left(P(0,s)q_0(s)\right)ds + (1-R)\int_0^T \left(P(0,s)q'_0(s)\right)ds \qquad (3.5)$$

and hence

$$c(0,T) = -\frac{(1-R)\int_0^T \left(P(0,s)q'_0(s)\right)ds}{\int_0^T \left(P(0,s)q_0(s)\right)ds}. \qquad (3.6)$$

C) Global Credit Derivatives Market

Data is obtained from the International Swaps and Derivatives Association's (ISDA) most recently updated semi-annual derivative markets survey (ISDA, 2009a). In compiling the data, ISDA surveys its member firms to respond with credit default swap data. More than 80 firms responded in the most-recent release. Credit derivatives data includes CDSs, baskets, and portfolio transactions indexed to single-names, indices, baskets, and portfolios. "ISDA adjusts the results to reflect double-counting amongst the dealer community", a common mistake by which the notionals outstanding are often overstated.

i. Evolution and Development

The credit derivatives market is mostly concentrated in New York (USA) and London (UK) which represent about 70% of trading volume (BBA, 2006). The market has been characterized by tremendous growth over the last decade, peaking at a market size of more than $60 trillion in the end of 2007 (Figure 3). Moreover, what becomes apparent is the high annual growth rate from the end of 2001 to the end of 2007, nearly doubling the amount of notionals outstanding each year. When comparing the credit to the equity derivatives market one sees that the former became six times as large as the latter in the end of 2007.

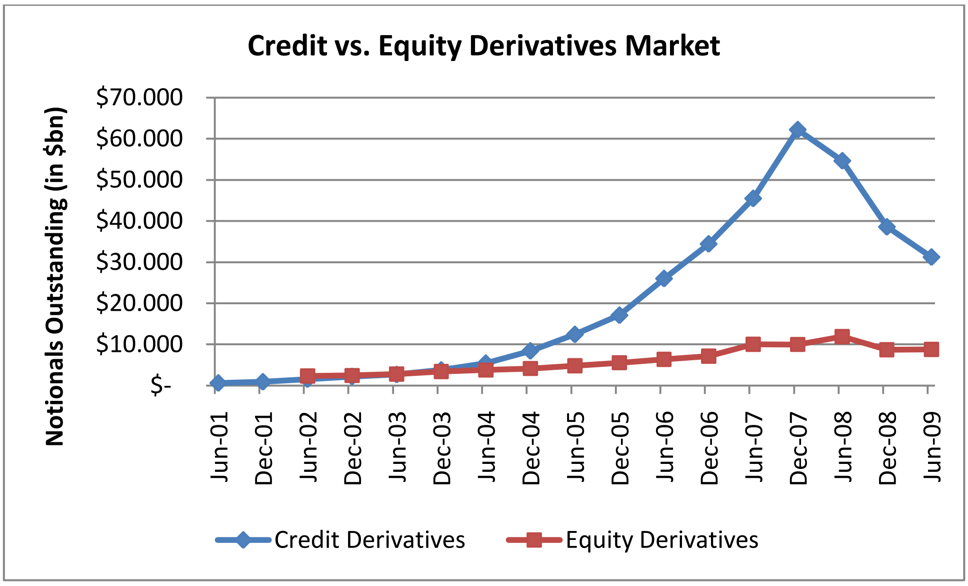


Figure 3 – Comparison of Growth in Credit Derivatives and Equity Derivates Market

While the equity derivatives market stayed at a constant level over recent years, the credit derivatives market decreased in size from its peak in the end of 2007. The decrease in size can be attributed to a range of activities, but "primarily [is] a result of trade compression and portfolio reconciliation" according to ISDA (2009b). Moreover, "auctions and settlements of the series of credit events, including Fannie Mae, Freddie Mac and Lehman Brothers, have proceeded smoothly".

A related aspect, which is illustrated in Figure 4, is the fact that costs of "protection against default has risen sharply as a result of the global credit crunch, as well as the growing risk of corporate defaults in a weakening economy" (ISDA, 2009b). Besides the above-mentioned activities, improving economic conditions helped reducing spreads to lower levels when compared to the peaks in the end of 2008, because defaults have become less likely. However, spreads are still a lot higher when compared to pre-crisis levels.

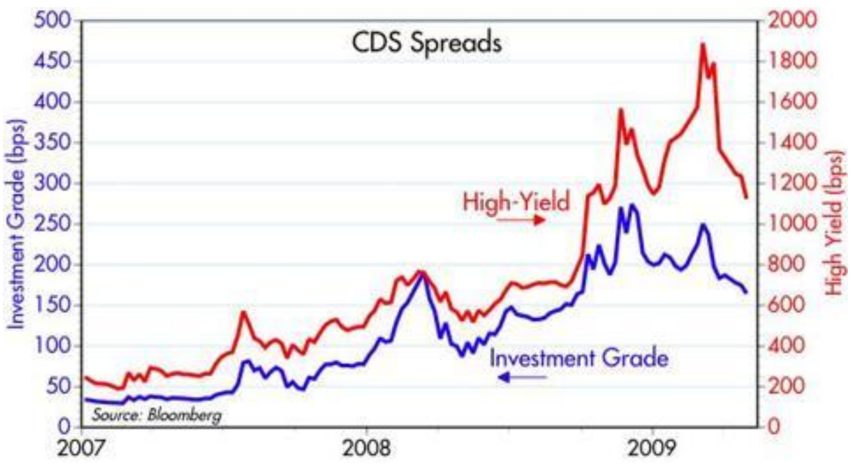


Figure 4 – CDS Spreads for the CDX.NA.IG and CDX.NA.HY Index (Source: Bloomberg)

ii. Composition

While the size of the CDS market seems large it still represents only about 7% of the total derivatives market. This is illustrated in Figure 5. Moreover, the composition of the credit default swap market is depicted based on numbers provided by the Office of the Comptroller of the Currency (OCC, 2009). The one to five year contracts represent the majority of contracts, accounting for 64% of outstanding contracts. Moreover, contracts of all tenors that reference investment grade entities (referred to as "IG" in Figure 5) are 65% of the market, while high-yield contracts (referred to as "HY" in Figure 5) account for the remainder.

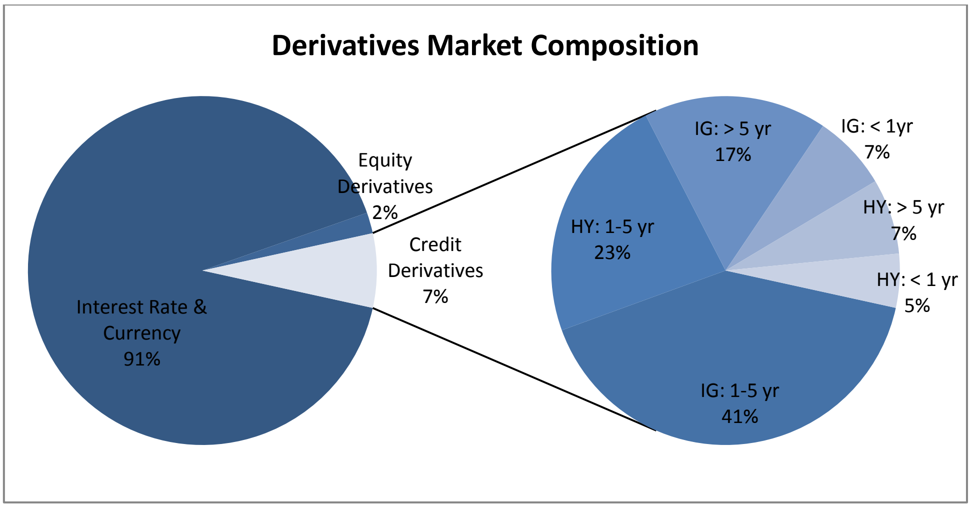


Figure 5 – Market and Credit Derivatives Composition by Grade and Maturity (IG = Investment Grade; HY = High-Yield)

iii. Product Range

Next to the tremendous growth in the credit derivatives market, the diversity of the product range has been growing, too (BBA, 2006). As can be seen in Figure 6, there has only been one major product in 2000 and 2002, namely single-name CDSs. However, starting in 2004 other diverse products were introduced, amongst which the most important products are full index trades, synthetic collateral debt obligations (CDOs), and tranched index trades. In fact, while single-name CDSs accounted for more than 50% in 2004, its share decreased to below 30% in 2008. The main reason for this trend is the rapid expansion of index trades and tranched index trades, which accounted for a combined portion of more than 39% in 2008.

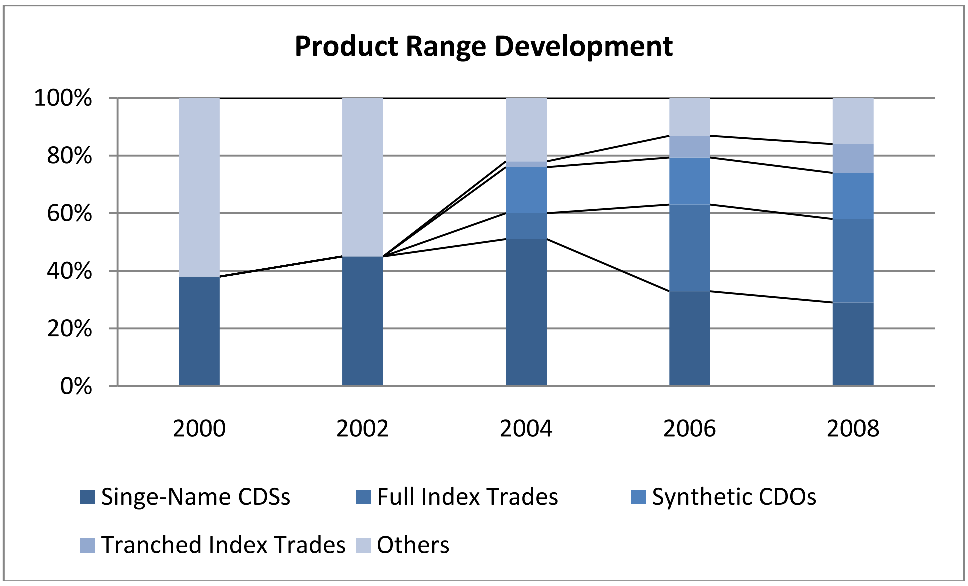


Figure 6 – Product Range Development from 2000 to 2008

iv. Market Participants

The main market participants have traditionally been banks and they "still constitute the majority of market participation" (BBA, 2006). However, since the evolution of new products and the recent growth in the credit derivatives markets, other institutions such as hedge funds, insurance companies, pension funds, and other corporates have been actively involved in the market. Especially hedge funds have become a major force in the market because of a new popular trading strategy, called capital structure arbitrage, which will be explained in more detail later on. Suffice to say at this point is that the hedge funds' "share of volume in both buying and selling credit protection [has] almost doubled since 2004".

D) Conclusion

This section has introduced the reader to the broad topic of credit default swaps. Definitions and a pricing formula were provided. Moreover, this section illustrated the importance of the global credit derivatives market. The composition of the market, different products within the market, and major market participants have been presented. This section sets the overall framework for the remainder of the thesis and the reader should now have an understanding of the intuition behind CDS contracts and their pricing. The next section reviews the existing literature regarding theoretical determinants of CDS spreads, different approaches in modeling CDS spreads, empirical evidence regarding the pricing performance of these models, and a trading strategy based on the link between equity and credit markets.

III. Literature Review

The literature review focuses on four important and interrelated areas in the field of credit pricing and provides the basis of my analysis. I will review the empirical evidence regarding factors that determine CDS spreads, which are not yet incorporated in structural pricing models. Next, I will review credit pricing models and provide the intuition and an overview of the landscape of these models. Moreover, evidence regarding the pricing ability of credit pricing models will be reviewed followed by a short overview of the profitability of trading strategies based on structural models. In this way, the foundation of answering the question of how well the chosen structural model is able to price CDS spreads is set. Moreover, in giving an overview of determinants of CDS spreads the stage for the second part of my research, i.e. analyzing the gap between market and model spreads, is set.

A) Overview of Credit Pricing Models

Credit risk modeling has become a major area in research and practice in the last decades since it represents a major part of risk management systems within companies, especially banks. Most models try to estimate the probability of default of a given company because this is the most important and uncertain variable in lending decisions. In this section the two major paths, i.e. structural models and reduced-form models, and associated models that developed over time are reviewed and introduced. A third path has recently developed, which employs both fundamental and accounting data. These models are called information-based models but are out of the scope of this thesis. Therefore, I only review the literature regarding structural and reduced-form models.

i. Structural Models – Merton’s Model

Structural models use fundamental firm data such as equity value, leverage ratio, and asset volatility in order to estimate credit spreads. The key insight in these models is that both equity and debt can be regarded as different contingent claims on the company’s assets and the value of these claims is similar to option contracts. In general, structural models consider default if the value of a company’s assets falls below a certain threshold associated with the company’s liabilities. Structural models assume full knowledge of very detailed information regarding the company, which implies that default is predictable. The main advantage of structural models is that they are based on sound economic arguments and that default is modeled in terms of firm fundamentals (Myhre et al., 2004).

The foundation of structural models has been set in the early 1970s, when Black and Scholes (1973) developed a model to price European options. Their approach is particularly attractive because only observable market factors are used to price these options. Both Black and Scholes and Merton (1973) recognized that this basic approach can be extended to corporate liabilities. Merton (1974) then introduced a model to price credit risk that considers equity and debt as contingent claims on the company's assets. Default occurs when the value of the company's assets is not sufficient to cover the company's liabilities at time of maturity. Thus, the following equation is central to the model because the value of debt can be derived from this basic relationship, as will be shown soon:

$$\text{Asset Value (A)} = \text{Value of Equity (E)} + \text{Value of Debt (B)}. \qquad (3.1)$$

Merton's approach (and others that follow) is therefore called 'contingent claim analysis' (CCA) and has become very important within the path of structural models.

Assumptions

Merton's model (1974) is developed along Black-Scholes lines and is based on the following assumptions:

- A.1 There are no transaction costs, taxes or problems with indivisibilities of assets.
- A.2 There are a sufficient number of investors with comparable wealth levels so that each investor believes that he can buy and sell as much of an assets as he wants at the market price.
- A.3 There exists an exchange market for borrowing and lending at the same rate of interest.
- A.4 There are no short-selling restrictions.
- A.5 Trading in assets takes place continuously.
- A.6 The Modigliani-Miller theorem holds in the sense that the value of the firm is invariant to its capital structure.
- A.7 The short-term risk-free interest rate is constant.
- A.8 The dynamics for the value of the firm through time can be described by a diffusion-type stochastic process.

Assumptions A.1 to 1.4 are basically "perfect market" assumptions and can be substantially weakened according to Merton (1974). In fact, Merton argues that only assumption A.5 and

A.8 are critical and these assumptions require that the market for these securities is open for trading most of the time and that price movements are continuous and that unanticipated returns on the securities be serially independent, which is consistent with the "efficient market hypothesis" of Fama (1970) and Samuelson (1965).

Pricing Formula

To obtain the pricing formula I first introduce a list of variables needed in the derivation:

E_0 = *present value of equity*
E_T = *value of equity at time T*
B_0 = *present value of debt*
B_T = *value of debt at time T*
D_0 = *present value of* D_T
D_T = *value promised to debt holders at time T*
A_0 = *present value of assets*
A_T = *value of assets at time T*

Suppose that a firm has only a single class of debt outstanding and the residual claim is equity. The debt issue is a zero-coupon bond that obliges the firm to pay a notional amount equal to D_T to bondholders on date T. If the payment cannot be met at time T, bondholders immediately take over control of the company and shareholders do not receive anything. Shareholders will wait until T before they decide on defaulting or not in order to not forgo the opportunity to gain from an increase in asset value and thus equity value. If the market value of assets falls below the book value of debt, the equity value becomes negative and shareholders will default on their investment but loose no more since they are not liable to the company. Moreover, since the value of assets does not completely cover the value of debt the firm is in default. Consequently, the default probability is the probability of the firm not meeting its promised debt payments on date T. This is illustrated in Figure 7.

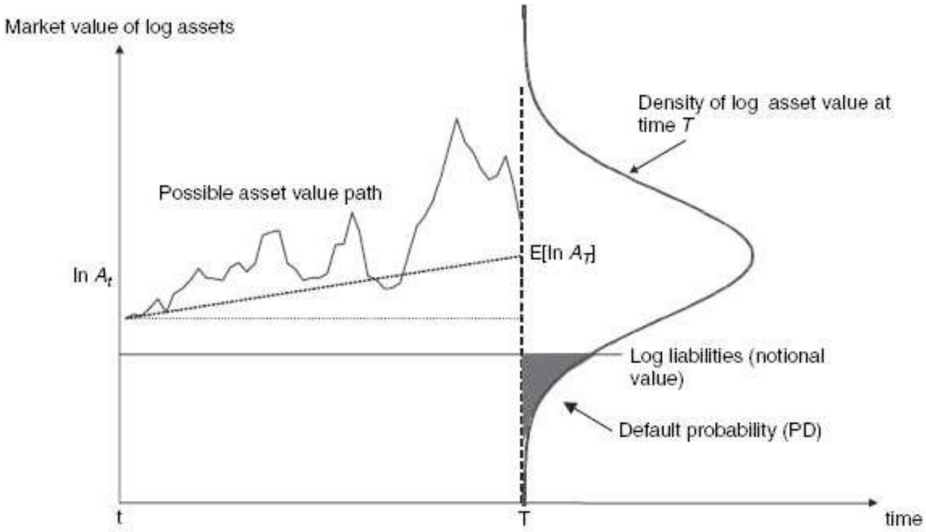


Figure 7 – Default Probability in Merton's Model (Source: Loeffler & Posch)

Furthermore, equity can be viewed as a call option on the company's market value of assets with a strike price equal to the book value of the company's debt at time T. The debt holders position can be represented by a written, i.e. sold, put option on the company's assets with a strike price equal to the debt payment at time T. This is illustrated in Figure 8.

