LAPPEENRANTA SCHOOL OF BUSINESS
Business Administration
Finance
31.8.2010

DETERMINANTS OF CREDIT DEFAULT SWAP SPREAD, THE EFFECT OF THE FINANCIAL CRISIS IN THE US MARKETS

Lappeenranta 31.8.2010

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ABSTRACT

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Title:	Determinants of Credit Default Swap Spread, the Effect of the Financial Crisis in the US Markets
Faculty:	Lappeenranta School of Business
Major:	Finance
Year:	2010
Examiners:	Professor Minna Martikainen Professor Eero Pätäri
Master's Thesis:	Lappeenranta School of Business 97 pages, 13 pictures, 20 tables, 4 appendices
Key words:	Credit Default Swap, Credit Markets, Credit Derivatives, Financial Crisis, structural models, Credit spread

The purpose of this study is to define what determinants affect the Credit spread. There are two theoretical frameworks to study this: structural models and reduced form models. Structural models indicate that the main determinants are company leverage, volatility and risk-free interest rate, and other market and firm-specific variables. The purpose is to determine which of these theoretical determinants can explain the CDS spread and also how these theoretical determinants are affected by the financial crisis in 2007.

The data is collected from 30 companies in the US Markets, mainly S&P Large Cap. The sample time-frame is 31.1.2004 – 31.12.2009. Empirical studies indicate that structural models can explain the CDS spreads well. Also, there were significant differences between bear and bull markets.

The main determinants explaining CDS spreads were leverage and volatility. The other determinants were significant, depending on the sample period. However, these other variables did not explain the spread consistently.

TIIVISTELMÄ

Tekijä:	Mika Redsven
Tutkielman nimi:	Determinants of Credit Default Swap Spread, the Effect of the Financial Crisis in the US Markets
Tiedekunta:	Kauppatieteellinen tiedekunta
Pääaine:	Rahoitus
Vuosi:	2010
Tarkastajat:	Professori Minna Martikainen Professori Eero Pätäri
Pro gradu -tutkielma:	Lappeenrannan teknillinen yliopisto 97 sivua, 13 kuvaa, 20 taulukkoa, 4 liitettä
Hakusanat:	Credit Default Swap, Credit Markets, Credit Derivatives, Financial Crisis, structural models, Credit spread

Tämän tutkielman tavoitteena on selvittää, mitkä tekijät vaikuttavat yritysten velkakirjojen ja riskittömän tuoton eroon. Tätä eroa mitataan Credit Default Swap –instrumenteilla. Strukturaalisten mallien mukaan vaikuttavia tekijöitä ovat yrityksen volatiliteetti, velkaantuneisuusaste sekä riskitön korko.

Tavoitteena on selvittää, miten nämä teoreettiset mallit toimivat käytännössä sekä tutkia, onko olemassa muita tuottoeroa selittäviä tekijöitä. Tavoitteena on myös perehtyä finanssikriisiin USA:ssa ja sen vaikutuksiin näissä tekijöissä. Yrityskohtainen data on kerätty 30 yrityksestä USA:n markkinoilta. Havainnot ovat kuukausittaisia ja aikaväli on 31.1.2004 – 31.12.2009.

Empiiriset tulokset osoittavat, että strukturaalisten mallien muuttujat selittävät hyvin tuottoeroja. Muut selittävät muuttujat eivät ole yhtä tehokkaita. Tulokset osoittavat, että selittävien tekijöiden merkitys vaihtelee suuresti taloudellisen tilanteen mukaan. Tärkeimmät muuttujat olivat velkaantuneisuusaste ja volatiliteetti. Tuloksista selviää myös, että finanssikriisi vaikutti tuottojen eroon selvästi.

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1. INTRODUCTION

Credit derivatives are the main investment vehicles to manage credit exposures, diversifying credit and default risk. They are contracts between two parties by means of bilateral agreements. Credit derivatives are contracts where the payoff depends upon the creditworthiness of a reference entity, which can be a company or a country. Default swaps protect its buyer from losses caused by the default or payment difficulties that can be interpreted as default by a debt issuer.

Credit markets are one of the largest markets in the world. The markets have grown rapidly since the 1990s. From 1996 to 2001, the credit markets have soared from US$ 40 billion to US$400 billion in the US alone. There are more than 400 financial institutes that use credit derivatives for risk management and trading. (Batten et al., 2002) In the end of 2009, according to ISDA (International Swaps and Derivatives Association) the size of the global derivatives market was nearly US$ 30.4 trillion (ISDA). In the end of 2007, the total outstanding notional of Credit Default Swaps was US$ 62.2 trillion. The derivatives market is a growing industry, thus the literature and studies are also increasing rapidly.

According to Hull (2005) the Credit Default Swaps account for about 70 % of all credit derivatives. The principals of CDSs are quite straightforward: The insurer pays periodic payments to the seller and in case of default the buyer of the CDS has the right to sell bonds issued by the company for their face value. The seller agrees to buy the bonds for their face value when the credit event occurs. The total face value in the contract is the swap’s notional principal.

Credit derivatives allow investors to trade risk in the same way they trade market risk. Previously banks and other financial institutions could do only little once they had exposed to credit risk. Now they can actively manage their debt exposure, keeping some and entering credit derivatives contracts to protect themselves. Banks have been the biggest buyers of credit risk and insurance companies have been the biggest sellers. (Hull, 2004)

Credit default spread is the fee that the buyer has to pay to the seller. It is also important to know that the last premium date is the default date of the reference entity. The buyer usually has to pay accrued interest from the last premium payment date to the date of default.

Lately there has been a lot of discussion whether to regulate or even ban “naked” Credit Default Swaps. For example Financial Times argues the necessity of these purely speculative positions in CDSs. (FT, 2010) It has also been argued whether these instruments are needed as they are now.

The credit crisis evolved from the housing crisis and for example AIG had big bets in mortgage backed securities, which were then highly rated, and received handsome returns, as long as the housing markets were booming. When the housing markets started to crumble, the derivatives value also plummeted. This affected AIG in billions in losses and, through the credit markets, it affected dozens of other companies because of their own positions to AIG through credit derivatives, such as CDSs. (Longstaff, 2010)

This was followed by a credit crunch, which affected both individuals and financial institutes. The subject has been studied by Longstaff (2010), who comes to the same conclusion. The original subprime crisis spilled over and became a catalyst for a much broader financial crisis.

The result of this crisis can be seen all over the world but in the US the effect has been more dramatic. We have seen the collapses/mergers/bailouts of such companies as AIG, Bear Stearns, Freddie Mac, Fannie Mae, Lehman Brothers, and Merrill Lynch. The crisis has even shaken the trust in U.S. Treasury and its long-term viability. In the crisis the companies' CDS spreads exploded. The reasons were financial distress followed by the credit crunch and uncertainty.

1.1 Motivation

The credit derivatives arrived in 1992. At first, the credit derivatives were an instrument for the banks to isolate and trade pure credit risk. Since then they have evolved into a multitrillion business with hundreds of counterparties and a lot of speculation. The fact that the derivative markets have increased dramatically in the past decades makes them an important object for study.

The credit crunch has had devastating effects on the US economy. The market-focused system froze to a stop. The cautiousness transferred to the CDS spreads and resulted in credit spreads over 7,000 bps. The motivation of this study is to investigate the relationship between market-specific and firm-specific determinants that would explain these incredibly high spreads never seen before.

According to Reoch, the credit markets can be divided into 3 groups: the credit default swaps, portfolio products, and the other products. The portfolio product group covers different products where the risk of multiple credits is in the structure, for example the Collaterized Debt Obligation (CDO) and the first-to-default structure. These will be examined more closely in the next chapters. As with other derivative markets, there are a lot of hybrid products emerging and they are used for example to transfer risk for another risk.

1.2 Purpose of this study

The purpose of this study is to define the theoretical determinants of Credit

Default Swaps and to test them from an empirical basis in the US markets. The main objective of this study is to determine which determinants affect the Credit Default Swap spread and how these determinants are affected by the financial crisis in 2007-2009.

1.3 Structure of this study

The next chapter reviews the credit markets and the credit derivatives and their implications. Chapter 3 discusses the credit models used in this study and the most commonly used model structures. In chapter 4 We will go through the previous empirical evidence of credit spreads. In chapter 5 the previously created model will be tested on empirical basis and the model's robustness will be examined. In chapter 6 we will explain the results of this study, and Chapter 7 reviews the conclusions.

2. CREDIT RISK AND CREDIT RISK MARKETS

2.1 Credit Risk

Credit risk can be divided into default risk and credit deteriorating risk. (Meissner, 2005) Default risk is the risk that the debtor does not meet a part or all of his obligations. Credit deteriorating risk is the risk that the credit quality of the debtor decreases significantly. Longstaff and Schwartz (1995) have found that market risk and default risk are highly correlated. In terms of finance, higher credit risk tends to affect the firms vulnerability to market risk. (Meissner, 2005) Market risk also affects the credit risk depending on the exposure that the firm has to the market risk.

The creditworthiness of a potential borrower affects lending decisions, the firm’s cost of capital, the credit spread, and the prices and hedge ratios of credit derivatives, because it is uncertain whether the firm will be able to meet its obligations. (Benos & Papanastasopoulos, 2007)

The counterparty risk of credit derivatives is not included in this study because it is difficult to observe. However, the extent of this study could include the counterparty risk through the bond prices of the issuing company.

2.1.1 Default Risk

Default risk is the risk that the reference entity is unable to meet its obligations. The default risk can also be considered as credit event risk. According to Choudhry (2006) credit event can be specified as financial or debt restructuring, bankruptcy or insolvency of the reference entity, default on payment obligations, technical default, for example the non-payment of a coupon when it falls due. The definitions may differ depending on the contract. The difference between default risk and credit deteriorating risk is that the creditor receives the full coupon or notional if the credit has only deteriorated. Therefore, the credit deteriorating may not affect the cash flow out of the company. In default, the creditor will only receive the recovery rate which can be considerably smaller. (Choudhry, 2006) It is because of this risk that the companies issuing bonds have to pay spread over default-free bonds, such as government bonds. (Denzler et al. 2006)

Default risk has been studied widely and studies such as Merton (1974), Black & Scholes (1973), Black & Cox (1976) have given the outlines from a theoretical point of view. There are two main theories of modelling default risk of corporate securities. They can be divided into structural models and reduced form models. These models are quantitative and based on either firm fundamentals or default intensities. These models are discussed in chapter 3.

Table 1. Cumulative Default rates (%) of Corporate Issues in years by credit rating 1970 -2001 (Hamilton et al. 2001)

Term (Years)	1	2	3	4	5	10	15	20
Aaa	0.00	0.00	0.00	0.04	0.14	0.79	1.60	2.03
Aa	0.02	0.04	0.08	0.20	0.31	0.89	1.76	2.87
A	0.02	0.07	0.21	0.35	0.51	1.57	2.97	5.44
Baa	0.15	0.46	0.87	1.44	1.95	5.09	9.10	12.47
Ba	1.27	3.57	6.20	8.83	11.42	21.27	30.75	37.97
B	6.66	13.99	20.51	26.01	31.00	47.60	55.95	57.20
Caa-C	21.99	34.69	44.34	51.85	56.82	77.31	80.55	80.55
Investment-Grade	0.06	0.19	0.38	0.65	0.90	2.51	4.60	6.96
Speculative-Grade	4.73	9.55	13.88	17.62	20.98	32.31	40.84	46.58

There have been studies (e.g. Altman et al. 2005, Bruche & González-Aguado, 2010 and Hamilton et al. 2001) which implicate that the recovery probability and the recovery rate are negatively correlated. Implying that, the Non-Investment-Grade companies' default rates and probabilities are high and the recovery rate low. This can be intuitively interpreted so that when the default does not come “out of the blue” the recovery rate is lower than if the default is not expected by the markets. The cumulative default rates can be seen in Table 1.

When an institution is involved in credit derivatives, it is important to seek counterparties whose financial condition is not correlated with the reference asset. The “two-name-paper” is akin to two entities defaulting at the same time, the reference asset and the derivative counterparty. (Banks et al. 2006)

2.1.2 Recovery rate risk

Recovery rate is the amount the creditor will receive after the default of reference entity. When a company goes bankrupt, those who owe money by the company are entitled to file claims against the assets of the company. The historical average default rates are presented in Table 2.

Sometimes, there can be a reorganization of the company, agreed by the creditors, where they receive only partial payment. In other cases, assets are sold and the proceeds are used to meet the claims as far as possible. (Hull, 2005)

The recovery rate is defined by the bond’s market value immediately after default. It is shown as the percentage of the face value. The determinants of default rates include structural characteristics of the firm, the position of the debt (i.e. the seniority), and macroeconomic conditions. (Hamilton et al., 2002) The recovery rate is an important factor in pricing credit derivatives and has direct impact on how wide the spread is.

Table 2. The average recovery rates of Issuer-level Bonds & Bank loans as a percentage (%) of the face value, 1982-2001. (Source: Hamilton et al. 2002)

	Investment Grade	Speculative Grade	All Rated
Sr.Sec. Bank Loan	68.33	71.42	71.28
Secured Bonds	73.44	52.76	53.32
Sr. Unsecured Bonds	52.48	35.29	36.57
Subordinated Bonds	35.75	31.74	31.84

2.1.3 Credit Deteriorating Risk

Credit deteriorating risk is the risk that the credit quality of the debtor decreases. In other words, the value of the assets decreases to an extent resulting in financial losses for the creditor. If the debtor is rated by a public rating agency, such as Standard & Poor's, Fitch, Moody's, credit deteriorating means downgrading to a lower category, for example from AAA to AA. The actual consequence of this is that investors require bigger yield for the bonds.

According to Benkert (2004), in investment grade firms the credit quality usually deteriorates for some time before default occurs. Therefore the credit deteriorating is important. However, there seems to be no theoretical evidence to support this argument. (Benkert, 2004) The fact that investors should recover more when the default comes suddenly compared to it having been on a brink of default, is not proven theoretically.

Studies on credit deteriorating are scarce. However, Hamilton et al. (2001) show that a correlation between credit quality and default rate can be found easily. This paper was done by Moody's Investor Service and the measurement of credit quality is their rating matrix. The deteriorating in credit quality was seen as a downgrade in their rating. Appendix 1 shows the average one-year transition matrix. It is shown in percentage as the probability that the company has the same rating from one year of the original rating. It also shows the probabilities that the credit quality deteriorates or upgrades.

Credit deteriorating risk can also be thought to include the risk of restructuring. The restructuring is usually separated from default but they both can be credit events. Restructuring can destroy the value of the debt but it is not a necessity. (Berndt et al. (2007)

According to Berndt et al. (2007) the restructuring could also affect the debt's subordination, reducing its priority in the event of default. They find that the premium for restructuring risk represents 6% – 8% of the swap rate without restructuring. They also find that when default swaps rates without restructuring increase, the increase in restructuring premium is higher for low-credit-quality firms than for high quality firms. The restructuring can affect some debtors' position in the case of default but not necessarily everyone's. So the effect of restructuring does not affect at a company level but more likely at the lender level.

2.2 Credit Risk Markets

The history of credit derivatives is derived from the several credit crises in the past, such as the Latin American debt crisis in the 1980s and the junk bond crisis in the same decade. The credit derivative markets have emerged to be the one of the most innovative and dynamic sectors of finance. These instruments have become the key of risk management and investment strategies of global investors. Credit derivatives are quite new, compared to other products – development since the mid-90s – the growth rates are impressive.

The figures speak for themselves as discussed earlier, the size of the global derivatives market was nearly US$ 38.6 trillion. According to Meissner (2005) the main end-users of credit derivatives are hedge-funds, banks, and insurance companies. In the year 2002, the Credit Default Swaps accounted for nearly 73 % of the credit derivatives markets. (Banks, 2006)

2.2.1 Credit Default Swap

Credit Default Swaps (henceforth CDS) are the most popular credit derivatives and they are traded in the OTC markets. (Hull, 2005) As discussed earlier, CDSs are contracts between two parties, the buyer and the seller. These contracts provide insurance against the risk of default of the reference entity. The buyer of the contract obtains the right to sell the bonds at their face value. The seller promises to make a payment if a default or a failure of payment occurs, of the reference entity. (Meissner, 2005) In the CDS contract, the buyer pays a periodic payment, fixed fee or one-off premium to the seller. The default payment can be agreed upon by the counterparties. (Choudhry, 2006)

As mentioned above, CDSs have periodic payments. The payments are usually quarterly, based on the maturity date of the contract. Most contracts have a "standard roll" maturity. If a 5-year contract is bought for example 31.3.2010, it means protection to 31.3.2015. (Choudhry, 2006) The maturity of the CDS does not have to match the maturity of the reference asset, and it usually does not.

