Credit Risk

- An Empirical Study of the Credit Default Swap Spread

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Executive Summary

This thesis investigates the determinants of the credit default swap spread by a multiple linear regression model, using ordinary least squares method. The thesis opens with an outline of credit risk and the credit derivatives market. Furthermore, the characteristics of a CDS contract and the credit default swap spread are covered.

On the basis of economic theory on credit risk and previous empirical researches, a set of determinants is identified. The thesis is highly inspired by the theory behind Merton's structural credit risk model, and the findings in three empirical studies by Collin-Dufresne et al. (2001), Benkert (2004), and Ericsson et al. (2009).

A model, which is consistent with the economic theories and at the same time both statistically and economically significant, is drawn up to investigate the linear relationship between the identified determinants and the credit default swap spread. The analysis is based on daily data from January 2005 to December 2016 on 79 American companies collected from the Markit CDX NA IG index.

Both macroeconomic and firm-specific factors prove to be of importance, when determining the credit default swap spread. The three theoretical factors proposed by Merton (1974): firm leverage, volatility, and the risk free rate level were all found to have a significant influence on the CDS spread.
CDS liquidity, GDP growth, and the firm-specific factors: credit rating and the price/book value also turned out to be statistically significant. However, the empirical analysis proposes that equity volatility, especially option-implied volatility, is the most central determinant of the credit default swap spread.

Since the dressed up model only seemed to explain a little less than half of the variation in the CDS spread, the model was divided into shorter periods, representing different economic stages, and also run on the individual years. It was found that the explanatory power of the model and the variables' behaviour vary, depending on the respective periods The leverage seemed to have a decreasing significant impact on the CDS spread over the years while at the same time, both of the volatility measures had an increasing impact on the CDS spread. By running the regression model on the individual years, it was found that the model, in general, is better at explaining the variation in the CDS spread in single years. The model and hence the identified determinants, proved to be much better at explaining the variation in the years prior to the financial crisis.

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1 Introduction

"Risk is like fire: If controlled it will help you; if uncontrolled it will rise up and destroy you."

(Theodore Roosevelt)

With this quote, this thesis is presented with focus on the determinants of the credit default swap spread (later on referred to as CDS spread).

During the last two decades, the financial market has gone through huge changes. An increased focus on credit risk has arisen as a result of the culmination of the financial crisis in 2008, and the importance of credit risk management in all institutions has obliviously been reinforced. Numerous credit risk models have been developed, and several studies on the subject have been conducted. Despite all this research, credit risk is still a field with large complexities and hence, a lot of knowledge on the topic still needs to be accounted for.

The development in the overall financial markets has changed drastically and at fast pace for the last decades, and new structural products including credit derivatives have emerged. The first credit derivatives were traded in the market in the beginning of the nineties and lead to a major upheaval in the credit market. These new financial products made it a lot easier to trade credit, and further eased the investors' possibilities of shorting credit risk.

The most popular credit derivative is the Credit Default Swap Contract (later on referred to as CDS contract), which grew explosively throughout the nineties and until 2007. The buyer of a CDS contract can eliminate the risk of default on a certain underlying asset by paying the contract seller a monthly or quarterly fee. This fee is called the CDS risk premium or the CDS spread[1]. If a default event occurs, the contract seller is obligated to cover the loss. However, there has been a lot of speculation about the CDS product being one of the core problems causing the financial crisis in 2008, because several major companies and banks went bankrupt as a result of the use of these CDS contracts. The critique especially concerned the lack of regulations on the credit derivative marked, and hereby the CDS marked. This, indeed, illustrates how vulnerable the credit market is, and shows that many investors have not understood the risk profiles associated with these complicated products. The CDS contracts

[1] CDS risk premium and CDS spread are synonyms and the latter will be used as reference throughout the thesis.

have in that context received much negative attention and interest, whereas they at the same time possess some clear advantages.

A major advantage of a CDS contract is that it constitute a relatively clear expression of the price of credit risk. This makes the market more flexible, wherefore investors easily can take short positions in credit, thus creating a market which reacts faster and acts more rationally. The credit derivatives allow the transfer of credit risk in an efficient, simple, and standardized way, where most actors can participate.

Because of the fact that the CDS spread is a relatively pure expression of the price of credit risk, it can be used in the investigation of which variables that drive credit risk. Which determinants that affect the level of the CDS spread is of high relevance in the understanding of the complexity of the credit derivate, and will lead to a deeper understanding of the various risks associated with the conclusion of a CDS contract.

Several researchers have completed different studies on the subject of investigating the determinants of the CDS spread. Ericsson et al. (2009), for instance, find that the theoretical variables used in pricing credit risk in the structural approach developed by Merton (1974): leverage, the volatility of the underlying asset, and the risk free rate level, are the key determinants when explaining the variation in the CDS spread.

Furthermore, Benkert (2004) experiences a higher explanatory power of the model by including not only the theoretical variables, but also option-implied volatility and some firm specific variables such as credit rating. However, in the majority of the previous studies, a significant part of the variation in the CDS spread cannot be explained, wherefore the field continuously will be subject to further research. Common for all the earlier studies is that they are all based on data from the late 90's and early 00's prior to the financial crisis and thus, comprehensive studies covering recent history do not really exist. Therefore, this thesis will contribute to the empirical evidences by exposing determinants of the CDS spread in more recent history.

The above presentation forms the foundation of the chosen research objective as defined in the following section.

1.1 Research Question

The purpose of the thesis is to carry out an ordinary least square linear regression on the relationship between the CDS spread and determinants suggested by economic theory and previous acknowledged studies on the topic. The thesis seeks to conduct an examination on how suggested variables affect the CDS spread, and to develop a model which is consistent with the economic theories and at the same time is both statistically and economically significant. The research objective can be defined as follows:

> *Which factors are crucial when determining the credit default swap spread and how do these determinants affect the credit default swap spread?*

In order to fully examine and answer the objective of the thesis, the problem statement gives rise to some sub-questions listed beneath which are relevant to study, as each of them contributes to a better understanding of the credit risk and the CDS product. Consequently, the sub-questions also form the foundation and constitute the disposition of the thesis:

- What is credit risk and how is it constructed?
- What is a Credit Default Swap and how is the contract structured?
- Which determinants affect the size of the credit default swap spread, according to theory on structural risk models and previous empirical studies?
- How do the suggested determinants affect the level of the Credit Default Swap Spread?

1.2 Methodology

The methodological foundation is essential to ensure the quality of both the data and the analysis itself. According to Jens Martin Knudsen:

"Science is about seeking the truth, and always be skeptic towards those who say they have found it" (Emmeche 2006).

It is important to recognize the research philosophy in order to assess the quality of the information being produced, and to be able to make a qualified choice between different research methods in regard to both the data collection and the later interpretation of the data.

As a part of determining the research philosophy, it is important to clarify which research design to use in order to guarantee the evidence, and to make sure that the thesis actually seeks to answer the problem. Lastly, it is important to be source critical and ensure that the collected data, which form the foundation of the thesis, are relevant, valid, and reliable. Especially this point is of great importance, as it has crucial impact on the conclusions of the thesis and ensures that the scientific arguments stay intact.

Research Philosophy

The scientific theoretical position of this thesis contains both positivistic and neo-positivistic paradigms according to Guba (1990).

The ontology is mainly realistic, as the data on CDS are public and in accordance with the truth, and a reality therefore exists, wherefore the epistemology is purely objective. Because the purpose of this thesis is to explain, predict, and examine causalities in the credit derivatives market, data accumulations and previous research on this specific topic will be used as the primary source for further experimental testing in verification or falsification of selected hypotheses.

The thesis also consists of neo-positivistic paradigms as regards selecting the different determinants for further testing and, furthermore, in the selection of data. In this selection process, limited realism is involved, and it is not entirely possible to stay impartial of ones cognition of the truth. The neo-positivistic paradigm allows one to explore new conjunctions, but because of the modified objectiveness that lies within the epistemology, it is important to be very critical in order to minimize the 'human bias' that might arise. When working with these specific paradigms, the quality must, according to Guba, be ensured through reliability, validity and a continuous discussion of the compliance of these quality requirements.

Research Design

The thesis is deduced as an empirical study where all results must be testable, and this asks for high requirements as regards the process of data collection. In order to fully exploit the objective of the thesis, both a descriptive and a causal research design are chosen to ensure relevance, validity, and reliability.

The descriptive design is used to give an overall theoretical understanding of the topic, as well as to support the selection of the relevant determinants for the later empirical analysis. The theoretical foundation and the use of previous acknowledged research on this specific topic furthermore increase the objectivity and thereby the reliability.

The overall objective is of course to identify, through an empirical analysis, which determinants that affect the CDS spread through an empirical analysis. The analysis is conducted using a causal research design, where the causative effects between the determinants and the CDS spread are measured through linear regression and the method of ordinary least squares (OLS).

To summarize, the descriptive design is used to build the foundation of the topic and the selections of testable determinants, whereas the causal design is used to actually answer the problem statement itself through the empirical analysis.

Critical Research Approach

The data used in the thesis are solely quantitative information collected through secondary sources which are all assumed to be of high scientific quality.

The data set is collected from Bloomberg, which is recognized as a reliable source of information. The selection of variables and their characteristics including indices, time period, and maturities is of course made on a more subjective basis, but relies heavily on the acknowledged theory and studies, so the subjectivity is restricted. The data collection and the process of the data derivation are described in further detail in chapter 6.

Furthermore, secondary literature in the form of relevant textbooks, articles, and previous research on the topic is used, all of which are composed by acknowledged authors wherefore these sources also are perceived as both reliable and valid.

Overall, the validity is assessed as reasonable as the range and number of observations are considered as large, both in regard to time period and number of contracts. The data therefore gives a representative, true, and fair picture of the market dynamics.

As argued above, it cannot be avoided that modified objectiveness will affect the selection of the determinants in review, the data collection as well as the economical interpretation of the model output. This, of course, affects both validity as well as reliability. However, by using previous research from acknowledged authors and the causal research design combined with a constant awareness of the paradigm challenges, the research quality of this thesis will not be compromised.

1.3 Delimitations

Throughout the analysis, some delimitations have been made in order to ensure that the analysis stays relevant and concrete, and that various complexities do not compromise the objective of the thesis.

The analysis is based on daily observations, and data are collected in the period from 01/04/2005 to 12/30/2016 in order to explore the development in the CDS spread before, during, and after the financial crisis.

The dataset only consists of companies from the Markit CDX NA IG index (Markit.com). The index consists of the 125 North American most liquid single-name CDS contracts on reference entities that are rated in the category investment grade.[2] The investigation is thereby solely concentrating on the American CDS marked. This selection was made as CDS contracts have the highest prevalence in America. Because of missing data in some years on some of the included variables, 46 companies have been removed from the dataset.

To simplify the analysis, this thesis only seeks to examine the determinants of the CDS spread on *single-name CDS* contracts, meaning the CDS contracts are only based on one underlying asset/company. As many of the variables in the analysis are firm specific, such as stock return, volatility, and credit rating, this further supports the use of CDS contracts with only one subsidiary company, since otherwise, it would be a very complicated process.