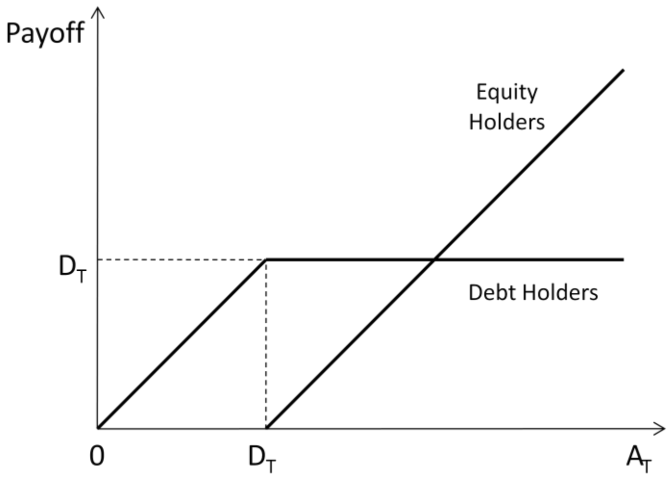


Figure 8 – The Value of a Company's Assets as Put and Call Option at Time T

As can be seen in Figure 8, the value of equity at time T is equal to

$$E_T = \max[A_T - D_T, 0] \tag{3.2}$$

and represents a long position in a call option with a strike price equal to the debt payment D_T at time T.

On the other hand, the bondholders' position is equal to

$$B_T = \min[A_T, D_T] \tag{3.3}$$

and represents a written put option on the market value of the company's assets with a strike price equal to the debt payment D_T at time T. Assuming constant volatility, the Black-Scholes pricing formulas for European call and put options can be used to derive pricing formulas for the firm's equity (3.4) and debt (3.6):

$$E_0 = A_0 N(d_1) - L\,N(d_2) \tag{3.4}$$

$$B_0 = A_0 - E_0 \quad ^{(4)} \tag{3.5}$$

$$B_0 = A_0[N(-d_1) + L\,N(d_2)] \tag{3.6}$$

where

$$d_1 = \frac{-\ln(D_T)}{\sigma_A\sqrt{T}} + 0.5\sigma_A\sqrt{T}$$

$$d_2 = d_1 - \sigma_A\sqrt{T}$$

and $L = D_0/A_0$.

Next, the value of the firm's total debt is defined either as

$$B_0 = D_T e^{-yT} \text{ or } B_0 = D_0 e^{(r-y)T}. \tag{3.7}$$

By substituting (3.7) into (3.6) and using $A_0 = D_0/L$, the yield to maturity of the bond is given

$$y = r - ln[N(d_2) + N(-d_1)/L]/T \tag{3.8}$$

Finally, it can be shown that the credit spread estimated by Merton's model is given by

$$s = y - r = -ln[N(d_2) + N(-d_1)/L]/T \tag{3.9}$$

The pricing of a credit spread under Merton's model therefore only depends on observable factors, i.e. the firm's leverage ratio (L), its asset volatility (σ_A), the bond's time to maturity

[4] Relationship first presented in Formula (3.1)

(T), and the risk-free rate (r). While Merton extended the Black and Scholes framework to account for coupon bonds, callable bonds, and stochastic interest rates, a major criticism is that default can only occur at the time of the bond's maturity, i.e. on the payment date T. The model does not consider the firm's asset value before maturity and therefore does not allow for an early default. For example, if a company's assets fall below a certain threshold but the firm is able to recover up to the maturity date, it would not default in Merton's approach. However, the firm would probably default on its debt or at least be insolvent and restructured in the real world. Therefore, many variations and extended models have been introduced later on, which will be presented next.

ii. Structural Models – Extensions

Due to the criticism many new models have been introduced to overcome the shortcomings of Merton's model. These models included more complicated debt securities to improve Merton's model, which limited the capital structure to equity and a simple zero-coupon bond. However, a firm's capital structure usually incorporates many different security classes and is therefore more complicated in reality. Moreover, other models included more sophisticated asset value processes and conditions that lead to a company's default.

Both Merton (1973) and Ross (1976) note that the Black-Scholes option pricing approach could be used to value other securities. Black & Cox (1976) extend Merton's model by introducing bond indentures, which are often found in practice. In particular, they look at the effects of safety covenants, subordination agreements, and restrictions on the financing of interest and dividend payments and find that these indentures do indeed introduce new features and complications into the valuation process. Furthermore, the authors look at the effects of bankruptcy costs and conclude that bond indentures increase the value of a bond. Another important aspect of their extension is that default can occur at any time when the stochastic process first hits a certain threshold, contrary to Merton's model in which default can only occur at the time of debt repayment. The Black & Cox model is thus called a 'first time passage' model and the default barrier can either be fixed or time varying.

Geske (1977, 1979) notes that corporations usually issue risky coupon bonds with finite lives that match the expected assets' lives being financed. He develops a formula that prices these risky discrete coupon bonds. Essentially, Geske views the firm's common stock as compound options on the firm when it has coupon bonds outstanding. Shareholders are given the option of buying a new option by paying the coupon to bondholders every time coupon payments are due until the final payment. If they decide not to pay the coupon they forfeit the company to bondholders. The final option gives shareholders the right to buy back the company by paying bondholders the notional amount of the bonds outstanding. Finally, Geske also extends the model by incorporating bond characteristics such as sinking funds (which is a method by which a firm sets aside money over time to retire its indebtedness), safety covenants, debt subordination, and payout restrictions.

Criticism regarding Merton's assumption of a constant and flat term structure is addressed first by Jones et al. (1984). The authors argue that "there is evidence that introducing stochastic interest rates, as well as taxes, would improve the model's performance" (Jones et al., 1984, p. 624). The introduction of stochastic interest rates allows for a correlation between interest rates and asset value and has been considered by Nielsen et al. (1993) and Longstaff & Schwartz (1995). Shimko et al. (1993) examine the combined effects of term structure variables and credit variables on debt pricing. The authors address the problem of constant interest rates by using Vasicek's (1977) stochastic interest rates environment, in which interest rates follow a mean-reverting process with constant volatility. They find that the credit spread is an increasing function of the risk-free term structure volatility. The correlation between interest rates and asset value may have a positive or negative effect on the credit spread and is an important variable in determining the credit spread on risky debt.

Longstaff & Schwartz (1995) also address the problem of constant interest rates and extend the Black & Scholes model by letting the risk-free interest rate be stochastic and using dynamics as proposed by Vasicek (1977). In this way, the value of assets interacts with a stochastic risk-free interest rate. Like all extensions presented thus far, the authors use an exogenous default barrier, which is mostly equal to the debt principal value or is triggered when a firm is unable to cover interest payments. Longstaff & Schwartz use the Black & Cox (1976) approach and add a pre-determined default barrier to the original Black-Scholes model. This allows a default to occur prior to debt maturity if a certain threshold was hit. The model has "great advantages over the Merton model as it relaxes some of the assumptions made [and] allows for a correlation between the Brownian motion of the firm value and the risk-free interest rate in Vasicek" (Myhre et al., 2004, p. 9). Unfortunately, Longstaff & Schwartz only provide an approximation to the proposed solution.

Leland (1994) was amongst the first who introduced an endogenous default boundary to the model. He models the company's asset value endogenously by incorporating factors such as firm risk, taxes, bankruptcy costs, risk-free interest rates, payout rates, and bond covenants. The optimal asset value at which the firm should declare bankruptcy is determined by using these factors. In this setting, “bankruptcy is triggered (endogenously) by the inability of the firm to raise sufficient equity capital to meet its current debt obligations” (Leland, 1994, p. 1214). Leland & Toft (1996) improve Leland’s original model by relaxing the assumption of infinite life debt, i.e. firms can decide on both the amount and the maturity of its debt. Again, bankruptcy is determined endogenously and depends on the maturity of debt as well as its amount. Their model can be used to a “much richer class of possible debt structures and permit[s] study of the optimal maturity of debt as well as the optimal amount of debt” (Leland & Toft, 1996, p. 987). Therefore, the model can be used to determine optimal leverage and risky corporate bond prices.

While all prior models use a diffusion process to model the evolution of the firm value, Zhou (1997) uses a jump-diffusion process, which allows a firm to instantaneously default because of a sudden drop in firm value. This approach solves the problem of zero credit spreads for short-term debt, which are the result of the diffusion process. If a firm cannot default instantaneously its probability of default should be close to zero and therefore short-term spreads near zero, too. However, short-term spreads are not close to zero in reality. By using a jump-diffusion process Zhou incorporates sudden drops in the asset value.

One of the most recent credit-pricing models is the CreditGrades (2002) model that was developed by the CreditRisk Group and three major investment banks. The model is a closed-end form model that is based on Merton’s and Black & Cox models. It has quickly become the industry standard and is very popular amongst investors because of its simple implementation. The CreditGrades model only needs some observable inputs to determine credit spreads. Simplicity and being the industry standard represent the two most prominent reasons for using the model in this research. A detailed description of the model and its extensions will be provided in Section IV.

Finally, Hull et al. (2004) provide an extension of Merton’s model that incorporates two implied option volatilities to model credit spreads. Thus, it relates the volatility skew, defined as the difference between an out-of-the-money option volatility and an at-the-money option volatility with the same strike price, to credit spreads. The authors use two-month at-the money and out-of-the-money put options to define two distinct relationships between asset volatility and leverage. Solving these two equations for asset volatility and leverage thus provides a way to entirely estimate credit spreads from equity markets data since no balance sheet data is needed anymore.

iii. Reduced-Form Models

Critics against the structural model approach argue that time to default will be a predictable stopping time because of the continuing diffusion process. Thus, if time to maturity approaches zero, credit spreads should also approach zero. However, this is clearly not the case in the real world and is also not consistent with empirical evidence. Therefore, another path has developed, namely the path of intensity-based or reduced-form models. A major difference between structural models and reduced-form models is the assumed information set available to the modeler. While structural models assume full knowledge of a particular firm, reduced-form models assume that the modeler has the same information available as the market, i.e. incomplete knowledge of the firm. Therefore, these models do not use fundamental firm data and default is modeled as an "unpredictable Poisson event involving a sudden loss in market value so default events can never be expected" (Zhou, 1997, p. 2). Figure 9 (Quant Notes, 2009)) shows a simulation of a standard Poisson process with a restriction on the jump size, i.e. the jump size is limited to one. The figure illustrates that changes occur instantaneously from one value to another at random times.

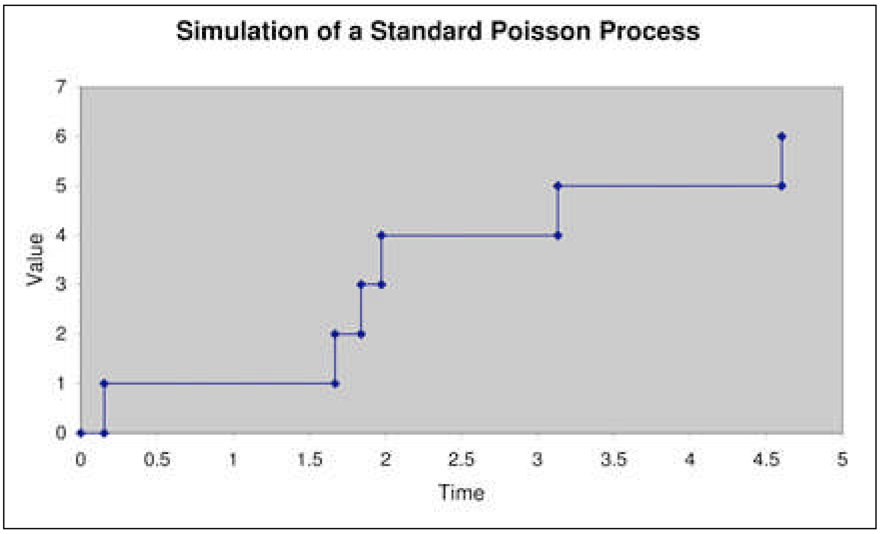


Figure 9 – Standard Poisson Process with Jump Size equal to One (Source: Quant Notes)

Default is modeled as exogenously defined instead of linking it to the company's capital structure as is the case for structural models. The instantaneous rate of default is also known as hazard rate or default intensity.

It follows a short overview of the major models that were introduced in this path of research. Basically, two models have developed over time: The first reduced-form model was introduced by Jarrow & Turnbull (1995) while the other model has been proposed later by Duffie & Singleton (1999). Jarrow & Turnbull model default as exponentially distributed and a constant loss given default (LGD). Jarrow et al. (1997) extend the basic framework and assume that the default time is following a continuous-time Markov chain with different states that represent various credit ratings. Default occurs once the chain hits the default state. The flexibility in calculating parameters from observable data makes this model attractive. Duffie & Singleton view default as an unpredictable event attributable to the before-mentioned hazard rate process. The model differs compared to Jarrow et al.'s extension in that the contingent claim at the time of default is continuous-time specified. Finally, Duffie & Singleton (1997) show how a structural model can be transformed into a reduced-form model. In this model, the company's assets are assumed to follow a diffusion process with default triggered when the assets' value hits a default boundary.

Advantages include its tractability and its empirically more appealing pricing performance, which is based on easier calibration and flexibility to fit market spreads. A major disadvantage, however, is that default as well as the recovery process is taken as exogenously given and no economic arguments for default can be made. Therefore, structural models provide more useful insights on default behavior. Also, the implication that firms can only default "by-surprise" seems unrealistic as Zhou (1997) adds. Finally then, while reduced-form models are useful in comparing the relative value of different forms of credit, they cannot provide a view contrary to the market or estimate a price where no market exists (CreditGrades, 2002).

I do not test and interpret any reduced-form model in this research, which is why this part of the literature review is not as extensive as before. I believe that the structural model chosen in this study, i.e. the CreditGrades model, is economically more suitable and provides a better framework when testing for the relationship between equity and credit markets.

B) Determinants of CDS Spreads

As could be seen in the introduction to CDS pricing and in the review of structural models, amongst the factors that determine CDS spreads are the risk-free interest rate, the firm's leverage, and the firm's volatility. These factors are also important inputs in structural models. In general, the risk-free interest rate is negatively related to CDS spreads, i.e. an increase in the risk-free interest rate leads to a decrease in CDS spreads. This is because a higher risk-free interest rate raises the risk neutral drift and lowers the probability of default, which in turn leads to lower spreads (Alexander & Kaeck, 2008). An increase in a firm's leverage obviously increases the CDS spread since the probability of default rises. The default barrier is often assumed to be the book value of debt, but other definition may apply. Finally, using the firm's equity volatility and its leverage approximates firm or asset volatility. An increase in asset volatility will lead to a rise in the CDS spread because higher volatility increases the chance of hitting the default barrier.

Skinner & Townend (2002) were amongst the first who use regression analysis in order to test for structural variables and their explanatory power of credit spreads. They suggest five factors that should explain CDS spreads and find that the risk-free rate, yield, volatility and time to maturity are significant while the payable amount of the reference obligation in the event of default is insignificant. Later, Ericsson et al. (2009) test for the statistical and economically significance of the outlined factors and also find that they are important determinants of CDS spreads. The explanatory power of these variables on CDS spreads is approximately 60%.

Understanding the determinants of credit spreads is important for financial analysts, traders, and economic policy makers (Alexander & Kaeck, 2008). That is why researchers have focused on the above-mentioned inputs and proposed additional factors that should be included in structural models to improve their pricing performance. Many of these studies are based on Collin-Dufresne et al. (2001) who study the theoretical determinants of credit risk on corporate bond spreads. With the rapid development of the CDS market empirical research has, however, shifted towards the more liquid and standard CDS spreads as a measure of credit risk.

Credit Ratings

Credit ratings are negatively related to CDS spreads, as one would expect. Thus, a downgrade of a firm's credit rating is associated with an increase in its CDS spread. Aunon-Nerin et al. (2002) find that a firm's credit rating provides important information for credit spreads. The authors control for other structural factors such as the risk-free short rate, slope of the default-free yield curve, time to maturity, stock prices, historical volatility, leverage, and index returns. They confirm prior research in that they find that most of the variables predicted by credit risk pricing theories are statistically and economically significant and add that credit ratings provide another source of information that explains the variation in credit spreads. Overall, they can explain 82% of variation in CDS spreads. However, they also note that ratings have strong non-linearity, threshold effects and work better for lower graded companies than on higher rated obligors. They conclude that structural variables provide complementary information to ratings and can be seen as the most important source of information on credit risk, in particular when obligors are of lower credit quality.

Hull et al. (2004) study to what extent CDS spreads increase (decrease) before and after downgrade (upgrade) announcements. They use a dataset with 233,620 individual CDS spreads over a five-year period (1998 to 2002) and find that reviews of downgrades from major credit rating agencies contain significant information regarding CDS spreads; positive rating events are less significant. However, as one might expect, downgrades itself and negative outlooks do not have an influence on CDS spreads. Thus, the CDS market anticipates downgrades and negative outlooks once a review of a given firm's credit ratings has been announced. The authors conclude that CDS spreads predict negative rating events.

In another study, Daniels & Jensen (2004) confirm the results and find that credit ratings provide additional information after controlling for other significant factors such as short rate, slope, and most industry and time dummies. Finally, Zhang et al. (2009) test for other important determinants of credit risk as will be shown soon but also confirm Aunon-Nerin et al.'s (2002) results. They find that rating information is an important factor in determining CDS spreads. In their sample, rating information alone can explain about 56 percent of the variation in credit spreads.

Liquidity

Liquidity has been an important factor in asset pricing in general. Research on the impact of liquidity on equity markets (e.g. Amihud (2002) and Pastor & Stambaugh (2003)) has shown that stock returns contain significant liquidity premiums. The same is true for the corporate and Treasury bond market, as e.g. De Jong & Driessen (2005) and Li et al. (2009) show.