CDSs can be viewed as an exotic knock-in put options. The default is the knock-in, thus triggering the payment of the default swap seller. (Meissner, 2005) The theoretical valuation of the CDS, if it is marked-to-market, in arbitrage-free markets can be derived from the basics of financial theory. Simply, the returns of two portfolios must be the same if the risk is identical. Thus the return of CDS can be written as

$$Return\ on\ risk - free\ bond = Return\ on\ risky\ bond - CDS\ premium \quad (1)$$

This equation ignores several important facts. For instance, it does not include counterparty risk; the risk that the seller of the swap may default. Including the counterparty risk would affect the equation in a lower CDS premium because the uncertainty of the sellers credit quality. Equation is also valid only if the no-default value of the risky bond and the risk-free bonds are sold at par. When considering that, risk-free and risky bonds should have the same duration and convexity. In practice, it is rarely the case. (Meissner, 2005) This equation also does not have the accrued interest of the risky bond. It does not include the liquidity risk, either.

Default swaps are usually purchased if the buyer owns the reference obligation and wants to hedge itself from default of this obligation. Now, CDS is owned as an insurance against default, seen in Figure 1. The default payment of CDS can be done in two ways: cash settlement or physical settlement. (Meissner, 2005) In cash settlement, the investor can sell the reference obligation to the markets at its final price and then receive 100 % – final price from default swap seller. The cash flows in a default swap can be seen in Figure 2. In physical settlement, the investor gives the obligation to the seller against its face value. (Meissner, 2005) The values of credit default swaps can be calculated for example with modified Black and Scholes' (1973) model. The theoretical formulas can be seen in Formula 1, 2 and 3.

Cash settlement can be determined as

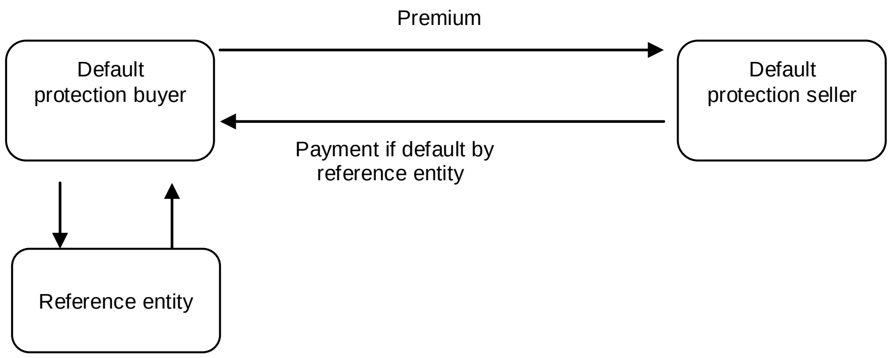
$$N[Reference\ price - (Final\ Price + Accrued\ interest)] \tag{2}$$

Physical settlement can be written as

$$N * Reference\ Price \tag{3}$$

Where N = the notional amount of the contract

Figure 1. The basic principles of hedging with Credit Default Swaps (Source: Meissner, 2005)



There are five different uses of CDS according to Meissner (2005):

1. *Pure hedging* – Entering into a CDS contract to reduce the risk of the original trade. CDSs provide protection against credit risk and, if marked-to-market, credit deteriorating risk. However, they do not cover market risk. They also protect against the company's operational risk to a certain level. Depending on the impact of the operational damage to reference entity's credit quality.

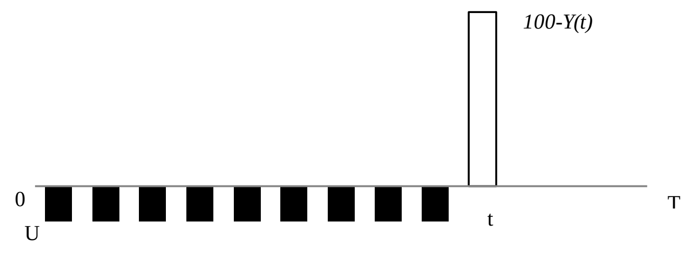
2. *Yield enhancement* – Usually by assuming credit risk on a reference entity. There are numerous ways to enhance yields with swaps. The main aspect to this is that the investors get above market yield by assuming default risk of the reference entity. The yield appetite depends, however, of the investors risk aversity.

3. *Convenience and Cost Reduction* – CDSs allow a lender to eliminate credit risk to a debtor without the debtor's knowledge. Swaps also allow the investor to take exposure with a higher yield than, for example, a normal bond.

4. *Arbitrage* – Risk-free profit achieved by Derivatives. Arbitrage exist if the equation, return on risk-free bond = return on risky bond – CDS premium, is not satisfied. We will not go into details of the arbitrage opportunities because they are so numerous that only naming a few would be useless.

5. *Regulatory Capital Relief* – CDSs can reduce the amount of regulatory capital in banks and financial institutions which are under Basel II regulations. Since the Credit Default Swaps can be situated in the trading book instead of the banking book. Basel II gives the OECD banks the opportunity to determine default probabilities, loss given default, and other components of risk on their own. Basel Accord grants 80 % capital relief for exposure hedged by CDS and 100 % if hedged with Total Return Swaps.

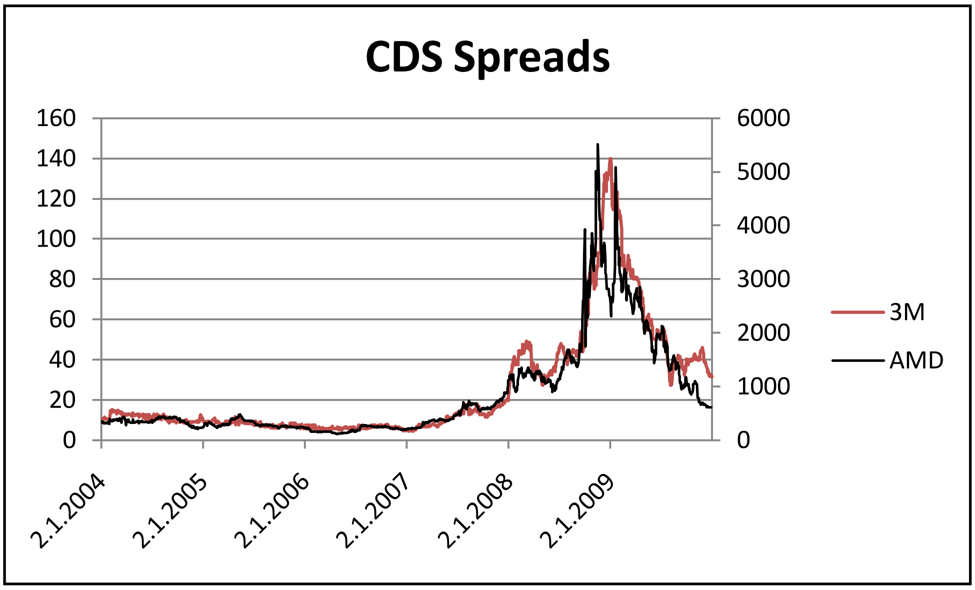
Figure 2. Credit Swap Cash Flows, *U* is the annual long payment of the swap, *t* is the time of default and the payment is *100-Y(t)*, market value of the bond (Source: Duffie, 1999)



Studies, such as Tang (2009), show that investor sentiment is the most important determinant of CDS spread at a market level. They also conclude that implied volatility is the most important factor at a firm-level. This conclusion has been made also by Benkert (2004), and Ericsson et al. (2009). Alexander & Kaeck (2008), however, conclude that the theoretical determinants have a strong regime dependant and sector specific behaviour. Bonfirm (2009) studies that the probability of default is affected by several firm-specific characters, which is quite intuitive considering that the firm-specific variables are the base of the swaps.

However, the effect of market-specific variables is interesting. The relationships between some market-specific variables are shown in Figure 4 and 5, and also the co-movement of two CDS spreads are shown in Figure 3.

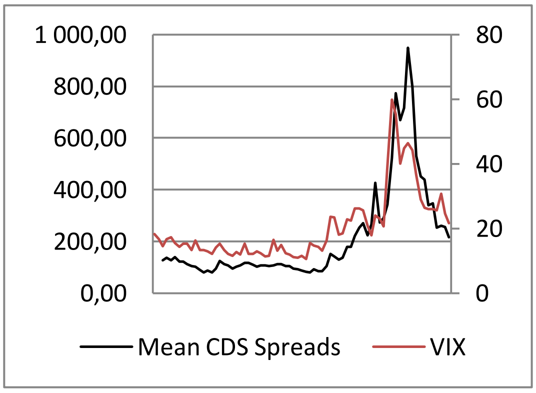
Figure 3. Figure shows the monthly spread of AMD and 3M. Credit Default Swap from January 2004 to 31.12.2009. The effect of the financial crisis to the company risk can be seen here. (Source: Datastream)

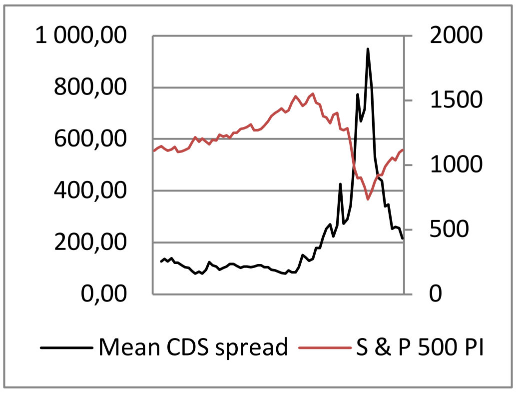


When the remaining maturity of the CDS becomes shorter, the value of the swap declines towards zero. The CDS starts to trade as a binary instrument; the value is driven by the risk that the reference entity will default rather than changes in the relative credit valuation. (Das, 2005)

According to Banks et al. (2006) there are five different factors that affect the price of a CDS. First is the time to maturity; the longer the maturity, the greater the likelihood of default and the higher the premium. Second is the probability of the reference asset to default. Third is the credit rating of the counterparty of the CDS, i.e. the seller. Fourth is the correlation between the CDS seller and the reference asset; the higher the correlation between the seller and the reference, the lower the premium. Fifth is the expected recovery rate; the higher the rate the lower the premium.

Figure 4 and 5. The relationship between CDS spreads and CBOE VIX Index and the S & P 500 (Source: Datastream)





2.2.2 Collaterized Debt Obligation

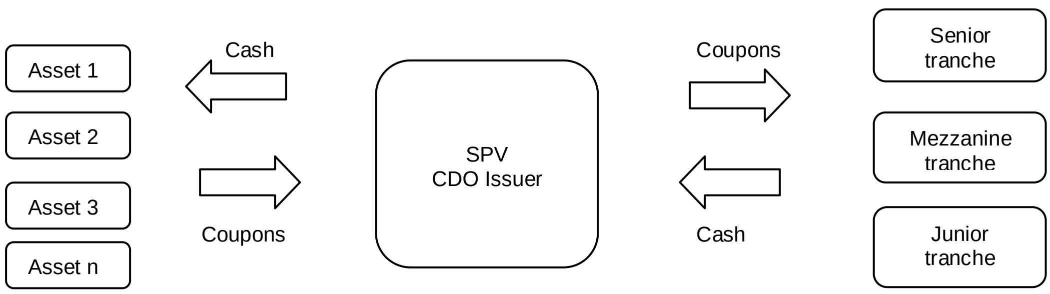
The Collaterized Debt Obligations (henceforth CDOs) are structured transactions that resemble a closed-end mutual fund and have an underlying debt exposure of variety of debt instruments. (Gregory, 2004) They belong to the group of Asset Backed Securities (ABS). The idea in securitisation is to convert cash flows from underlying assets or debt, due to the originator, in to a stream of payments allowing the originator to raise asset backed finance through a loan or an issue of debt. The securitisation began with mortgages, contracting long term future payments, but has now developed into short-term financing assets, such as credit card, or auto loan receivables. (Deacon, 2004)

CDOs usually provide exposure up to 200 or more credits. (Meissner, 2005) They are usually tranched, providing different risk profiles for different investors. There are two different kinds of CDOs, cash and synthetic. The difference between these two is that the synthetic CDOs use credit derivatives to achieve the desired credit positions. The illustration of cash and synthetic CDOs are given in Figures 6 and 7.

The idea of tranching has been used in many cases, for example, the mortgage backed securities (MBS). The idea behind it is that, in this case, the mortgage payments flow to the first tranche, when that notional is full, then the payments flow to the second and so forth. It is reversed to the CDOs but the junior tranche always takes the first "blow".

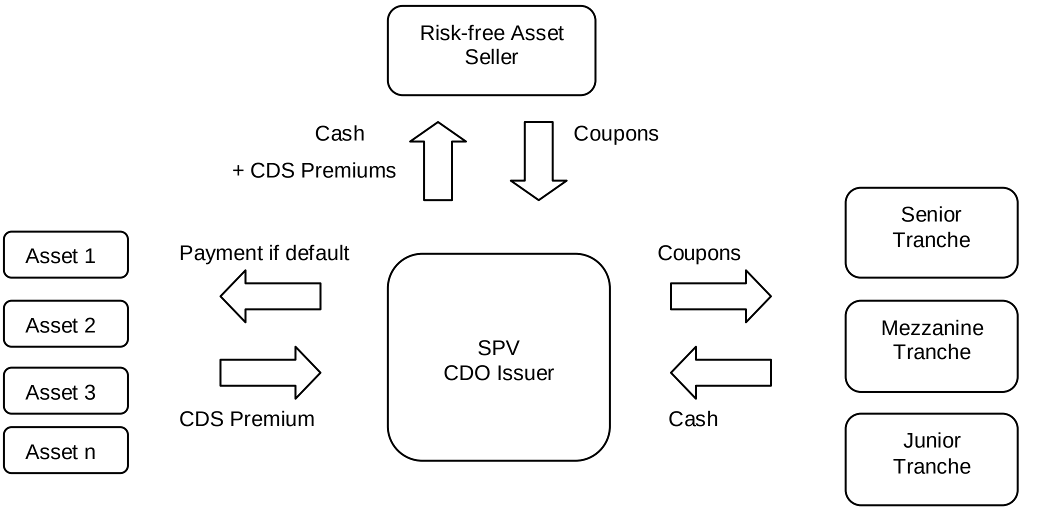
In CDOs the principal is the same. A default of any asset in the basket leads to a loss of coupon and/or notional for the investors of the junior tranche, if the basket is first-to-default. In some cases, when the defaults have exceeded a certain threshold, the investors start losing their coupon and notional. (Meissner, 2005) Junior tranche has the highest risk; therefore it receives the highest coupon. The cash flows of CDO are seen in Figure 6.

Figure 6. The typical structure of a Cash CDO (Source: Meissner, 2005)



Synthetic CDOs are traded more than cash CDOs. The difference between cash and a synthetic CDO is that the SPV in a synthetic CDO does not acquire the original asset in cash but it gains long credit exposures to the assets by selling credit protection. (Meissner, 2005) By doing this the SPV transfers the credit risk to the synthetic CDOs' tranche holders. The SPV uses the cash from the sale of the tranches and the CDS premium to purchase risk-free bonds, seen in Figure 7.

Figure 7. The structure of a pure synthetic Collaterized Debt Obligation (Source: Meissner, 2005)



In terms of valuation, the CDOs rely heavily on the default correlation. The most commonly used valuation method is the one-factor Gaussian Copula Model. (Hull, 2005)

The popularity of synthetic CDOs lies in the fact that the ownership of the assets is not legally transferred to the CDO issuer, therefore the assets do not appear on the balance sheet. Furthermore, the CDO issuer has no operational risk with respect to the original asset. (Meissner, 2005)

CDOs are mainly driven by investors. As discussed earlier, the main reason is to create synthetic exposure to credit. The advantages are derived from the access to specific credit risk and the capacity to avoid market frictions. (Das, 2005) The main reasons for the use of synthetic CDOs are:

- Regulatory framework may prevent investor from directly purchasing a security
- Complex and cumbersome procedures to obtain approval for investment
- Lack of securities available

- Difficulties in trading in the markets, lack of liquidity etc.
- Lack of development in infrastructure of investments

2.2.3 Other Derivatives

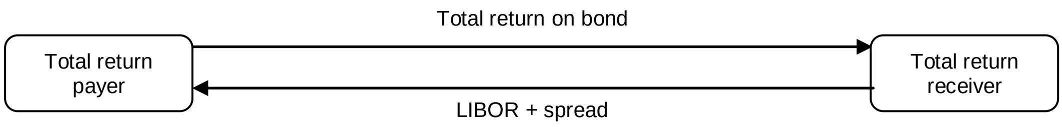
Besides these main instruments in the credit markets, there are a number of other derivatives that are quite similar to the ones mentioned: Basket Default Swap, Equity Default Swap, Total Return Swap, Credit Linked Notes, First-to-Default Baskets. The following chapter will go shortly through the most common credit derivatives.

Total Return Swaps are contracts to exchange the total return on a bond or an asset for LIBOR plus a spread. The total return includes coupons, interest and the gain or loss on the asset in the contract’s maturity.

Total Return Swaps (TRORs) are non-funded position in an obligation. The TROR receiver is synthetically long the obligation, which means he will benefit from price increases. The TROR payer is synthetically short and will benefit if the price declines. The TROR receiver takes the default risk and the credit deteriorating risk; if the reference asset defaults the TROR receiver has to pay the price decline. (Hull, 2004) The illustration of a non-funded TROR is presented in Figure 8.