The CDS contracts on which the analysis is based, all have a maturity of 5 years as this, in accordance with later chapters, is the most frequently traded CDS contract. A majority of the previous studies also base their analysis on 5-years maturity CDS contract.

Finally, counterparty risk will not be accounted for nor explained in further detail in the analysis, as counterparty risk is a large and highly complex topic, which requires a more thorough analysis with room for absorption.

[2] Investment grade is the category of bonds with BBB or higher credit rating. This will be further elaborated in chapter 2.

1.4 Disposition

The thesis includes a descriptive part, an analysing part, and finally a discussion, a conclusion and future implication.

Initially, the current chapter outlined a short motivation of the objective of this thesis, and presented the problem statement. The chapter also contained an in-depth treatment of the methodological basis of the thesis and a review of the delimitations, both of which ensure the quality of the thesis through validity, reliability, and adequacy.

The chapters 2-5 are descriptive, and seek to cover the theoretical foundation of the subject, in order to ensure the reader a thorough understanding of credit risk and CDS contracts, with the objective to understand which factors that drive the credit risk.

Credit risk will be defined in chapter 2, and the different risk components will be reviewed to deepen the understanding of credit risk. Default risk, recovery risk, downgrade risk, spread risk, and liquidity risk are notions, which will be examined as a part of the foundation of the later empirical analysis.

The purpose of chapter 3 is to clarify, how credit risk is priced. Two different models of credit risk are outlined. The purpose is to examine which variables that are important when pricing credit risk on corporate bonds, and thus which variables that are expected to influence the level of the CDS spread.

Chapter 4 presents and reviews the CDS contract, starting with a definition and an explanation of the contractual conditions, and leading on to review the market for credit derivatives in regard to size and development. A further audit on various application possibilities will be conducted, and the CDS spread will be described in further detail. Finally, the chapter will compare CDS spread to bond spread, as it is argued that the two spreads can be used analogously in research.

In chapter 5, which completes the descriptive part of the thesis, three previous empirical studies will be discussed. Common for all the included studies is that they are all based on the variables of Merton's structural model. Collin-Dufresne et al. (2001) base the research on corporate bond spreads, whereas Benkert (2004) and Ericsson et al. (2009) base their research on CDS spreads. The studies are reviewed in order to create further evidence for the selection of the included variables in the later analysis.

The chapters 6-9 will, contrary to the previous chapters, form the testing and analysing part of the thesis, taking a more reflective and discussing position with a high focus on causative effects. This part seeks to examine how different variables affect the CDS spread, inspired by the theoretical perspectives and previous studies outlined.

Chapter 6 outlines the foundation of the empirical analysis, presenting the model specifications. This includes an explanation of the selected data, the dependent variable, and all the independent variables included in the analysis. Furthermore, the regression equation for estimation will be presented, and 9 hypotheses representing the included variables' expected effect on the CDS spread are outlined. The chapter is concluded by statistics describing the dataset in order examine the characteristics of the variables and the relationship between them.

In chapter 7, the model regression will be conducted, the regression results will be presented and analysed, and the hypotheses outlined in chapter 6 will be examined.

Chapter 8 examines the model verification of the regression model in the previous chapter. To check the adequacy of the model, the adherence of regression model assumptions is examined.

Chapter 9 reviews additional regression results, and a robustness analysis is conducted to check, if the model is robust over time.

The chapter completing the analysing part of the thesis will be chapter 10, which seeks to conduct a model interpretation and inference. This will be done through a discussion of the regressions results, and a comparison to findings in previous empirical studies.

Chapter 10 consists of a conclusion, where the main findings and highlights of the thesis will be set forth, and the results of the analysis will be summarized in order to ensure that the objective of the thesis is fulfilled and the problem statement is answered.

Finally, chapter 11 concerning future implications will finalize the thesis by presenting other potential determinants of the CDS spread and factors, which could be interesting to investigate further.

PART I

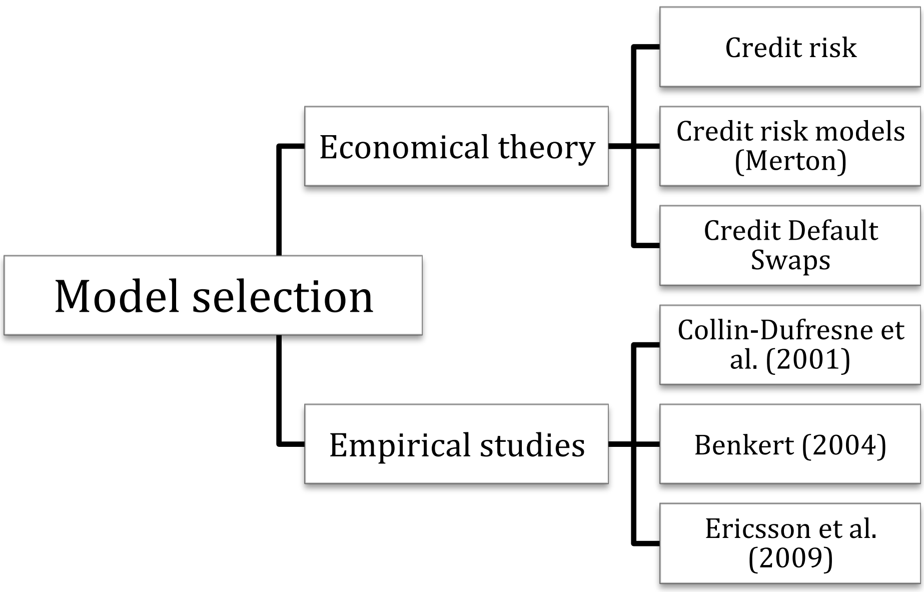
As outlined in the preceding chapter, the objective of the thesis is to build a model which allows an investigation of the determinants on the level of CDS spread.

In order to create this model, one must decide what type of model to use and which variables to examine. The process of identifying a set of likely determinants should highly rely on appropriate economic theory and studies that provide a rationale for the model and this selection.

Part I of the thesis consists in ensuring this rationale foundation to enable an adequate model specification, which is the first and important stage in the model building process. The model building itself, comprising the four stages elaborated in later chapters, will constitute part II of the thesis.

The figure below illustrates this prefatory phase, where the foundation for the model selection is created, and the figure further illustrates the design of Part I as regards both content and chronology.

Figure 2.0 – The Prefatory Phase of Model Selection



Source: Own creation

To develop the economic theoretical foundation, an examination of: credit risk, credit risk models and credit default swaps will be disclosed. The purpose of including these three parts is to provide a theoretical foundation for and understanding of the analysis. In order to identify which factors affect the CDS spread, one must understand how credit risk is constructed, and which factors that are crucial when pricing credit risk. Furthermore, the techniques and the function of the CDS contract must be assessed, in order to understand which variables that influence the CDS spread.

All of the above should then provide a clear indication of which variables that could explain the variation in the CDS spread.

Furthermore, three empirical studies and their findings will be presented. The studies composed are Collin-Dufresne et al. (2001), Benkert (2004), and Ericsson et al. (2009).
All studies seek to analyze determinants of the CDS spread, with inspiration from the structural credit risk model developed by Merton (1974). Each study contributes to a supplementary cognition and perspectives on the determinants of the CDS spread. Combined, the empirical studies provide evidence and rationale for the model and the selection process.

2 Credit Risk

The CDS spread is a measure of credit risk, wherefore this chapter will define credit risk and review the different risk components which have an impact on the magnitude of the risk. It is relevant to give a deeper understanding of credit risk and review the different determinants affecting the bond spread, as there are many similarities between bond spread and CDS spread. This will be further examined in the chapter on CDS, and will be of essence in the later empirical analysis on CDS spreads. Focus will not be on the mathematical derivation but instead be based on historical data.

2.1 Definition

According to Hull, credit risk is defined as: *"The risk that a loss will be experienced because of a default by the counterparty in a derivatives transaction"* (Hull, 2006).

However, CDS spread is not a completely pure measurement of credit risk, as a non-default component must be taken into account as well. So when trading with bonds, two types of risk are present, 1) being credit risk as defined above and 2) being market risk that refers to all the remaining risks associated with investment in bonds. Credit risk is thereby said so consist of a default component and a non-default component respectively.

The primary focus will be on the composition of credit risk, as this poses the greatest impact on the CDS spread, but some aspects of the market risk, for instance liquidity risk, will have an impact on the bond spread, wherefore it is of relevance to assess this aspect briefly as well.

As mentioned, bond spread is used as a measure of credit risk, and furthermore, credit ratings can be used to obtain a measure of credit risk. These two subjects give a good conception of what credit risk is, and how it is expressed in the market. Both will be described in further detail in the later relevant sections where credit risk is examined.

Throughout the following, the definition and standards stated by Moody´s Investor Service (Moody's) will be used to ensure consistency in and reliability of the treatment of credit risk. Moody's is one of the big three credit rating agencies, the other two being Standard & Poor's (S&P) and Fitch Group (Fitch) respectively. These agencies undertake an on-going monitoring of the majority of the larger companies in the market, and assess their reimbursement and general financial health. In the light of this assessment, the agencies rank the creditworthiness of borrowers by using a standardized rating scale, which measures expected investor loss in the event of default. The rating conducted by these particular agencies are perceived as highly reliable and trustworthy, as the agencies have access to more information about the specific companies than the market, and therefore are able to better evaluate their actual economic health.

Beneath, table 2.1 shows the rating scale within which Moody operates. In comparison, it should be mentioned that an Aaa rating by Moody's corresponds to an AAA rating by S&P or an AAA rating from Fitch. The complete and detailed comparison of the rating agencies' credit scales is enclosed as table 14.2 in appendix.

Table 2.1 – Global Long-term Rating Scale

Aaa	*Obligations rated Aaa are judged to be of the highest quality, subject to the lowest level of credit risk.*	Investment grade
Aa	*Obligations rated Aa are judged to be of high quality and are subject to very low credit risk.*	
A	*Obligations rated A are judged to be upper-medium grade and are subject to low credit risk.*	
Baa	*Obligations rated Baa are judged to be medium-grade and subject to moderate credit risk and as such may possess certain speculative characteristics.*	
Ba	*Obligations rated Ba are judged to be speculative and are subject to substantial credit risk.*	Speculative grade
B	*Obligations rated B are considered speculative and are subject to high credit risk.*	
Caa	*Obligations rated Caa are judged to be speculative of poor standing and are subject to very high credit risk.*	
Ca	*Obligations rated Ca are highly speculative and are likely in, or very near, default, with some prospect of recovery of principal and interest.*	
C	*Obligations rated C are the lowest rated and are typically in default, with little prospect for recovery of principal or interest.*	

Source: Moody´s Investor Service (Moody's 2016-2)

Returning to the presentation of credit risk, it can be divided into several different risk types. However, various studies emphasize different risk components and their individual effect. Despite this somewhat ambiguous picture, a general consensus exists that default risk and recovery risk constitute the primary impact on the credit risk. Default risk and recovery risk will be reviewed first, followed by the derived risk components in the below listed order:

- Default risk
- Recovery risk

- Downgrade risk
- Spread risk
- Counterparty risk
- Liquidity risk

An assessment of their individual meaning and impact on the credit risk will be conducted, in order to evaluate their effect on the bond spread. This will help clarifying the determinants of interest, when conducting the empirical analysis of the CDS spread later on.