Liquidity was a long observed but unidentified factor in determining CDS spreads though. Many researchers have identified a common factor that explains a large part of the variation in CDS spreads but could not identify it. However, studies by Tang & Yang (2007) and Bongaerts et al. (2007) show that liquidity in the CDS market has a substantial impact on

CDS spreads after controlling for firm-specific and market factors. Fabozzi et al. (2007) uses theoretical determinants such as the risk-free rate, industry sector, credit rating, and liquidity factors in their study. They use a linear regression model that focuses on the liquidity factors and find that all factors have an influence on CDS spreads. They conclude that credit default swaps that trade with greater liquidity have a wider credit default swap spread.

Volatilities, Volatility Skews & Jump Risk

Byström (2005) studies the relationship between iTraxx CDS index changes and stock returns and finds that the stock market tends to lead the CDS index market. In a later study Byström (2006) compares market prices of iTraxx indices with CreditGrades model spreads and finds that spread changes are significantly correlated. Also, lagged model spread changes are correlated with current iTraxx spread changes. Alexander & Kaeck (2008) extend Byström's studies and find that CDS spreads display pronounced regime specific behavior. Using the iTraxx Europe indices the authors show that spreads are extremely sensitive to stock volatility during periods of CDS market turbulence. Spreads are more sensitive to stock returns rather than stock volatility in regular times. This is in line with earlier research where e.g. Yu (2005) showed that single-name CDS spreads might behave different during volatile CDS periods compared to ordinary periods.

Benkert (2004) was amongst the first who used regression analysis to study the effect of implied rather than historical volatilities on credit pricing. He uses single-name, five-year CDS spreads of 120 international borrowers from 1999 to 2002 and controls for factors such as credit rating, liquidity, leverage, historical volatility, and implied volatility. He finds that option-implied volatility is a more important factor in explaining variation in CDS spreads than historical volatility. Papers by Cremers et al. (2006) and Cremers et al. (2007) confirm Benkert's findings and additionally show that including the implied volatility skew[5] as determinant of market spreads to proxy for potential jump risk premiums in equity is important. It is now conventional wisdom that implied volatilities are superior to historical volatilities in explaining CDS spreads.

Zhang et al. (2009) base their study on Campbell & Taksler (2003) who find that recent increases in corporate yields can be explained by the upward trend in equity volatility. Zhang et al. find that volatility risk and jump risk are important determinants of CDS spreads. In

[5] In this study, the volatility skew is defined as the difference between two implied volatilities of two options with the same strike price but different maturities.

their study volatility risk alone predicts 50 percent of the variation in CDS spread levels. Realized jump risk alone forecasts 19 percent, while historical measures for jump risk account for only 3 percent. Together, volatility risk and jump risk can predict 54 percent in variation. After controlling for common factors such as credit ratings, macro-economic factors, and balance sheet data 77 percent of total variation in CDS spreads can be explained. The proposed factors apply equally to both investment grade and high-yield obligors.

Macro-Economic Factors

Several studies suggest that, besides fundamental factors, macro-economic factors can provide additional information to explain variations in credit spreads. Collin-Dufresne et al. (2001), Schaefer & Strebulaev (2004), Amato (2005), Longstaff et al. (2005), Avramov et al. (2007), and Imbierowicz (2009) show that pure economic factors such as unemployment rate, inflation, industrial production, and indicators for expectations of future economic prospects such as consumer confidence, business confidence, and market sentiment provide important additional information in explaining credit spreads. Finally, Tang & Yan (2008) e.g. show that average credit spreads are decreasing in GDP growth rate, but increasing in GDP growth volatility. Moreover, the authors show that spreads are negatively related to market sentiment, i.e. spreads are lower when investor sentiment is high and vice versa.

Accounting-Based Information

Das et al. (2009, p. 2) state: “Anecdotal evidence suggests that accounting information has a potentially important role to play in predicting distress. For example, the case of Enron is indicative of the possible pitfalls of relying exclusively on market information.” Therefore, the authors use a sample of 2,860 quarterly CDS spreads over the period from 2001 to 2005 to show that purely accounting-based models perform comparable to market-based structural models. Accounting variables included, for example, are firm size, ROA, interest coverage, sales growth, book leverage, or retained earnings. Both models are able explain about half of the variation in CDS spreads. More important, however, the authors find that both accounting-based and market-based information are complementary in pricing CDS spreads; a hybrid model using accounting-based and market-based information can explain three-quarters of the variation in CDS spread. Therefore, the authors conclude that that accounting information is value-relevant for users of credit derivatives.

C) Pricing Ability of Structural Models

As could be seen in the previous sub-sections several extensions and new factors have been introduced in order to improve the pricing accuracy of Merton’s model. Although a lot of researchers have focused on improving the model there has only been limited research conducted in the field of using market data. The difficulty in testing models lies in the complexity of real-world bonds, which have coupons, calls and sinking funds (Gemmil, 2001). Moreover, other complications and changing capital structures further increase the complexity. For these reasons, there is only limited empirical evidence regarding the pricing ability of structural models compared to market spreads. Moreover, most of the times yield spreads rather than CDS spreads have been tested although the overall conclusions remain valid for CDS spreads as Blanco et al. (2005) note. It follows a brief overview of the available evidence regarding the pricing ability of credit risk models.

i. Merton’s model

One of the first studies that tested Merton’s model is attributable to Jones et al. (1984). They implement Merton’s model by using Contingent Claim Analysis, meaning that the company’s liabilities are viewed as simple options. The authors find that the model consistently underestimates spreads and that it works better for high-yield bonds than for investment grade bonds. The same conclusions are reached by Lyden & Saraniti (2001) who find that Merton’s model underestimates by between 80 to 90 basis points. They compare Merton’s model to Longstaff & Schwartz’ (1995) model and find that the former more accurately predicts spreads than the latter. Thus, although the Longstaff & Schwartz model allows for early default and stochastic risk-free rates this does not improve accuracy. The authors also tried to improve accuracy by using industry average recovery rate with little success.

An extensive study has been conducted by Eom et al. (2005) who test five credit risk models – Merton (1974), Geske (1977), Longstaff & Schwartz (1995), Leland & Toft (1996), and Collin-Dufresne & Goldstein (2001) – by using a sample of 182 bond prices from firms with simple capital structures during the period from 1986 to 1997. They find (in line with Jones et al.) that Merton’s models in general predicts spreads that are too low compared to market spreads while the other models predict spreads that are on average higher than markets spreads. The newer models severely overstate the credit risk of firms with high leverage or volatility while underestimating spreads for safer bonds. Finally, all models perform poorly when estimating spreads for financial institutions.

A study by Gemmil (2002) stands out in that it uses a unique database of zero-coupon bonds issued by closed-end funds in the UK. The advantage of this dataset is that it includes only bonds that pay no coupon; each company only has one bond outstanding; and the bonds are liquidated at maturity. Therefore, this dataset overcomes the major obstacle of Merton's simplified assumptions of repayment in one go, which is highly unrealistic in the real world. Gemmil tests Merton's model using bonds over the period from 1992 to 2001 and finds contrary to previous research that model and market spreads are on average of similar magnitude. However, in line with previous empirical evidence he also finds that predicted spreads are lower than market spreads for bonds, which have low leverage and volatility, i.e. low risk, and that are close to maturity.

Hull et al. (2004) extend the original Merton model by including implied option volatilities. In their study, they find that there is a positive relationship between credit spreads and at-the-money volatilities as well as volatility skews in situations where volatility is high. Another study by Cremers et al. (2006) supports the finding for at-the-money volatilities but shows contrary to Hull et al. that there is a partly negative relationship between the credit spread and the historical volatility skew.

Other studies include Anderson & Sundaresan (2000) and Ericsson & Reneby (2003), who use variations of Merton's model and show that it is superior to reduced-form models but suffers from predicted spreads that are too low and almost negligible for short-term maturities (Khurana et al., 2003). I turn now to empirical evidence regarding of the pricing ability of the CreditGrades model, which is subject to tests in this research study.

ii. CreditGrades

Research on the CreditGrades model is very limited although it was originally introduced in 2002. A reason for the confined research in this area is that the credit default swap market developed only in the beginning of this decade and data availability represented a major obstacle. These two aspects, however, do not represent severe problems anymore, which is a major motivation for conducting this study and extending the research body in this area. The CreditGrades (2002) technical document provides some tests of the model and finds that historical volatility works best for higher grade firms in terms of their credit rating while spreads of lower quality obligors are estimated better when using option-implied volatilities. Byström (2006) published a study that examines the correlation between CreditGrades spreads and the iTraxx CDS index, which tracks the most liquid names in Europe and Asia.

His study suggests that the iTraxx CDS index lags behind model spreads and that both market and model spreads are highly autocorrelated.

In a recent paper Bedendo et al. (2008) compare market and model CDS spreads for a sample of 80 North American, non-financial, investment grade obligors over the period from 2002 to 2005. Model spreads are estimated using CreditGrades and implied volatilities. The authors find that model spreads display a significant correlation with market spreads, which is in line with Byström's study. The gap between model and market spreads widens substantially when equity volatility is high though. In particular, model spreads consistently overestimate market spreads in the more turbulent sub-sample from 2002 to 2003. Finally, the authors investigate various micro-economic and firm-specific determinants of this gap in order to highlight shortcomings of the model.

Finally, Imbierowicz (2009) investigates CDS model and market spreads over a period from 2002 to April 2008. He uses CDS data from all major markets (North America, Europe, Asia) and investment grade and non-investment grade obligors. Model spreads are estimated for a total of 759 firms from three different models: CreditGrades (2002), Leland & Toft (1996), and Zhou (1997). He finds that Zhou's model is best able to estimate spreads in some industries but also often substantially deviates from market spreads. The Leland & Toft and the CreditGrades model have about the same mean error in spread estimations and are closer to market spreads when looking at the entire sample and not only specific industries. Zhou's and Leland & Toft's model underestimate spreads for obligors with credit rating below B+ and BB-, respectively. For the remainder all models overestimate market spreads. Unfortunately, the author did only use historical volatilities in estimating credit spreads with the CreditGrades model while it has been shown earlier that implied volatilities substantially improve the model's performance. He also runs panel regressions to identify missing macro-economic factors that may explain the gap between model and market spreads. The results disclose the necessity to also account for possible market exaggerations when pricing CDS.

D) Trading Strategies

Fixed-income arbitrage strategies and other traditional hedge fund strategies have been popular but have suffered declining returns (Skorecki, 2004). Therefore, new trading strategies emerged amongst which capital structure arbitrage is one of the newer strategies that has not been researched in-depth thus far. In general, capital structure arbitrage exploits the mispricing of different security classes traded on the same capital structure, i.e. equity and credit default swaps. The arbitrageur is searching for relative value opportunities and uses a structural model to infer the richness or cheapness of a given CDS contract. By using the CreditGrades model, for example, the arbitrageur uses the market value of equity, a related volatility measure, and the liability structure of the obligor to compare the implied spread from the model with the market spread. If the market spread was substantially larger (smaller) than the model spread, he sells (buys) a CDS and sells (buys) equity to hedge. Then, if the market and the equity-implied spread converge the arbitrageur profits, while he loses if the market spread stays or widens.

Since the tremendous growth of the CDS market over the last decade, the topic has become important to both academics and practitioners. Many hedge funds, for example, have used this trading strategy in order to generate abnormal returns. Moreover, although it is called an arbitrage trading strategy, it is by no means a classic textbook example of arbitrage. There is a lot of risk inherent in single trades as prior research shows.

In a pioneering study, Yu (2006) conducts the first large-scale study regarding the profitability of capital structure arbitrage. He uses the CreditGrades model with 1000-day historical volatilities for 261 North American obligors over a period from 2001 to 2004. This yields 135,750 daily spreads. He finds that if there was a large divergence between markets the strategy leads to positive abnormal returns on the aggregate, i.e. if trades were made on a portfolio level. However, single trades can be extremely risky and can lead to severe losses as some case studies conducted by the author show. Moreover, most losses occur when the arbitrageur went short on the CDS but then finds out the market spread actually rapidly widens rather than contracts. This makes the equity hedge ineffective and the arbitrageur loses substantially.

In another study Bajlum & Larsen (2008) repeat the exercise using 221 North American obligors over a period from 2002 to 2004. They use both the CreditGrades model and Leland

& Toft's (1996) extended model. Moreover, they also focus on two major problems the arbitrageur faces when entering positions: model misspecification and mismeasured inputs. They find that timely key inputs, in particular the use of option-implied volatilities, are a lot more important than the structural model chosen and the assumptions regarding default and calibration. On the subject of the trading strategy the authors confirm Yu's results, i.e. the trading strategy is profitable on the aggregate but very risky on the individual level. However, in Bajlum & Larsen's sample the strategy is only profitable on the portfolio level if implied rather than historical volatilities are used. When using historical volatilities the excess returns are insignificant. Finally, profits are highest for high-yield obligors and cannot be explained from systematic market risk.

While there have been other studies (see for example Duarte et al. (2006), Rousseau (2007), Leclercq (2007), or Bedendo et al. (2008)), there is still a lot of room for further research. It may, for example, be interesting to investigate the profitability of the strategy using a longer time period, including the financial crisis where spreads sky-rocketed. Also, extended studies using implied volatilities may shed more light on the impact of more market-responsive factors in pricing models.

E) Conclusion

This section has outlined the determinants of CDS spreads as analyzed in various academic studies. Amongst the most influential factors are credit ratings, implied volatilities and skews, jump risk, liquidity and macro-economic factors. Furthermore, the two major paths, i.e. structural models and intensity-based or reduced-form models, of credit pricing models based on equity behavior have been described. Structural and reduced-form models both have advantages and disadvantages, but in my opinion structural models are better suited for this study. That is why the CreditGrades model is used in this research and why only the pricing ability of structural models has been presented in this literature review. Finally, to put the topic of credit pricing into perspective a review of capital structure arbitrage – a popular trading strategy amongst hedge funds and other financial institutions – has been provided. The stage is now set for a detailed look at the CreditGrades model.

IV. Model Choice

Many different extensions of structural models have been presented in the previous section. There are many appealing approaches and due to the introduction of the widely-known and easy to use CreditGrades model, every investor can easily estimate credit spreads based on their own assumptions. In this section, some arguments for using the CreditGrades model in this study are presented. After that, there is a more detailed explanation of the model itself followed by some of the advancements suggested by other researchers. Finally, the calibration process and important parameters are described.

A) Rationale

Structural models have some disadvantages compared to reduced-form models as became apparent above. However, while reduced-form models are useful for comparing the relative value of different forms of credit they cannot provide a contrary to the market or suggest a price where no market exists. Thus, I believe that the structural models' advantages of easier implementation and their link to economics and firm fundamentals provide more insights in this study. That is why I use the CreditGrades model to test for its pricing ability over a period of almost five years (including the financial crisis) in this study.

There are some studies that test for the pricing ability of structural models but compared to other research areas the number of available studies in this area is very limited. As was presented in the literature review there are only very few studies that put structural models at work and test for their ability to track or predict market movements. While it is sometimes very difficult and complex to implement some of the proposed extensions, the CreditGrades model is easy to implement and calibrate. This is one of the reasons why I chose to use this model. Moreover, although popular there are only few studies that explicitly investigate the model's pricing ability. Most of these studies, however, are rather outdated and only cover the period up to mid-2000; there is no single study to date that has tested the CreditGrades model amid the financial crisis. While Imbierowicz (2009) has tested the CreditGrades model (amongst others) up to April 2008 he did not employ option-implied volatilities, which is a major drawback especially during turbulent times since historical volatilities are slower to respond to rapid market movements. Therefore, I want to expand the current literature by providing updated results regarding the CreditGrades model's pricing ability using implied volatilities and its ability to correctly predict market directions in turbulent periods.

B) CreditGrades

i. Original Model

The CreditGrades model is a structural model based on Merton's framework (1974) introduced before. It was jointly developed by Deutsche Bank, Goldman Sachs, J.P. Morgan, and RiskMetrics. The model is "designed to track credit spreads well and to provide a timely indication of when a firm's credit becomes impaired" (CreditGrades, 2002). Since the model is relatively simple to implement in that it uses only information from broad and liquid markets it has become attractive to both academics and practitioners. Thus, the CreditGrades approach is more practical than other models because it uses simple formulas combined with only a small number of inputs, which are readily observable.

Merton (1974) assumes that default occurs when the firm's asset value falls below its debt value. The main assumptions of the CreditGrades model are based on the same notion and are illustrated in Figure 10 (CreditGrades, 2002).

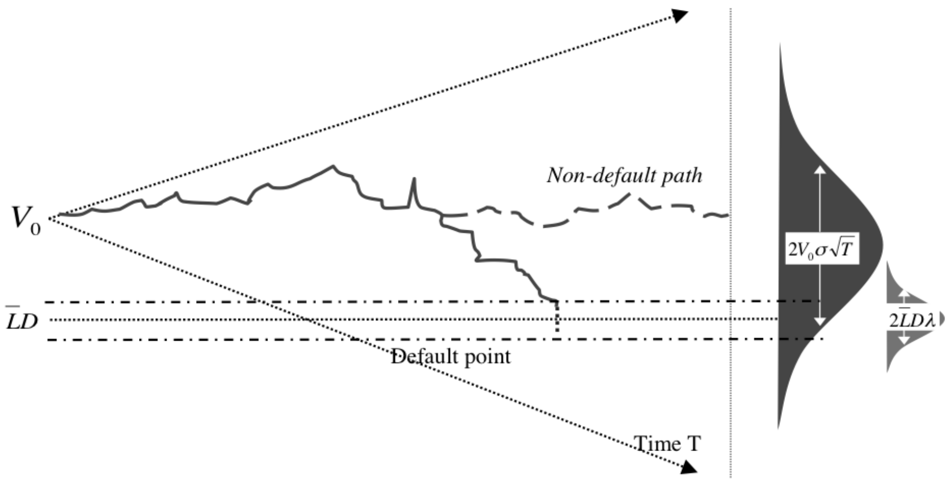


Figure 10 – CreditGrades Model Description (Source: CreditGrades Technical Document)

The firm value is defined as the sum of its equity and its debt. Similar to Merton, the asset value is assumed to follow a geometric Brownian motion process[6]

$$\frac{dV_t}{V_t} = \sigma dW_t + \mu_D dt \tag{4.1}$$

[6] The solution to this stochastic differential equation is $V_t = V_0 e^{\sigma W_t - \sigma^2 t/2}$ when μ=0 (Neftci, 2000)

where W_t is a standard Brownian motion, σ is the asset volatility and μ_D is the asset drift. The asset value is assumed to have zero drift, i.e. $\mu_D=0$, as it is assumed that the firm would issue debt to keep the leverage level steady over time.