The benefits of Total Return Swaps are: First, the receiver does not have to take a loan to take a long position in an asset; however, the credit quality of the TROR receiver affects the spread he has to pay. Second, TRORs make the leverage of the receiver extremely high. Third, currently TRORs are off-balance sheet investments, so they do not need any regulatory capital. Fourth, TRORs are more likely more liquid than the reference asset. (Meissner, 2005)

Figure 8. The cash flows of Total Return Swaps. (Source: Meissner, 2005)

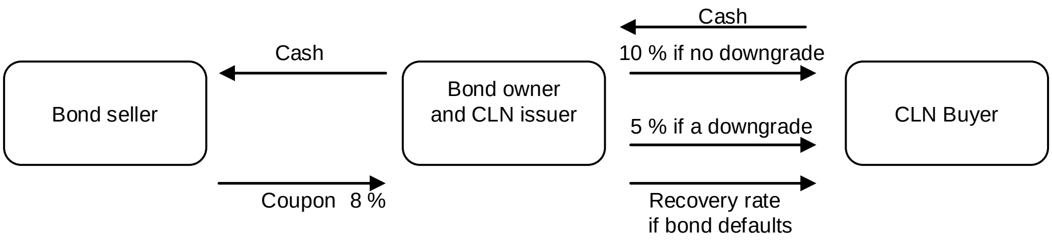


Credit Linked Notes (CLN) are in the simplest form just a bond or a loan with embedded credit feature. The CLN issuer pays an above market coupon if the reference asset is not downgraded, presented in Figure 9. If the asset is downgraded, the coupon payment reduces. The profit (loss) is the difference between the coupons the issuer receives for the bond it owns and +/- the coupon the issuer pays to CLN buyer. If the asset is downgraded (upgraded) the issuer pays (higher) lower coupon to the CLN buyer. (Meissner, 2005)

The CLN buyer can enhance yield. The CLN buyer is willing to take the bond default risk and credit deteriorating risk for an above market return. Here also the CLN buyer has counterparty risk. If the CLN issuer defaults, the CLN buyer loses the original investment + coupons. CLNs have a significant correlation risk between the reference asset and the CLN issuer.(Meissner, 2005)

The use of CLN has the same benefits as other credit derivatives. However, there are two types of CLNs available. Standard CLN act as pass-throughs by forwarding cash flows from a risky asset to investors, and repackaged CLNs, which alter the restructure cash flows before passing them to investors. (Banks et al. 2006)

Figure 9. The basic principles of Credit Linked Notes where the bond owner transfers credit risk via CLN. (Source: Meissner, 2005)



3. CREDIT RISK MODELS

The key issue in modelling credit risk is to model default probability. The literature is mainly based on Black and Scholes (1973) and Merton (1974). These individual models will be examined more closely in the next chapters. In the reduced model, the credit risk is determined by the occurrence of default and the recovery rate.

3.1 Structural Models

Structural models are the first category in modelling CDS spreads; they provide the framework for valuing corporate liabilities. The structural approach provides an intuitive framework for studying spreads. (Collin-Dufresne et al., 2001) In structural approach the default is triggered when the value of the firm's assets fall below a certain threshold and the threshold is usually the notional of the debt. Basically structural models assume that holding a debt claim is the same as holding a same risk-free claim and sold an option to the shareholders to put the firm at the value of the risk-free debt.

The structural models have been built by Black and Scholes (1973) who proved that equity and debt can be valued by using contingent-claims analysis. This means that the value of a debt claim is determined by the expected future cash flow, discounted at the risk-free rate. This study was also used by Merton (1974) who created the framework for models that are used today.

Structural models were introduced by Black and Scholes (1973) and Merton (1974). The Merton's model is the most commonly used one in the valuation process of CDSs. Interpretation is rather difficult in these models because the assumptions are quite unrealistic. There is a lot of literature in which the original Merton's model has been developed further. For example, Geske (1977) extended the model so that the firm issues a coupon bond and the default occurs also when the firm is unable to serve the coupon payment in full. Wang (1999) added incorporated stochastic risk-free interest rates into the framework. Also the debt's seniority has been studied. (Benkert, 2004)

However, Pierides (1997) argues that the effect of interest rates to corporate bonds is not clear and used a constant interest rate. Yildirim (2006) defines default as the first time the firm value process crosses a barrier, and the area under the barrier is greater than the exogenous level. In other words, Yildirim's model lets the firm's equity to cross the boundary and stay below it a certain time until default occurs.

According to Collin-Dufresne et al. (2001) the credit spread $CS(t)$ is defined through the price of the debt claim, this debt claim's contractual cash flow and the risk-free rate. Hence we can write that:

$$CS(t) = CS(V_t, r_t\{X_t\}) \tag{4}$$

Where V is the firm value, r is the spot rate and $\{X_t\}$ represents all of the other state variables that are needed to specify the model. Merton's (1974) studies are focused on the valuation or risky assets. Since the credit spreads are defined by these variables, the changes in credit spreads can be explained by the changes in these variables.

3.1.1 Merton's Model

Merton (1974) initiated the modern corporate debt analysis by pointing out that the holders of risky corporate debt can be thought of as owners of risk-free bonds who have sold put options to the holders of the firm's equity.

The framework is a frictionless market where trading is continuous. The risk-free rate is constant and equal to r. This model assumes that the firm operates and has the simplest of all capital structures that allow a default to occur. (Benkert, 2004) The firm is financed by a homogenous class of debt, with face value of B, and maturity in T.

The assumption is that default can only occur in T and only if the value of the firm's assets Vt is below B. In other words, the firm is worth less than it owes to the markets. Merton assumes that default caused by liquidity is ruled out due to frictionless markets: Should the borrower's capital be tied up in long-term investment, it is able to borrow from a third party. In perfect markets, the lender would, naturally, be willing to extend the loan. (Benkert, 2004) Further assumptions are that the dynamics of the firm value are observable and given by the stochastic differential equation.

Merton (1974) used some assumptions:

A1. There are no transaction costs, taxes, or problems with indivisibilities of assets

A2. There are a sufficient number of investors with comparable wealth levels and each investor believes that he can buy and sell as much of an asset as he wants at the market price

A3. There exists an exchange market for borrowing and lending at the same rate of interest

A4. Short-sales of assets are allowed

A5. Trading is continuous

A6. Modigliani-Miller theorem holds

A7. Term structure is "flat" and known with certainty, the interest rate is constant

A8. The dynamics of the value of the firm can be described as

$$dV = (\alpha V - \delta)dt + \sigma V dz \qquad (5)$$

Where α is the expected rate of return, δ is the total payout, either to its shareholders or liability-holders (i.e. dividend or coupon payment). If positive, payouts from the firm, if negative received payouts by new financing. σ is the variance of the return on the firm; dz is a standard Gauss-Wiener process. This is usually referred to as a geometric Brownian motion, meaning that, in this case, the variable grows with an average drift rate. (Meissner, 2005) Black and Scholes' model gives the framework for pricing corporate debt. The bondholders receive at maturity:

$$\min(V_T, B) = B - \max(B - V_T, 0) \tag{6}$$

The basic equation is that shareholder's equity (E) = the firm's assets (V_T) – the liabilities (B). If the value of the firm, V_T, is lower than the face value of the debt, B, bondholders receive the assets and shareholders receive nothing. Therefore the bondholders lose B-V_T. If the value of the firm is higher than the face value, the shareholders receive V_T-B. The illustration of Merton's model is in Figure 10.

The Merton Call - Merton assumes that there is only one single class of homogenous debt; firm consists basically of this debt and equity. In Merton's (1974) model the approach was via the price of an European call option on the firm's equity, E, written as

$$E_0 = V_0 N(d_1) - Be^{-rT} N(d_2) \tag{7}$$

Where

$$d_1 = \frac{\ln\left(\frac{V_0}{Be^{-rT}}\right) + \frac{1}{2}\sigma_V^2 T}{\sigma_v \sqrt{T}} \tag{8}$$

$$d_2 = d_1 - \sigma_V \sqrt{T} \tag{9}$$

The function $N(d_1)$ and $N(d_2)$ are the cumulative probability distribution function. The expression for d_1 and d_2 are given in formulas 8 and 9. In other words, it is the probability that a standard distribution variable $\Phi(0,1)$ will be less than x. In this model, the probability that $B > Vt$, the call option is out-of-the-money, is $N(-d_2)$. σ_v is the volatility of the company's assets.

Hence, the value of the debt can be written as $V_0 - E_0$. In Merton's model the equity can be seen as call option on the value of the firm with a strike price equal to the value of the liabilities. The value of the corporate debt can be calculated as the risk-free value of the debt minus the value of the default option. The strike of this option equals the face value of the debt. In other words, besides the risk-free rate, investors require a compensation for the written option. (Hottinga & Zwanenburg)

If the market value of the debt is the risk-free component plus the short position in a default option, the decrease in the *asset* market value increases the value of the default option and therefore decreases the value of the debt. From this point of view, the credit spread depends on the asset value and the asset volatility. (Keenan et al.)

Merton's model states that there are three major variables that explain the credit spread. First is the leverage ratio. In the Equation 7, the increase of debt is affecting the equity's value and so is the increase in firm's value. The bigger the firm value V_0, the more certain it is that the debt will be paid. Second is the asset volatility; it defines the process of firm value. When the volatility is zero, the equity's value can be written as

$$\max(V_0 e^{rT} - B, 0) \tag{10}$$

Third, the risk-free rate because the debt in this model is discounted with risk-free interest rate and that also is the firm value drift rate. The higher the risk-free rate, the higher the drift, and the lower the possibility of default.

The Merton Put - The value of credit risk and the probability of default can also be found be expressing credit risk as a put option on the firm's assets. The idea behind this is simple; the equity holders can hedge their investment by purchasing a put option at strike B, the put seller in this case is the asset holder. If $V_T<B$, the equity holders deliver the assets to asset holders, the loss for the asset holders is the same as in the European call, B-V_T. The put option is expressed as following:

$$P_0 = -V_0 N(-d_1) + Be^{-rT} N(-d_2) \tag{11}$$

Where P_0 is the current value of the put option on the firm's assets V, with strike B. The equity holders will exercise B, at time t, if $B>V$. This is the bankruptcy in Merton's model. The probability of exercising the put is the same, $N(-d_2)$, as in the European call.

If we rewrite the equation 11, we get the interpretation of the default risk and the recovery rate. These are presented in equation 12.

$$P_0 = \left(-\frac{N(-d_1)}{N(-d_2)} V_0 + Be^{-rT}\right) N(-d_2) \tag{12}$$

The term $\frac{N(-d_1)}{N(-d_2)} V_0$ represents the amount retrieved of the asset value V_0 in case of default. In other words, this term is the recovery rate. This put option in Equation 11 gives us the basis to value credit risk, presented in Equation 13.

$$D_0 = B_T e^{-rT} - [-V_0 N(-d_1) + B_T e^{-rT} N(-d_2)] \tag{13}$$

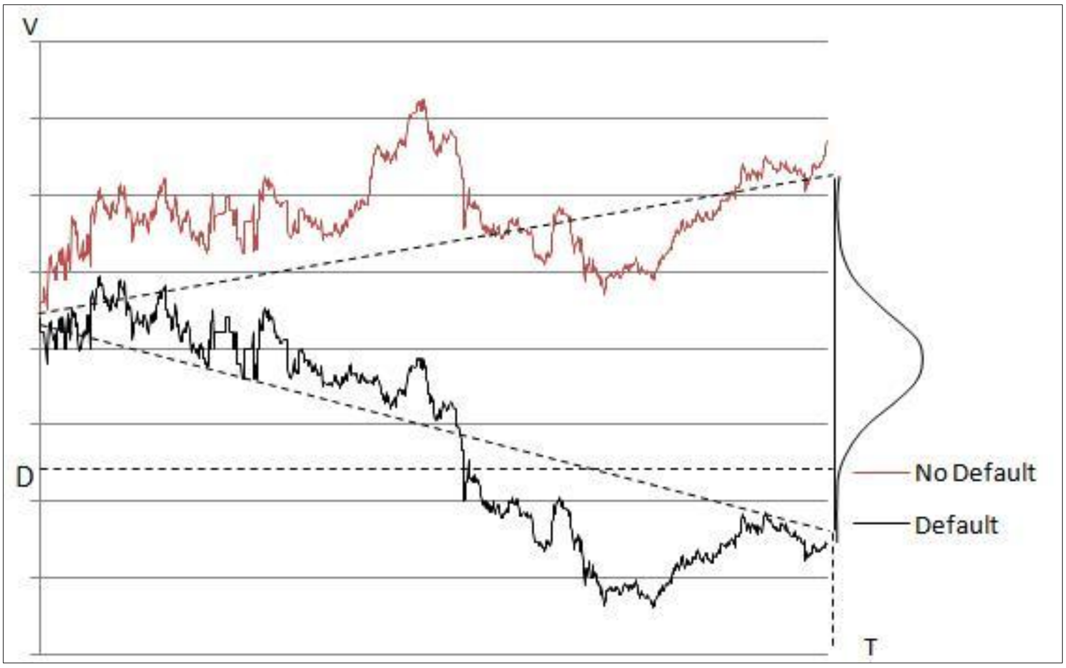
D_0 is the debt B to be repaid at time T, discounted by e^{-rT} minus the value of credit risk. Equation 13 simplified:

$$D_0 = B_T e^{-rT} N(d_2) + VN(-d_1) \tag{14}$$

Where the $N(x)$ is the same as in equations 8 and 9.

The advantage of the model is that the estimation does not require demanding inputs. To estimate the value of equity, one needs the current value of the firm's assets, the volatility, the risk-free rate and the par value of the debt, and the time to expiration. The Merton's model indicates that equity is a call option on the firm's assets, and then its price can be raised by increasing the volatility of the firm's assets. This can only be done in the expense of bond holders.

Figure 10. Merton model's implication to default. The red and black lines indicate the stochastic process of firm's asset's values with variance σ. The default occurs in maturity T, when the asset's value falls below the face value of debt. (Source: Merton, 1974)



3.1.2 Black-Cox Model

Black & Cox (1976) improved the Merton's and Black & Scholes' models of valuing corporate debt. This model is also a first-time passage model. Black and Cox suggest that there is an exogenous reorganization boundary $V_d = Ce^{-\gamma(T-t)}$, where C and γ are exogenous constants.

In a sense, a high value of C and a low value of γ forces the company to bankruptcy. This is the most important feature of this model, to principally protect the asset holders. The illustration of Black & Cox's model is presented in Figure 11.

If the assets' value V drops below V_d, during time t to T, the company can be forced to bankruptcy or restructuring, allowing the bondholders to obtain the ownership of the company's assets. With this arrangement, the coupon payments do not play a critical role. The default or restructuring can happen at any point during the period of debt, whereas in Merton's original model default can only occur at the maturity of the debt.

This mandatory bankruptcy or restructuring, defined also as the safety covenant, is the key feature of this model. These safety covenants are common in bond indentures.

Black and Cox also investigate the subordination arrangements, how the value of the debt changes, depending on the seniority, and restrictions for the equity holders to finance interest and dividend payments. In other words, the stock holders are not allowed to sell the firm's assets to make payments to bond holders. These are usually seen in bond indentures and also increase the value of a risky bond.

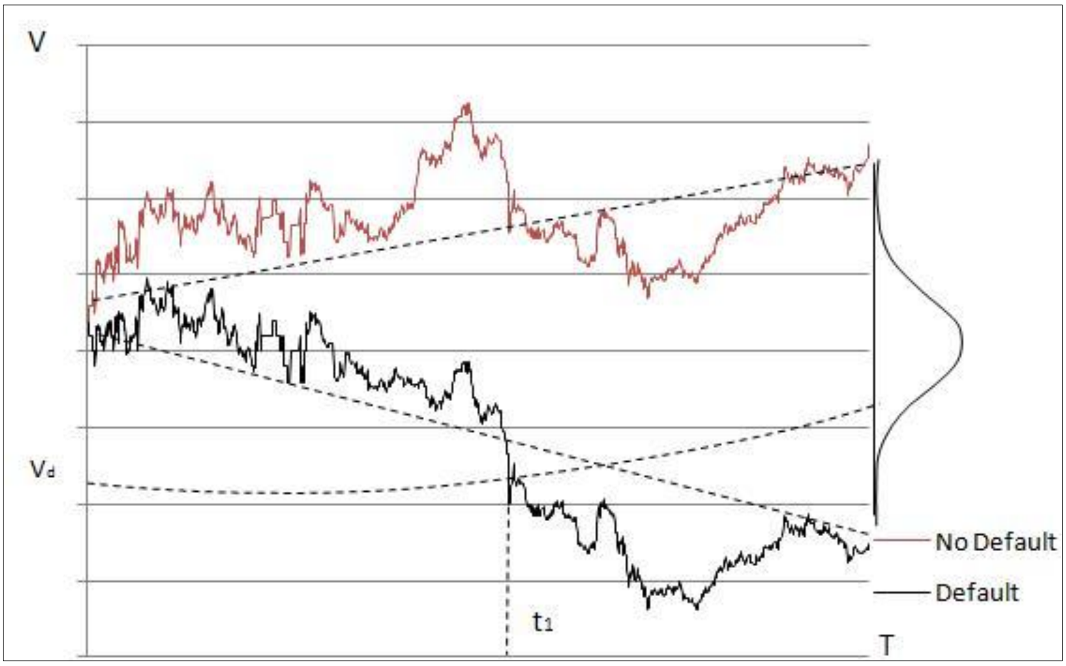
Black and Cox's valuation formula[1] for a risky bond B (including dividends, a, to shareholders) is:

$$B(V,t) = Pe^{-r(T-t)}\left[N(z_1) - y^{2\theta-2}N(z_2)\right] + Ve^{-a(T-t)}\left[N(z_3) - y^{2\theta}N(z_4) + y^{\theta+\xi}e^{a(T-t)}N(z_5) + y^{\theta-\xi}N(z_6) - y^{\theta-\eta}N(z_7) - y^{\theta-\eta}N(z_8)\right] \quad (12)$$

Where P= the notional amount of the bond, and
V= the value of assets.