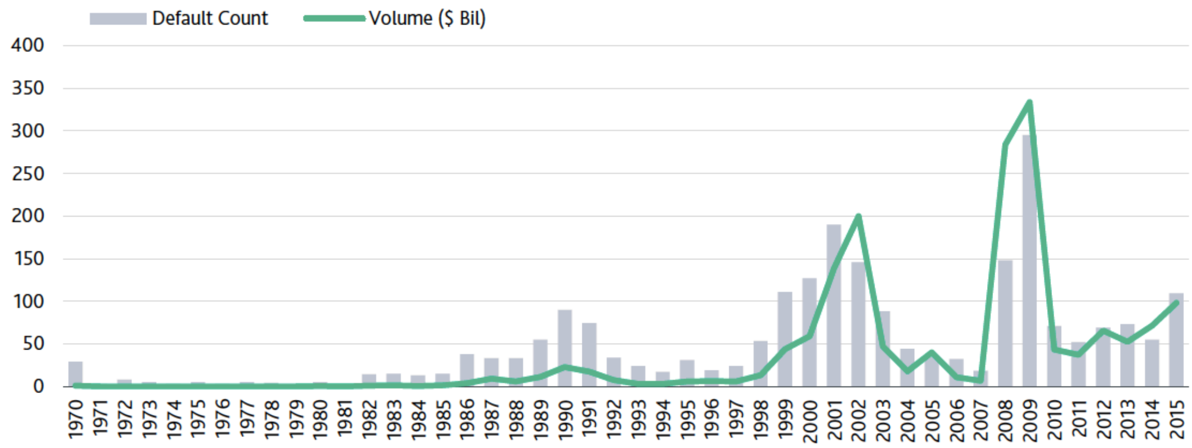
2.2 Default Risk

Default risk can very simply be explained as the risk that a company cannot meet its payments of interests and/or principal. For the purpose of a more detailed and standardized treatment, Moody's definition is used as guideline throughout the further analysis:

Moody's definition of default includes three types of credit events:

- *A missed or delayed disbursement of interest and/or principal, including delayed payments made within a grace period;*
- *Bankruptcy, administration, legal receivership, or other legal blocks (perhaps by regulators) to the timely payment of interest and/or principal; or*
- *A distressed exchange occurs where: (i) the issuer offers debt holders a new security or package of securities that amount to a diminished financial obligation (such as preferred or common stock, or debt with a lower coupon or par amount, lower seniority, or longer maturity); or (ii) the exchange has the apparent purpose of helping the borrower avoid default.* (Moodys.com)

Figure 2.1 – Development in Defaults 1970-2015



Source: Exhibit 1 (Moody's 2016)

Above graph illustrates the development in number of defaults from 1970-2015. The financial distress after 2007 clearly results in an increase in the number of defaults, and the graph furthermore indicates a jump in defaults from 2014 to 2015. In relation to our objective, it would be interesting to see if this development was reflected in the size of the CDS spreads in the same periods. Moody's analysis points out that, unlike 2009 where defaults were widely spread among a variety of industries due to the financial crisis affecting the entire economy, the defaults in 2015 reflected sector-specific problems. In 2015, there was a high concentration of defaults in industries like "Metals & Mining" and "Oil & Gas", which represented the highest default rates and was responsible for up to 30% of the total count of defaults and close to 45% in regard to volume (Exhibit 5&6, Moody's 2016).

Default rate is used as a measure of default risk, and is the probability that a specific company or bond defaults. As a part of Moody's yearly statistics on defaults, the companies are classified according to rating so that an average default rate is found for each credit rating. Table 2.2 shows the average cumulative default rates classified by ratings over a 10-year period, and it illustrates how credit ratings and time affect the default rates. Moody's calculations are based on the senior unsecured bonds defaulting from 1970-2015.

The market often uses these default rates as a measure of default probability in credit risk models, and the data are cumulated to attain an independence of time.

Table 2.2 – Average Cumulative Issuer-weighted Global Default Rates by Letter Rating, 1970-2015.

Rating	1	2	3	4	5	6	7	8	9	10
Aaa	0.000	0.011	0.011	0.031	0.087	0.141	0.198	0.259	0.325	0.396
Aa	0.022	0.061	0.112	0.196	0.305	0.420	0.540	0.646	0.725	0.807
A	0.056	0.170	0.357	0.555	0.794	1.063	1.345	1.652	1.982	2.313
Baa	0.185	0.480	0.831	1.252	1.668	2.105	2.525	2.972	3.476	4.033
Ba	0.959	2.587	4.501	6.538	8.442	10.220	11.788	13.311	14.852	16.455
B	3.632	8.529	13.515	17.999	22.071	25.699	29.028	31.828	34.303	36.298
Caa-C	10.671	18.857	25.639	31.075	35.638	39.105	41.812	44.202	46.145	47.843
Inv Grade	0.093	0.251	0.457	0.697	0.956	1.234	1.512	1.804	2.118	2.447
Spec Grade	4.070	8.273	12.252	15.764	18.850	21.513	23.836	25.869	27.733	29.416
All rated	1.500	3.004	4.387	5.579	6.604	7.485	8.246	8.925	9.564	10.161

* Data in percent.

Source: Exhibit 33 (Moody's 2016)

From the tabel it clearly appears that the default rates are negatively correlated with higher credit ratings, which means that a higher credit rating is accompagnied by a lower probability of default. Furthermore, the tabel illustrates that uncertainty increases over time, which is refleced by higher default rates in later years in the table.

Studies agree that the default risk constitutes a large weight of the total credit risk. Longstaff et al. (2005) actually seek to consolidate this view by performing a study explaining how much of the corporate yield spread is attributable to default risk, and how much originates from other factors such as liquidity and taxes, also reffered to as the non-default component of credit risk. The study shows that the majority of the bond spread is caused by default risk, and that a coherence between the credit rating and the weight of the default risk exists, just as revealed by table 2.2. Longstaff et al. calculate the spreads relative to the Treasury curve, and find that the default component represents 51% of the spread for AAA/AA-rated bonds, 56% for A-rated bonds, 71% for BBB-rated bonds, and 83% for BB-rated bonds[3]. These results indicate that the market incorporates the default risk in the pricing of bonds, and that default risk is weighted higher, the lower the credit rating of the bond is, which was also illustrated by table 2.2.

2.3 Recovery Risk

Recovery risk is the second risk type suggested to constitute a high weight of the total credit risk.
The recovery risk is the risk that an investor will owe much more than the size of the recovered amount in case of a default event. In relation to recovery risk, two notions are important to explore further as each of them constitutes a measurement of the recovery risk present; they are *recovery price* and *recovery rate* respectively. Recovery price is the amount of money received in the event of a default, and the recovery rate is the the amount recovered after the default, expresed as a percentage of the facevalue of the bond.

With regard to the *recovery price,* one must be aware of the difference between the amount repayed to the bondholders, and the recovery price observed in the credit derivatives market. The two prices are based on different conditions, wherefore the recovery price will vary in the two cases.

In short, bondholders must go through the full workout process of liquidating all the assets of the company, and distributing them among the different debt holders, and only then the recovered amount can be settled. However in the credit derivatives market, the recovery price is determined as the price of some defined deliverable obligation, and this is done within 72 days after the default event (O'kane, 2011).

[3] Longstaf uses S&P's credit rating scale

O'kane further argues that the recovery price and the recovered amount that bondholders receive to some extend must be closely related, but also emphasizes various circumstances that can cause a difference in the two prices to arise. He points out that there is a negative conjunction between recovery and default rates and periods with economical fluctuations, and also how supply and demand can affect the recovery rates and thereby the recovery price. Furthermore, it might be conceivable to believe that the actual time, at which the recovery price is estimated might have an impact, f.ex. if new information becomes available in the period between the event of default and untill the workout process is finalized. This could lead to this difference in pricing.

The Recovery rate is a good indication of the loss potential to which the investor is exposed. Two circumstances affecting the recovery rate are worth mentioning, and they are the senority of the bond, and the rating of the bond respectively.

The most important driver of the recovery rate is the position of the bond. Just like creditors are prioritized differently when a company is liquidating due to a default, bonds have different priorities according to which they are covered after a default.
It is therefore seen that the senority of the bond affects the extent of the recovery rate.

The table beneath illustrates this specific conjunction, and is Moody's caculation of average recovery rates on bonds with different senorities based on data from the period 1983-2015.

Table 2.3 – Average corporate debt recovery rates measured by trading prices

	Issuer-weighted recoveries			Volume-weighted recoveries		
Lien Position	2015	2014	1983-2015	2015	2014	1983-2015
1st Lien Bank Loan	63.4%	78.4%	66.6%	52.0%	80.6%	62.3%
2nd Lien Bank Loan	32.1%	10.5%	31.8%	21.5%	10.5%	27.6%
Sr. Unsecured Bank Loan	n.a.	n.a.	47.1%	n.a.	n.a.	40.2%
1st Lien Bond	53.5%	73.6%	53.4%	58.2%	86.5%	53.4%
2nd Lien Bond	26.0%	51.0%	49.7%	20.6%	75.5%	47.4%
Sr. Unsecured Bond	37.9%	46.4%	37.6%	33.3%	40.8%	33.7%
Sr. Subordinated Bond	36.6%	39.1%	31.1%	20.3%	24.3%	25.8%
Subordinated Bond	58.5%	38.8%	31.9%	56.8%	38.0%	27.1%
Jr. Subordinated Bond	14.0%	n.a.	24.2%	14.0%	n.a.	17.1%

Source: Exhibit 7 (Moody's 2016)

It emerges from the table that over the past three decades, recovery rates were generally correlated with the priority of the bond, and it indicates that a higher senority accompanies a higher recovery rate on average. For example, the issuer-weighted recovery rate for senior unsecured bonds was 37.6% on average from 1983-2015, whereas the recovery rate for junior subordinated bonds was 31.9%. This conjunction is present regardless of whether the recovery rates are assessed from a issuer-weighted perspective or a volume-weighted perspective. The table further shows the development in the recovery rate from 2014-2015, and it is seen that recovery rates were in large part lower in 2015 compared to 2014's recovery rates. In the light of the previous section on default risk, this suggests a negative correlation between recovery rates and default rates, which is further reinforced by the study by O'kane referred to above.

Beside the senority of the bond, the rating also has a large influence on the size of the recovery rate. This is illustrated in table 2.4 below, which shows the conjunction between the credit rating of the bond and the recovery rate.