A stochastic process is supposed for the default barrier LD, which is in contrast to Merton's model, which uses a fixed default barrier. The default barrier is defined as the average debt recovery rate $\bar{L}$ times the company's debt per share D, i.e. the amount of a firm's assets that are available to debt holders in the event of default. It is assumed that the recovery rate L follows a lognormal distribution with mean $\bar{L}$ and percentage standard deviation λ. The barrier is independent of the underlying asset process and is modeled as

$$LD = \bar{L}De^{\lambda Z-\lambda^2/2} \tag{4.2}$$

where Z is a standard normal variable. In this way, uncertainty in the actual level of debt is modeled. There is some true level of L that does not evolve over time, but that cannot be observed with certainty. Therefore, with an uncertain recovery rate the default barrier can be hit unexpectedly, resulting in a jump-like default event. Default occurs when the asset value crosses the default barrier for the first time. This is one of the major improvements over Merton's models, which incorporates a fixed default barrier, thereby not allowing for jump-like defaults and thus creating unrealistic short-term spreads.

The survival probability P(t) (Lardy et al., 2000) of a company is based on the firm's ability to pay its total debt service, i.e. the asset value's probability of not reaching the default barrier before time t. Based on the above assumptions, the closed-form approximation for the survival probability P(t) is

$$P(t) = \Phi\left(-\frac{A_t}{2}+\frac{\log(d)}{A_t}\right)-d*\Phi\left(-\frac{A_t}{2}-\frac{\log(d)}{A_t}\right) \tag{4.3}$$

where

$A_t^2 = \sigma^2 t + \lambda^2$,

$d = \frac{V_0}{\bar{L}D}e^{\lambda^2}$ with $V_0 = S_0 + \bar{L}D$

and Φ() is the cumulative normal distribution function[7].

[7] I adopt the convention that log denotes the natural logarithm.

Asset volatility can be approximated by

$$\sigma = \sigma_S * \frac{S}{S + \bar{L}D} \tag{4.4}$$

where S is the firm's equity price (per share) and σ_S is the equity volatility.

In order to derive a credit spread two additional inputs are needed: the risk-free interest rate and the recovery rate R on the underlying credit. R is different from $\bar{L}$ since it specifies the expected recovery rate on a firm-specific debt class while $\bar{L}$ is the expected recovery rate averaged over all debt classes. Thus, the asset-specific recovery rate R for an unsecured debt obligation is likely to be lower than $\bar{L}$ because it includes also secured debt, which has a higher recovery rate.

Now that all inputs have been specified, one can solve for the credit spread as was illustrated in the section about CDS pricing, i.e. solving for the continuously compounded spread c(0,T) such that the expected premium payments on the CDS equal the expected loss payments. Thus, when the CreditGrades survival probability is known, the theoretical spread is equal to

$$c(0,T) = r(1-R)\frac{(1 - P(0) + Ht)}{P(0) - P(T)e^{-rT} - Ht} \tag{4.5}$$

where Ht equals

$$Ht = e^{\frac{r\lambda^2}{\sigma^2}}\left(G\left(T + \frac{\lambda^2}{\sigma^2}\right) - G\left(\frac{\lambda^2}{\sigma^2}\right)\right)$$

and the function G is given by Rubinstein & Reiner (1991)

$$G(T) = d^{z+0.5} * \Phi\left(-\frac{\log(d)}{\sigma\sqrt{T}} - z\sigma\sqrt{T}\right) + d^{z+0.5} * \Phi\left(-\frac{\log(d)}{\sigma\sqrt{T}} - z\sigma\sqrt{T}\right)$$

with $z = \sqrt{0.25 + 2r/\sigma^2}$.

Byström (2005) and Myhre et al. (2004) point out that the CreditGrades model represents a simplified but powerful version of Merton's model. It uses simple closed-form formulas combined with robust approximations, which are all based on observable parameters. For a more elaborate explanation of the credit spread calculation please refer to the CreditGrades Technical Document (2002).

ii. Advanced CreditGrades

The major drawback of the CreditGrades model in its original form is its reliance on historical volatility data. As researchers found out that option-implied volatilities improve the pricing ability and the ability to track and predict market directions, the CreditGrades model was extended. Stamicar & Finger (2005) provide three extensions of the original model, which are called market-based approaches. The authors provide a framework with which it is possible to back out the asset volatility and leverage of a given firm using only market data, i.e. two option-implied volatilities (one at-the-money (ATM) put option and one out-of-the-money (OTM) put option) or an option-implied volatility (ATM) and a CDS spread. Anecdotal evidence, however, indicates that these two approache are difficult to implement since they involve the solution of two complex optimizations problems. For a detailed description of the methodology and important formulas please refer to Stamicar & Finger.

The solution that is easiest to implement – while introducing the benefit of using a more timely input – is Stamicar & Finger's Approach (A). This approach involves the use of an option-implied volatility (ATM) and consolidated balance-sheet data. The option-implied volatility is used to back out asset volatility while balance sheet data is used to estimate the firm's leverage. Therefore, given an at-the-money implied volatility σ_S^{imp}, it can be shown that the implied asset volatility σ^{imp} is approximately given by

$$\sigma^{\text{imp}} = \sigma_S^{imp} \frac{S}{S + LD} \tag{4.6}$$

where S is equal to the value of equity, D is the company's debt per share, and L is the average debt recovery rate. The exact formula is given in Stamicar & Finger's equation (14). However, the authors show that the approximation works very well compared to the exact formula and produces spreads that are extremely close to those estimated with the exact formula. Consequently, I make use of this approximation to back out asset volatility from an at-the-money volatility.

iii. Calibration

The CreditGrades model requires equity per share S, debt per share D, an equity volatility σ_S, a risk-free rate r, the global recovery rate $\bar{L}$ and its standard deviation λ, and a bond-specific recovery rate R as inputs. While the first four of these inputs are easily observable, the latter inputs are not. Equity per share is simply the company's market capitalization divided by share outstanding, i.e. the firm's stock price. Debt per share is calculated according to the CreditGrades Technical Document (2002): all short-term and long-term interest-bearing debt plus half of all other liabilities is summed up and divided by number of outstanding shares. Thus, it is assumed that half of other liabilities are also interest-bearing debt. The Technical Document uses historical equity volatility estimates as input for the model. However, as has been shown in the literature review, implied volatilities are a better and more responsive estimate that is used to back out asset volatility. Consequently, I use equity volatility estimates from at-the-money put options. The risk-free rate chosen is a five-year U.S. Treasury rate, consistent with the existing literature that uses either Treasury or swap rates.

Values for $\bar{L}$, λ, and R are estimated for North-American obligors using J.P. Morgan's proprietary database in the CreditGrades Technical Document and are assumed to be 0.5, 0.3, and 0.5, respectively. In the Technical Document the authors use the pre-determined values for $\bar{L}$ and λ and calibrate the model by fitting R. In practice, traders also usually leave R as a free parameter to fit the model to market spreads as Yu (2005) states. However, using this approach I find unreasonable values for R most of the times, which is in line with Yu who finds similar values. Values for the bond-specific recovery rate that are negative or close to one do not make sense. The default barrier is given by $\bar{L}D$ and the existing literature (Leland, 1994; Leland & Toft, 1996) argues that this barrier should depend on firm-specific fundamentals and not be exogenously determined. The rationale behind this reasoning is that less risky firms have lower asset volatilities and should thus be able to take on more (short-term) debt. Then, ceteris paribus, a higher portion of short-term debt in the capital structure should correspond to a higher default barrier. Therefore, I follow Yu in his approach by specifying R to be exogenously defined as 0.5 and leaving $\bar{L}$ as the free parameter that is used to calibrate the model.

Finally, the model is calibrated by fitting the first 15 daily CDS market spreads at the start of the sample period to the CreditGrades model. This is done by minimizing the sum of squared pricing errors, i.e. market spread minus model spread, over $\bar{L}$.

C) Conclusion

This section has presented the CreditGrades model, which is used for the analyses of market and model spreads, and reasons for why this model is chosen in this study. Moreover, the theoretical framework of the model has been outlined. Compared to the original model several researchers have found that option-implied volatilities are superior to historical volatilities, which is why the original model has been extended to account for the more timely option-implied volatilities. I also use these volatilities to better fit model spreads to market spreads, especially during the time period of the financial crisis. Finally, all model inputs and the values of some important parameters have been outlined followed by a description of the calibration process I used to fit model to market spreads. In the next section, the dataset I used in my analysis is presented.

V. Data

The data used in this study can be split into two distinct sets: The first set is comprised of all data necessary to estimate model spreads using the CreditGrades model while the second set includes control variables for the panel regressions I run to identify and test for missing factors in the CreditGrades model. The first set uses daily time-series data for the companies included in this study whereas the second set is comprised of monthly data. My final sample consists of 135,934 daily spreads from 106 North-American investment grade and high-yield obligors for the period starting in January 2004 and ending in August 2009.

A) Credit Default Swap Data

CDS spreads have been obtained from Datastream. In particular, I use daily composite spreads on five-year CDS contracts on senior unsecured debt of North American obligors, denominated in US dollars. These CDS spreads ensure liquidity since they are the most liquid contracts on the credit risk curve. The sample is limited to companies that are current constituents of both the Markit CDX.NA.IG and CDX.NA.HY index for the same reason. I use these two indices to obtain a sample of the most liquid CDS contracts in the market, which is especially important when it comes to non-investment grade obligors. The market for these CDS contracts tend to be thinner and it makes therefore sense to limit the sample to only the most liquid contracts. The data covers the period from January 1st, 2004 to August 31st, 2009 which makes this the first study that explicitly covers the financial crisis. Additionally, enough observations are available for the earlier period and spreads are not stale for prolonged periods because the CDS market has been well developed in 2004. Each quote contains the following information:

1. The date on which the quote was made,
2. the name of the reference entity,
3. the maturity of the CDS,
4. the type of the quote, i.e. bid (buying protection), ask (selling protection) or mid,
5. and the CDS spread quote is in basis points.

The CreditGrades model was originally developed for industrial companies and it has been shown that it does not perform well when pricing spreads of financial companies or insurers. Also, companies from the utilities sector with complex debt structures that are difficult to interpret are not supported by the model. This is why I exclude those companies from the sample. Therefore, my original sample was comprised of 149 companies from both indices.

B) Other Data

As outlined in the section about the CreditGrades model some other inputs are needed in order to estimate theoretical spreads. Stock prices and the number of shares outstanding for each company have also been obtained from Datastream. I follow Bedendo et al. (2008) in the choice of option-implied volatilities, which have been provided by IVolatility[8]. IVolatility provides data based on moneyness (defined as the ratio price/strike) ranging from 0.5 to 1.5 and maturities from one month to two years. In particular, I use daily quotes of one-year at-the-money and out-of-the-money put options with delta of around -0.5 and -0.25, respectively. These options provide a good compromise between liquidity and skewness. Quarterly balance sheet data, in particular a firm's short and long-term interest-bearing liabilities as well as other liabilities, has been obtained from Compustat. The data was transformed to a daily interval and lagged for one month from the end of the quarter to avoid look-ahead bias. Daily time-series data on the five-year U.S. Treasury rate have been obtained from Datastream again.

C) Merged Dataset

I applied several filters to the dataset. First, I merged the CDS data with option-implied volatility data and excluded firms for which either no CDS spread data or volatility data were available. This reduced the number of entities from 149 to 128. The next filter was applied at the stage of the availability of balance sheet data. Firms for which no balance sheet data was available were also excluded from the sample. This reduced the number of entities to 106. Daily stock prices and the number of shares outstanding are available for all entities. Finally then, my sample includes 106 North-American companies – 69 investment grade obligors and 37 high-yield obligors – with a total of 135,934 daily spreads over the period from January 2004 to August 2009.

[8] I thank Igor Novikov and his team from IVolatility for providing me with time-series data of option-implied volatilities for my sample.

D) Control Variables

The second dataset consists of various monthly control variables used in the panel regressions that are run to analyze the gap between market and model spreads. Variables included can be classified in two groups, namely firm-specific and macro-economic factors.

Firm-specific factors include the change in annual ATM volatility, volatility skew (defined as the difference between volatilities of a one-year ATM and a one-year OTM put option), CDS liquidity (defined as bid minus ask, normalized by the mid spread), and the company's credit rating. A transformation from alpha numeric rating classes into a numeric scale (ranging from 1 for the lowest to 18 for the highest credit rating) has been conducted in order to use credit ratings in the analyses. Log-returns of the company have been included, too. Option data was provided by IVolatility, whereas log-returns have been calculated using equity time-series data from Datastream. Credit ratings were obtained from Compustat on a monthly basis.

The macro-economic factors include the US unemployment rate (in thousands), the consumer price index (in percent), the industrial production index (in levels), and the consumer confidence (in levels). Moreover, changes in the risk-free rate as well as in the risk-free yield curve (defined as the difference between ten-year and two-year Treasury yields) are included. Finally, based on Reinhart & Rogoff (2008) I include two additional macro-economic factors, namely a real public housing price index (in levels) and the public debt level (in $million). The authors show that these two factors (amongst others), can predict financial crises since they have been common in all prior crises. All data has been obtained on a monthly basis from Datastream.

E) Descriptive Statistics

To provide you with information of how the sample is composed some descriptive statistics are shown in this sub-section. Table 1 gives an overview of how the sample is distributed amongst industry sectors. I adopt the industry classifications from Markit's CDX indices. Most companies belong to the cyclical consumer industry, whereas the fewest companies are part of the materials sector. Mean spreads are highest for the cyclical consumer sector (268 bps) and lowest for the industrial sector (129 bps). The next column gives the maximum spread observed for an industry over the entire sample period. While high in magnitude overall the energy and the materials sector stand out at the lower boundary with 1,101 bps and 1,172 bps, respectively. However, for both consumer sectors spreads have been as high as 11,877 bps and 14,625 bps, which illustrates how high spreads jumped during the crisis period. The communication & technology and the industrial sector are in between the two extremes with 7,275 bps and 5,509 bps, respectively.

				Spread (in bps)			
Sector	**N**	**%**	**Observations**	**Mean**	**Max**	**Min**	**STD**
Comm. & Techn.	14	13%	17,992	216	7,275	2	(419)
Consumer Cyclical	34	32%	36,664	268	14,625	1	(608)
Consumer Stable	18	17%	25,632	191	11,877	1	(423)
Energy	12	11%	16,667	161	1,101	5	(177)
Industrial	20	19%	28,517	129	5,509	2	(299)
Materials	8	8%	10,462	170	1,172	9	(219)
Total	106	100%	135,934	189			(357)

Table 1 – Overview of Industry Sector Composition

Panel A of Table 2 provides an overview of how the observations are distributed over years and grade class. The observations are evenly distributed over different years with only the last year having fewer observations, because the sample period ends in August 2009. This motivates the choice of five-year spreads and the use of only the most liquid contracts, which are represented in the two Markit CDX indices.

PANEL A - OBSERVATIONS

	2004	**2005**	**2006**	**2007**	**2008**	**2009**	**Total**
Investment Grade	17,650	17,981	18,103	18,067	17,362	11,597	100,760
Non-Investment Grade	4,802	5,947	6,145	6,222	7,177	4,881	35,174
Full Sample	22,452	23,928	24,248	24,289	24,539	16,478	135,934

PANEL B - MEAN SPREADS (IN BPS)

	2004	**2005**	**2006**	**2007**	**2008**	**2009**	**Average**
Investment Grade	52	41	34	36	115	147	71
Non-Investment Grade	245	268	232	293	821	1,180	507
Full Sample	119	121	103	126	361	508	223

PANEL C - ATM VOLATILITIES (IN %)

	2004	**2005**	**2006**	**2007**	**2008**	**2009**	**Average**
Investment Grade	0.259	0.245	0.251	0.268	0.412	0.477	0.307
Non-Investment Grade	0.437	0.407	0.394	0.438	0.771	0.886	0.549
Full Sample	0.304	0.288	0.289	0.312	0.517	0.608	0.373

Table 2 – Overview of the Sample by Observations (Panel A), Mean Spreads in Basis Points (Panel B), and ATM Volatilities per Year (Panel C)

Panel B of Table 2 shows the mean CDS spread per year for both investment grade and high-yield obligors. It becomes apparent that high-yield obligors have spreads that are a lot higher than investment grade obligors, no matter what time period is chosen. Moreover, spreads are staying flat or even decrease slightly in the period from 2004 to 2006 but increase in 2007. Major increases in spreads of both investment grade and non-investment grade obligors are observed in the subsequent period, i.e. 2008 to 2009, which represents the time of the financial crisis. This coincides, of course, with increased ATM volatilities (Panel C) during this time period. As can be seen in the table, annualized volatilities tremendously increase for the full sample from 31.2% in 2007 to 51.7% and to 60.8% in 2008 and 2009, respectively. For high-yield obligors the increase is the most severe since volatilities increase from 43.8% in 2007 to 77.1% and 88.6% in the last two years. However, even volatilities for high-grade investors, which were comparably low during the bubble period, increase from 26.8% in 2007 up to 41.2% and 47.7% in 2008 and 2009, respectively.