The interest rates do not follow a stochastic process but are assumed constant at a rate r. The recovery rate is set to the asset value V at the time of default.

Figure 11. The Black & Cox model. The default can occur at any point of time during the maturity. The asset's value must hit a boundary K in order for the firm to default. In this model the default would occur at t_1 (Source: Black & Cox, 1976)



[1]The more detailed explanation of this formula can be found in Black & Cox article (1976) or Meissner (2005).

3.1.4 Longstaff-Schwartz Model

Longstaff-Schwartz (1995) suggests quite a similar model to Black & Cox (1976) model. It is a first-time passage model with exogenous default boundary but it also has an exogenous recovery rate. Longstaff-Schwartz's solution for pricing risky discount bonds is:

$$P(X,r,T) = D(r,T) - wD(r,T)Q(X,r,T) \tag{12}$$

Where P=*price* of the risky bond, X=default boundary for V, D=price of a risk-free bond, T=maturity, w=1-recovery rate.

The first term $D(r,T)$ represents the value of a risk-free bond. The second term $wD(r,T)Q(X,r,T)$ represents the discount for the default risk of the bond. The first part, $wD(r,T)$, defines the write-down value if a default occurs and the other part, $Q(X,r,T)$, is the probability that a default occurs under a risk-neutral measure.

In this model, if the value of the assets, V, falls below the boundary K, restructuring occurs. In the formula it is expressed as X, as in the ratio V/K. This is a good implication, that risky debt can be valued without V and K of the model. Coupon bonds can also easily be valued as a portfolio of discount bonds.

The key finding of this model is that credit spreads decrease when the risk-free rates increase. This is because the actual drift of V is μV, but in the risk-neutral process the drift depends upon r and is independent of μ. The definition for firm value is a Wiener process:

$$dV = \mu V dt + \sigma V dZ_1 \tag{13}$$

The definition of r in the well-known Vasicek model, used by Longstaff-Schwartz is:

$$dr = (\zeta - \beta r)dt - \eta dZ_2 \qquad (14)$$

Note that the correlation between $Z_2$and Z_1 is ρdt.

The findings of Longstaff-Schwartz's model are quite interesting. They find that the higher the interest rate, the lower the probability of default, because of the interest rates' effect to the value of the firm. They also find that the lower the credit quality, the stronger impact the interest rate change has on the credit spread. This is quite intuitive because the strong growth in value changes more the equity-debt ratio. They also conclude that the higher the assets' value, the lower the credit-spread. Again, the relationship is higher for low-rated companies.

3.2 Reduced Form Models

Reduced Form Models are the second category for estimating credit spreads. The Reduced Form Models assume that default is a random process.

Reduced Form Models use debt prices as a main input to model the bankruptcy process. Default is modelled by a stochastic process with an exogenous hazard rate. Hazard rate multiplied by a certain time frame and the result is the risk-neutral default probability. The reduced form models only model the timing of the default, not the severity. In reduced form models the recovery rate is exogenous. (Meissner, 2005) Reduced form models also assume that default intensity is correlated with macroeconomic variables.

Modelling firm value as a stochastic process has its flaws in the short term because time has to pass in order the default to occur, and even though it is theoretically sound, it has been hard to prove in empirical analysis.

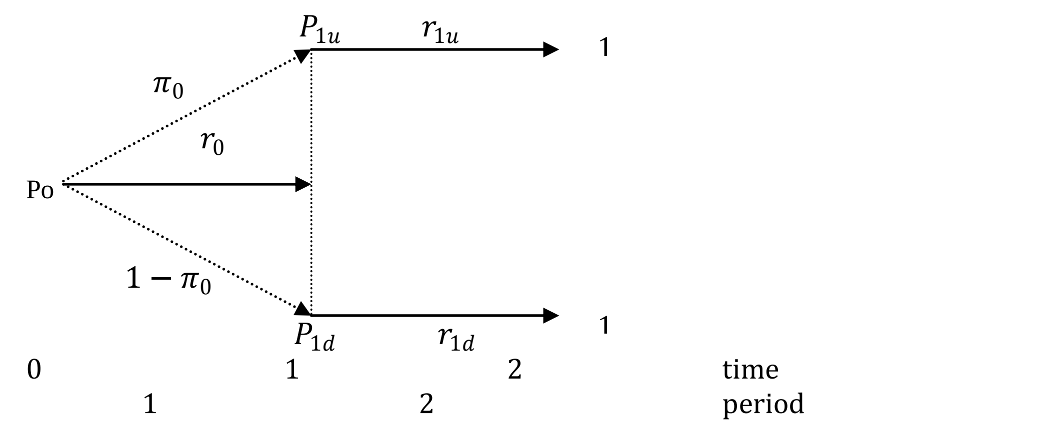
(Batten and Hogan, 2002) This is the reason for the development of reduced form models.

This chapter will briefly go through the basic idea of Jarrow-Turnbull (1995) model just to give the reader the basic concepts of the reduced form models.

3.2.1 Jarrow and Turnbull's Model

Jarrow and Turnbull (1995) were the first to derive a new model of valuing risky debt. They combine a process for risk-free interest rates and a bankruptcy process to derive default probabilities and credit derivative prices. These two processes are assumed to be independent from each other. They present a new way to value risky debt. This model uses a foreign currency analogy which uses stochastic term structure of default-free interest rates and a stochastic maturity specific credit-risk spread. Jarrow and Turnbull start with a simple binominal interest rate tree and a bankruptcy process tree, as seen in Figure 12 and 13.

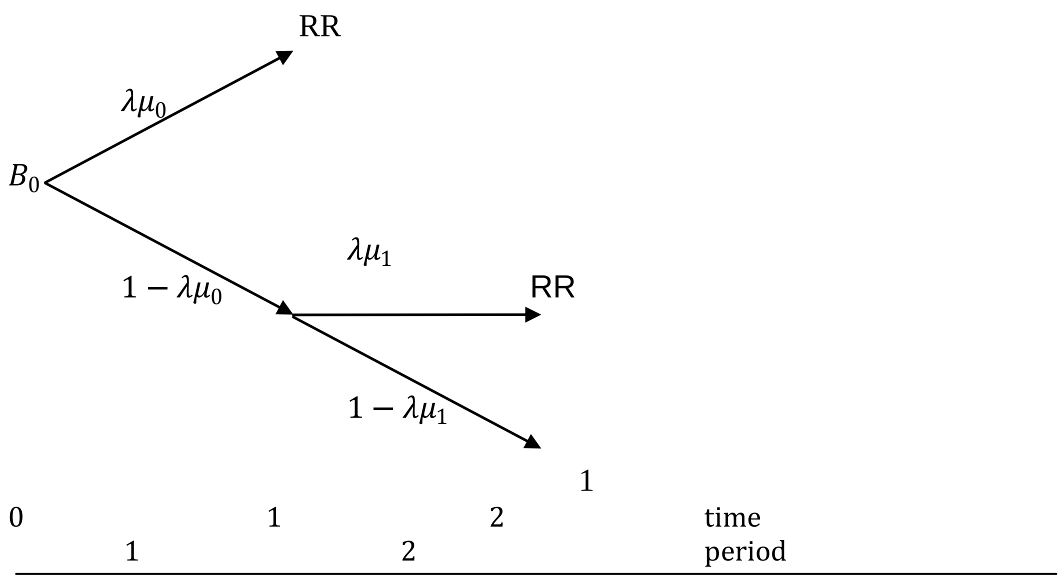
Figure 12. Jarrow and Turnbull's interest rate tree, where r=risk-free rate, P=risk-free zero coupon bond, π_0= risk-neutral probability of an interest rate increase. (Source: Jarrow & Turnbull, 1995)



In the interest rate tree the pseudo-probability is denoted with π.Jarrow and Turnbull assume here that the spot interest rate process in Figure 13 and the bankruptcy process in Figure 12 are independent under the pseudo-probabilities. (Shimko, 2004)

XYZ zero-coupon bonds can be written according to the pseudo-probabilities and the expected future payoff ratios can be calculated. In this model the pseudo-probability of a default is denoted with $\lambda\mu$.The pseudo-probabilities require that relative bond prices are martingales, meaning that the trading in these securities is a 'fair-game' i.e. the expected values equals current values. The market's completeness is also required, meaning that these securities can be synthetically constructed via trading in the primary securities.

Figure 13. The bankruptcy process tree in the Jarrow-Turnbull model, where $\lambda\mu$=the risk-neutral probability of default, $1-\lambda\mu$=the probability of survival, RR=recovery rate in case of default, B_0=price of the risky zero-coupon bond. (Source: Jarrow & Turnbull, 1995)



Combining these two processes, we are able to calculate the probability of default at a given time.

Jarrow and Turnbull conclude that the price of a risky zero-coupon bond is $B_1(t,T) = p_0(t,T)\tilde{E}_t(e_1(T))$. The discounted expected payoff at time t, using the pseudo-probabilities. The discount factor is a risk-free zero-coupon bond. Here we can see that the price of a risky zero-coupon bond is lower than the price of a default-free bond. Hence, the positive credit spread is necessary to justify the formula. $\tilde{E}_t(e_1(T))$ is the expected payoff at time T.

The mathematics behind this simple-looking formula is very difficult and because it is not the model used in this study, it is included only to clarify the extent of the current models. Further information can be found in the article of Jarrow & Turnbull (1995).

3.3. Critical appraisal of risky bond pricing models

Both models have drawbacks which are discussed in this chapter. The Firm Value Models are viewing the contingent claims, not on the securities themselves but the assets that are underlying the securities. (Jarrow & Turnbull, 1995) There are a few issues underlining this model. First, the assets underlying the securities are often non-tradable and also unobservable. Second, all the firm's liabilities should be valued simultaneously. As to the pricing, in the Firm Value Models the default boundary involves an exogenous constant and this is not the case in the real world. Third, also the recovery rate involves an exogenous constant. These are difficult to determine for practical purposes (Meissner, 2005)

The performance of credit spread and default risk models have been studied by for example Sobehart & Keenan (2004) and Teixeira (2007). For example Teixeira (2007) says that Merton's model overestimates the bond prices. Furthermore, the author states that the Merton's model can estimate either high or low spreads, not in the between. Merton's model also seems to perform better with companies that have high credit quality. The author concludes that structural models have difficulties in accurate bond pricing. However, it depends on several bond- and firm-specific factors as well the market conditions.

Sobehart & Keenan (2004) studied the same subject and concluded that structural models provide powerful insight but they often use unrealistic assumptions to make the problem analytically tractable.

However, the original Merton's model has been improved because of the unrealistic assumptions and unobservable variables. This has led to the reduced form models. Jarrow & Turnbull (1995) also stated that the values of some securities are not traded and thus they can't be valued. All the other corporate debts in the company must also be valued and that is difficult from computational point of view.

The Jarrow-Turnbull's Reduced Form Model has some drawbacks. The models assume that the bonds are priced to reflect the probability of default. However, bond prices are usually overestimating the probability of default. Also some bonds are illiquid and the fair market price is hard to determine.

Also the default intensity is assumed as a constant over the life of the debt and the recovery rate is exogenous. These assumptions, as we know, are quite unrealistic.

4. PREVIOUS STUDIES

Credit spreads have been studied mainly from two different angles, structural or reduced form. First, the spreads are explained via structural approach. Structural approach assumes that the firm will default when the value of the asset's fall below a constant threshold. Reduced Form Models assume that default is a random process.

4.1. Results of previous studies

In this chapter we will go through the studies of Ericsson et al. (2009), Greatrex (2009), and Collin-Dufresne et al. (2001).

First, Collin-Dufresne et al. (2001), who studied the corporate bond spread differences. The dataset was 688 bonds, 261 issuers and the time-frame was from July 1988 to December 1997. The variable for credit spread was the actual spread of a corporate bond and the US Treasury yield. However, the basic principals are the same so this study can be used as a comparison. The theoretical framework used was the structural model approach.

As for the variables, they used spot interest rate, the spot yield curve, leverage, volatility, measured by VIX Index, changes in the business climate and a probability of a downward jump in firm's value. They divided the data according to the firm's leverage ratio and the maturity of the bond. The findings of their studies indicate that the leverage has a little explanatory power in their model. They also find that the increase in the risk-free rate reduces the credit spread. The slope of the yield curve did not have a significant effect on their model. The VIX Index, however, was significant and had a big impact. This result is clouded by the collinearity between the S&P 500 Index. The greatest explanatory variable was the return for the S&P 500 Index.

Table 3. The results of the Collin-Dufresne et al regression The time span of the test was from July 1989 to December 1997. (Source: Collin-Dufresne et al. 2001)

Leverage Group	<15 %	15-25 %	25-35 %	35-45 %	45-55 %	>55 %
			All Maturities			
intercept	0.022	0.016	0.013	0.013	0.01	-0.002
t	(8.76)	(10)	(6.57)	(4.59)	(2.73)	(-0.2)
Δlev_t^i	-0.005	0.007	0.003	0.004	0.008	0.033
	(-1.74)	(4.89)	(1.86)	(2.2)	(3.35)	(3.75)
Δr_t^{10}	-0.124	-0.14	-0.181	-0.215	-0.215	-0.342
	(-17.84)	(-30.23)	(-18.93)	(-17.63)	(-11.93)	(-6.15)
$(\Delta r_t^{10})^2$	-0.01	-0.001	0.009	0.048	0.004	0.164
	(-0.54)	(-0.05)	(0.67)	(2.4)	(0.1)	(2.31)
$\Delta slope_t$	0.006	0.001	-0.028	0.008	0.004	-0.033
	(0.3)	(0.07)	(-2.29)	(0.48)	(0.15)	(-0.73)
ΔVIX_t	0.001	0.002	0.003	-0.001	0.005	0.001
	(0.82)	(3.44)	(2.85)	(-0.94)	(2.65)	(0.11)
$S\&P_t$	-0.016	-0.015	-0.016	-0.017	-0.016	-0.019
	(-21)	(-29.56)	(-22.68)	(-15.6)	(-10.65)	(-6.85)
$\Delta jump_t$	0.004	0.004	0.003	0.002	0.004	0.003
	(16.86)	(18.5)	(7.76)	(5.83)	(7.87)	(1.889
Adjusted R^2	0.244	0.23	0.211	0.216	0.197	0.192
N	100	162	138	123	91	74

The formula for the regression is:

$$\Delta CS_t^i = \alpha + \beta_1^i \Delta lev_t^i + \beta_2^i \Delta r_t^{10} + \beta_3^i (\Delta r_t^{10})^2 + \beta_4^i \Delta slope_t + \beta_5^i \Delta VIX_t + \beta_6^i S\&P_t + \beta_7^i \Delta jump_t + \epsilon_t^i.$$

The explanatory power of this study was quite low and the same applies to other studies. The adjusted R^2 is approximately 20 basis points in the spread. However, the findings of the remaining variable have been limited to some macroeconomic variable that has effect on all the companies. They run a secondary regression, now including many macroeconomic variables and gained a bit higher explanatory power but still the common variable was not found.

The study of Ericsson et al. (2009) was done by investigating the actual credit default swap spreads instead of spreads in the corporate bonds. The study was done on both levels and differences data. They find that the theoretical coefficients are consistent with the structural approach and statistically significant. Volatility and leverage have substantial explanatory power. The testing of residuals indicates that there is no common factor to explain the remaining variation.

The dataset includes the daily Credit Default Swap quote spreads from 1999 to 2002 for senior debt. The maturities are from 4.5 to 5 years since that is the most traded maturity. The explanatory variables include the leverage ratio of companies, which is the same as we are using in this study. For volatility, they used an exponentially weighted average of equity returns. Treasury bond yields were 10-year US Treasury bonds. They used 4813 bid and 5436 offer quotes.