Table 2.4 – Average Sr. Unsecured Bond Recovery Rates by Year Prior to Default, 1983-2015*

	Year 1	Year 2	Year 3	Year 4	Year 5
Aaa**	n.a.	3.33%	3.33%	61.88%	69.58%
Aa	37.24%	39.02%	38.08%	43.95%	43.18%
A	30.36%	42.57%	44.97%	44.48%	44.17%
Baa	42.88%	44.42%	44.65%	44.60%	44.41%
Ba	44.51%	43.50%	42.63%	42.27%	42.37%
B	37.58%	36.62%	36.94%	37.34%	37.93%
Caa-C	37.96%	38.39%	38.44%	38.87%	38.98%
Investment Grade	40.02%	43.51%	44.39%	44.62%	44.41%
Speculative Grade	38.26%	38.12%	38.23%	38.60%	38.97%
All Rated	38.33%	38.45%	38.71%	39.15%	39.54%

* Issuer-weighted, based on post default trading prices

** The Aaa recovery rates are based on five observations, three of which are Icelandic banks that have an average recovery rate of 3.33%.

Source: Moody's 2016, Exhibit 21

Attention must be drawn to the fact that the calculations of the recovery rate is made prior to the default, wherefore one cannot be sure that the rating has not changed. But as the later section on credit downgrade risk will illustrate, bonds tend to retain their credit rating over time. With this reservation in mind, table 2.4 can be used to illustrate the relationship between credit ratings and the recovery risk. With some variations, it indicates that a higher credit rating leads to a higher level of recovery rate, which is most obvious when the investment graded bonds and the speculative graded bonds are held against each other. Investment grade retaining a recovery rate of 40.02% a year prior to default, against 38.26% on speculative graded bonds. Furthermore, the table suggests a correlation between time horizon and the recovery risk, showing that the recovery rate will decrease when nearing the default event, which can be explained by an increased certainty of the approaching default.

Furthermore Moody's calculations of recovery rates conjunction with rating and senority of bonds are made on a basis of a longer period. Thus the age of the bond and the economic circumstances are not taken into consideration in these calculations. Moody's findings should be used as an indication of this conjunction, but the found relation must be taken with some reservations.

Despite these few reservations, this sections concludes that the recovery risk is negatively correlated with both higher rating and higher senority on the bond.

2.4 Credit Downgrade Risk

Credit downgrade risk is actually derived from the default risk and recovery risk, it is interesting to inspect as it tells something about the general investment risk in a given bond.

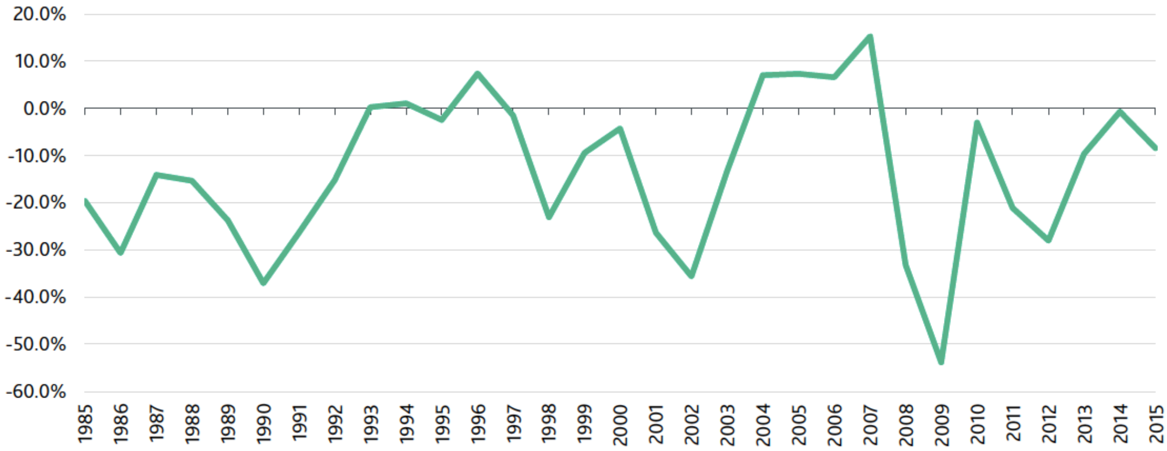
Credit downgrade risk refers to a downgrade of a bondholder's creditworthiness. Actually, it refers to a specific bond's credit rating, as different bonds issued by the same company can have different ratings. But according to Hull et al. (2004), it is reasonable to assume that these are the same, as different ratings on bonds of the same company are rarely given.

As it also emerged from Moody's credit rating scale presented earlier, the bond market is classified into investment-grade bonds and speculative-grade bonds. The latter is also known as junk-bonds or high-yield bonds. The investment-grade bonds consist of bonds rated Aaa-Baa, and the speculative-grade bonds are the bonds rated Ba-C. Speculative-grade bonds pose a greater risk, which is suggested by Moody's definition in table 2.1 and also supported by the findings in previous sections. In the examination on default risk and recovery risk, evidence was found that speculative-grade bonds are encumbered with higher default risk and higher recovery risk reflected in lower recovery rates.

As a part of Moody's report on corporate default and recovery rates, the development in rating drift is also enclosed.

Rating drift is a measure of the credit quality, and is calculated by the total number of upgrades subtracted by the number of downgrades and divided by the number of issuers.

Figure 2.2 – Development in Rating Drift, 1985-2015



Source: Exhibit 3 (Moody's 2016)

From the development in rating drift expressed by figure 2.2 above, it emerges that rating downgrades outpaced upgrades in 2015, which indicates that the credit quality among Moody's rated issuers weakened in 2015. This reinforces the findings on the development in credit risk in the section on default risk, and further emphasizes the conjunction between the default rate and credit downgrade risk.

Table 2.5 illustrates the probability of a bond retaining the same rating from one year to another, classified in the different letter ratings.

Table 2.5 – Average One-Year Letter Rating Migration Rates, 1970-2015

From/To:	Aaa	Aa	A	Baa	Ba	B	Caa	Ca-C	WR	Default
Aaa	87.480%	8.135%	0.590%	0.058%	0.024%	0.003%	0.000%	0.000%	3.709%	0.000%
Aa	0.833%	85.151%	8.448%	0.438%	0.064%	0.036%	0.017%	0.001%	4.991%	0.021%
A	0.056%	2.572%	86.601%	5.366%	0.510%	0.113%	0.043%	0.005%	4.679%	0.056%
Baa	0.036%	0.159%	4.296%	85.442%	3.744%	0.694%	0.163%	0.021%	5.261%	0.183%
Ba	0.006%	0.044%	0.466%	6.174%	76.172%	7.173%	0.679%	0.124%	8.246%	0.916%
B	0.008%	0.032%	0.149%	0.449%	4.784%	73.515%	6.486%	0.562%	10.604%	3.412%
Caa	0.000%	0.009%	0.027%	0.108%	0.416%	7.021%	66.772%	2.806%	14.321%	8.521%
Ca-C	0.000%	0.000%	0.056%	0.000%	0.623%	2.461%	9.468%	39.589%	23.714%	24.089%

Source: Exhibit 26 (Moody's 2016)

Moody's have presented the above table of adjusted annual broad rating mitigation rate based on credit rating data from 1970-2015, and it shows the historical yearly changes in percentage.

From the table it emerges that the companies with the highest ratings have the highest probability of retaining their rating over time, whereas the lower rated bonds are far more likely to receive a different rating than the year before. The table further shows that a bond with a higher rating has a higher probability of upgrading than downgrading, compared to a lower rated bond which has higher probability of downgrading than upgrading, again this is in relative terms. As expected, a shift sets in around the Baa rating which is where the bonds shift from investment-grade to speculative-grade and therefore are subject to higher risk, which explains why these bonds might have a higher likelihood of downgrading than upgrading.

So by obtaining a higher credit rating, companies have a higher probability of retaining their credit rating. By holding a high credit rating, it is furthermore showed that the companies have a lower risk of not meeting its debt obligations, and this illustrates how a lower credit downgrading risk leads to a lower default risk, which consequently ensures a lower credit risk.

2.5 Spread Risk

The bond spread is calculated as the difference between the risk-free interest rate and the interest rate on a credit bond, and it is an expression of the price an investor would be willing to pay to take on credit risk.

Spread risk is closely related to downgrade risk, and like the latter, spread risk is largely derived from both default risk and recovery risk. Spread risk is very simply defined as the risk of an increase in the bond spread.

If a change in the spread occurs, either as an expansion or a narrowing, it will indicate a change in the market's perception of the company's risk. A shift in the expectations to as well a default occurrence as to the level of recovery will have an impact on the perceived risk exposure of a given company. A change in the bond spread can be caused by numerous different things, among others the general economic situation, or circumstances only affecting the specific company or industry. The market's perception of credit risk in general can actually also have an either positive or negative influence on the bond spread.

As mentioned, credit downgrade risk and spread risk can in some way be compared as they are both measures of credit risk, and are both impacted by both macro- and micro economic conditions. Spread risk is continuously changing over time, whereas a change in the rating of a company happens in discrete time. Spread risk is therefore often used, when credit quality of a bond in a shorter time perspective needs assessment. The two types of risk can be distinguished between by saying that downgrade risk is a qualitative expression of credit risk, whereas spread risk is more of a quantitative expression of credit risk. In later chapter, the CDS spread as an additional measure of credit risk will be introduced and compared to the described bond spread.

2.6 Counterparty Risk

Another risk type, which is important to mention in relation to CDS contracts is the counterparty risk. The counterparty risk is the risk that the other party in an agreement will either default or not live up to his contractual obligations.

However, as outlined in the delimitation section, the complexity of calculating the counterparty risk is very high, and because of its wide scope it deserves a separate scrutinize, wherefore this thesis will only touch upon it briefly and mention it as a remark in the later treatment of CDS spreads.

2.7 Liquidity Risk

As initially described, the risk of trading with bonds consists in a default component, the credit risk, which has been the focus of attention throughout the chapter. Furthermore, it was mentioned that the bond spread also consists of a non-default component, the market risk. In relation to market risk, the liquidity risk is highly relevant and describes how easily convertible an asset is.

Liquidity risk is an uncertainty, which is not associated with the individual company, but to a higher degree driven by the market. A market can be said to be liquid when larger positions can be redeemed at a reasonable price. Liquidity risk can be described as the risk of a loss due to fluctuations in the redemption costs of a specific position.

In the study from earlier on the components attributing to the bond spread, Longstaff et al. (2005) find that a portion of the bond spread is influenced by a liquidity component, and further argue that two different liquidity effects can occur in the pricing of bonds - one being an idiosyncratic impact on the individual bond, and the other one being a systematic effect driven by the market. In economic stressful periods, for example during a financial crisis, the so-called "flight to liquidity" will be observed. In such situations, investors will switch away from illiquid risky assets such as government bonds, and this shift in investor preferences will lead to an increase in the bond spread.

The liquidity risk is a component of the bond spread which is not related to the default component, and it is therefore not assumed to be of significance to the CDS spread and the later empirical analysis.