Finally, summary statistics of most of the macro-economic factors used as control variables in the regression analyses are listed in Table 3. All values are mean value for the respective year. The consumer confidence index is based on survey data and provided as an index for the North American region with a base of 100 in 1985. Inflation is in percentage levels while the public debt level is in $millions. The housing market index and production index are again in levels with a base of 100 in 1991 and 2005, respectively. The three-month U.S. T-Bill is in percentage levels and unemployment is an absolute number in thousands.

MACRO-ECONOMIC FACTORS

	2004	2005	2006	2007	2008	2009	Average
Consumer Confidence	88	77	76	76	57	61	72
Inflation	3.07%	3.34%	3.23%	2.87%	3.85%	-0.01%	2.77%
Public Debt Level	229,157	297,040	381,087	443,240	505,061	528,942	402,426
Housing Market	193	207	219	222	209	200	210
Production Index	98	100	102	103	101	91	100
3-Month T-Bill	1.75%	3.21%	4.75%	4.32%	1.29%	0.17%	2.80%
Unemployment	8,038	7,578	6,992	7,076	8,960	13,699	8,463

Table 3 – Summary Statistics of Macro-Economic Factors

The summary table shows a run-up in the public debt level and a steadily increasing housing market index until 2007, the year of the beginning of the financial crisis. From then on, the housing market index declines, which is in line with historical events. These two factors may add additional explanatory power, but this is subject to formal analyses, which follow in the next section.

VI. Empirical Results

This section presents the results of my analyses. In general, the analyses is sub-divided into two distinct time periods, namely the period from January 2004 to June 2007 and from July 2007 to August 2009. I follow Imbierowicz (2009) and argue for a bubble formation in the CDS market based on very low spread levels and the progression of these over time in the former period. The latter period can be clearly characterized as crisis period. Moreover, I will provide most results not only for the two different sub-periods but also for the two different obligor classes, i.e. non-investment grade or high-yield obligors and investment grade obligors. The analysis starts with an examination of the gap in model and market spreads. Panel regression results are outlined next in order to clarify, which control variables can add explanatory power to the model itself. Finally, a discussion of the results follows.

A) Market and Model Spreads

i. Correlation

In order to investigate the relationship between market and model spreads, it is crucial to verify whether there is enough correlation between those two series. If there is only some correlation, it is hard to justify any comparison between the two series. As can be seen in Table 4, correlation is high no matter whether the full sample or sub-samples are chosen. The correlation between the two series is higher in the bubble period than in the crisis period.

CORRELATIONS

	Bubble Period	Crisis Period	Full Period
Investment Grade	0.787	0.854	0.863
High-Yield Grade	0.889	0.748	0.804
Full Sample	0.921	0.820	0.843

Table 4 – Correlations between Market and Model Spreads

While it is true that structural models track market spreads better in periods of high volatility (Table 6), I think that the second period does not represent a period of high but rather extreme volatility. Therefore, in line with Bedendo et al. (2008), I find that the correlation between model and market spreads is stronger for high-yield obligors in the first period with high volatility and weaker in the second period, which is characterized by extreme volatility. For investment grade obligors, the reverse is true. This is logical, since the crisis period for investment grade obligors is characterized by volatilities comparable to those for high-yield obligors in the bubble period, which therefore implies stronger correlation between spreads.

Moreover, it can be intuitively understood that market spreads increased to extreme levels in the crisis period because of increasing risk aversions and declining liquidity. Imbierowicz (2009) adds that a re-evaluation of investors' portfolios including CDS positions took place because spreads have been too low for an extended period of time before the crisis. This explains why market spreads increase much more than model spreads in the crisis period. These findings are verified in Table 5, which shows mean spreads, the standard deviation (absolute measure of dispersion), and the coefficient of variation[9] (relative measure of dispersion) of market (Panel A) and model spreads (Panel B).

PANEL A - MARKET SPREADS (IN BPS)							
	2004	2005	2006	2007	2008	2009	Total
Full Sample							
Mean	111	116	101	124	357	496	202
Standard Deviation	(170)	(226)	(147)	(188)	(610)	(867)	(447)
Coefficient Variation	1.53	1.95	1.46	1.52	1.71	1.75	2.21
Investment Grade							
Mean	57	45	39	43	129	161	73
Standard Deviation	(64)	(33)	(27)	(38)	(110)	(177)	(94)
Coefficient Variation	1.13	0.73	0.70	0.88	0.85	1.10	1.29
Non-Investment Grade							
Mean	311	334	287	359	909	1199	567
Standard Deviation	(262)	(372)	(192)	(246)	(897)	(1241)	(745)
Coefficient Variation	0.84	1.11	0.67	0.69	0.99	1.04	1.31

PANEL B - MODEL SPREADS (IN BPS)							
	2004	2005	2006	2007	2008	2009	Total
Full Sample							
Mean	85	74	70	91	353	550	185
Standard Deviation	(152)	(202)	(140)	(224)	(511)	(583)	(374)
Coefficient Variation	1.79	2.73	2.00	2.46	1.45	1.06	2.02
Investment Grade							
Mean	34	16	17	20	149	263	70
Standard Deviation	(71)	(28)	(35)	(40)	(209)	(281)	(157)
Coefficient Variation	2.09	1.77	2.01	2.00	1.40	1.07	2.24
Non-Investment Grade							
Mean	272	252	227	298	847	1153	508
Standard Deviation	(211)	(347)	(226)	(365)	(664)	(594)	(567)
Coefficient Variation	0.78	1.38	1.00	1.22	0.78	0.52	1.12

Table 5 – Mean, Standard Deviation, and Coefficient of Variation of Market Spreads (Panel A) and Model Spreads (Panel B)

[9] The coefficient of variation is a dimensionless number and defined as the ratio of standard deviation and mean.

As can be seen, coefficient variation is smaller for investment grade market spreads compared to model spreads over the entire sample. Moreover, except for the last two years, the same is true for the coefficient variation of high-yield spreads. This can again be explained by the tremendous jumps in spreads during the crisis period, where the model is not able to capture these effects. The absolute measure of dispersion, i.e. standard deviation, shows the same pattern. It is especially the increased standard deviation of market spreads compared to model spreads in case of high-yield obligors that lead to more dispersion and weaker correlation in the crisis period, while relatively stable standard deviations for investment grade obligors support stronger correlation.

Finally, the abovementioned results are also confirmed by panel regression analysis. Monthly changes of market spreads are regressed on monthly changes of model spreads, its first lag[10], and a coefficient. To correct for heteroskedasticity and serial correlation I use robust errors. Each regression's adjusted R^2 is reported in Table 6. A tremendously higher fraction (34.6% compared to 9.1% in the bubble period) of variation in market spread is explained for investment grade obligors during the crisis period, which is in line with prior results. For high-yield obligors a smaller fraction of variation is explained during the crisis period (43.3% compared to 46.7% in the bubble period). Therefore, in line with prior results, weaker correlation between market and model spreads for high-yield obligors during the crisis period leads to a smaller portion of the change in market spread that is explained by the change in model spread.

ADJUSTED R^2 OF PANEL REGRESSIONS

	Bubble Period	Crisis Period	Full Period
Investment Grade	0.091	0.346	0.323
High-Yield Grade	0.467	0.433	0.444
Full Sample	0.260	0.383	0.373

Table 6 – Adjusted R^2 of Panel Regressions of Monthly Changes in Market Spreads on Monthly Changes in Model Spreads, its First Lag and a Coefficient

To conclude then, the CreditGrades model shows a better fit for high-yield obligors even when taking the crisis period into account. Correlations are stronger for investment grade obligors during the crisis period and a higher portion of variation in market spreads can be

[10] More lags had originally been included, but were removed since they were not statistically significant

explained during this period. For high-yield obligors, correlations are weaker during the crisis period and a lower portion of market spread variation can be explained.

ii. Preliminary Examination

While the focus of the first analysis was on the correlation between market and model spreads, which has to be strong in order to justify any examination of the two series, this part of the analysis aims at the (almost) consistent underestimation of spreads. Table 7 shows the difference between market and model spread and is based on the numbers of Table 5. Model spreads are generally lower than market spreads. This is true for both investment grade and high yield obligors.

	2004	2005	2006	2007	2008	2009	Total
Full Sample							
Mean	-26	-42	-31	-33	-4	54	-18
Standard Deviation	(66)	(71)	(72)	(90)	(319)	(544)	(241)
Coefficient Variation	2.54	1.69	2.32	2.73	87.88	10.07	13.39
Investment Grade							
Mean	-23	-29	-21	-23	21	102	-3
Standard Deviation	(32)	(25)	(32)	(29)	(139)	(149)	(90)
Coefficient Variation	1.43	0.86	1.52	1.26	6.62	1.46	35.16
Non-Investment Grade							
Mean	-39	-82	-59	-61	-62	-46	-59
Standard Deviation	(117)	(129)	(128)	(167)	(545)	(928)	(444)
Coefficient Variation	2.97	1.57	2.17	2.74	8.79	20.17	7.53

Table 7 – Difference in Model minus Market Spread (in bps)

For the investment grade class, however, model spreads become larger than market spreads in crisis years (i.e. 2008 and 2009) but are low compared to market spreads in the bubble period. There seems to be a systematic underestimation of model spreads in this period with spreads close to zero. Model spreads are systematically 24 bps lower on average than market spreads during the bubble period. This can be seen in Table 7 but also becomes apparent in the regression analysis presented above (Table 6) where only 9.1% of variation in the change of the market spread can be explained by the change in model spreads. On the other hand, spreads are consistently overestimated during the two last year, which represent the major part of the crisis period. The overestimation is smaller in the beginning (21 bps on average) and becomes larger in the last year (102 bps on average). However, the standard deviation rises more sharply in the former year leading to a very high coefficient of variation.

A graphical representation of this behavior is shown in Figure 11, where model and market spreads and the at-the-money (ATM) volatility of The Black & Decker Corporation are depicted as an example. Model spreads are consistently below market spreads and only in the last two years, characterized by higher volatility, spreads are (significantly) overestimated.

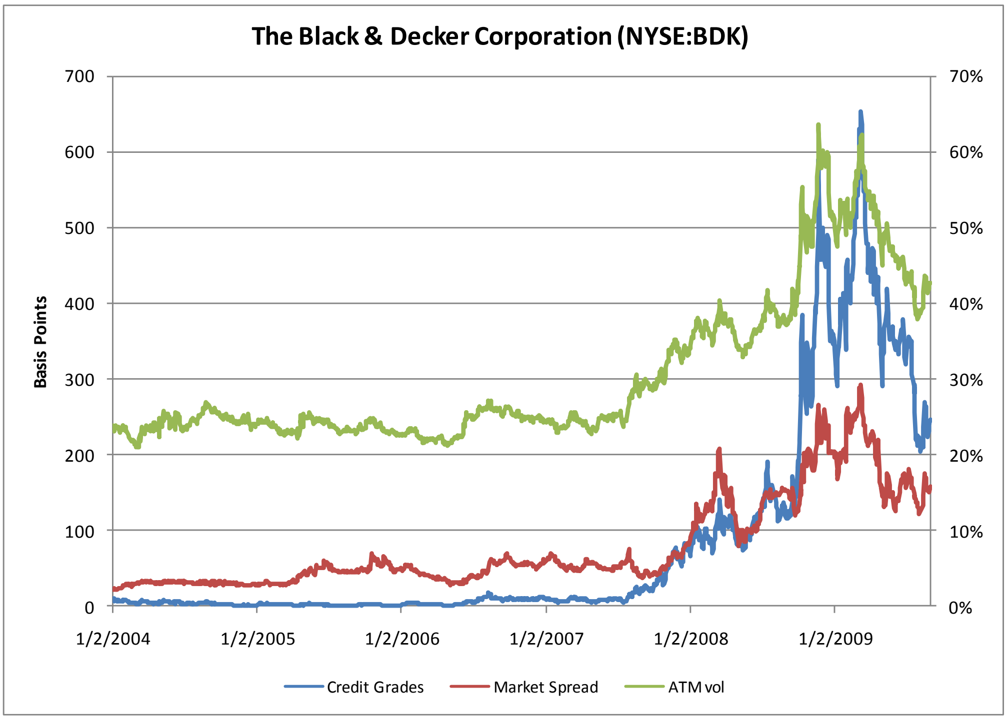


Figure 11 – Market and Model Spreads of The Black & Decker Corporation

The CreditGrades model, like the majority of structural models, tends to underestimate spreads in the short term. In this case, spreads are not close to the observed spreads in the period up to mid-2007. Reasons are those mentioned in the literature review, namely that the model does not allow for short-term bankruptcy because the short-term default probability is underestimated. This effect is enhanced in particular when looking at investment grade obligors. A suggestion to correct for this weakness would be to integrate jumps in the asset value process. The tracking is still reasonable though, but the overall level of spreads is too low. However, once volatility rises the model tracks the movements of the market spread a lot better but overshoots when the volatility rises further to more than 60%, which was the case during 2008 and 2009. Model spreads, however, also decline very quickly once volatility decreases again as in early 2009.

The underestimation of high-yield obligors can be explained by two arguments. The first one remains the same, although it can be said that the tracking is better for high-yield obligors in earlier periods than for investment grade obligors as was shown by the regression results above (Table 6). Nevertheless, the second argument introduces another aspect not yet covered. It is especially the crisis period that is characterized by high and sudden jumps in both volatilities and credit spreads, which cannot be fully captured by the model. While these jumps are overestimated in case of investment-grade obligors, the jumps are of such a great magnitude in case of high-yield obligors that the model is not able to capture them sufficiently. That is why model spreads stay below market spreads for most of the times during the crisis period. This behavior is depicted in Figure 12, where spreads of the AMR Corporation are depicted. Spreads became so high (more than 10,000 bps in this case) that not even the increased volatilities (up to 160% in the most extreme case) can account for such a tremendous jump in the spread.

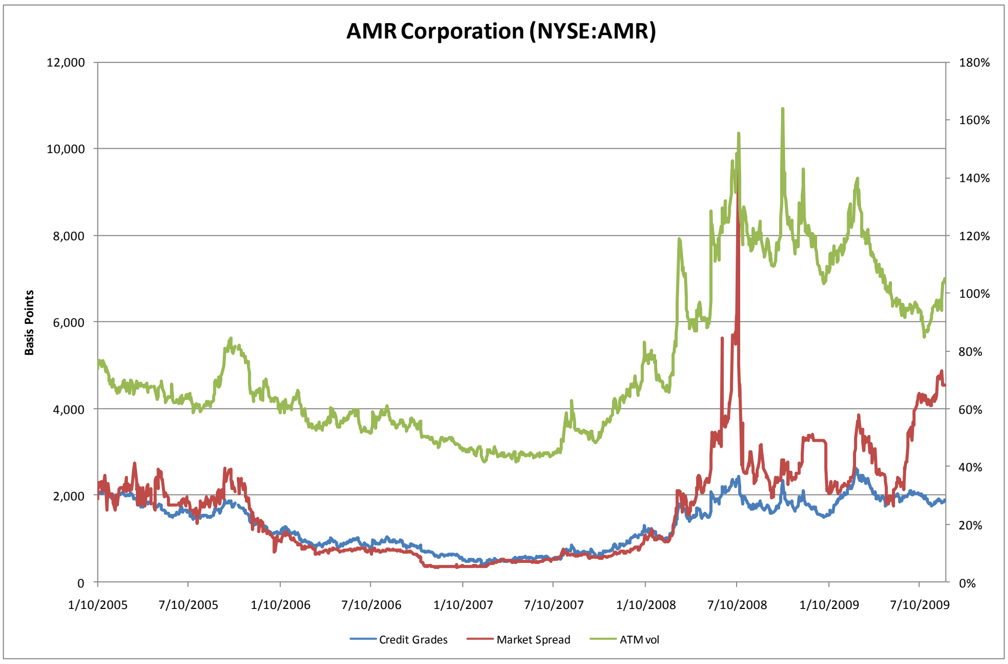


Figure 12 – Market and Model Spreads of AMR Corporation

In conclusion then, I observe a consistent underestimation of credit spreads for both investment grade and high-yield obligors during the bubble period. While the effect is reverses to an overestimation for investment grade obligors in the crisis period, this is not true for high-yield obligors because of massive jumps in spreads not captured by the model. I suggest the inclusion of jump risk to correct for low short-term spreads, which in turn will lead to higher short-term default probabilities and thus higher short-term spreads.

iii. Comparison by Rating Class

The tracking ability of market spreads by the CreditGrades model on the portfolio level is pretty good, especially in periods of sudden movements. Bedendo et al. (2008) stresses the point that structural models are not intended to provide accurate fair valuation per sé but that they provide a direction in which market spreads should move based on firm fundamentals. In the Appendix some case studies are presented that (visually) illustrate the tracking ability of the implemented CreditGrades model.

It is further interesting to note that the differences in model and market spreads are generally a lot smaller compared to prior research results. This is surprising since this study explicitly takes the crisis period into account, which introduces tremendous jumps in spreads, especially for high-yield obligors. However, a comparison to prior research results cannot be easily done since the datasets of prior research are likely to be very different from my dataset since other companies, time periods, and estimation methods of model spreads have been used. This has to be kept in mind when comparing my results to prior results. Imbierowicz' (2009) differences in spreads are by and large higher for sectors (not reported here) and different rating classes. This suggests that the use of implied volatilities does add enormous value to the tracking and pricing ability of the CreditGrades model since he uses historical volatilities to estimate spreads. I estimated CreditGrades model spreads using historical volatilities for a reduced sample and can confirm (on a limited basis) that the deviation in model and market spreads is indeed a lot smaller when using implied volatilities. Panel regression analyses (not reported here) also confirm these results with model spreads estimated using implied volatilities being able to explain a significantly higher portion of variation in the change of market spreads than model spreads estimated using historical volatilities. Unfortunately, I cannot easily compare my results to Bedendo et al. (2008) who use implied volatilities. This is because they only test for investment grade obligors and for the period from 2003 to 2005, whereas most of my data only starts in 2004. Nevertheless, it is surprising that although my sample period includes very turbulent market times the tracking ability and prediction of spreads are very good. This is a result that was not expected based on prior research results.