Ericsson et al. (2009) also used similar variables to their regression to increase explanatory power and to model default risk and recovery risk: Treasury Bond Yields for 2 and 10 years, the Slope of the Yield Curve, the Square of the Two-Year Yield, the Return on the S&P 500, and the Slope of the Smirk. The main concept was to use the interest rates to model the instantaneous short rate, the square of the 2-year bond to capture any non-linearity between the spreads and the S&P 500 was a proxy for overall market condition.

The slope of the smirk was calculated on equity options using out-of-the-money S&P 500 American futures put options. Ericsson et al. (2009) calculated implied volatilities using American options technique. And they calculated the dependence of the smirk to maturities. The regression formula was the following:

$$\Delta S_t^i = \alpha + \beta_i^l \Delta lev_t^i + \beta_i^v \Delta VOL_t^i + \beta_i^r \Delta r_t^2 + \beta_i^{r2} (\Delta r_t^2)^2 + \beta_i^{r3} \Delta TSSLOP_t + \beta_i^{S\&P} S\&P_t + \beta_i^{sm} \Delta SMSLOP_t + \epsilon_t^i$$

The regression results were similar to Collin-Dufresene et al. (2001) and they are presented in Table 4.

Table 4. The results of the regression by Ericsson et al. (2009) The results are, as shown, in differences and in levels. (Source: Ericsson et al. 2009)

Coefficients	Differences Bid quotes	Differences Offer quotes	Differences (theoretical) Bid quotes	Differences (theoretical) Offer quotes	Levels (theoretical) Bid quotes	Levels (theoretical) Offer quotes
Constant	0.012	0.004	0.005	0.01	-0.492	-1.513
	(1.74)	(-0.74)	(1.09)	(1.47)	(-0.78)	(-2.11)
Leverage	0.048	0.046	0.056	0.048	0.063	0.073
	(6.18)	(5.88)	(7.52)	(6.66)	(7.72)	(7.87)
Equity volatility	0.007	0.013	0.008	0.014	0.01	0.015
	(4.81)	(5.48)	(5.24)	(5.71)	(3.99)	(4.34)
2-year yield	-0.118	-0.2				
	(-1.93)	(-2.67)				
Yield curve slope	-0.055	-0.050				
	(-0.61)	(- 0.49)				
S&P500	-1.104	-0.667				
	(-2.79)	(-1.33)				
Smirk slope	-0.003	-0.188				
	(-0.01)	(-0.68)				
Sq 10-year yield	-0.116	0.042				
	(-1.23)	(0.39)				
10-year yield			-0.212	-0.278	-0.345	-0.2
			(-4.97)	(-3.86)	(-4.13)	(-2.35)
R2	29.50 %	32.30 %	22.30 %	23.70 %	61.40 %	56.10 %

The formulas for the regressions are
$\Delta S_t^i = \alpha + \beta_i^l \Delta lev_t^i + \beta_i^v \Delta VOL_t^i + \beta_i^r \Delta r_t^2 + \beta_i^{r2} (\Delta r_t^2)^2 + \beta_i^{r3} \Delta TSSLOP_t + \beta_i^{S\&P} S\&P_t + \beta_i^{sm} \Delta SMSLOP_t + \epsilon_t^i$ and $\Delta S_t^i = \alpha + \beta_i^l \Delta lev_t^i + \beta_i^v \Delta VOL_t^i + \beta_i^r \Delta r_t^{10}$

For the minimal set of variables, leverage, volatility and risk-free rate, the R^2 was approximately 23 % for the changes in spread. For levels data the explanatory power was about 60 %. And when added the recovery risk and default risk variables, the R^2 is almost 70 %. As the authors concluded, some of the variation remained unexplained.

Greatrex (2008) has a similar approach, only that her study is more market focused. The time-frame is from January 2001 to March 2006. The author uses 333 companies and 16,748 observations in total. The dependent variable is the change in CDS spreads. The variables that were used are found in Table 5. It is important to note that the key determinants were firm-specific and that the macroeconomic determinants did not perform as well. The results of three models in Greatrex's study can be seen in Table 5.

CDS Index based rating was the single best explanatory variable in the study. This means that there is a systemic component that could explain the spreads better altogether. The author found that 35 % of the variation could be explained in differences and 87 % in levels. The levels regression, however, was suspected to be biased.

Greatrex also concluded that leverage and volatility are the key determinants and they account almost half of the explanatory power. The author also said that leverage and equity returns are comparable proxies for firm health over a relatively short time period. The coefficients in leverage and volatility should be noted. One bps increase in the leverage or volatility increases the spreads from 300 to 472 bps.

Table 5. The results of three regressions (Greatrex, 2008). The time-frame of the test was from Jan 2001 to March 2006. (Source: Greatrex, 2008) This test was done by observing CDS spread changes

Model specification	1	3	6
Intercept	-0.937	-1.252	-1.697
	(-3.14)	(-3.25)	(-2.37)
ΔLEV	381.403	352.867	387.956
	(8.78)	(8.73)	(8.09)
ΔVOL		299.312	472.623
		(4.51)	(6.95)
ΔVIX	0.235		
	(0.87)		
ΔINDX	0.635	0.621	
	(14.18)	(14.52)	
CRSP			
S&P			-0.951
			(-3.53)
ΔSPOT	-0.43	-0.322	-5.903
	(-0.40)	(-0.32)	(-4.66)
ΔSLOPE	-5.530	-6.307	1.416
	(-1.41)	(-1.65)	(-0.25)
ΔCDS_{t-1}	-0.024	-0.047	-0.023
	(-2.18)	(-4.31)	(-1.95)
ΔCDS_{t-2}	-0.04	-0.045	-0.028
	(-3.68)	(-4.22)	(-2.69)
Adjusted R^2	34.80 %	35.00 %	22.00 %

The effect of leverage and volatility in Greatrex's study differ from Ericsson et al. and Collin-Dufresne et al. One reason could be that the sample period is in the 2000s, since that the credit markets have evolved from the previous studies rapidly. Also, when compared to other studies Greatrex uses smaller samples and monthly observations.

The summary of the studies of Ericsson et al. (2009), Collin-Dufresne (2001), and Greatrex (2008) are found in Table 6. The similarity in results indicates that the actual model is robust and can explain about 25 % of the variation. The explanatory variables were according to Merton's model, however some of the variables have been added depending on the study and that does not increase the explanatory power significantly. Company based data is the most important common variable in these studies.

Table 6. The outline of results of studies by Ericsson et al. (2009), Collin-Dufresne (2001), and Greatrex (2008)

Author	Type	Explained	Data	Variables used	Results
Collin-Dufresne, Goldstein, and Martin (2001)	Bond	ΔCS	Monthly Corporate Bond Δspreads, sample size: 688 bonds	Δs in the spot rate (10yr), slope of the yield curve, leverage, VIX, slope of the smirk, S&P 500 return	Explain 25 % of variation in corporate bond spreads, common factor identified by investigating residuals
Ericsson, Oviedo and Jacobs (2002)	CDS	ΔCDS and CDS	Monthly CDS spreads and Δspreads, 1999 - 2002 (4813 bid, 5436 offer quotes)	Leverage, volatility, risk-free rate, slope of the yield curve, S&P 500 return, slope of the smirk	Leverage, volatility and the risk-free rate explains approx. 60% of the variation in levels and in differences, 23 %
Greatrex (2008)	CDS	ΔCDS	Monthly Δspreads from Jan. 2001 - Mar. 2006, 16 748 observations, 333 companies	Leverage, equity returns, equity volatility, VIX, spot rate, slope of the yield curve, CDS rating based index, CRSP returns, S&P 500 returns	Explain about 35% of the variation, company rating affects explanatory power

5. EMPIRICAL ANALYSIS

5.1 Methodology

5.2 Regression using levels data

The data in this study consists of the cross-sectional and time series dimensions, i.e. it is panel data. Linear regression model will be applied into the time-series part of our data. Therefore the panel data regression framework is applied in one part of this study.

The same procedure as Ericsson et al. (2009) and Collin-Dufresne et al. (2001) is used by running a series of time-series regressions, one for each company. These regressions emphasize the relationship between spreads and the explanatory variables. These are the most interesting regressions for example from managerial point of view to witness the effect of low/high leverage ratio and also the effect of firm equity volatility to credit spreads. The more detailed description for the data is found in the Chapter 5.5.

The first part of the study is to perform a regression using levels data. For each CDS i at date t with credit spread CDS_t^i the following regressions can be estimated:

(i) $$CDS_t^i = \alpha + \beta_1^i lev_t^i + \beta_2^i yld_t^i + \beta_3^i slope_t^i + \beta_4^i VIX_t^i + \beta_5^i histvol_t^i + \beta_6^i mrktrtrn_t^i + \beta_7^i eqrtrn_t^i + \beta_8^i CCI_t^i + \epsilon_t^i$$

(ii) $$CDS_t^i = \alpha + \beta_1^i lev_t^i + \beta_2^i yld_t^i + \beta_3^i histvol_t^i + \epsilon_t^i$$

However, because of linear relationship between the independent variables, VIX and CCI variables are removed. The explanations for this are in the next chapter.

5.3 Regression using differences data

This study also tests the effect of the differences data. If the variables affect the spreads, then the changes in these variables also affect the spread changes. For the differences data the following regressions are estimated:

(iii) $$\Delta CDS_t^i = \alpha + \beta_1^i \Delta lev_t^i + \beta_2^i \Delta yld_t^i + \beta_3^i \Delta slope_t^i + \beta_4^i \Delta VIX_t^i + \beta_5^i \Delta histvol_t^i + \beta_6^i mrktrtrn_t^i + \beta_7^i eqrtrn_t^i + \beta_8^i CCI_t^i + \epsilon_t^i$$

(iv) $$\Delta CDS_t^i = \alpha + \beta_1^i \Delta lev_t^i + \beta_2^i \Delta yld_t^i + \beta_3^i \Delta histvol_t^i + \epsilon_t^i$$

Also in the differences data, the model needs to be adjusted to fit the OLS standards. The equity return had a high negative correlation between leverage; hence the *eqret* is removed from the model. Equity return is not considered in the theoretical model but more as a proxy for the overall company health.

5.4 Panel data regressions

The panel regression framework will be done by taking 3 one year cross-sectional samples from the timeframe and combining the data into panel regression; taking two periods, pre-crisis, 2004 – 2006, and crisis period 2008 – 2009. The idea is to capture differences or similarities from the bull and bear markets using the cross-sectional dimension of the data. The panel data framework is according to Baltagi (2001).

Panel data contains obviously more data than pure time-series or cross-sectional data. Panel data gives more degrees of freedom and permits more efficient estimation. (Brooks, 2002) However, with panel data, either ‘*fixed effects*’ model, ‘*random effects*’ model or basic ‘*panel data’* model must be used.

Panel data regression differs from normal time-series or cross-sectional regressions because it has a double subscription on its variables.

$$y_{it} = \alpha + X_{it}^{'}\beta + u_{it} \qquad i=1,....,N;\ t=1,.....,T$$

Where i denotes the firms and t denotes the time. In other words, the i is the cross-sectional dimension and t is the time-series dimension. α is the constant, β is $K\ x\ 1$ and X_{it} is the itth observation on K explanatory variables. The error term, u_{it}, is defined as $u_{it} = \mu_i + v_{it}$. Where μ_i is the unobservable individual specific effect and v_{it} is the remainder disturbance. (Baltagi, 2001)

It is important to remember that μ_i is time-invariant and accounts for any individual-specific effect that is not included in the regression. The v_{it} can be thought of as the usual disturbance in the regression. (Baltagi, 2001)

5.1.1 Fixed effects model

In the fixed effects model, μ_i is assumed to be fixed parameters to be estimated and the remaining disturbances stochastic with v_{it} being independent and identically distributed. X_{it} is considered to be independent of the v_{it} for all the i and t. The idea of the fixed effects model is to find a specific effect outside the regression model that is firm-specific.

5.1.2 Random effects model

In the random effects model, the μ_i is assumed to be random and also independent from v_{it}. The random effects model is good if we are drawing random individuals from a large population. The individual effect is characterized as random and inference pertains to population from which the sample was drawn. The use of random effects in the study is justified by Hausman test which indicates that the fixed-effects model cannot be used. The random-effects model is used because we want inferences about the whole population, not only the examined sample.

5.5 Research data

The study will be made by observing 30 companies[2] from Datastream. The time gap is from 31.1.2004 to 31.12.2009 for the levels data. For the differences data the time-frame is from 28.2.2004 to 31.12.2009 because the first close-value for the CDS was 31.1.2004 for nearly all companies, the difference value could not be calculated. The data will be divided into high and low markets according to the average returns of S & P 500.

The returns of S & P 500 divides the data roughly to the high return period 2004 - 2006 and the low return period 2007-2009. These will also be the time-periods used in the regression. The panel data section defines the more accurate timeframes used in the panel regression. The idea in that is to find the extreme high and extreme low periods during the crisis.

All the research data is taken from Datastream and Thomson One Banker. 2125 month-end observations are used for levels data and 2101 for the differences.

Credit spreads – The Credit Default Swap spreads are obtained from Datastream. Only 5 year maturity default swaps are used. Monthly observations are for the period 31.1.2004 through 31.12.2009. The Credit Swaps are for senior debt in all the companies.

Treasury Rate Level – The monthly US Treasury 10-year yield is obtained from Datastream. Monthly yields are used.

[2] The list of companies used in the study is found in the Appendix 2, the industry sectors are also included.

Slope of the Yield Curve – The slope of the yield curve is obtained from Datastream and calculated as the difference between 10-year and 2-year US Treasury yields. This indicates the short interest rates and signals of overall economic health.

Firm Leverage Ratio – Firm Leverage Ratio is obtained from Thomson One Banker. The leverage ratio is defined as:

$$Leverage\ Ratio = \frac{Total\ Liabilities}{Market\ Value\ of\ Equity + Total\ Liabilities}$$

Financial statements are issued every quarter, semi-annually. The monthly ratios are linearly interpolated from the quarterly/semi-annual/annual data. In some cases the data was revised and not available so the interpolation has been done on a longer period. This should not bias our model and the same method has been used by Collin-Dufresne et al. (2001) The Market Value of Equity is obtained from Datastream.

Volatility, historical – obtained from Datastream as the historical price index of the firm's equity. Volatility is calculated from historical stock log-returns with a 45-day running window and annualized to equal the yearly volatility for better comparison. This should not bias the test results.

Volatility, implied, market volatility – The implied volatility is used on a market-basis since the individual company implied volatility is not available. The best alternative variable is the CBOE VIX-index. It is the weighted average of eight implied volatilities of near-the-money options on the S&P 100 index. The data is obtained from Datastream. The use of this index instead of individual volatilities assumes a strong correlation between these two.

Changes in the Business Climate – The total return of S&P 500 index is used as a proxy for the overall business health. Monthly log-returns are used.

Changes in the Business Climate - The Consumer Confidence Index is used to represent the state of the businesses. This reflects the consumer's confidence in business and labour market conditions. The Consumer Confidence is based on a representative sample of 5,000 U.S. households. (The Bond Buyer, 2010) Also studies, for example Jansen & Nahuis (2003) conclude that the correlation between stock markets and consumer confidence is positive. In this case, since a stock index was included in the study, it is logical to test whether the confidence of consumers has effect to CDS spreads. Consumer confidence is very closely tracked in the business press, as it is believed to provide useful information about the future state of the economy. (Oest & Frances, 2008)

The explanatory variables and the predicted signs are presented in Table 7.

Table 7. Explanatory variables and expected signs of the regression

Variable	Description	Predicted sign
Lev	Firm Leverage Ratio	+
ΔLev	Change in Firm Leverage Ratio	+
YLD	Yield on 10-year Treasury	-
ΔYLD	Change in Yield on 10-year Treasury	-
Slope	10-year minus 2-year Treasury yield	-
ΔSlope	Change in 10-year minus 2-year Treasury yield	-
VIX	Market's implied volatility	+
ΔVIX	Change in Market's implied volatility	+
VOL	Historical Volatility	+
ΔVOL	Change in Historical Volatility	+
Market return	Return on S&P 500	-
Equity return	Return on the firm's equity	-
CCI	The monthly Consumer Confidence Index	-

Since the first regressions are more time-series regressions, the data must be tested for stationarity. In time-series it is important for the dependent variable to be a stochastic or a random process. This means that a variable is stationary, the mean and variance are constant over time and the covariance of between two values depends only on the length of time separating them instead of the actual times at which these variables are observed. (Hill et al., 2001) In the panel data regressions the stationary of the dependent variable is not a problem.

Stationarity might be a problem in the levels data, and it is highly likely that it has a unit root. The stationarity was tested with augmented Dickey-Fuller test and it proved that our dependent variable is stationary, in the levels data and in the changes data. So the time-series linear regression can be used for testing the whole time-frame.

5.6 Descriptive statistics

The descriptive statistics can be found in Table 8. Note that the number of observations of ∆CDS is smaller because the testing interval is 31.1.2004 – 31.12.2009 and the first available information on 5 year CDS was from 31.1.2004, so the change could not be calculated for the first month in 2004. Also some variables were missing in the leverage and CDS spreads. The reason for this is that in one case the newest financial statement was not available so the total liabilities could not be calculated.