However, as explained in the chapter on CDSs, the CDS contract also contains a liquidity component which will be elaborated on in the relevant section.

2.8 Summary

The chapter on credit risk was intended to elaborate on what credit risk is in broad terms. It has been defined that credit risk is the risk that the counterparty fails to meet its obligations, leading to the lender suffering a loss. Credit risk is an important variable, especially in the valuation of bonds. Credit ratings are essential information to the investor in the determination of which return to require for a given investment.

Moody's ratings and analyses were used as baseline and as a tool to illustrate the conjunction between credit risk and the different risk components examined throughout the chapter. The credit rating of a bond reflects the credit risk related to a business or specific bond. The rating is determined by rating agencies which conduct continuous quantitative and qualitative analysis of a company's creditworthiness. A clear advantage of ratings is the rating agencies' higher degree of access to confidential information on the individual companies, which is not publicly available in the market.

It was found that credit risk could be divided into two types of risk; Default risk and recovery risk respectively. Furthermore, downgrade risk and spread risk could be added as derivations, and are both considered as measures of the volatility of the two aforementioned.

Default risk is the risk that the company cannot meet its obligations. Recovery rate refers to the recovered amount which the investor receives after a default as a percentage of the original principal. Previous studies found that the majority of the bond spread is explained by the default risk and the recovery risk, and that the share of these risks will increase, the lower the bond is rated. Likewise, historical data show that bonds with superior seniority and a high rating on average have a higher recovery rate.
It has been shown that the credit downgrade risk reflects the risk that a reduction in the credit quality of a bond will occur as a result of macro and micro economic conditions. Another way of expressing the credit risk is in terms of bond spread or spread risk. The spread risk is the risk that the bond spread will increase, and is affected by some of the same elements as downgrade risk, the latter is referred to as a more qualitative measurement of the risk, whereas spread risk is more of a quantitative measurement which is continuously changing over time. The advantage of using the bond spread preference to rating as a measure of the credit risk on a bond, is that the bond spread is derived

directly from the market, which means that the spread will represent a picture of all the information available to the market at any given time, including the rating.

In addition to the default component of credit risk, the non-default component representing the market risk also exits, liquidity risk included. This liquidity risk occurs due to both idiosyncratic and market driven factors, which are influenced respectively by the company and the market conditions. This non-default component was assumed not to have any impact in the CDS spread. However, the CDS spread is also influenced by a form of liquidity risk, which will be examined further in the chapter on CDSs.

The material visited in this chapter is of relevance in the understanding of the later empirical analysis, which seeks to examine which determinants that drive the CDS spread. CDS spread is an expression of the default component of credit risk on a bond, and consequently the determinants affecting the default component in the bond spread will also have an effect on the CDS spread. In a separate chapter, this specific credit derivative will be examined in further detail.

3 Credit Risk Models

In this chapter, it will be examined how credit risk is modelled and priced. The chapter presents and reviews two types of credit risk models: the structural form and the reduced form. However, the focus of the thesis will be on the structural model developed by Merton (1974), which will be further reasoned in the chapter.

A credit risk model must capture the types of credit risk pointed out in chapter 2: default risk, recovery risk, downgrade risk and spread risk.

The pricing of credit derivatives is a quite complicated process, primarily since the background history of the derivatives is limited, and the factors used in the pricing model are often unobservable. For modelling credit risk, two types of models are used: the structural form and the reduced form. The key distinction between the two models is the informational assumptions, and hence whether default time can be predicted or not. The structural model assumes complete knowledge of all detailed information in the firm as held by the manager in the particular firm, while the reduced model assumes less detailed information as available in the market. Otherwise, the models are quite similar. A structural model can easily be converted into a reduced form model simply by chancing the information base. The models can also be used in combination, as they are not necessary mutually excluding (Jarrow & Potter, 2004).

According to Jarrow and Potter, the reduced form model is the most correct model when pricing and hedging credit risk since prices are determined by the market, and hence, the information set observed by the market is the most relevant one, rather than a fully detailed information set. Despite that, the focus in this thesis is on the structural model since we are investigating the determinants of the credit default swap premium, rather than pricing credit default swaps, and hence not using the model directly. Furthermore, previous studies concerning determinants of the credit default swap premium are based on the structural model, and the variables used in the model are proven to have an explanatory effect on the credit default swap spread (Chapter 5, Previous Empirical Studies).

3.1 The Reduced Form Model

The reduced form model tries to predict the time of default rather than the factors that cause default. The information reflects the information available in the market, and the model does not take the capital structure of the firm into account.

As the reduced form model will not be used in the thesis, the theory and the mathematical approach will not be treated further.

3.2 Merton's Structural Model (1974)

Merton (1974) was the first to develop a model for corporate default. The model is based on Black-Scholes option pricing theory from 1973. The basic idea behind the model is that default is seen as the event which occurs, when the value of the firm's debt exceeds the firm's assets. The model assumes a simple capital structure of the company, consisting of shares that pay no dividend and with total value of E, and the debt is consisting of T-maturity zero-coupon bond with face value F and total value D. The total asset value of the company is equal to the value of the debt plus equity. Put in a mathematical way, this implies (O' Kane, 2011):

$$A(t) = D(t) + E(t)$$

Where: A(t) equals the asset value of the firm, D(t) equals the value of the debt, and E(t) equals the value of equity.

Another assumption is the fact that default can only occur at time T, which corresponds to the maturity of the debt. At time T, the firm can be in a stage where it is either solvent or insolvent, depending on the values of the firm's assets, A(t). If the value of the firm's assets, A(t), exceeds the face value of the debt, F, then the company is solvent, since it is able to pay it's liabilities. In the opposite case, if the face value of the debt, F, exceeds the value of the firm's assets, A(t), the firm is said to be insolvent, since it is not able to pay outstanding debt. In case of default, the recovery rate is the value of the firm's assets.

The payoff for the bondholders at time T is as follows:

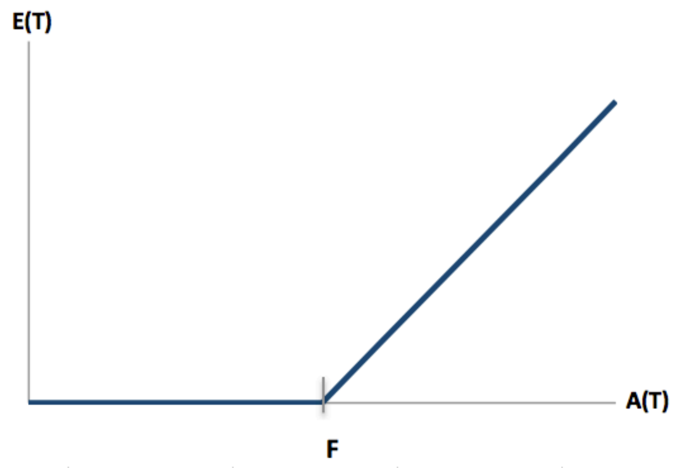
$$D(T) = F - \max[F - A(T), 0] = \min[F, A(T)]$$

The payoff for the equity holders can be expressed as:

$$E(T) = \max[A(T) - F, 0]$$

With the equations outlined above, the value of equity at time T can be seen as the payoff profile of an European call option on the asset value of the firm with strike price of the face value of the debt, F, and maturity T. The payoff profile of the equity holders is illustrated in figure 3.1 below.

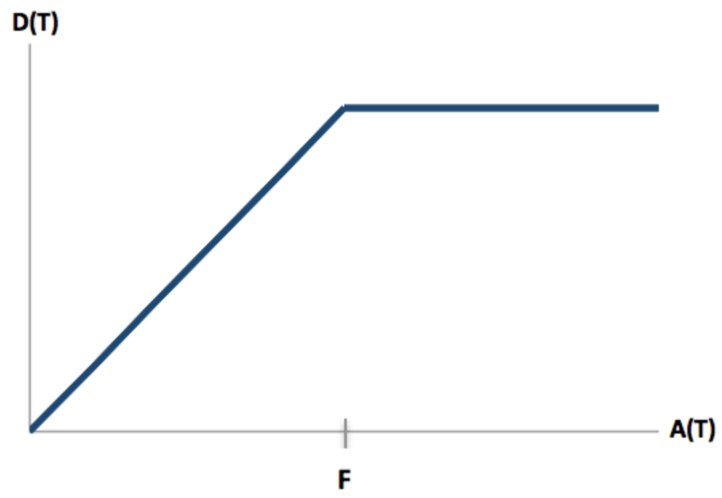
Figure 3.1 – Value of Equity at Maturity as a Function of the Asset Value



Source: Own creation based on O' Kane, 2011

The value of debt has a payoff profile equivalent to a portfolio consisting of a long position in a risk free asset with the amount of the face value of the debt, F, combined with a short put option on the firm's assets with exercise price at F. The payoff profile of the bondholders is illustrated below in figure 3.2.

Figure 3.2 – Value of Debt at Maturity as a Function of the Asset Value



Source: Own creation based on O' Kane, 2011

As long as the firm's assets comply with the assumptions behind Black-Scholes option pricing model, it can be used when pricing shares and credit bonds. The assumptions behind the structural model can be listed as:

- There exist no transaction cost, taxes or any problems with the indivisibilities of assets
- A sufficient number of investors with comparable level of wealth so that each investor can buy and sell as much as he wants of an asset at the market price
- All investors can borrow and lend at the same rate of interest
- Short-sale of assets is allowed
- Asset trading is continuously in time
- The Modigliani-Miller theorem that the value of the assets is independent of its capital structure applies
- The Term-structure is flat and known with certainty

(Merton, 1974)

To determine the value of the debt and equity, we need to have a model to calculate the value of the company, A(T). Merton assumes that the value follows a lognormal process as expressed in the equation below:

$$\frac{dA(t)}{A(t)} = \mu dt + \sigma_A dW$$

Where; σ_A expresses the volatility of the assets, μ equals the risk free interest rate, r, and dW is a standard wiener process. With these assumptions, we can use the Black & Scholes equation to determine the present value of the debt and equity. As mentioned, the value of the equity can be seen as a long position in a call option on the firm's assets with exercise price F, and hence the equity can be priced with the following equation:

$$E(t) = A(t)\,\Phi(d_1) - F * \exp\big(-r(T-t)\big)\,\Phi(d_2)$$

Where ϕ(x) is the Gaussian cumulative distribution and:

$$d_1 = \frac{\ln\left(\frac{A(t)}{F}\right) + \left(r + \frac{1}{2}\sigma_A^2\right)(T-t)}{\sigma_A\sqrt{T-t}}$$

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

The equation: $E(t) = A(t)\,\Phi(d_1) - F * \exp\big(-r(T-t)\big)\,\Phi(d_2)$, points the fact that the shareholders are entitled to the firm's assets. The value of the equity is expressed as a function of the present value of the assets when A(t) > F, minus the present value of the debt, times the probability of the firm's survival. $A(t)\,\Phi(d_1)$ is the present value of the firm at time t, given that default does not occur for the firm, such as A(t) > F. $\Phi(d_2)$ is the risk neutral probability that the firm will survive, and therefore default will not occur. Put in a mathematical way, it expresses the probability that A(T) > F. If the value of the assets increases, the value of the equity increases as well, without any upper limit. On the other hand, if the value of the debt exceeds the value of the assets, then default will occur and the bondholders will receive the value of the assets. In this case, the value of the equity equals to zero.