However, there are tremendous differences in the model's pricing ability of spreads. This is revealed if spreads are displayed according to their credit rating. Table 8 shows an overview of average CDS spreads across rating classes. I combine the highest and lowest credit rating in order to have sufficient observations. The mean credit rating is between BBB- and BBB. On a portfolio level, the CreditGrades estimates of the spreads are on average 59 bps too low compared to market spreads. While this appears high compared the investment grade class, it is low when compared to other studies. Imbierowicz (2009) finds a gap on the portfolio level of 112 bps for the speculative grade class. Again, it should be kept in mind that the samples are likely to be different and no inference can be made from these observations. As can be seen from the table, however, there are substantial differences in the gap between market and model spreads for different rating classes within the non-investment grade class.

			Market		CreditGrades		Difference	
Rating Class		Observations	Mean	STD	Mean	STD	Mean	STD
CCC-/CC	High-Yield (HG)	59	2,046	(1131)	2,235	(1961)	189	(613)
CCC		242	1,353	(611)	1,682	(430)	330	(477)
CCC+		416	2,305	(2471)	1,086	(683)	-1219	(1927)
B-		3,274	1,370	(1000)	1,232	(692)	-137	(543)
B		4,410	792	(657)	716	(492)	-76	(365)
B+		7,116	484	(366)	403	(425)	-80	(192)
BB-		5,108	465	(366)	546	(541)	80	(289)
BB		7,977	258	(177)	253	(275)	-5	(160)
BB+		6,572	250	(247)	191	(248)	-58	(161)
BBB-	Investment Grade (IG)	16,632	129	(137)	141	(234)	12	(130)
BBB		23,086	87	(97)	84	(161)	-4	(93)
BBB+		21,065	65	(68)	62	(134)	-3	(84)
A-		13,413	61	(90)	53	(134)	-9	(63)
A		13,792	40	(35)	34	(84)	-6	(65)
A+		7,205	40	(43)	36	(106)	-46	(87)
AA-		986	39	(30)	31	(53)	-8	(34)
AA		2,161	22	(23)	5	(19)	-17	(15)
AA+/AAA		2,420	17	(22)	7	(24)	-10	(15)
HY		35,174	567	(744)	508	(566)	-59	(444)
IG		100,760	73	(94)	70	(156)	-3	(90)
Total		135,934	202	(446)	184	(373)	-18	(241)

Table 8 – Mean and Standard Deviation (STD) of Market and Model Spreads and their Differences in Basis Points by Rating Class for the Full Period from January 2004 to August 2009

Spreads for the lowest rating classes, i.e. below B-, are either significantly overestimated in case of CC to CCC or significantly underestimated in case of CCC+ obligors. However, the number of observations is comparably low for these rating classes so no conclusive evidence can be drawn. Also, since those obligors are companies near bankruptcy the model is most likely not be able to capture the jumps in credit spreads sufficiently. For the remainder of the speculative grade class the gap between market and model spreads varies between -137 bps for B- obligors to 80 bps for BB- obligors. As already noted before standard deviations are very large for market and model spreads, which suggests a high variation in spreads within rating classes. This diminishes the interpretability of individual firm spread estimations.

However, on the portfolio level the model does well in predicting spreads. This is in particular true if one takes the high standard deviation of market spreads into account.

For investment grade obligors the picture is more favorable when it comes to the gap. For the entire investment grade class the average gap is only -3 bps. This is a striking result and a lot better than Imbierowicz' (2009) estimations, who finds a gap of 75 bps for investment grade obligors. Bedendo et al. (2008) does not report numbers for the full sample but aggregated calculations of the gap of different sectors show that their estimates are also higher. Results from my limited sample using historical volatilities show that the gap increases substantially. Again, implied volatilities add enormously to the pricing ability of the CreditGrades model. The gap of investment grade obligors is very small compared to the high-yield obligors' gap on average, ranging from -46 bps for A+ obligors to 12 bps for BBB- obligors. I could not find an apparent reason for why the gap is so large for A+ obligors, especially when taking into account the gap of all other obligors in the investment grade rating class, which is on average only -8 bps. The smaller gap can be explained by less dispersion and an offsetting effect of the underestimation of spreads during the bubble period and an overestimation of spreads in the crisis period as noted before. Therefore, although the gaps are on average smaller for investment grade obligors, this is only one side of the medal. As the initial regression analyses (Table 6) show a higher portion of the variation in market spreads is explained by model spreads of high-yield obligors. This result is consistent with prior research.

iv. Determinants

I run panel regressions in order to get a better understanding of which of the control factors impact market and model spreads. Therefore, I regress the change in market and model spread each on all control variables mentioned in the data section for investment grade and speculative grade obligors for each time period, i.e. the full period, the bubble period, and the crisis period. The Hausman Test for random effects models reveals that it is more appropriate to use fixed effects model, i.e. a model with constant slopes but intercepts that differ according to cross-sections. Thus, I use fixed effects models with robust standard errors to correct for heteroskedasticity and serial correlation. I generally estimate regressions in first differences, which completely eliminate unit roots in my sample. The results are presented in Table 9 and build the basis for the analysis of the determinants of the gap coming next.

PANEL A - HIGH-YIELD GRADE OBLIGORS

	Full Period		Bubble Period		Crisis Period	
	Market	Model	Market	Model	Market	Model
Δ Consumer Confidence	0.000	0.000	0.000 *	0.000 *	0.000	0.000 ***
Δ Inflation	-0.066	-0.060 **	-0.043	-0.010	0.006	-0.031
Δ Public Debt	0.000	0.000	0.000	0.000	0.000	0.000
Δ Housing Prices	0.000	0.000	0.000	0.000 *	0.000	0.000
Δ Industrial Production	0.000	0.000	0.000	0.000 **	-0.001	0.000 *
Δ Unemployment Rate	0.000	0.000	0.000	0.000	0.000	0.000 **
Δ Slope Yield Curve	-0.397	-0.024	0.052	0.133	-0.509	-0.053
Δ Risk-Free Rate	-0.002	0.002 **	-0.001	0.001 **	0.000	0.000
Δ ATM Volatility	0.092 ***	0.167 ***	0.050 ***	0.119 ***	0.106 ***	0.169 ***
Δ Volatility Skew	0.046	0.031	-0.118 ***	-0.049 **	0.177	0.064 ***
Company Returns	-0.102 *	-0.158 ***	-0.041 **	-0.107 ***	-0.068	-0.158 ***
Δ CDS Liquidity	0.002	-0.001	-0.002 **	0.000	0.049	-0.010
Δ Credit Rating	-0.002	0.000	-0.001 **	0.000	-0.002	0.000
Δ Spread(-1)	0.142 ***	0.024 **	0.168 ***	0.051 ***	0.135 **	0.022
Δ Spread(-2)	-0.187 ***	-0.027 **	-0.098 **	-0.030 *	-0.247 ***	-0.036 **
Constant	0.000	0.000	0.000 ***	0.000	0.002	-0.001
Observations	2,144	2,144	1,226	1,226	918	918
Firms	37	37	37	37	37	37
Adjusted R^2	0.399	0.940	0.295	0.762	0.429	0.958

PANEL B - INVESTMENT GRADE OBLIGORS

	Full Period		Bubble Period		Crisis Period	
	Market	Model	Market	Model	Market	Model
Δ Consumer Confidence	0.000	0.000	0.000	0.000	0.000	0.000 *
Δ Inflation	-0.005	-0.039 **	-0.009	0.000	0.009	-0.015
Δ Public Debt	0.000	0.000 **	0.000 ***	0.000 **	0.000	0.000
Δ Housing Prices	0.000	0.000	0.000	0.000	0.000	0.000
Δ Industrial Production	0.000	0.000 **	0.000	0.000 *	0.000	0.000 **
Δ Unemployment Rate	0.000	0.000	0.000	0.000	0.000	0.000
Δ Slope Yield Curve	-0.067	-0.022	0.000	0.017	-0.060	-0.064
Δ Risk-Free Rate	-0.001 *	0.002 ***	0.000 **	0.000	0.000	0.002 *
Δ ATM Volatility	0.023 ***	0.109 ***	0.010 ***	0.018 ***	0.025 ***	0.119 ***
Δ Volatility Skew	-0.017 *	-0.027	-0.023 ***	0.001	-0.011	0.030
Company Returns	-0.023 *	-0.078 ***	-0.003	-0.005	-0.023	-0.126 ***
Δ CDS Liquidity	-0.001 **	0.000	0.000 **	0.000	-0.007 ***	0.003
Δ Credit Rating	0.000	0.000	0.000	0.000	-0.001 *	0.000
Δ Spread(-1)	0.249 ***	0.134 **	0.212 ***	0.065	0.243 ***	0.131 ***
Δ Spread(-2)	-0.135 **	-0.139 ***	-0.140 ***	-0.065 *	-0.153 **	-0.155 ***
Constant	0.000	0.000	0.000 ***	0.000	0.000	0.000
Observations	4,247	4,247	2,455	2,455	1,792	1,792
Firms	69	69	69	69	69	69
Adjusted R^2	0.349	0.808	0.247	0.405	0.398	0.874

Table 9 – Estimates of Panel Regressions of Monthly Changes in Market and Model Spreads on Changes in all Control Variables. All Estimates include two Lags of the Dependent Variable and a Constant. Sample Period January 2004 to August 2009.

*** Statistically significant at 10% level.**
**** Statistically significant at 5% level.**
***** Statistically significant at 1% level.**

Panel A of Table 9 shows the estimations from panel regressions for high-yield grade obligors for the full period and the two sub-samples. As expected, I find that ATM volatility positively impacts model spreads stronger than market spreads in all periods, i.e. increased equity volatility yields higher spreads. The result is expected since ATM volatility is a crucial input of the model. Company returns are negatively related to spreads, i.e. higher returns lead to lower spreads, and again influence model spreads stronger than market spreads. CDS liquidity only impacts market spreads in the bubble period, which is logical, since the model does not incorporate any measure of CDS liquidity as input. The macro-economic factors only have limited influence on market and model spreads, a result that indicates that high-yield obligors seem to be more influenced by firm-specific factors rather than overall market trends. The first two lags of the change in spreads are positive and negative with different magnitudes. Current market spreads are stronger impacted by recent changes than model spreads in all periods. It is moreover interesting to note that the selected control variables are able to explain up to 95.8% in the variation of model spreads in the crisis period, whereas only 42.9% of changes in market spreads can be explained.

The picture is different for investment grade obligors (Panel B of Table 9). Whereas the risk-free rate only has an impact on model spreads in case of high-yield obligors, the risk-free rate is statistically significant for market and model spreads in case of investment grade obligors, over the full sample period. ATM volatility is again highly significant (at the 1% level) in every period and affects both market and model spreads. Model spreads are affected stronger again, a result consistent with prior findings. The volatility skew is significant for the full period at the 10% level and highly significant (at the 1% level) during the bubble period. This is in line with Bedendo et al. (2008) who find the volatility skew to be a determinant of CDS spreads of investment grade obligors during the bubble period. Company returns negatively influence both market and model spreads over the full period with model spreads being stronger affected. CDS liquidity, again in line with prior research, appears to be an important determinant for investment grade obligors and is significant for market spreads in each period. The first two lags of the dependent variable are significant for market spreads over all periods. However, in case of model spreads the first lag is insignificant and the second lag only significant at the 10% level during the bubble period. This hints at the underestimation of model spreads during the bubble period, in particular for the investment grade class. The selected control variables are able to explain as much as 87.4% of changes in market spreads during the crisis period, whereas they can explain 39.8% in case of market spreads.

B) Determinants of the Gap

What became apparent in the previous section is that while model spreads track market spreads reasonably well on the portfolio level, there is a high variation in both individual market and model spreads. Moreover, they can differ substantially in magnitude, especially in the speculative grade class. Also, as became apparent in Table 9 some control factors are more important in explaining market and model spreads than others. Therefore, while the determinants of market and model spreads alone have been identified in the previous sub-section I try to determine factors and identify situations where the gap between market and model spread widens or narrows significantly compared to its mean level in this section. This means that I try to isolate effects that affect market and model spreads with different intensities, because these effects are the source of a narrowing or widening of the gap.

I run panel regressions for investment grade and speculative grade obligors for each time period, i.e. the full period, the bubble period, and the crisis period, in order to investigate this aspect. Again, I use fixed effects models with robust standard errors to correct for heteroskedasticity and serial correlation. Fixed effects models add explanatory power (as measured by the adjusted R^2) to the different specifications. Moreover, it makes intuitively sense to include fixed effects since there is much variation and significant differences between cross-sectional groups, i.e. companies, in the sample. Two lags of the dependent variable are included in each model and the decision is mainly motivated by the approaches used in prior research. The inclusion of the lagged dependent variable circumvents problems with serial correlation and allows to investigate whether there is a "persistent […] discrepancy between market spreads and firm fundamentals" (Imbierowicz, 2009, p. 17) present. Unit roots are again eliminated by using variables in their first differences.

I specify three models in order to test for different effects. The first model contains all macro-economic factors mentioned in the data section and based on Imbierowicz' (2009) approach, i.e. I regress monthly changes in the gap between market and model spreads on monthly changes in: the consumer confidence level, inflation, the public debt level, real housing prices, the industrial production index, the unemployment rate, the slope yield curve, the risk-free rate; two lags of the dependent variable, and a constant. The second model contains all firm-specific factors and is based on Bedendo et al.'s approach (2008), i.e. I regress monthly changes in the gap on monthly changes in: the ATM volatility, the volatility skew, company log-returns, CDS liquidity, the credit rating; two lags of the dependent variable, and a constant. ATM volatility is of course included as a major input to the CreditGrades model. Nevertheless, Bedendo et al. include those variables, which serve as input to the CreditGrades model, as explanatory variable in the regressions in order to investigate the reaction of market and model spreads to changes in these variables. Therefore, it might be expected that model spreads react faster and more significantly to changes in the variables that are inputs of the CreditGrades model, which in turn means that market spreads may be seen as more stable. The third specification combines the first and second model. In this way, the most important variables that explain the gap between market and model spreads can be identified while redundant variables will become apparent as well.

i. Full Period

I start with the investigation of the full period to get a first overview of the control factors and their impact on the gap. I test for differences in the sub-samples subsequently. Table 10 shows the results for the full period for investment grade and high-yield obligors for each model. In general, coefficients with a negative sign indicate that the gap between market and model spreads narrows while coefficients with a positive sign indicate a widening of the gap.

The chosen control factors can explain a significantly higher portion of the variation in the gap between market and model spreads for the investment grade class compared to the high-yield class. For the investment grade class I find that the macro-economic factors (first specification) are able to explain 28% (as measured by the R^2) compared to only 10.8% in case of the high-yield class. Changes in the consumer confidence level, which is a proxy for expectations in the market, are significant at the 5% level. Next to changes in inflation (significant at the 5% level), changes in real housing prices (significant at the 1% level) help explain the gap between market and model spreads. The risk-free rate is significant at the 10% level. The variables all have positive coefficients, meaning that an increase in each of the variable causes the gap to widen. The results suggest that market spreads react faster and more significantly to changes in these variables, which makes sense since – except for the risk-free rate – none of these variables are included in the CreditGrades model. Moreover, since the risk-free rate is employed as input to the model, the overall effect on the gap is difficult to predict. In case of high-yield obligors only the change in real housing prices is significant (at the 5% level). A possible explanation for this result is that in case of high-yield obligors other firm-specific factors may be more important in explaining credit spreads compared to overall macro-economic conditions or factors. The result is consistent with prior results of the separate regressions of market and model spreads run in the previous section (Table 9), where it became apparent that spreads of high-yield obligors seem to be more reliant on firm-specific rather than macro-economic factors.

FULL PERIOD						
	Investment Grade			High-Yield Grade		
	(1)	(2)	(3)	(1)	(2)	(3)
Δ Consumer Confidence	0.000 **		0.000	0.000		0.000
Δ Inflation	0.069 **		0.031 *	0.102		-0.025
Δ Public Debt	0.000		0.000 ***	0.000		0.000
Δ Housing Prices	0.000 ***		0.000	0.001 **		0.000
Δ Industrial Production	0.000		0.000 ***	0.000		0.000
Δ Unemployment Rate	0.000		0.000	0.000		0.000
Δ Slope Yield Curve	-0.219		-0.052	-0.547		-0.272
Δ Risk-Free Rate	-0.001 *		-0.002 ***	-0.003		-0.004 ***
Δ ATM Volatility		-0.067 ***	-0.071 ***		-0.060 ***	-0.065 ***
Δ Volatility Skew		0.004	0.009		0.013	0.023
Company Returns		0.046 ***	0.043 ***		0.069	0.067
Δ CDS Liquidity		-0.001 ***	-0.001 *		0.000	-0.003
Δ Credit Rating		0.000	0.000		-0.002	-0.002 *
Δ Gap(-1)	0.247 ***	0.162 ***	0.131 ***	0.166 ***	0.125 ***	0.122 ***
Δ Gap(-2)	-0.288 ***	-0.226 ***	-0.242 ***	-0.247 ***	-0.224 ***	-0.241 ***
Constant	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4,267	4,448	4,247	2,146	2,229	2,144
Firms	69	69	69	37	37	37
Adjusted R^2	0.280	0.572	0.612	0.108	0.239	0.248

Table 10 – Estimates of Panel Regressions of Monthly Changes in the Difference between Market and Model CDS Spreads viz. (1) Changes in Macro-Economic Factors; (2) Changes in Firm-Specific Factors; (3) Changes in the Combined Factors of (1) and (2). All Estimates include two Lags of the Dependent Variable and a Constant. Sample Period January 2004 to August 2009.