The correlation matrices of the variables can be found in Appendix 3 and Appendix 4. There we can find strong correlations between explanatory variables. For example, the Consumer Confidence Index seems to have a strong correlation with the US Treasury 10-year yield and a strong negative correlation with the slope of the yield curve, and the VIX Index, which is quite surprising. The correlation between CCI and VIX Index is anticipated because VIX Index is measuring the health of the markets so these two are obviously linked. There are also a few quite alarmingly high correlations, so multicollinearity tests must be performed. The results are found in Table 9.

In the differences data, the correlations are much weaker. The only strong and negative correlation is between the VIX Index and market return. This also is an expected result. There were also high correlation between equity returns and leverage.

In levels data there seems to be a high correlation between the Consumer Confidence index and the 10-year Treasury yield. So it is intuitive to assume that multicollinearity is present. Therefore, to test and determine which variables need to be left out, if any, from the regression, an '*auxiliary regression*' is performed. It is quite simple, the basic principle is that from the original regression, one explanatory variable is picked and used as an explained variable. If the R^2 of this regression is high, then variation of the x_{t2} is explained by the variation of another explanatory variable. According to Hill et al. (2001) the formula for auxiliary regression is:

$$x_{t2} = a_1 x_{t1} + a_2 x_{t2} + \cdots a_K x_{tK} + error \tag{15}$$

This must be done in the case of levels data and to determine which variable or variables must be left out from the study. The results from the auxiliary regressions can be found in Chapter 6.1.

There seems to be heavy multicollinearity between the Consumer Confidence Index and the VIX-Index, which is our proxy for implied volatility. These two variables have to be left out from our model because of the high multicollinearity which would bias our results.

Multicollinearity is nearly eliminated by removing the VIX and CCI variables from the equation in the levels regression. This conclusion can be made by observing Table 9. In the differences regression, the equity return, *eqret*, is removed because of its high negative correlation between leverage. Leverage will not be removed because it is part of the theoretical framework and has only little correlation between other independent variables.

The reason why multicollinearity is not tested with auxiliary regression in the differences data is that the correlations are low and there is no reason to assume that linear relationship between independent variables exists. In the levels data, the correlations were much higher all around the sample, so auxiliary regressions needed to be performed.

The Kolmogorov-Smirnov test performed suggests that none of the variables are normally distributed. This can also be seen from the skewness and kurtosis. Normally distributed curve is not skewed and has a kurtosis of 3. However, in financial data normality is not a necessity and the data rarely is normally distributed.

Interestingly, the equity return on average has been slightly positive for the sample time-frame. And also the skewness indicates that the results have been more positive because it is left-tailed. The credit spread has been around 220 basis points, which is explained by the rather low credit spreads from the year 2004 through to the midst of 2007. However, the upper quartile indicates that the 25 % of the highest values are from 210 basis points and the mean is 221.4 indicating that most of the values are above 200 basis points and more. The skewness of the differences in CDS spreads is negative indicating that the spreads have been mainly increasing over the sample period. This is naturally explained by the financial crisis and the bad market sentiment.

The company leverage ratio is rather an interesting factor. The mean is only about 49 %, which indicates that the overall company health in the light of leverage has been rather good. Even the upper quartile is at about 66 % which is also not as high as expected. This can be because the companies are mainly S & P Large Cap and the overall credit ratings are good.

The volatility of the sample period has been fairly low on average, only 34 % for the historical volatility and 20 % for the implied volatility index. This is also because of the low volatility period from 2004 to 2007. Both variables are right-tailed meaning that a great number of variables are on the lower side of the mean, i.e. the volatility has been fairly low.

The Consumer Confidence Index has been increasing over time and the mean is quite high, and that is quite expected. The market conditions also have been positive around the sample period so the CCI reflects this.

The descriptive statistics in Table 8 clearly show the effects of the financial crisis. Even though the observations are "buffered" by the growth period, the effects of the crisis can be seen in the increasing variances and lowering returns. For example the market return's mean is only 0.0002 indicating the meltdown of markets.

Table 8. The Descriptive statistics of all the variables

	Mean	Std Dev	Variance	Upper Q	Lower Q	Skewness	Kurtosis	N
Equity return	0.002	0.114	0.013	0.056	-0.041	-0.051	16.221	2125
CDS	221.388	548.132	300448.180	210.000	25.200	9.518	135.422	2125
ΔCDS	1.606	268.359	72016.620	6.700	-6.000	-6.090	252.617	2101
YLD	4.136	0.614	0.377	4.590	3.830	-0.718	0.215	2125
ΔYLD	-0.007	0.280	0.079	0.140	-0.160	-0.474	2.336	2125
Slope	1.078	0.946	0.895	1.920	0.080	0.144	-1.514	2125
ΔSlope	0.005	0.198	0.039	0.090	-0.100	0.570	1.237	2125
Lev	0.492	0.229	0.053	0.657	0.299	0.113	-0.818	2125
ΔLev	0.001	0.022	0.000	0.009	-0.010	0.820	5.641	2125
VIX	20.361	10.715	114.821	24.510	12.950	1.797	2.967	2125
ΔVIX	0.055	4.752	22.580	1.290	-2.020	1.449	7.278	2125
Market return	0.002	0.044	0.002	0.026	-0.017	-1.400	3.660	2125
VOL	34.750	26.176	685.184	39.512	19.321	2.711	9.345	2125
ΔVOL	0.053	10.824	117.156	3.088	-3.211	0.357	11.597	2125
CCI	84.666	25.528	651.684	105.300	58.100	-0.812	-0.844	2125

5.7 Hypotheses

The hypotheses are based on the theory related to the subject (H1-H3) and to previous studies. The existing models provide a good framework of study, and to develop them further in empirical sector we must add non-theoretical (H4-H6) hypotheses to complete the model.

H1. The relationship between the company's leverage ratio and the CDS spread is positive. The structural approach indicates that the leverage ratio or the debt/equity ratio effects directly on the price of the debt and therefore on the credit spread. In financial crisis the effect of the leverage ratio on spread is thought to be more dramatic.

H2. The relationship between interest rates and CDS spread is negative. The structural approach involves the risk-free rate. That is for two reasons, first the price of the debt is discounted with risk-free rate and second, the value of the firm is thought to increase with the risk-neutral process.

H3. The relationship between volatility and CDS spread is positive.
The structural approach indicates that the debt claim can be seen as a short position in a put option. The value of options increases when volatility rises, this can be implied to this context too. When volatility raises the value of the debt claim falls because the probability of the debt to default increases faster than the firm value. This is the main hypothesis to test the financial crisis effect to spreads. Volatilities tend to increase in financial crisis and can be thought of as the main determinant in observing market sentiment.

H4. The relationship between market conditions and CDS spread is negative. This is more of a behavioural finance aspect to this study. This assumption means that the worse the market conditions get, the wider the credit spreads grow ignoring the firm fundamentals. This is also used to test the financial crisis effect to spreads. This is also a good determinant to test the original objective of the study; the financial crisis effect. The markets have performed poorly in previous crisis and this is a good proxy for testing the effects.

H5. The relationship between equity return and CDS spread is negative. The equity returns are used to test the overall company health and also the correlation between the market health. Equity returns have been used for example by Greatrex (2008). The objective is to use several firm-specific variables to capture differences in these. This is because the leverage ratio is partly driven by the equity markets. Greatrex found that equity returns were a good proxy for overall firm health and that there was a negative effect to spreads.

H6. The relationship between Consumer Confidence Index and CDS spread is negative. This also is a proxy for market conditions. The basic principle of how this should affect the spreads is through the macroeconomic approach. When the consumers see the future poor, they are more likely to save as much money as possible, thereby reducing the amount in circulation. This is seen in industry firms as lowering sales and therefore reduced manufacturing and smaller profit margins. The CCI has been found to impact the future consumption and correlating with future spending. (Oest & Franses, 2008)

6. RESULTS

In this section we will discuss the results of the regressions. The regressions are made in levels and changes. Furthermore, we will test the panel data of different time-frames and try to capture firm-specific variables that are outside out regression model.

6.1 Results from auxiliary regressions

The results from auxiliary regressions are found in Table 9. The test is performed with the levels data only and it consists of 2125 observations. The results indicate that there is some heavy multicollinearity in the original model. The table indicates that there are two problematic variables in the model. The Consumer Confidence Index seems to have a big correlation between slope and yield, significant negative correlation between the VIX Index, and these variables have a significant p-statistic also in the regressions. The adjusted R^2 is 86.75 %, which means that a great deal of the variation in the CCI variable is explained by the other explanatory variables.

Another variable is the implied volatility index, VIX, which has a significant correlation between yield, slope of the yield curve and the CCI. The regressions indicate that historical volatility and market returns are significant when testing the multicollinearity, and the adjusted R^2 is 89.28 %. Our reference threshold for multicollinearity is 80%, or 0.80. The overall explanatory values are high because the two variables explain many of these other variables.

When the regressions are re-run without these two variables, the explanatory power reduces by average of 30 %[3].

[3]The results are not shown

Meaning, that multicollinearity is not an issue when testing the credit spreads without the Consumer Confidence Index and the implied volatility Index, CBOE VIX.

In some of the regressions, the t-statistics are quite good and seem to have good explanatory power and they are not at the same time statistically significant on a 5 % level so this makes the results harder to interpret. However, one has to remember that here the original model was tested for multicollinearity and we are looking for results contrary to the original regression.

In the case of VIX Index, historical volatility and market return can explain the most and they are also statistically significant. So the information in the VIX Index is also in the market return and the company volatility. For the Consumer Confidence Index, the slope and yield variables explain the most in that model and are also statistically significant. Therefore, the information in the CCI is included, at least partly, in these two variables.

The explanatory power reduces if the significant variables are removed from the model, in this case the CCI and CBOE VIX. The high explanatory power occurs when explaining market returns, slope of the yield curve, historical volatility and the US Treasury yield. Therefore the removal of these two variables makes our model statistically valid and good for testing the original theory.

Table 9. The results from auxiliary regression. The results are averages from the total regressions.

	CCI	Equity return	Leverage	Market return	Slope	VIX	VOL	YLD
CCI	**86.75 %**							
t-stat								
p-stat								
eqret		**39.61 %**						
	(0.08)							
	(0.45)							
Leverage			**65.12 %**					
	(-1.15)	(-1.80)						
	(0.13)	(0.19)						
Market return				**57.08 %**				
	(-0.69)	(4.66)	(0.82)					
	(0.35)	(0.01)	(0.38)					
Slope					**67.39 %**			
	(-3.63)	(0.41)	(1.49)	(0.18)				
	(0.04)	(0.45)	(0.07)	(0.58)				
VIX						**89.28 %**		
	(-2.27)	(-0.19)	(-0.42)	(-4.59)	(1.35)			
	(0.14)	(0.39)	(0.14)	(0.01)	(0.27)			
VOL							**79.08 %**	
	(-0.41)	(0.60)	(2.48)	(1.21)	(-2.20)	(7.37)		
	(0.35)	(0.33)	(0.13)	(0.24)	(0.15)	(0.00)		
YLD								**76.42 %**
	(3.90)	(-0.33)	(-0.55)	(-1.68)	(-1.01)	(-1.32)	(-0.16)	
	(0.00)	(0.37)	(0.26)	(0.19)	(0.44)	(0.26)	(0.45)	

The regression formula is $x_{t2} = a_1 x_{t1} + a_2 x_{t2} + \cdots a_K x_{tK} + error$. Where x represents every possible variation of the variables tested on every company available.

6.2. Results from levels data regressions

This chapter goes through the results from the regressions done with the levels data for each company and the results are reported as the average. The time-frame is the total sample period, 31.1.2004 - 31.12.2009. The results from the regressions (i) and (ii) are found in Table 10.

Table 10. The results of the levels regressions. The results are averages, both theoretical and overall. The t-statistics are in brackets. * is significant on 5 % level, ** is significant on 10 % level, *** significant on 15 % level.

	Predicted sign	(i) Coefficient	(ii) Coefficient
Intercept		-6.801***	-8.702
		(0.7170)	(0.6900)
YLD	-	-1.036**	-1.104**
		(-3.9267)	(-4.5980)
Slope	-	0.038	
		(0.2003)	
Leverage	+	14.765**	17.066***
		(3.8990)	(4.0913)
Market return	-	-4.603	
		(-1.3040)	
Equity return	-	0.401	
		(0.0173)	
VOL	+	0.030*	0.033*
		(6.1410)	(6.9660)
Adjusted R^2		83.23 %	80.78 %

The problem in the levels data is that the residuals seem to be, at some level, correlated. This phenomenon is called autocorrelation and it biases the estimator, in this case upwards when the autocorrelation is positive.

Therefore it is difficult to get statistically significant results because 60 % of the 30 regressions indicate, strong or weak, positive autocorrelation, at such point that the H_0 of no autocorrelation is rejected. The autocorrelation biases the OLS, therefore it is not BLUE and inflates the explanatory powers and biases the standard errors.

The autocorrelation has a few possible reasons according to Brooks (2002). These are overreactions in the markets and inertia of the dependent variable. In this case it is more likely to be the market's overreaction to bad news. This could be the reason why it wasn't a problem for example in the study of Ericsson et al. (2009) because the nature of the crisis was different.

As seen from the Table 10, the model's explanatory power is extremely high for the sample period. The results are in line with Merton's theory, because the most significant variables were leverage, volatility and risk-free rate. There is not much difference when testing only these three variables. The explanatory power declines from about 83 % to 81 %. These three variables also have the same sign as predicted and the most volatile variable seems to be leverage. When the leverage increases (decreases) 1 %, CDS spread increases (decreases) almost 15 %.

The regressions in Table 10 are divided by the company's average median CDS spread. The spread serves as a proxy for credit rating. The higher the spread, the worse the rating. This of course is not totally in line with the rating services but gives us some reference. The results are presented in Table 11. The companies are divided by the median spread level of the average company spreads. There are 15 companies below and 15 companies above the median.

However, the market returns are significant in the high credit rating companies. Also, the explanatory power increases slightly from 83.23 % to 84.80 %. Interestingly, the leverage ratios effect decreases quite dramatically. One percent increase in the leverage ratio increases the CDS spread only 2.1 % in the high rated sample. In the low rated sample, the one percent increase leverage increases the spreads nearly 27.4 %. These results are intuitive because in the low rated companies the increase in leverage affects the company's ability to survive more than the same increase in a well rated company.

Also the volatility's coefficient changes dramatically between the low and high rated groups. One percent change in volatility counts for 1.4 bps change in spreads in the below median group. For the above median group the equivalent change is 4.7 bps.

Table 11. The results of the levels regressions divided by company ratings. The results are averages. The t-statistics are in brackets. * is significant on 5 % level, ** is significant on 10 % level, *** significant on 15 % level. The CDS Levels is the results from regression (i), in Table 10.

	CDS Below Median Coefficient	CDS Levels Coefficient	CDS Above Median Coefficient
Intercept	0.007	-6.801***	-13.609***
	(1.855)	(0.717)	(-0.421)
Equity Return	0.117	0.401	0.684
	(0.198)	(0.017)	(-0.163)
YLD	-0.236**	-1.036***	-1.836***
	(-5.039)	(-3.927)	(-2.814)
Slope	-0.006	0.038	0.081
	(0.141)	(0.200)	(0.259)
Leverage	2.142***	14.765**	27.389**
	(3.443)	(3.899)	(4.355)
Market Return	-1.167***	-4.603	-8.039
	(-1.947)	(-1.304)	(-0.661)
VOL	0.014*	0.030*	0.047*
	(7.177)	(6.141)	(5.105)
Adjusted R^2	84.80 %	83.23 %	81.60 %

Interestingly, equity return and slope of the yield curve take different signs than expected. It means that when equity returns increase, the spread of the CDS decreases. Also, the bigger the slope of the yield curve, the smaller the CDS spread is. This is controversy to the intuition of the slope. The bigger the slope, the more uncertainty there is in the markets and it should be transferred to the CDS spread. However, this is not the case in this time period. For further usage, the usage of weekly data and dividing the data to crisis and pre-crisis period would give more accurate results.

6.3 Results from differences data regressions

The differences data is better for linear regression because it is for example well distributed. The test results are harder to interpret because for example the leverage ratios are not observed at a monthly level and therefore, intuitively, it should not be statistically significant.

The regressions are also tested with Durbin-Watson autocorrelation test and in every case we can conclude that no autocorrelation exists, in some cases the results indicate that the existence of autocorrelation is indecisive.

Table 12 presents the results from the differences regressions for the whole sample period. As we can see, the explanatory power is much lower than for the levels data but that is expected due to the nature of the data.

On average, the data is statistically insignificant but that is because there were a few companies whose p-values were significantly higher than in most of the companies. The industry sectors were analyzed but no consistency between the sectors with the t- and p-statistics was found. This means that the company's industry sector has no effect on the results. The t-statistics are fairly low in the regression (iii) and increase for the regression (iv), meaning that the variables in the regression (iv) are more significant.