As mentioned earlier, the value of the debt can, from the bond investor's point of view, be seen as a portfolio consisting of a long position in the risk free bond combined with a short position in a put option on the value on the firm's assets with exercise price, F. Hence, using the Black & Scholes equation, the value of the debt can be priced with the equation below:

$$D(t) = F * \exp\big(-r(T-t)\big)\,\Phi(d_2) + A(t)\,\Phi(-d_1)$$

The value of the debt is expressed as a function of the present value of the debt, times the probability of default, plus the value of the firms' assets when A(t) < F. The equation above can be divided into two separate equations.

The first part, $F * \exp\big(-r(T-t)\big)\,\Phi(d_2)$, expresses the default risk. As mentioned, $\Phi(d_2)$ is the risk neutral probability, that the asset value at time T, A(T), is larger than the face value of the debt, F, and hence the probability that the firm will survive. In a non-risk neutral world, $\Phi(d_2)$ equals the probability that A(T) ≥ (F + risk premium). This implies that $F*\Phi(d_2)$ is the expected value of the bond at time T, given the assumption that the bond holder will receive nothing in the case of F ≥ A(T). The entire first part of the equation then expresses the price of a bond with a recovery rate equal to 0 in the case of default.

The second part of the equation, $A(t)\,\Phi(-d_1)$, expresses the recovery risk. $\Phi(-d_1)$ is the recovery rate times the probability of default in the risk neutral framework. The entire second part of the equation then expresses the expected value of the recovery price.

Using the equation for the value of the debt, we can establish an equation for the credit spread, s. s is defined as the continuously compounded spread over the constant and continuously compounded risk-free rate which reprices the debt. This implies that:

$$D(t) = F * \exp(-(r+s)(T-t))$$

Can be converted to:

$$s = \frac{1}{T-t} \ln\left(\frac{D(t,T)}{F}\right) - r$$

With this equation, it is possible to calculate the term structure of the credit spreads for different values of the input variables (O' Kane, 2011).

It is also possible to determine the expected recovery value of the bond, which is the expected value of the firm in the case of default which implies that F > A(T). We have that:

$$\mathrm{D(t)} = \mathrm{F} * \exp\big(-\mathrm{r}(\mathrm{T}-\mathrm{t})\big)\,(\Phi(\mathrm{d}_2) + \Phi(-\mathrm{d}_2)\mathrm{R})$$

The recovery rate, R, is then defined as the value of the portion paid at default divided by the face value of the bond. Setting the equation above equal to the original equation of D(t), $\mathrm{D(t)} = \mathrm{F} * \exp\big(-\mathrm{r}(\mathrm{T}-\mathrm{t})\big)\,\Phi(\mathrm{d}_2) + \mathrm{A(t)}\,\Phi(-\mathrm{d}_1)$, we then have that:

$$R = \frac{A(t)\,\Phi(-\mathrm{d}_1)}{F * \exp\big(-r(T-t)\big)\Phi(-\mathrm{d}_2)}$$

Moreover, it is also possible to determine a link between the volatility of the value of the assets, and the volatility of the value of the equity. These equations can then be applied in the model to determine the asset volatility parameter, using the volatility of equity (O' Kane, 2011).

$$\sigma_E = \frac{\partial \mathrm{E(t)}}{\partial \mathrm{A(t)}} * \frac{\mathrm{A(t)}}{\mathrm{E(t)}} \sigma_A$$

The equation is then computed to:

$$\sigma_E = \sigma_A\,\Phi(\mathrm{d}_1)\frac{A(t)}{E(t)}$$

From the equations of the value of the debt and equity, we can derive that the event of default in Merton's model depends on three factors:

1) Firm leverage
2) Volatility
3) The risk free rate

An increase in the firm's debt level leads to an increased value of the put option, but a decreased value of the call option. A higher rate level will lead to the opposite, that is a higher value of the call option, but a lower value of the put option. An increase in the volatility of the firm's value leads to an increase in both the value of the call option and the value of the put option. We can then transfer these interpretations to decide the three factors' impact on the value of the debt and equity. An increase in the put option, and hence the value of the debt, will lead to an increase in the credit spread since the credit default spread is an expression of the credit risk.

3.2.1 Limitations and Critique of the Structural Model

Even though Merton's model is very acknowledged and widely used by researchers in studies of the credit spread, there are several limitations to the model. The limitations and critique of the model originate from the highly simplified assumptions, especially as regards the very simplified capital structure and the fully detailed information set, which is quite unrealistic. The model does not allow one to take into account the priority of the different seniorities of the debt. Another critical factor is that, according to Merton, default can only occur at maturity time, T, which means that all bonds should have identical maturity. This is very unlikely to be the case in the real world. The model also assumes all bonds to be zero coupons (O' Kane, 2011).

Even though the assumptions associated with the model are quite unrealistic, many later models are based on Merton's structural model. Several of the models are trying to deal with these simplified assumptions. As mentioned earlier, this thesis will not use the model with the purpose of pricing credit derivatives, but it will investigate the determinants of the CDS spread. Therefore, the pricing process and models will not be discussed further.

3.3 Summary

Two types of models are used when pricing credit risk: the structural form and the reduced form. The structural model assumes complete knowledge of all detailed information on the firm as held by the manager of the particular firm, while the reduced model assumes less detailed information as available in the market. The focus in this thesis is on the structural model, since we are investigating the determinants of the credit default swap spread rather than pricing credit default swaps, and hence, the model is not used directly but more as an approach to determine the key factor in pricing credit risk.

With the structural model developed by Merton (1974), based on Black-Scholes option pricing theory, the value of equity at time T can be seen as the payoff profile of an European call option on the asset value of the firm, with strike price of the face value of the debt, F, and maturity T. The value of debt is equivalent to a portfolio consisting of a long position in a risk free asset with the amount of the face value of the debt, F, combined with a short put option on the firm's assets with exercise price at F. It can be derived that the event of default in Merton's structural model depends on three factors: (1) Firm leverage, (2) volatility, and (3) the risk free rate. There exists several limitations and critique of the model concerning the highly simplified assumptions, especially as regards the very simplified capital structure and the fully detailed information set. However, many later models are based on Merton's structural model and furthermore, previous studies concerning determinants of the credit default swap spread are based on the structural approach by Merton.

4 Credit Default Swaps

In this chapter, a thorough study of credit default swaps (CDSs) and their functioning will be conducted. First of all, the CDS contract will be described in detail, and the variables exerting an impact on the premium, which the buyer of the contract must pay in order to be protected from the credit risk, are assessed to give the reader a full understanding of this type of credit derivative. Then the chapter proceeds to establish the framework of these derivatives by giving an overall introduction to the derivatives market, with a high focus on CDSs and the parties interacting on this particular market, as well as the size and the development in the market. Thereafter, the application potentials of the contracts will be reviewed, and it will be illustrated how the contracts can be used to hedge against credit risk in obligations, but also how the contracts keep evolving and are used for various speculative purposes. Finally, in order to establish which relevant determinants should be included in the later empirical analysis, the chapter seeks to examine which variables that effect the CDS spread. This examination relies highly on the findings in previous chapter on credit risk on bonds.

O'kane (2011) makes a very thorough presentation of credit default swaps, which will be used as a general reference through this chapter.

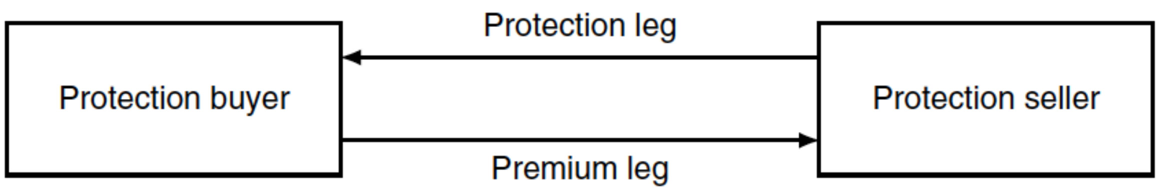
To make a very simple introduction, a CDS is a contract that can be bought as a protection against the default of the underlying bond. The buyer of this contract then agrees to pay a serial of premiums to the seller of the contract, against an assurance of replacement of the buyer's loss in the event of a default. Trading with CDSs thereby makes it possible to hedge against the credit risk on bonds, and CDSs are traded between investors without any initial payments or having to own the underlying bond.

4.1 The Contract

The CDS contract was invented in the mid/late nineties, and is a derivative instrument based on underlying fixed income securities such as corporate or government bonds. The CDSs are the most liquid derivatives in the marked. A CDS is a financial swap agreement, and is an over-the-counter contract between the protection buyer and the protection seller as figure 4.1 illustrates in a very simple way. The contract can be described as the buyers insurance against his bonds reducing in value as a result of a default of the bond issuer.

The CDS contract not only insures against the "pure" default event, but can also cover variations of default such as restructuring of debt, wherefore the notion credit event should be used instead of default. The different established CDS credit events and their effect will be reviewed in further detail later on.

Figure 4.1 – The mechanics of a Credit Default Swap



Source: O'Kane (2011)

4.1.1 Parties

No money is exchanged between the two parties at the conclusion of the contract. However as figure 4.1 further illustrates, the CDS contract consist of two legs. The two legs are referred to as the protection leg and the premium leg, and demonstrate the money exchange between the two parties.

If a credit event occurs prior to the scheduled termination date, the protection seller must compensate the protection buyer for the loss he suffers as a result. In return for carrying this credit risk, the protection seller receives a serial of payments from the protection buyer, until either a credit event occurs or the contract expires. The size of this payment is called the credit default swap spread (CDS spread), which is expressed in annualized payments. Payments are typically quarterly and fall on IMM dates, which are defined in the later section on contract maturity. It is standard that the protection buyer pays the premium accrued since last payment date, if a credit event should occur.

The fact that the CDS contract is traded over-the-counter means that it does not involve an intermediary, and the two parties in the swap are dealing directly with each other. Because of this, the parties can design the contract themselves, but usually it is in line with one of the standardized contracts made by The International Swaps and Derivatives Association (ISDA). The contract will typically specify the following terms, all of which are included in the following review of the CDS contract.

- Maturity
- Reference entity
- Deliverable bond

- Definition of credit event
- Payment settlement

4.1.2 The Maturity

The insurance against a credit event is effective from the calendar day after the contract has been entered, the effective day, and until the scheduled termination date, which is specified in the contract.

Inspired from the interest rate future market, the scheduled termination date of a CDS contract falls on IMM dates (IMM= International Money Market), which refers to the conventional four quarterly termination dates 20th March, 20th June, 20th September and 20th December. This implies that a 5-year CDS contract is effective 5 years plus the days up to closest IMM date, ensuring a larger liquidity in the market.