*** Statistically significant at 10% level.**
**** Statistically significant at 5% level.**
***** Statistically significant at 1% level.**

The second specification includes only firm-specific factors but is able to explain 57.2% and 23.9% of the change in the gap for investment grade and high-yield obligors, respectively. For both classes ATM volatility is highly significant and negatively related to the gap, which is in line with prior research. As indicated in the introduction and the results of the separate regressions (Table 9) this means that model spreads react faster and more significantly to changes in the ATM volatility than do market spreads. This is a logical consequence since the ATM volatility is an important input to the CreditGrades model whereas the market spread is not as much dependent on the variable and depends more on other (macro-economic) factors. Also in line with prior research is the significance of CDS liquidity (although only for investment grade obligors), as can be seen at the highly significant negative coefficient. CDS liquidity is approximated by the bid-ask spreads normalized by the mid-quote. Thus, one might expect market spreads to increase as bid-ask spreads are becoming larger. However, prior research has found a negative relationship between bid-ask spreads and CDS levels for actively traded contracts (Acharaya & Johnson, 2007; Tang & Yang, 2007; Bedendo et al., 2008; Imbierowicz, 2009). The reason for this unintuitive relationship is that increased trading activity for these contracts hints to informed trading, which lowers the search costs as measured by the bid-ask spread. While lower search costs per sé indicate lower spreads, it may in turn lead to higher spread levels due to increased demand that exceeds supply. Nevertheless, since CDS liquidity is no input to the CreditGrades model, changes in CDS liquidity only impact market spreads as was shown in the separate regressions (Table 9). Monthly individual company log-returns are highly significant and positively related to the gap for investment grade obligors. Company returns are added as a proxy for a company's individual health. An increase in a company's returns leads to a decrease in CDS spreads as the default probability of a healthy company should decline in case of better returns, which in turn leads to a decrease in the spread. The gap between market and model spreads widens though, which can be explained by the different intensity of variable's impact on each spread. In the separate regression analyses (Table 9) I find that model spreads are stronger influenced by a change in companies' returns than market spreads. Therefore, an increase in companies' returns, ceteris paribus, leads to a widening of the gap. The change in volatility skew is not significant for the full sample, a result that is in contrast to Bedendo et al. (2008) who find the volatility skew to be an important determinant of the gap. However, the volatility skew is significant in the bubble period, which coincides with Bedendo et al.'s sample period. Moreover, changes in the credit rating of a given firm have no impact on the gap. I suspect that actual changes are priced in CDS spreads a lot earlier due to rumors or rating review announcements. Thus, it is no surprise that the actual credit rating change has no impact on the spread and the gap since the change was anticipated by the market earlier.

In the third specification the variables of the first and second specification are combined. This model is best able to explain the variation in the gap of both spreads. As can be seen in Table 10, the adjusted R^2 is 62.2% and 24.8% for investment grade and high-yield obligors, respectively. The firm-specific variables do not change in sign, i.e. ATM volatility, company returns, and CDS liquidity remain significant for the investment grade class while ATM volatility and the change in credit rating are significant for the high-yield class. The change in credit rating has not been significant in the second specification, so this result is puzzling. Some interesting aspects in the macro-economic variables can be observed. For both classes the risk-free rate is highly significant and shows a negative relationship. This means that an increase in the risk-free rate, which is also an input to the CreditGrades model, leads to a narrowing of the gap. Inflation remains significant for investment grade obligors. Next, it is interesting to note that consumer confidence and real housing prices, which have been significant in the first specification, turn insignificant in the third specification while the public debt level and industrial production turn significant. I suspect that the industrial production index captures some of the effects of consumer confidence. Moreover, the inclusion of the ATM volatility, which serves as a proxy for market expectations, may capture even more expectation effects previously captured by the consumer confidence index. The explanation for the significance of public debt is more puzzling though since I do not think that there is a one-to-one substitution effect with real housing prices. Thus, possible explanations remain up to discussion.

Finally, all specifications include two lags of the dependent variable, which are in all cases highly significant. The first lag, i.e. last month's change in the gap, is positively related to the current change in the gap whereas the second lag, i.e. the second-last months' change in the gap, is negatively related to the current gap. Thus, the most recent changes in the gap (first lag) tend to widen the gap while the change two-months ago (second lag) leads to a narrowing of the current gap. In consequence, one can observe an offsetting effect in which today's gap is corrected for the overreaction of model spreads to changes in volatility conditions in the earlier months. Overall, the effect is that the current gap rather narrows than widens based on the two first lags since the narrowing effect is larger in magnitude than the widening effect when looking at the coefficients.

ii. Bubble Period

In this sub-section I provide results only for the bubble period, which is from January 2004 to June 2007. The explanatory power of the selected control variables is significantly lower than for the full-sample as reported in Table 11. This in turn means that the adjusted R^2 must be higher in the crisis period. This result is confirmed in the next sub-section. Although low compared to the full period, a higher fraction of the variation in the gap can be explained for high-yield grade obligors during the bubble period. The best specification is again the third one, which combines the first two specifications. This is why I focus on this model from now. The model can explain 7.8% and 19.4% of the variation in the current gap for investment grade and high-yield obligors, respectively.

BUBBLE PERIOD

	Investment Grade			High-Yield Grade		
	(1)	(2)	(3)	(1)	(2)	(3)
Δ Consumer Confidence	0.000		0.000	0.000 *		0.000 **
Δ Inflation	-0.011 *		-0.010	-0.027		-0.037
Δ Public Debt	0.000 ***		0.000 **	0.000		0.000
Δ Housing Prices	0.000		0.000 *	0.000		0.000 **
Δ Industrial Production	0.000		0.000	0.000		0.000
Δ Unemployment Rate	0.000		0.000	0.000		0.000
Δ Slope Yield Curve	-0.017		-0.021	-0.225		-0.167
Δ Risk-Free Rate	0.000 *		0.000 *	-0.002 **		-0.003 **
Δ ATM Volatility		-0.003 *	-0.004 ***		-0.039 ***	-0.048 ***
Δ Volatility Skew		-0.022 ***	-0.021 ***		-0.109 ***	-0.112 ***
Company Returns		-0.005	-0.002		0.025	0.036 *
Δ CDS Liquidity		0.000 ***	0.000 ***		-0.003 **	-0.002 **
Δ Credit Rating		0.000	0.000		0.000	0.000
Δ Gap(-1)	0.114 ***	0.096 ***	0.095 ***	0.019	0.013	-0.023
Δ Gap(-2)	-0.116 ***	-0.136 ***	-0.132 ***	-0.084 ***	-0.036	-0.080 **
Constant	0.000 **	0.000	0.000 **	0.000	0.000	0.000 **
Observations	2,475	2,656	2,455	1,226	1,311	1,226
Firms	69	69	69	37	37	37
Adjusted R^2	0.064	0.035	0.078	0.021	0.120	0.194

Table 11 – Estimates of Panel Regressions of Monthly Changes in the Difference between Market and Model CDS Spreads viz. (1) Changes in Macro-Economic Factors; (2) Changes in Firm-Specific Factors; (3) Changes in the Combined Factors of (1) and (2). All Estimates include two Lags of the Dependent Variable and a Constant. Sample Period January 2004 to June 2007.

*** Statistically significant at 10% level.**
**** Statistically significant at 5% level.**
***** Statistically significant at 1% level.**

The signs of the coefficients do not change and are in accordance with expectations for all specifications. For investment grade obligors the change in public debt is significant at the 5% level. Changes in real housing prices and the risk-free rate are significant at the 10% level. When it comes to firm-specific factors the change in the ATM volatility and CDS liquidity is significant at the 1% level. Moreover, during this period the volatility skew becomes highly significant, too. This confirms results by Bedendo et al. (2008) who find the volatility skew to be an important factor in explaining variation in the gap from 2002 to 2005. For the non-investment grade class more factors turn out to have explanatory power. Changes in consumer confidence, housing prices, and the risk-free rate are significant in the macro-economic factor spectrum, while all company-specific factors except for the change in a firm's credit rating are significant. Again, the volatility skew is economically and statistically significant here, a result that has not been observed before because Bedendo et al. only run their analyses for investment grade obligors. The two first lags of the dependent variable are significant at the 1% level for the investment grade class but only the second lag is significant (at the 5% level) and has a negative impact on the current gap for the high-yield grade class. This confirms that model spreads are likely to overreact to changes in volatility conditions more quickly than market spreads, a result found before. Therefore, convergence is more likely to occur when model spreads move back to market spreads.

It is still puzzling why only such a small fraction of variation in the gap is explained for investment grade obligors. While many factors are statistically significant they cannot explain much of the variation in the gap during this period compared to both the crisis period (as will be seen next) and the full period. This may have something to do with the systematic underestimation of spreads of investment grade obligors during this period, which introduces a potential bias. Since the constant also becomes significant in this period (and only in this period) there seem to be an important factor missing that help explain the variation in the gap during the bubble period. Probably, this is a "bubble factor" as was suggested by Imbierowicz (2009).

iii. Crisis Period

Lastly, this sub-section presents the results for the crisis period (Table 12), which starts in July 2007 and ends in August 2009. The adjusted R^2 is high for both grade classes, with 71.7% for investment grade obligors being the highest observed R^2 in all conducted analyses. Although lower for the first two specifications the adjusted R^2 is comparable to the third specification for the high-yield grade class in both sub-samples.

While all factors except for changes in industrial production and the risk-free rate are significant in the first specification in case of investment grade obligors, only these two factor are significant (at the 5% level) in the third specification. This shows again that firm-specific factors are more important and add more explanatory power than macro-economic factors. Changes in ATM volatility and CDS liquidity and company returns are all highly significant (at the 1% level) in the second specifications and remain so in the third specification. Thus, while macro-economic factors can explain 45.5% of the variation in the gap between market and model spreads, firm-specific factors alone can explain 68.8%. However, the third specification, which combines the first two ones, can explain 71.7%, which clearly shows that firm-specific factors have more explanatory power and add more to the understanding of the gap. Macro-economic factors add only 2.9% to the adjusted R^2. Therefore, while macro-economic factors can explain a substantial fraction of the variation in the gap alone, they do not add much explanatory power when combined with firm-specific factors during the crisis period. While true for the crisis period, the same holds for the full period in which the adjusted R^2 increases on by 3% when macro-economic factors are added to the second specification that only includes firm-specific factors. This clearly indicates that firm-specific factors, in particular ATM volatility, CDS liquidity, and company returns, rather than macro-economic factors should be included in structural models in the first place.

CRISIS PERIOD

	Investment Grade			High-Yield Grade		
	(1)	(2)	(3)	(1)	(2)	(3)
Δ Consumer Confidence	0.000 ***		0.000	0.001 **		0.000
Δ Inflation	0.062 **		0.025	-0.004		-0.050
Δ Public Debt	0.000 **		0.000	0.000		0.000
Δ Housing Prices	0.001 ***		0.000	0.001 **		0.000
Δ Industrial Production	0.000		0.000 **	0.001		0.000
Δ Unemployment Rate	0.000 ***		0.000	0.000 **		0.000
Δ Slope Yield Curve	-0.306 **		0.013	-0.562		-0.178
Δ Risk-Free Rate	0.001		-0.002 **	0.003		-0.001
Δ ATM Volatility		-0.077 ***	-0.082 ***		-0.059 ***	-0.060 ***
Δ Volatility Skew		-0.017	-0.010		0.108	0.103
Company Returns		0.093 ***	0.084 ***		0.094	0.092
Δ CDS Liquidity		-0.016 ***	-0.013 ***		-0.046	-0.065
Δ Credit Rating		0.000	0.000		-0.003	-0.002
Δ Gap(-1)	0.129 *	0.148 ***	0.111 **	0.156 ***	0.130 **	0.136 **
Δ Gap(-2)	-0.175 ***	-0.217 ***	-0.229 ***	-0.256 ***	-0.271 ***	-0.273 ***
Constant	0.003 ***	0.000	0.000	0.006 **	0.001	0.002
Observations	1,792	1,792	1,792	920	918	918
Firms	69	69	69	37	37	37
Adjusted R^2	0.455	0.686	0.717	0.152	0.238	0.234

Table 12 – Estimates of Panel Regressions of Monthly Changes in the Difference between Market and Model CDS Spreads viz. (1) Changes in Macro-Economic Factors; (2) Changes in Firm-Specific Factors; (3) Changes in the Combined Factors of (1) and (2). All Estimates include two Lags of the Dependent Variable and a Constant. Sample Period July 2007 to August 2009.

*** Statistically significant at 10% level.**
**** Statistically significant at 5% level.**
***** Statistically significant at 1% level.**

For the high-yield class only the change in ATM volatility is statistically significant (at the 1% level). Interestingly, the third specification can explain more of the variation in the gap in the crisis period than in the bubble period, although many more factors are significant during the latter period. Finally, changes in the first two lags are again highly significant for both classes and have the same signs as before, i.e. a positive coefficient for the first lag and a negative coefficient for the second lag. The constant becomes statistically insignificant again, a result that indicates that no crucial factor is missing during this period.

C) Discussion

What becomes apparent when examining the results presented is that model spreads do show a high correlation (Table 4) with market spreads. In the bubble period, model spreads of high-yield obligors show the highest observed correlation, while for the crisis period the correlation is highest for investment grade obligors. This can be explained by the fact that there is a systematic underestimation of model spreads for investment grade obligors during the bubble period, which turns into a positive overestimation of spreads during the crisis period (Table 7). Moreover, model spreads of high-yield obligors are able to explain more of the variation in market spreads during both periods (Table 6), whereas a substantially higher fraction of market spreads can be explained by model spreads in case of investment grade obligors in the crisis period. This result confirms the previous observations.

Determinants of market and model spreads have been identified (Table 9) with the help of panel regressions in a first step. The results indicate that firm-specific factors are better able to explain spreads compared to macro-economic factors. In particular, changes in inflation and the risk-free rate are significant macro-economic variables whereas ATM volatility and company returns are significant firm-specific factors. In order to explain changes in the gap between market and model spreads panel regressions reveal that both macro- and firm-specific factors can explain a varying degree of the variation in the gap, a finding consistent with my initial results. Whereas macro-economic factors can explain substantial fractions of the variation in the gap for investment grade obligors (Table 12) and a lower fraction for high-yield obligors during the crisis period, the explanatory power of those factors diminish once firm-specific factors are added to the specification. In all cases except for investment grade obligors in the bubble period (Table 11) firm-specific factors are better able to explain the variation in the gap. Overall then, for investment grade obligors the following factors have explanatory power: the public debt level, the industrial production index, the risk-free rate, ATM volatility, and company returns. For high-yield obligors only the risk-free rate and ATM volatility are statistically significant over the full period (Table 10).

In summary, the CreditGrades model shows high correlation with market spreads over all periods. The estimation of spreads is better for high-yield obligors than investment grade obligors in every period, since the spreads of the high-yield obligors are able to explain more in the variation of market spreads. Nevertheless, a high fraction of the variations in the gap between market and model spreads can be explained for investment grade obligors during the crisis period. That said the estimations are better for the crisis period for both grade classes, a result that can be attributed to the inclusion of equity volatilities as input of the CreditGrades model. Macro-economic factors alone can explain substantial portions of the variation in spreads in the crisis period but only poorly explain the variation in the bubble period. However, once firm-specific factors are added to the model the explanatory power of the macro-economic factors substantially declines. Furthermore, there are substantial differences in the factors that can explain the gap in terms of credit rating class. A higher portion of variation with more statistically significant factors can be explained for investment grade obligors, whereas only ATM volatility seems to be an important determinant of CDS spreads in case of high-yield obligors. This suggests that high-yield companies are evaluated more in terms of company-specific determinants whereas spreads of investment grade obligors are comprised by a mix of macro- and firm-specific factors.

Finally then, my results suggest that important determinants of CDS spreads are missing in the current implementation of the CreditGrades model. In case of the macro-economic factors it seems to improve estimations of credit spreads if variables such as the public debt level, real housing prices, and industrial production were incorporated. The risk-free rate is also an important determinant of CDS spreads and should be included in structural models, as is the case for the CreditGrades model. Moreover and more important though is the inclusion of firm-specific factors. In particular, the inclusion of equity volatilities and the volatility skew is important and improves the estimation of spreads substantially. Furthermore, in line with prior research, the inclusion of CDS liquidity adds value – especially during the crisis period – although I find that that CDS liquidity only impacts spreads of investment grade obligors. Lastly, company returns should be incorporated in structural models since they are highly significant, especially during the crisis period.

VII. Conclusion

This section contains a summary of the study, its methodology, and the most important results. Next, the study's contribution to academics and practitioners is presented. As no study is without limitations the most important limitations will be outlined afterwards. Finally, ideas for further research, some of which are based on the previously presented limitations, are offered.

A) Summary

This paper investigates the pricing and tracking performance of the CreditGrades model, which is a popular structural model amongst practitioners and academics, and provides empirical evidence over a period of almost six years (January 2004 to August 2009). This study is the longest to date and the first that explicitly tests the model during the crisis period. For this purpose the CreditGrades model was used to estimate CDS spreads for a total of 106 North-American companies over the entire time horizon. In total, CDS spreads for 37 high-yield grade obligors and 69 investment grade obligors have been estimated and subsequently compared to historical market spreads. The correlation between market and model spreads has been analyzed, followed by an in-depth examination of the gap between market and model spreads by means of panel regressions. Several macro- and company-specific factors, which are partly included in the model, have been used in order to identify determinants of the gap. A separation between high-yield obligors and investment grade obligors has been made since factors impact spreads differently based on the company's credit rating. Furthermore, the time period has been split into a bubble period (January 2004 to June 2007) and a crisis period (July 2007 to August 2009) in order to examine the effects and the performance of the model during the financial crisis.