However, it is hard to make robust conclusions from this model because the significances are low. The differences data is more difficult to estimate with this model. For the regression (iii), in Table 12, the signs differ from what was expected for the CBOE VIX Index. Interestingly in the regression (iii) the market return is the most explaining variable, indicating that the market conditions play a crucial role in the change of the spread. For the regression (iv) the signs are as was determined above. It is hard to make any assumptions from this finding because of the low t-statistic and statistical insignificance of the variables. For the regression (iv) the leverage is the only variable statistically significant on 15 % level.

These results are indicating that in the overall model, only market conditions are significant and in the theoretical model, the leverage ratio. Both are explaining the variation well, according to t-statistics. This indicates that the stock and CDS markets are correlated and they have a strong impact on CDS spreads. The leverage ratio is also significant and indicates that at least one firm-specific factor is able to explain the spreads. This however is true only in the theoretical model and would indicate that the information in the leverage ratio is included in the market conditions.

Table 12. The results of the differences regressions. The results are averages, both theoretical and overall. The t-statistics are in brackets. * is significant on 5 % level, ** is significant on 10 % level, *** significant on 15 % level.

	Predicted Sign	(iii) Coefficient	(iv) Coefficient
Intercept		0.018	0.004
		(0.2450)	(0.1097)
ΔYLD	-	-0.202	-0.472
		(-1.8477)	(-2.2053)
ΔLeverage	+	1.915	22.257***
		(0.9193)	(2.7937)
ΔSlope	-	-0.742	
		(-0.0463)	
ΔVIX	+	-0.005	
		(-0.0247)	
ΔVOL	+	0.005	0.007
		(1.9543)	(2.6220)
Market return	-	-12.462***	
		(-2.1333)	
Adjusted R^2		39.91 %	32.29 %

6.4 Results from panel data regressions

In this section we will go through the results from the panel data regressions. The affect of the financial crisis will best be seen in the panel regressions. First, we will test the period of normal returns, 31.1.2004 - 31.12.2006, 1049 observations, then compare these results with the high volatility and low return period, 31.1.2008 - 31.12.2009, 717 observations. Second, we will also test three yearly panel regressions in the financial crisis in 2007 - 2009.

The explanatory powers are significantly lower than for the time-series regressions. This is mostly because we use the one-way random effects model, and it uses Generalized Least Squares model and assumes the error term individually. GLS model also adjusts for autocorrelation, which would partly explain the lower explanatory powers. The different time-frame could also explain the differences.

Table 13 presents the results from differences regressions. It is obvious that the explanatory power is higher for the growth period. The R^2 for the years 2004 – 2006 is 9.54 % and for the years 2008 – 2009 6.11 %. Also the model fits better in the regression (v). When we look at the t-statistics and significances, we can notice that every variable is significant, compared to regression (vi), where only leverage and market returns are significant.

In Table 13 we can see that the signs differ from our intuitive framework. The slope of the yield curve, again, is controversial to the theory. Also the CBOE VIX Index is opposite to what was assumed. This might be due to the fact that VIX index was quite stable and did not differ much from the historical volatility in terms of the differences. However, in the years 2008 – 2009, all the signs, except the volatility are as expected. Interestingly, the VIX and historical volatility are opposite to each other. This might indicate that the implied volatility was more closely observed in the crisis than the historical volatility. The main difference in these determinants is that the CBOE VIX is the “future” volatility, whereas the equity volatility is historical.

The results show that, when comparing the regressions (v) and (vi), the t-statistics becomes closer to zero. This means that the explanatory power of the model reduces and becomes more insignificant, when the markets become more unstable. The coefficients are also affected by the crisis. For instance, the effect of company leverage is much higher in the crisis and in the pre-crisis period. The number of significant variables also reduces significantly.

In regression (vi) the market returns and company leverage are the key determinants. This would indicate that in crisis - high volatility, low market sentiment, and low returns - the markets determine the premium by company-specific data. As it was discussed earlier, increased market risk increases the default probability of a single company.

Table 13. The results of the panel data differences regressions. The t-statistics are in brackets. * is significant on 5 % level, ** is significant on 10 % level, *** significant on 15 % level. The regression (v) is the years 2004 – 2006 and regression (vi) is the years 2008 - 2009

	Predicted Sign	(v) Coefficient	(vi) Coefficient
Intercept		0.043*	-0.074
		(2.71)	(-0.41)
ΔYLD	-	-0.140*	-0.391
		(-2.67)	(-0.67)
Δslope	-	0.246**	-1.113
		(1.89)	(-1.26)
ΔLeverage	+	4.296*	14.253*
		(6.35)	(1.97)
Market return	-	-3.342*	-12.387*
		(-4.62)	(-3.04)
ΔVIX	+	-0.016*	0.012
		(-2.12)	(0.3)
ΔVOL	+	0.005*	-0.012
		(2.71)	(-1.01)
R^2		9.54 %	6.11 %

Table 14 presents the results of the levels regressions. Here we can see that the results are indicating the same type of results as the differences regression. The explanatory power reduces from 21 % to 18.5 % in the theoretical model. The regression (vii) gives only two significant variables, volatility and leverage. However, the high t-statistics indicate that there might be some autocorrelation or heteroskedasticy. The signs are as expected, except for the equity return in the years 2004 - 2006. Even though the explanatory power reduces in the years of financial crisis, the variables are more significant and therefore the results are more reliable.

Both, market and equity returns are not significant in either regression. If we look at the significances, the leverage and firm volatility are by far the best explanatory variables in the levels regression, for both time periods. The changes in the variables are dramatic and the coefficients of leverage and volatility almost triple in the crisis periods.

Table 14. The results of the panel data levels regressions. The t-statistics are in brackets. * is significant on 5 % level, ** is significant on 10 % level, *** significant on 15 % level. The regression (vii) is the years 2004 – 2006 and regression (viii) is the years 2008 - 2009

	Predicted Sign	(vii) Coefficient	(viii) Coefficient
Intercept		-1.993*	-1.252
		(-4.75)	(-0.42)
Equity return	-	0.058	-1.012
		(0.18)	(-0.61)
YLD	-	-0.014	-1.043**
		(-0.2)	(-1.83)
Market return	-	-1.920	-1.866
		(-1.66)	(-0.43)
slope	-	-0.021	-0.853***
		(-0.71)	(-1.63)
VOL	+	0.0278**	0.051*
		(8.07)	(4.81)
Leverage	+	5.313**	14.985*
		(12.74)	(4.85)
R^2		21.41 %	18.55 %

The levels panel regression indicates the same as the levels linear regression. Here also the leverage and volatility explain the most and are also statistically significant. It seems that these two variables can give the best estimate for the CDS spread in levels. Also, in this regression, the risk-free rate can be considered the third variable to explain spreads in some level, but the consistency must be proven to make further conclusions.

These findings confirm that Merton's theoretical model can explain also credit spreads in practice. However, it is interesting that in the levels data the market returns are not statistically significant. The effect of financial crisis obviously makes it more difficult to estimate the spreads with the Merton's model but still the theoretical determinants are mainly significant.

6.5 Robustness test

To test the model's robustness, we divide the data in 3 one year groups. The objective is to find whether there are any common factors in financial crisis that could explain CDS spreads. The sample periods are years 2007, 360 observations, 2008, 360 observations, and 2009, 356 observations. The year 2007 is considered as a pre-crisis period. The regression is performed as a panel regression with random-effects model as described in the chapter 6.4.

In the regression (ix) and (x), in Table 15, we can see the panel regression results of the year 2007. It is remarkable that the explanatory power is much higher than in the regression (vii) and (viii). In the regression (ix) and (x) the R^2 is about 64 %, and in the seasonal regressions only about 20 %, indicating that the overall pre-crisis period has much more fundamentals in pricing the derivatives. Here we can again note that leverage and volatility are both significant. The t-statistics are however quite large, meaning that they explain a great deal of the variation or that the estimates can be biased due to the slight autocorrelation.

The equity returns and market returns are significant in these regressions, whereas in the regression (vii) and (viii) they are not. This might be because the market conditions and firm conditions were included in the premiums. This, however, is not the case in the pre-crisis period 2004 - 2006 nor the crisis period 2008 - 2009.

Table 15. The results of the panel data levels regressions in year 2007. The t-statistics are in brackets. * is significant on 5 % level, ** is significant on 10 % level, *** significant on 15 % level. The regression (ix) includes all the variables and regression (x) includes only the theoretical variables.

	Predicted Sign	(ix) Coefficient	(x) Coefficient
Intercept		-4.785*	-4.238*
		(-4.29)	(-5.77)
Equity return	-	-1.472*	
		(-2.41)	
YLD	-	0.223	0.045
		(1.05)	(0.34)
Slope	-	0.0943	
		(0.51)	
Leverage	+	7.253*	7.796*
		(8.41)	(8.95)
Market return	-	-2.2982***	
		(-1.48)	
VOL	+	0.06738*	0.069*
		(13.99)	(15.23)
R^2		64.63 %	63.37 %

The results of the differences panel regression for the year 2007 are presented in Table 16. Here we can see that the explanatory power is again higher than in the seasonal regressions, 9.5 % and 6.11 %. The leverage and volatility are the key determinants. Remarkable in these regressions is that in the regression (xi) the risk-free rate and the slope of the yield curve actually tightens the CDS spread. This is the same as in some of the levels regressions. The volatility and the CBOE VIX Index are both statistically significant and by their t-statistic, explaining the spreads well. Therefore both of these volatilities can be used to measure the volatility.

The market return, risk-free rate and the slope of the yield curve are statistically insignificant. This can be interpreted so that the CDS spreads are mainly consistent with the company specific fundamental data. The overall market conditions did not affect as much as the firm-specific conditions.

Table 16. The results of the panel data differences regressions in year 2007. The t-statistics are in brackets. * is significant on 5 % level, ** is significant on 10 % level, *** significant on 15 % level. The regression (xi) includes all the variables and regression (xii) includes only the theoretical variables.

	Predicted Sign	(xi) Coefficient	(xii) Coefficient
Intercept		-0.005	0.057**
		(-0.08)	(1.87)
ΔYLD	-	0.223	-0.204***
		(1.18)	(-1.5)
ΔSlope	-	0.478	
		(1.38)	
ΔLeverage	+	11.987*	13.329*
		(6.16)	(7)
ΔVIX	+	0.044**	
		(1.93)	
Market return	-	1.050	
		(0.37)	
ΔVOL	+	0.009**	0.011*
		(1.95)	(2.35)
Adjusted R^2		20.63 %	18.55 %

The results of the levels regression for the year 2008 are presented in Table 17. Interestingly, the slope of the yield curve has become a significant determinant in this regression even though the risk-free rate itself is not. This probably is due to the fact that the Federal Reserve rapidly lowered the Fed Funds Rate from 3.50, 22.1.2008 to 0 – 0.25, 16.12.2008. The credit spreads were also widening by the worsened economic and firm conditions, which could explain the significance. (Federal Reserve, 2010) This move, of course, did not itself affect our determinants but it reduced the yield of the US Treasury notes for that moment and adjusted the yield curve.

We can conclude that the slope of the yield curve itself is not the key factor when the interest rate changes are modest. However, when the changes are dramatic, it affects the spreads, and as discussed earlier, the slope is a factor of uncertainty in the markets. 1 % increase in the slope of the yield curve decreases the spread by 2.8 %. This finding is interesting and means that, basically, when the slope is normal – the uncertainty is higher in the future – the spread is smaller.

Table 17. The results of the panel data levels regressions in year 2008. The t-statistics are in brackets. * is significant on 5 % level, ** is significant on 10 % level, *** significant on 15 % level. The regression (xi) includes all the variables and regression (xii) includes only the theoretical variables.

	Predicted Sign	(xiii) Coefficient	(xiv) Coefficient
Intercept		-0.681	-3.573
		(-0.19)	(-1.25)
Equity return	-	-0.692	
		(-0.32)	
YLD	-	0.122	-0.256
		(0.19)	(-0.45)
Slope	-	-2.802*	
		(-2.17)	
Leverage	+	8.857*	10.049*
		(2.54)	(2.96)
Market return	-	-2.084	
		(-0.31)	
VOL	+	0.075*	0.058*
		(5.41)	(5.17)
Adjusted R^2		23.33 %	22.05 %

The results for the differences data in the year 2008 are interesting, shown in Table 18. The explanatory power is reduced significantly. However, the overall model has no statistically significant determinants. It seems that the spreads were determined by some other market-specific factors.

In the theoretical model we can find that the volatility, firm leverage and the risk-free rate affect the differences in spreads. However, only leverage is significant on 5 % level. The company's leverage ratio was considered as the main determinant in the market turbulence. This is intuitive when the future becomes more volatile, the companies that have for example a cash buffer are thought to survive bigger crisis or depressions without defaulting.

Table 18. The results of the panel data differences regressions in year 2008. The t-statistics are in brackets. * is significant on 5 % level, ** is significant on 10 % level, *** significant on 15 % level. The regression (xv) includes all the variables and regression (xvi) includes only the theoretical variables.

	Predicted Sign	(xv) Coefficient	(xvi) Coefficient
Intercept		-0.187	-0.020
		(-0.62)	(-0.08)
ΔYLD	-	-0.313	-0.992**
		(-0.31)	(-1.73)
ΔSlope	-	-1.439	
		(-1.37)	
ΔLeverage	+	12.552	18.581*
		(1.43)	(2.26)
ΔVIX	+	0.016	
		(0.21)	
Market return	-	-11.392	
		(-1.14)	
ΔVOL	+	0.006	0.021***
		(0.39)	(1.49)
Adjusted R^2		5.24 %	3.82 %

Table 19 presents the results of the levels regression for the year 2009. By comparing these regressions to regressions (xi) and (xii) we can clearly make the conclusion that the model's explanatory power reduces quite significantly. The explanatory power in these regressions is only 18.20 %

and 14.98 % for the theoretical regression. In the regression (xi) the equivalent percentages are 64.63 % and 63.37 %, respectively.

In these regressions the leverage and historical volatility are the crucial determinants. The signs are here also as expected, except again for the risk-free rate. It seems that in the levels regressions the risk-free rate is the opposite to the theoretical framework in the overall model. However, in the theoretical models, the risk-free rate is tightening the CDS spread. When comparing the t-statistics, the theoretical model seems to be more accurate.

It is interesting that in the year 2009, the explanatory powers are lower than in the year 2008. The economy’s volatility peaked in the late 2008 and started declining after February 2009. By observing only by the means of volatility, the economy was far more stable in the year 2009 and should give better results. Here we can make a conclusion that the investors were far more cautious in terms of credit derivatives and the markets remained quite stagnant at least in some level. The risk-free rate is significant in this regression and a 1 % increase in the risk-free rate reduces the spread for 2.5 %. The leverage’s effect is also significant to the spread.

Table 19. The results of the panel data levels regressions in year 2009. The t-statistics are in brackets. * is significant on 5 % level, ** is significant on 10 % level, *** significant on 15 % level. The regression (xv) includes all the variables and regression (xvi) includes only the theoretical variables.

	Predicted Sign	(xv) Coefficient	(xvi) Coefficient
Intercept		-0.224	0.550
		(-0.04)	(0.1)
Equity return	-	-2.811	
		(-1.08)	
YLD	-	0.232	-2.498**
		(0.08)	(-1.86)
Slope	-	-2.866	
		(-0.75)	
Leverage	+	13.720*	17.174*
		(3.39)	(3.41)
Market return	-	-4.385	
		(-0.58)	
VOL	+	0.063*	0.051*
		(3.06)	(2.53)
Adjusted R^2		18.20 %	14.98 %

Table 20 presents the results of the differences regression in the year 2009. The most significant result is that the explanatory power has increased from the year 2008. In the year 2009, the explanatory power is 6.57 % for the whole model and 4.66 % for the theoretical model. The equivalent values for the year 2008 are 5.24 % and 3.82 %, respectively.

Also the market return is significant in the whole model. It is also to be noted that the sign of the historical volatility is opposite to what was expected. This means that in the year 2009, the increase in historical volatility actually decreased the CDS spreads. The t-statistics also indicate that the assumption is robust.

Table 20. The results of the panel data differences regressions in year 2009. The t-statistics are in brackets. * is significant on 5 % level, ** is significant on 10 % level, *** significant on 15 % level. The regression (xvii) includes all the variables and regression (xviii) includes only the theoretical variables.

	Predicted Sign	(xvii) Coefficient	(xviii) Coefficient
Intercept		-0.008	-0.308
		(-0.02)	(-1.07)
ΔYLD	-	-1.988	-1.089
		(-1.26)	(-1.22)
ΔSlope	-	-0.236	
		(-0.1)	
ΔLeverage	+	14.197	33.492*
		(1.15)	(3.47)
ΔVIX	+	-0.079	
		(-0.88)	
Market return	-	-17.875*	
		(-2.5)	
ΔVOL	+	-0.035**	-0.040*
		(-1.84)	(-2.09)
Adjusted R^2		6.57 %	4.66 %

Here the market conditions actually do affect the spread and are statistically significant. This is an important finding because in the less volatile seasons, the market conditions are affecting the prices. It can be said that the market conditions affect the change of the CDS spreads in fair or good times.[4] In crisis it has no effect on the change of the spread.