4.1.3 The Reference Entity

The reference entity describes which bond issuer the contract applies for, and it is this entity that triggers the CDS contract. This means that if a credit event occurs in the reference entity, the protection seller must settle with the protection buyer, and the CDS contract is terminated. At the conclusion, a contract must contain at least one reference entity, which will typically be a company or a country.

4.1.4 The Deliverable Bond

The CDS contract must also specify the underlying obligation to which a credit event is related. This could be a single reference bond, but often the credit event is related to several loans or bonds. Should such a credit event occur before the contract expires, a settlement between seller and buyer of the protection must be made. The details of this settlement will be presented in the later section on settlement.

4.1.5 Credit Event

As mentioned, CDS contracts do not only apply in the event of a default, but cover various credit events as well.

Credit event is the legal term describing the event that triggers the contract, leading the protection seller to pay the buyer the protection leg. The legal framework of these events is settled by ISDA. The credit events are divided into hard and soft credit events respectively, and the most common ones are listed below.

Table 4.1 – Established CDS Credit Events

Credit event	Hard or soft	Description
Bankruptcy	Hard	*Corporate becomes insolvent or is unable to pay its debts. The bankruptcy event is not relevant for sovereign issuers.*
Failure to pay	Hard	*Failure of the reference entity to make due payments, taking into account some grace period.*
Obligation acceleration	Hard	*Obligations have become due and payable earlier than they would have been due to default or other and have been accelerated. This event is used mostly in certain emerging market contracts.*
Obligation default	Hard	*Obligations have become due and payable prior to maturity. This event is hardly ever used.*
Repudiation/moratorium	Hard	*A reference entity or government authority rejects or challenges the validity of the obligations. Used in emerging market sovereign CDS.*
Restructuring	Soft	*Changes in the debt obligations of the reference creditor but excluding those that are not associated with credit deterioration such as a renegotiation of more favourable terms.*

Source: O'kane (2011)

The "hard" credit events lead to an immediately due of the entire debt of reference entity, and all obligations will be priced equal. This classification of event falls under the previous definition by Moody's and was discussed in the chapter on credit risk.

Restructuring of debt is the only soft credit event. By restructuring a company's debt, the creditors are worse off than before the restructuring, but because the debt is not due, the assets will still be traded in the market. Contrary to the hard credit event, the soft credit event can lead to obligations being traded at different values. After a debt restructuring, liabilities with long maturities tend to decrease more in value than those with short maturities. This emerged difference in value gives the protection buyer a possibility to create a delivery option (O 'Kane, 2008), which is beneficial for the buyer but not the protection seller. In the following section, these delivery options, the so-called CTD-options, and the derived restructuring clause will be reviewed, as it might cause an effect on the CDS spread.

4.1.6 The Settlement

If a credit event should occur, three different payment settlements exist: *physical settlement*, *cash settlement* or a *pre-agreed share*. The actual settlement is agreed upon at the conclusion of the contract. According to British Bankers' Association (2006), the physical settlement is the most applicable type of settlement (73%), followed by the cash settlement (24%), and the settlement where the share is pre-agreed is hardly ever used (3%) in the market for CDS contracts. The settlements will be reviewed in further detail with exception of the pre-agreed share, as this type of settlement is considered insignificant in the larger perspective.

4.1.6.1 Physical Settlement

Physical settlement means that, in the occurrence of a credit event, the protection buyer delivers the deliverable obligation issued by the reference entity to the protection seller and in return, the buyer receives the par value in cash.

As mentioned earlier, several different deliverable obligations exist, and when a contract is physically settled, the protection buyer is free to choose which to deliver to the protection seller. The buyer can benefit from this by delivering the bond with the lowest value in the market. This means that the buyer actually possesses a delivery option, also called a Cheapest-to-deliver option (CTD option). The option will only have value on the settlement date, if there is a difference in prices of deliverable bonds. This will typically occur only after a "soft" credit event, which results in long-term bonds falling in value relatively more than those with short maturities. The option will then have a positive value to the protection buyer, but a negative value to the protection seller. Because of this, a seller will not enter into such a contract without some kind of compensation which must, of course, be reflected in the CDS spread.

As a consequence of this, a restructuring clause on CDS contracts called *Modified-Restructuring clause* was introduced on the US market in May 2001 (O'Kane, 2011). This limited maturity of the delivery bonds after a restructuring is an effort to reduce the value of the CTD-option. A *No-Restructuring clause* also exists, where debt restructuring is completely excluded as a credit event in certain contracts. The choice of debt restructuring clause will clearly have an impact on the bond spread, the No-Restructuring clause would for instance lead to a decrease in the bond spread as the risk is limited.

The effect on the CDS spread caused by a given clause is difficult to calculate, and for this reason, clause effects are not taken into account in the later empirical analysis, but one should generally be aware that these clauses will have an impact on the present value of the CDS spread.

4.1.6.2 Cash Settlement

Alternatively to the physical settlement, contracts can be settled in cash, which means that the protection buyer receives a payment which is equal to the face value of the deliverable bond minus the recovery price of the reference obligation in cash. The deliverable obligation is agreed at the conclusion of the contract, and is a single specified bond or loan issued by the reference entity (O'Kane, 2011).

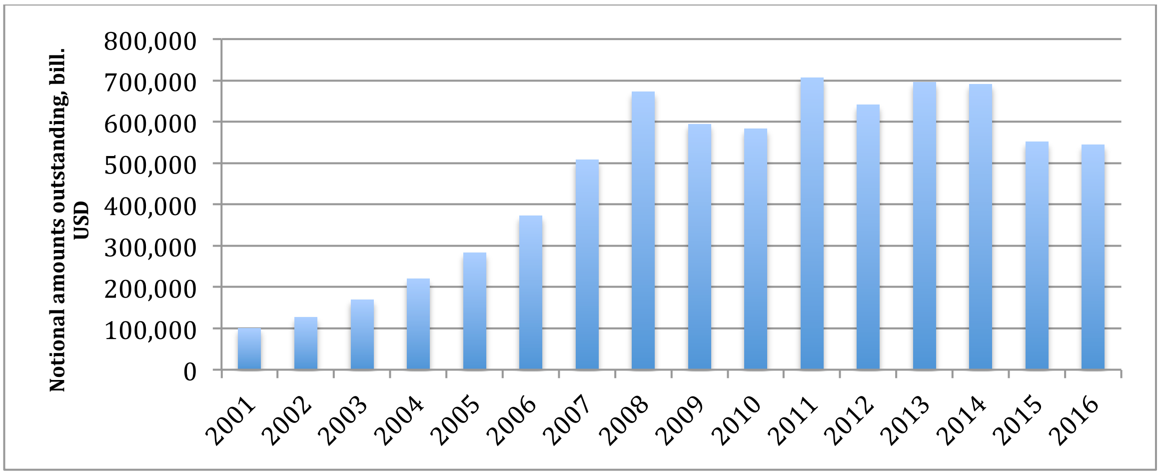
As referred to earlier, the total outstanding amount of contracts with cash settlement was 24% in 2006. Compared to 2006, where the outstanding amount was 11% (BBA, 2006), the settlement method seems to be in rapid growth. Unfortunately, it has not been possible to obtain recent data that can confirm or deny this, but one could imagine that the reason for this growth is the lower risk due to the exclusion of the CTD-option issue in the cash settlement.

How the contract is constructed proves to have an impact on the premium paid by the protection buyer. However, the effect on the CDS spread is difficult to calculate, wherefore an attempt might give an even more misleading result. Furthermore, the effects originating from the contractual circumstances are assumed to be of smaller significance to the CDS spread and therefore, these will not be taken into consideration in the later empirical analysis, but again, it is important to note that they do exist.

4.2 The Derivatives Market

To get an understanding of the size of the CDS market and the actors in it, the derivatives market with a high focus on CDSs will briefly be reviewed.

Figure 4.1 – Total Outstanding Amount of Derivatives on Global OTC Markets



Source: Own creation, Bank for International Settlements

The development on the derivatives market shows a rapid growth in financial products from 2002 until 2007 where the outstanding amount of credit derivatives reached the highest notional amount of nearly 600 billion USD; this constitutes a growth of 360% since 2002. Furthermore, it emerges from the graph that the boom in derivatives recesses as a result of times with financial distress, but after the financial crisis, the financial products seem to continue to grow – however at a smaller rate.

In the period from 2002 until 2014, the development in the use of credit derivatives has experienced an overall growth of 442%, which constitutes an enormous change. However, the last couple of years show a decline of 21% in the marked for derivatives, which among others is due to increased regulation and the use of clearinghouses on this specific market and furthermore, the increase in trade compression and netting have had an impact on the notional amount of outstanding OTC derivatives.

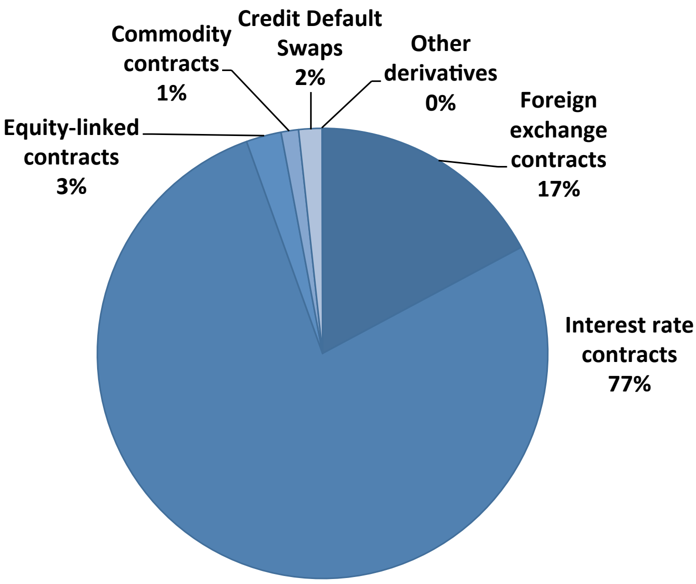
Ever since the financial crisis, an on-going debate on how best to establish common standards to ensure greater stability in the financial markets has taken place. Regulators have pushed for more derivatives to be cleared through the clearinghouses rather than through private arrangements between buyers and sellers. Most recent, in the beginning of February 2016, American and European regulators reached an agreement on derivative regulation. The Commodity Futures Trading

Commission and the European Commission agreed on a common set of regulative requirements to the derivatives clearinghouses, an action that is said to ease capital constraints for those banks that clear derivatives trades through derivatives clearinghouses (Moyer 2016).

According to the semi-annual report published by the Bank for International Settlements, the decline in notional amount of outstanding derivative is assumed to be a result of an increase in trade compression. The new capital rules and leverage ratio in Basel III are based on gross notional exposure, wherefore trade compression allows banks to reduce the capital requirements needed in the trading with derivatives (BIS 2016).

Beneath chart illustrates the different products traded in the derivatives market, and which market share each of them represents.