I find that the CreditGrades model prices CDS spreads reasonable well and show high correlation with market spreads. The fit is generally better for high-yield obligors in all periods as panel regressions reveal, although the gap between spreads is often smaller for investment grade obligors on an absolute level. This is on the one hand based on a systematic underestimation of investment grade obligor spreads during the bubble period and an offsetting overestimation during the crisis period. This result suggests the inclusion of jump risk to increase short-term default probabilities, which in turn will lead to higher short-term spreads and less underestimation. On the other hand, the tracking of CDS spreads is especially well during the crisis period for both credit classes, a result attributable to the inclusion of equity volatilities. The difference between market and model spreads can be explained by several factors, some of which are partly included in the model. In particular, the CreditGrades model should incorporate macro-economic factors like the public debt level, real housing prices, and industrial production. Also, the risk-free rate turns out to be important but is already included in the model. In terms of company-specific factors option-implied volatilities, the volatility skew, CDS liquidity, and company returns are important determinants.

B) Contribution

The contribution of this study is three-fold. First, it is the first study that explicitly examines the pricing and tracking ability of a structural model during the financial crisis since no study to date has used a data sample longer than April 2008. Thus, this study uses the most extensive time period up to date. Moreover, while Imbierowicz (2009) examines CDS spreads up to 2008 he does not test for sub-periods and only considers the full period. Another drawback of his study is that he uses historical volatilities, which are inferior to implied volatilities, which in turn leads to less accurate spread estimations by the model. Therefore, this study provides important insights into the pricing and tracking ability of the CreditGrades model during the financial crisis. Second, the study provides a survey of all identified factors to date, which are missing in structural models, and uses most of these factors as control variables in order to determine the impact of each of these factors on the gap between market and model spreads. Thus, the study provides important insights into the significance of factors, especially in light of the underlying credit rating class as well as different sub-periods. Third and finally, the study provides an up-to-date view to practitioners of how the most advanced structural model performs in pricing CDS spreads, especially during a crisis period. Since many professionals use the model for trading purposes or portfolio evaluations the results of this study can be used to improve the model by incorporating the identified missing factors.

C) Limitations

There are several limitations in my study that will automatically lead to suggestions for further research. First of all, my sample is comprised of only U.S. companies. While the U.S. credit derivatives market is the largest worldwide, regional differences exist as prior research

(Imbierowicz, 2009) finds. Second, although the sample includes high-yield obligors the fraction of those obligors is small compared to investment grade obligors. Inclusion of more high-yield obligors would increase the inference of the results. It would probably also be of added value if not only the most liquid CDS contracts would be analyzed but also less liquid ones. Third, an analysis of industry effects may provide additional insights in what factors can explain the gap between market and model spreads. Fourth, the control variables used provide a broad range of variables and includes nearly all factors found to be important determinants in prior research. However, factors like the CDS slope[11] or credit rating review announcements have been found to have explanatory power. Due to data availability I was, however, not able to incorporate these variables. Fifth, the robustness of the results could be enhanced by running separate regressions for each sample company in order to put more emphasis on the time dimension of the regression analyses. Additionally, the robustness of results could be enhanced by using another (dynamic) panel regression estimation method, e.g. the GMM (General Method of Moments). Sixth, the estimation of spreads using historical volatilities could be done in order to directly compare these estimations to estimations of spreads using implied volatilities. Due to time constraints I was not able to estimate spreads using historical volatilities for the entire sample, which is why I can only provide limited evidence regarding the improvement of model spreads when using implied volatilities. Seventh and finally, while the results suggest that the CreditGrades model prices and tracks CDS spreads reasonably during the crisis there may be another model (either reduced-form or information-based), which might be even better to price and track CDS spreads during this period.

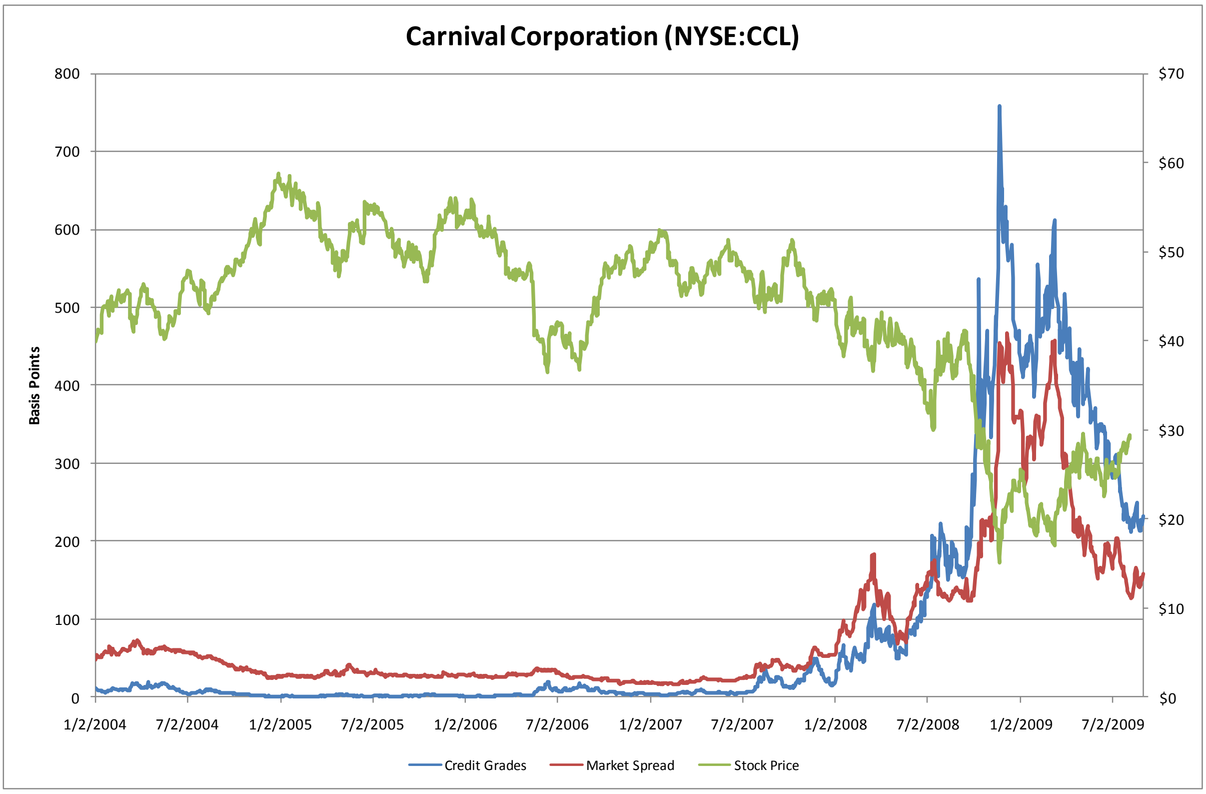
D) Further Research

The limitation and results of my study provide suggestions for further research for academics as well as practitioners. Related to the last aspect of the limitations of this study, it may be good to compare different credit pricing models with a focus on the financial crisis to evaluate whether there is a model that is able to price CDS spreads better during a crisis. The inclusion of implied equity volatilities does add much to the tracking and pricing ability of the CreditGrades model. However, the results also suggest the inclusion of some important variables that are currently missing in the model. Inclusion of these variables should further increase the accuracy of estimated spreads. In particular, forward-looking factors and

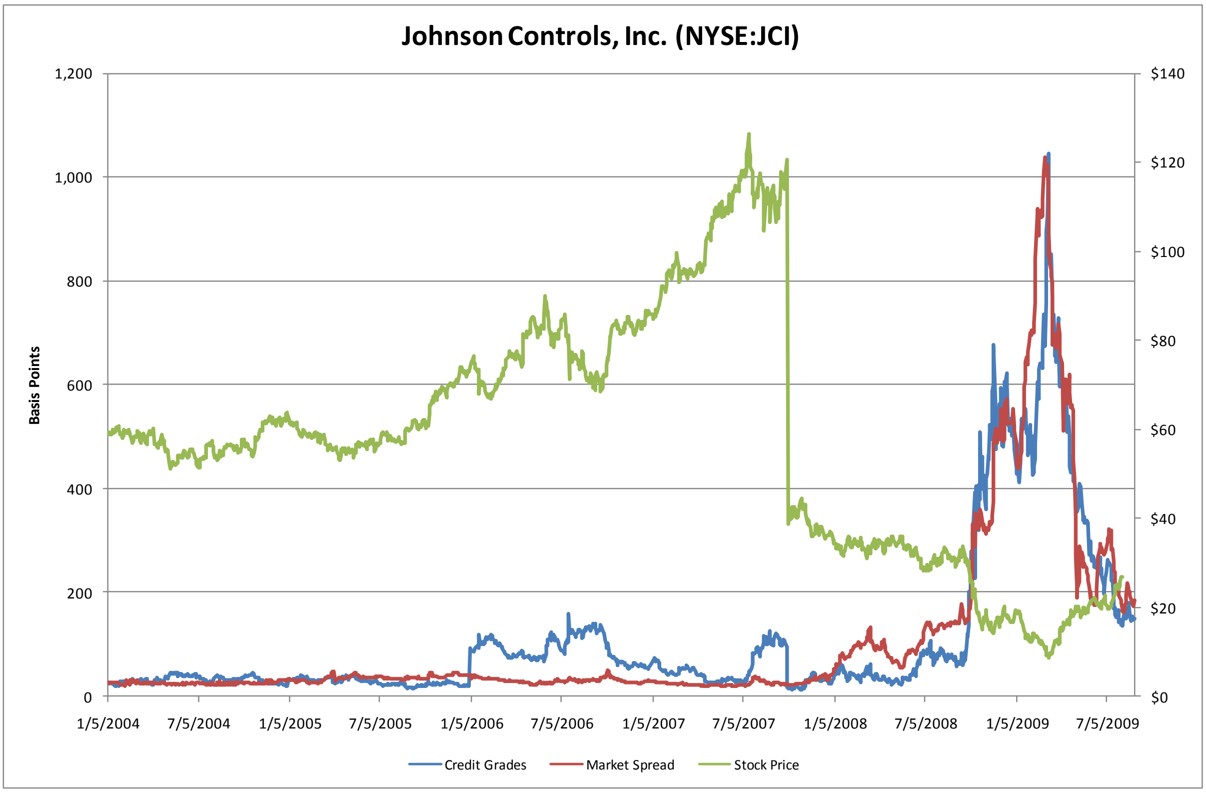
[11] 10-year market CDS spread minus the 3-year CDS spread

liquidity measures should be incorporated. As the CDS market is expected to grow further the model should be extended and incorporate the identified factors. Furthermore, it would be interesting to see a trading strategy exercise, i.e. capital structure arbitrage simulation, based on the model's spread estimations during the financial crisis. To my knowledge there is no research on this topic to date that includes the period of the financial crisis. Since I find a good tracking ability I suspect that results returns should be as profitable or even be more profitable during the crisis, if implied volatilities are used. Related to this aspect is a comparison between the models performance using historical volatilities during the financial crisis. In preliminary results I find a substantial decrease in accuracy of spreads and tracking ability of the model. Therefore, I further suspect that the tracking ability would substantially decrease and be lagged for several days or even weeks during a crisis period and that the model would not be able to track sudden jumps.

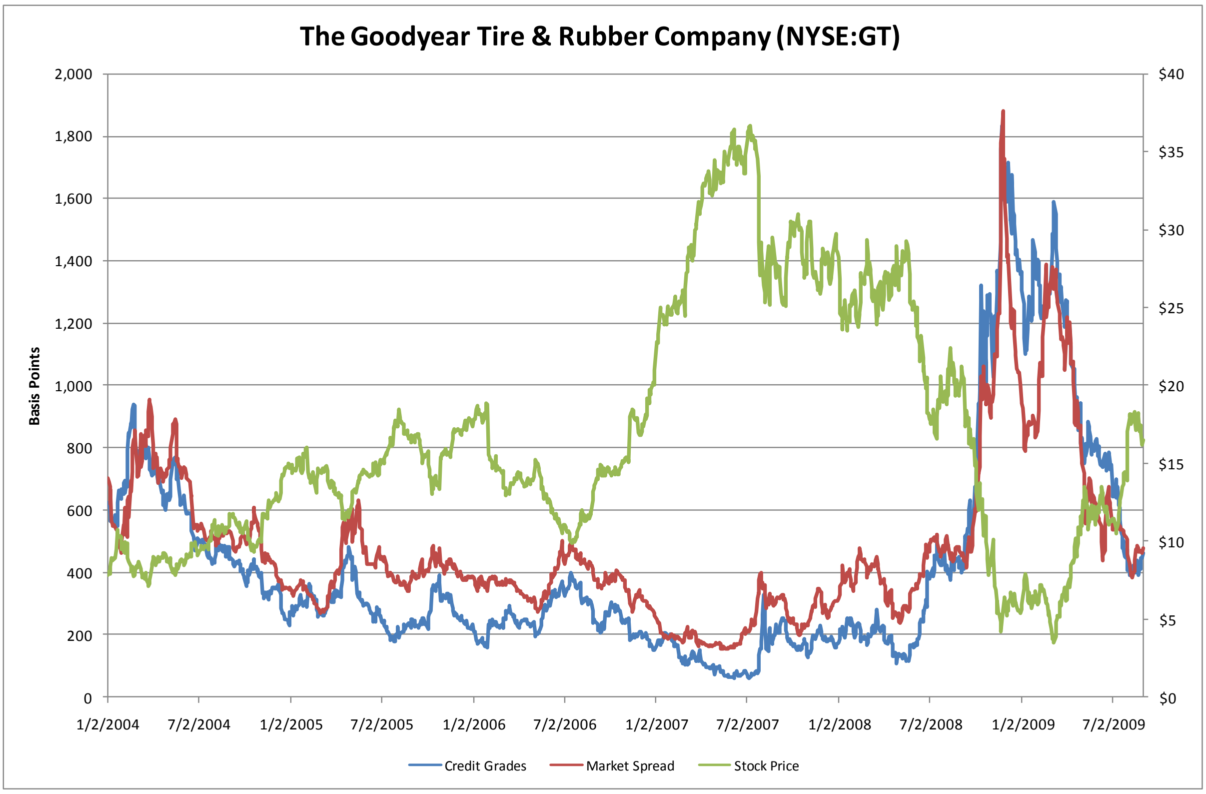
VIII. Appendix



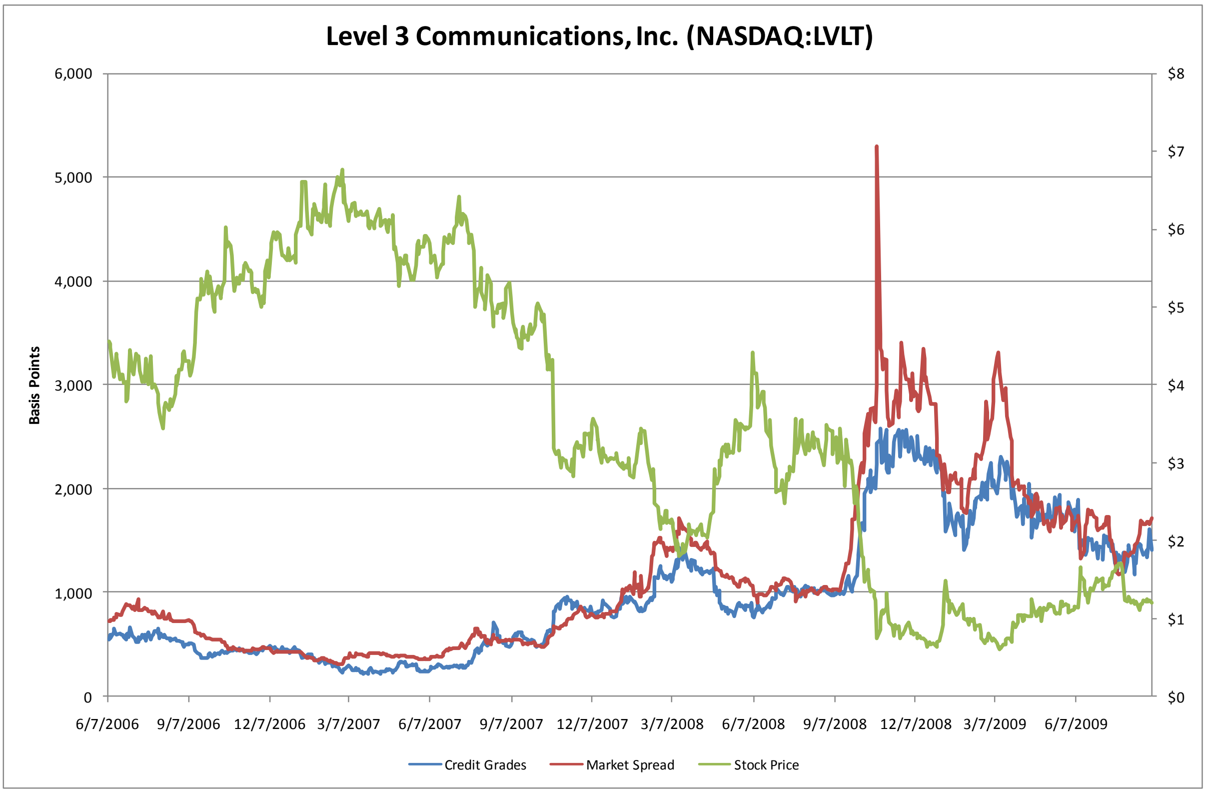
Case Study 1 – Carnival Corporation (Investment Grade) – Example of Consistent Underestimation of Spreads during the Bubble Period and Overestimation of Spreads during the Crisis Period



Case Study 2 – Johnson Controls Inc. (Investment Grade) –Example of Better Pricing and Tracking Performance of the CreditGrades Model over the Full Period



Case Study 3 – The Goodyear Tire & Rubber Company (High-Yield) – Example of Good Pricing and Tracking Performance of the CreditGrades Model over the Full Sample Period



Case Study 4 – Level 3 Communications Inc. (High-Yield) – Example of Good Pricing and Tracking Performance with an Underestimation of Spreads During the Very Turbulent Period in End-2008

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