Here the market returns decreases the spreads almost 18 % and the increased leverage increases the spread almost 34 %. These findings are of significant interest. Also the fact that the leverage is not significant in this regression is a significant finding. The reason might be that the information in the leverage could have been discarded and the correlation between stock markets and CDS markets was high. This means that the bullish stock markets affected the investor sentiment in the credit markets.

This would partly explain why the leverage is significant in the theoretical model but not in the overall model.

6.6 Discussion of the results

The model fits the data well. All the variables are somewhat significant in different economic conditions. It is observed that the model fits best in the low volatility periods. In high volatility periods, other market or company variables might hold better explanatory power. It was found that over 83 % of the variation can be explained by the model when estimated in levels. For the differences regression the percentage of variation explained was 39.91 %. The high explanation power in levels regression can be due to the slight autocorrelation between the residuals. For further study, the variables should be modified or changed to eliminate the autocorrelation totally.

The results indicate that for all the regressions, firm leverage and historical volatility are the main determinants that can explain the CDS spread. The overall explanatory power is in the linear regression model extremely high for levels data. For the differences data it is lower. This is due to the nature of the data and differences are harder to estimate. These findings are also suggested by for example Greatrex (2009). The macroeconomic determinants did not work as well as the firm-specific variables.

The significance in the regressions varied in the panel regressions. However, it is a significant finding that in the crisis overall market conditions affected the CDS spread, whereas in the more stable markets it did not. This would indicate that the markets' sentiment did affect more than expected. Maybe a variable exists that could explain the market sentiment's affect, if there is any, to CDS spreads.

[4]The regression (v) indicates that in the years 2004 – 2006 the market return is the only significant determinant.

The affect of the risk-free rate was smaller than the theoretical model would assume. In the theoretical panel regressions, it was significant, however in the overall model regressions it was not. It could be that the information contained in the risk-free rate is in some of the other variables. Also in real life the Brownian motion as a company's drift is probably not a constant and does not follow normal distribution.

There were significant differences between the years 2007, 2008, and 2009. The explanatory powers decreases from 63 % to 18 % for the levels data and for the differences from 21 % to 7 %, respectively. Therefore the model works in the less volatile markets and can explain the spread well. The main determinants were, in every regression, leverage and volatility. It remains unsolved how much the other variables affected. However, it seems that the market conditions definitely affect the spreads at some level. The risk-free rate had a little affect but the slope of the yield curve did explain some of the variation in the crisis. This finding does help us at some level, because the interest rate changes were rapid in the year 2008, and if such decreases happens again, this model would help to estimate the CDS spread with the slope.

There seems to be only little difference in the levels data in different years. In the year 2007 the equity returns were a significant determinant and in the year 2008 it was the slope of the yield curve. This indicates that the stock markets and CDS markets were correlated. In the year 2008, the slope of the curve was positive and we believe that the markets gained confidence from the year 2007, which affected the CDS premium. It is to be noted here that in the years 2006 and 2007 the slope was actually slightly negative. The investors settled for lower yields, believing that the short-term economy is slowing down.

In the levels data, the leverage's coefficient changes significantly. In the year 2007 the coefficient was about 8 and in the year 2009 it was 17. It means that if the spread increased 1 %, or 100 bps, the leverage would increase 8 %, or 800 bps, or 17 %, 1700 bps. This indicates that the markets actually allowed companies to increase leverage significantly. One conclusion can be made from this finding; the investors did not want to default the debts but allowed the companies to increase the amount of debt just to keep on a going concern. Even though the spreads did increase, they did not increase exponentially. In the more stable years the increase in leverage was smaller per 1 %, or 100 bps, in spread. The same results can be seen in the one-year panel regressions or in the seasonal regressions.

The volatility does not change much when spread changes and the coefficients are at the same level through the sample periods. In the seasonal regressions, however, the volatility's coefficient almost doubles. The changes are still lower than one would expect.

For the coefficients, the results are much higher than for example in the study of Ericsson et al. (2009). For example the 1 % increase in leverage increased the spread on average by 6.3 and 7.3 bps. The equity volatility is from 1.0 to 1.5 bps. In this study the similar results are 1 % change in leverage which means about 17 % change in the CDS spread. A 1 % increase in volatility increases the spread by 3 bps, or 0.03 %. Obviously the firm-specific data has more concrete effect to the spreads.

The hypotheses were determined in chapter 5.7 and are discussed here. The relationship between company leverage and CDS spreads is positive, H1, holds in every regression, and it is statistically significant. It is important to notice that the effect of the leverage ratio to CDS spreads increase in financial crisis. The leverage ratio provides information regardless of the economic conditions. It is the single most explanatory variable in the model.

The hypothesis that the relationship between interest rates and CDS spreads is negative, H2, holds in all the cases where the interest rate was statistically significant. The H2 yields from the Merton's model as the drift rate of the company's value in a risk-neutral procedure. The effect of interest rates is present in the theoretical regressions but does not show consistent effect. So the conclusion that the in financial crisis the interest rates are not the main factor driving the CDS spreads can be made.

The relationship between volatility and CDS spread, H3, was thought to be positive. However, in the year 2009 the relationship was negative, indicating that H3 is not always consistent in financial crisis or bear markets. This finding is interesting, because now it can be said that volatility's effect is not always widening the spread. The year 2009 should be investigated more closely to explain this anomaly. This result has been also captured by Ericsson et al. (2009). They do not make any conclusions on that matter. What then reversed the relationship in the year 2009? The explanation might be that the correlation between stock and CDS markets is negative in that period. Even though the investors started to invest in stock markets the uncertainty remained in the CDS markets for a longer period.

The relationship between market conditions and CDS spreads, H4, is at some level indecisive. It is difficult to say whether the market conditions even affect the spreads in every situation. However, the results indicate that the relationship is negative, when they are statistically significant. Perhaps the S & P 500 returns are not the best proxy for market conditions and further studies should be made.

The relationship between equity returns and CDS spreads, H5, remain also indecisive. The significance was low in the regressions and we must make the conclusion that the company leverage ratio provides better firm-specific information than the equity returns. This finding indicates that in financial crisis, the equity returns are not included in the spreads. This could also be because of the low and/or negative correlation between stock and credit markets. The equity returns had strong negative correlation with the company leverage ratio.

However, the equity returns were significant in the year 2007 and the t-statistics indicate that the explanatory power was good. In the following years the significance was reduced. The results of the year 2007 are consistent with Greatrex (2008).

This would indicate that in crisis, the only company-specific determinant in this model is the leverage ratio. This variable determines straightforwardly whether the company can meet its obligations in the near future or will it default.

The relationship between the Consumer Confidence Index and the CDS spread remains unproven. The CCI Index is difficult to include in these regressions because of the high multicollinearity and the fact that the same information is included in the other variables.

On the whole, the theory remains robust and we can without a doubt say that the variables that are indicated by Merton's (1974) original theory still hold. The interest rates had less effect than predicted but when the results were statistically significant, they were consistent with the theory.

7. CONCLUSIONS

This study investigates the relationship between theoretical determinants of Credit Default Swap spread and the actual spread. We empirically and theoretically investigate the determinants of Credit Default Swap spreads and the effect of the financial crisis in the US markets. The CDS spread was explained, both in levels and in differences. Theoretical determinants were company leverage, volatility, and risk-free interest rate. We also added variables as proxies for company health, market conditions and the expectations of the future. The sample companies were industrial firms, mainly S & P 500 Large Cap. The amount of companies was limited to 30 due to the lack of consistent data. The data is from Datastream and Thomson One Banker. Month-end observations are used. The time-frame is from 31.1.2004 to 31.12.2009. The financial crisis is thought to start from the midst of 2007 and to continue through the year 2009.

The regressions are performed in time-series framework and in panel data framework. The regressions using levels data in time-series framework are autocorrelated when using levels data and the results are difficult to compare. However, the explanatory power is over 83 % in the levels and almost 40 % in the differences. The results in differences indicate that for the whole period, only market returns are significant for the overall model. As to the theoretical model, the leverage ratio was the single significant variable. Interestingly, in the differences data, the theoretical model proves that the firm-specific data and the market conditions are the most important determinants across the sample period. The fact is that the results varied significantly on a company basis and the companies should be divided into groups by their industry sector to further study the model’s fit.

We find that the theoretical determinants are statistically significant and can explain the variation of CDS spread up to 63 % for the levels data and about 21 % for the differences data. The explanatory power mainly depended on the overall market conditions and investor sentiment. The effect of the financial crisis to our model is obvious. The theoretical determinants remain robust all over the sample period but the explanatory power reduces.

This would indicate that there are variables that could explain the variation in the crisis, outside the model. The theoretical model fits best for estimation and the adjusted R^2 reduces only a few percentages, compared to overall model.

The stock and the CDS market are somewhat correlated; it is not shown in the results. Also the stock markets and the CDS markets provide separate information, which is seen in the year 2009. This would be a great extent for further studies. For example, the level of correlation and the cross-market effect could be studied.

The panel data regressions and more precisely, the differences data give more accurate results because of the slight autocorrelation in the levels data. It is an issue in the linear regression models; however, the panel data regressions are not affected by the autocorrelation as much due to the usage of different econometric model. Therefore the results of the linear regression for levels data are probably biased upward, to 83 %. The differences regression is unbiased and the results are robust. The statistical significance is however inadequate. Only market returns are significant in the overall model and leverage for the theoretical model. This is due to the fact that there were a small number of companies where none of the variables were significant and the mean calculation is affected by them. However, the removal of these companies would synthetically upgrade and/or bias the model.

On the whole, the results were better than expected. The volatility of the markets and the poor investor sentiment in the crisis was probably the main reason why the explanatory power was low in 2008 and 2009. The overall explanatory power for levels data was on average 35.4 % and 33.5 % for the theoretical model. These findings are consistent with previous studies. For the differences data the averages are 10.8 % and 9 %. The latter is the theoretical model's explanatory power. The explanatory power is lower in the panel regressions than in the linear regressions. The time-series regressions in differences yield approximately the same results for the two time-periods; pre-crisis and crisis.

The results are consistent with previous studies and the model was able to capture majority of the variation. There were two key determinants and both were firm-specific. The results are also expected since the swaps are company credit products. However, we did find that some market information does affect the spreads in different market conditions.

The effect of the financial crisis can be seen in the regressions as the lowering explanatory power. The coefficients also have changed dramatically over the years. However, the best variables remain somewhat constant. The leverage is the best variable regardless of the economic conditions. This indicates that the only thing that concerns the markets in the crisis is a company's ability to survive it. This finding would indicate that the other company fundamentals are discarded.

For further studies, the more accurate market data should be used and the financial crisis should be studied based on daily or weekly data. These studies should also include credit rating based indexes of CDS or the companies to test the affect of the ratings. Also the risk-free interest rate should be studied. In this study the 10-year US Treasuries rate had only a little effect, so maybe the 5-year Swap rate could be used. Swap rates are also considered as risk-free rates and they could provide better information.

Also the more precise analysis of the company fundamentals would make improvements to the model. The objective is to find what key figures are observed and what are discarded in the crisis.

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APPENDICES

Appendix 1. The Average One-Year Rating Transition Rates (Source: Hamilton et al., 2002)

	Rating To:																	
	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa-C	Default
Rating From:	Aaa	85	5.88	2.9	0.47	0.71	0.28	0.16	0	0	0	0.04	0	0	0	0	0	0
	Aa1	2.54	76.02	7.87	6.58	2.31	0.32	0.05	0.18	0	0	0.09	0	0	0	0	0	0
	Aa2	0.7	2.9	77	8.39	3.93	1.35	0.58	0.16	0	0	0	0	0.05	0.08	0	0	0
	Aa3	0.08	0.61	3.36	77.88	8.89	3.14	0.85	0.24	0.21	0.16	0	0.04	0.09	0	0	0	0
	A1	0.03	0.11	0.6	5.53	77.68	7.2	2.88	0.78	0.27	0.13	0.36	0.25	0.05	0.12	0.01	0	0
	A2	0.05	0.06	0.29	0.77	5.34	77.47	7.18	2.87	0.8	0.39	0.28	0.1	0.11	0.03	0.07	0	0.03
	A3	0.05	0.1	0.05	0.23	1.48	8.26	71.77	6.69	3.65	1.43	0.54	0.19	0.22	0.33	0.05	0.04	0.01
	Baa1	0.08	0.02	0.13	0.18	0.2	2.71	7.67	71.19	7.37	3.14	1.04	0.46	0.35	0.55	0.09	0	0.02
	Baa2	0.07	0.1	0.12	0.17	0.17	0.87	3.67	6.9	71.5	7.02	1.68	0.52	0.65	0.48	0.45	0.23	0.03
	Baa3	0.03	0	0.03	0.07	0.18	0.57	0.65	3.22	9.33	67.03	6.38	2.59	1.9	0.8	0.31	0.18	0.16
	Ba1	0.08	0	0	0.03	0.22	0.12	0.67	0.75	2.94	7.68	66.47	4.6	3.88	1.12	1.27	0.81	0.33
	Ba2	0	0	0	0.03	0.04	0.15	0.13	0.35	0.7	2.3	8.35	63.96	6.2	1.67	3.7	1.35	0.53
	Ba3	0	0.02	0	0	0.04	0.16	0.17	0.17	0.26	0.69	2.71	5.04	66.66	4.83	5.16	2.22	0.85
	B1	0.02	0	0	0	0.06	0.09	0.15	0.07	0.24	0.3	0.42	2.52	5.7	66.89	5.22	4.58	1.78
	B2	0	0	0.06	0.01	0.11	0	0.07	0.17	0.12	0.18	0.29	1.63	2.95	5.75	61.22	7.61	3.69
	B3	0	0	0.06	0	0.02	0.04	0.06	0.11	0.12	0.2	0.18	0.35	1.17	4.02	3.36	62.05	6.84
	Caa-C	0	0	0	0	0	0	0	0	0.48	0.48	0.64	0	1.36	1.85	1.23	2.87	54.21

Appendix 2. The list of companies and the industries used in the study

Company	Industry
3M	General Industrials
AES	Electricity
Alcoa	Industrial Metals
AMB Properties	Real Estate Investment Trusts
American Express	Financial Services
AON	Nonlife Insurance
AT&T	Fixed Line Telecommunications
Berkshire Hathaway	Nonlife Insurance
Boeing	Aerospace & Defense
Boston Properties	Real Estate Investment Trusts
Caterpillar	Industrial Engineering
CMS ENERGY	Electricity
Colgate-Palmolive	Personal Goods
Commercial Metals	Industrial Metals
Deere	Industrial Enginering
El Paso	Oil Equipment, Services & Distribution
Exxon	Oil & Gas Producers
Ford Motor	Automobiles & Parts
Goodyear	Automobiles & Parts
Jetblue Airways	Travel & Leisure
McDonald's	Travel & Leisure
MGM Mirage	Travel & Leisure
Occidental Petroleum	Oil & Gas Producers
Procter & Gamble	Household Goods
Southwest Airlines	Travel & Leisure
Standard Pacific	Household Goods
Texas Instruments	Technology Hardware & Equipment
UnitedHealth	Health Care Equipment & Services
Viacom	Media
Xerox	Technology Hardware & Equipment

Appendix 3.

The Spearman correlation matrix of the levels data

	eqret	CDS	YLD	slope	lev	VIX	mrkret	VOL	CCI
eqret	1								
CDS	-0.096	1							
YLD	0.0274****	-0.420	1						
slope	-0.034***	0.384	-0.748	1					
lev	-0.061	0.718	-0.163	0.158	1				
VIX	-0.180	0.439	-0.700	0.754	0.148	1			
mrkret	0.487	-0.075	0.041**	-0.037**	-0.009****	-0.254	1		
VOL	-0.108	0.690	-0.456	0.401	0.393	0.543	-0.093	1	
CCI	0.061	-0.436	0.841	-0.781	-0.173	-0.776	0.063	-0.519	1

**significant on 10 % level ***significant on 15 % level, ****statistically not significant

Appendix 4.

The Spearman Correlation matrix of the differences data

	eqret	ΔCDS	ΔYLD	Δslope	Δlev	ΔVIX	mrkret	ΔVOL
eqret	1.000							
ΔCDS	-0.327	1.000						
ΔYLD	0.051	-0.185	1.000					
Δslope	-0.125	0.114	0.264	1.000				
Δlev	-0.904	0.314	-0.029****	0.121	1.000			
ΔVIX	-0.346	0.272	-0.088	0.346	0.333	1.000		
mrkret	0.487	-0.392	0.144	-0.156	-0.455	-0.620	1.000	
ΔVOL	-0.153	0.220	-0.100	0.102	0.160	0.209	-0.217	1.000

**significant on 10 % level ***significant on 15 % level, ****statistically not significant