Figure 4.2 – Market Shares of Products on the Global OTC Derivatives Market



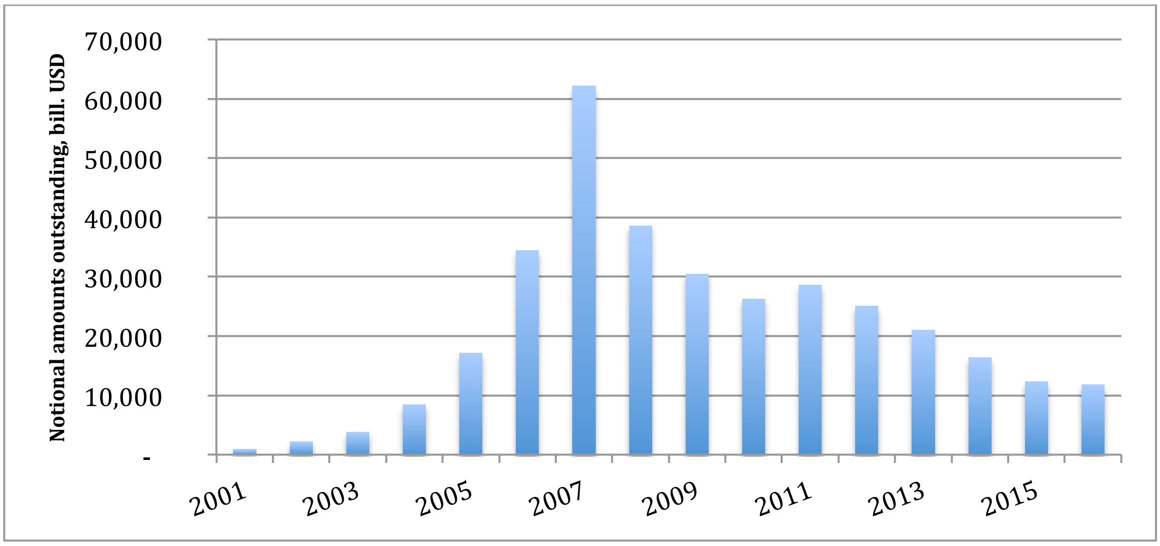
Source: Own creation, Bank for International Settlements 2016.

From this illustration, it is clear that with 77%, the interest rate contracts constitute the largest share traded on the OTC derivatives market, and this picture does not differ from previous years. In comparison, CDSs constitute only 2% of the total derivatives market. The market share is furthermore an indication of the competitive situation in the market. From assessing the development it appears that the OTC products are highly correlated, as the individual products development follow one another over time.

4.2.1 Credit Default Swaps

The market for CDSs has grown enormously since the introduction of the product at the end of the nineties.

Figure 4.3 – Outstanding amount of CDSs on the global OTC market

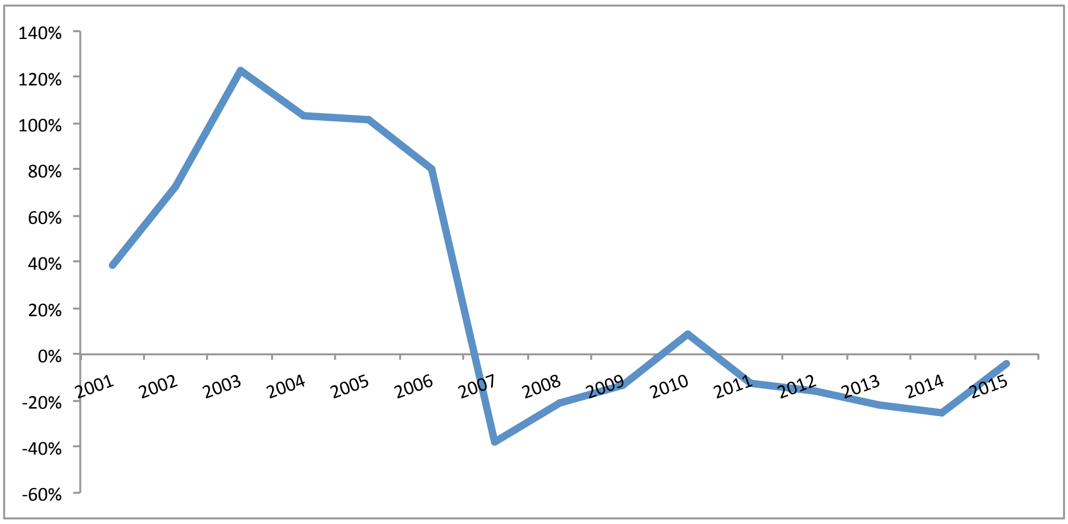


Source: Own creation, Bank for International Settlements & International Swap and Derivatives Association

According to ISDA, the nominal amount of outstanding CDSs increased from 919 trillion USD in 2001 to 12,294 trillion USD at the end of 2015. However, the volume and value of outstanding CDS contracts have substantially declined since the occurrence of the financial crisis. The value peaked in 2007 with an outstanding nominal amount of 62,173.20 trillion USD (ISDA 2010).

Figure 4.5 assists the described development in the credit default swap market, showing the yearly change in percentage. The illustration puts further emphasis on the drastic development which the market has experienced.

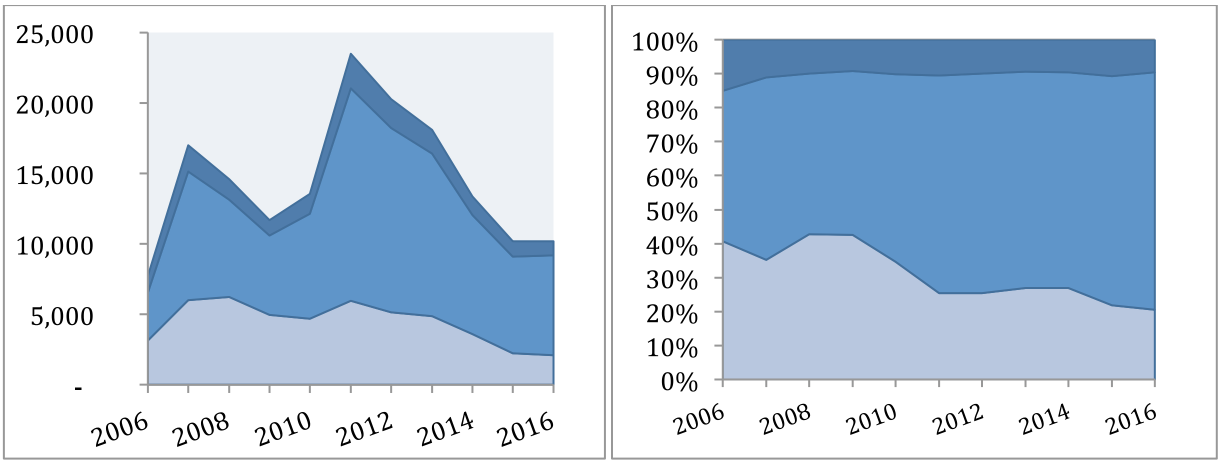
Figure 4.4 – Percentage Yearly Change in the Amount of CDSs Outstanding



Source: own creation, Bank for International Settlements & International Swap and Derivatives Association.

Despite a positive change in 2010, it emerges from figure 4.5 that the market for CDSs has been declining ever since the financial crisis hit in 2007. An explanation could be that the financial crisis struck, the market had to scale down its risk, and CDS contracts where no longer issued for speculative purposes to the same degree. However, this is only a presumption and would require a larger study to confirm. The graph suggests that the market has been subject to a larger degree of uncertainty, as the market for CDSs has continued to decline every year since the financial crisis, with the only exception of 2011 where the notional amounts of CDSs outstanding rose 9% from the year before.

Figure 4.5 – Development in Ratings on Deliverable Bonds for CDSs



Source: own creation, Bank for International Settlements

One last interesting statistic on the market for CDS contracts is in relation to the rating of the deliverable bond. The two figures above illustrates the development in ratings on deliverable bond, where the left hand figure illustrates the development in notional amounts outstanding, in billions of USD and the right hand figure shows the percentage distribution of the three rating classifications over time.

From the graph above, it emerges that 79% of the deliverable bonds were rated Aaa-Bbb, and the remaining 21% were rated below investment grade in 2016. It is further illustrated how the junk-bonds have experienced a downward trend and constitute a lower share relative to the investment graded bonds from year to year.

4.3 Application Potential

To achieve a greater understanding of what a CDS is, it is considered relevant to review the parties interacting in the contract and the different application possibilities in practice. The application potential will be assessed first from a protection seller perspective, then from a protection buyer perspective, and finally by further exploring the development and speculative potential of the contract. As the application potential is numerous, only the most common ones will be reviewed.

4.3.1 From a Protection Seller Perspective

As an investor entering a CDS contract, the protection seller receives a cash flow which is similar to buying the underlying bond. Instead of receiving the spread above the risk-free rate, as it would be the case with an investment in the underlying bond, the protection seller receives the CDS spread from the protection buyer. The CDS spread consists of a serial of premiums specified in basis points per annum, and will typically level with the bond spread. Intuitively, the CDS spread should lie a little under the bond spread, as the protection seller must be compensated for the non-default component in the latter.

The benefit of entering a CDS contract contrary to investing in the deliverable bond is that the CDS contract does not require any initial payment. Investing in the a CDS contract gives the investor the opportunity to diversify his credit portfolio, as he do not need admission to a specific market or bond in order to be exposed to a given company.
Furthermore, he is able to take on credit positions in bonds with maturities differing from the maturities which the bond market offers. He also has the possibility of taking on illiquid bonds in which he would otherwise not have invested due to the lack of liquidity.

In short, a CDS contract can be described as a synthetic substitute for a bond, which gives the investor an alternative to the bond market at fairly the same risk.

4.3.2 From a Protection Buyer Perspective

The protection buyer is the party on the other side of the CDS contract. By entering the contract, he is able to reduce his credit risk on a given bond against the quarterly payments, the CDS spread.

A good example could be the banks, which could benefit from entering a contract in order to increase their bond portfolio without taken on additional credit risk. In this case, the bank would enter a CDS contract as the protection buyer, and the reference entity of the CDS contract would then be the company, to which the bank has issued a loan. By trading this credit derivate, the bank is able to further increase its lending position while still meeting the requirements of minimum capital relative to credit exposure, stated in Basel II (Hull 2005).

4.3.3 Speculative Potential

CDSs were originally developed to control and hedge against credit risk. However, the financial market typically finds other uses of the financial products, which is also the case with the CDSs. Hence, the CDSs are used to take on positions in credit risk and to construct various other credit products. For instance, an investor could enter a contract as the protection seller if he believes that the credit risk on a given reference entity will decline. A profit can then be gained if the spread on the CDS increases later on.

Alternatively, the investor could enter a reverse swap contract as the protection buyer, and pay a spread smaller than the one received on the first contract, but in this case without taking on any credit risk. The advantage of this strategy is that it is an easy way to hedge the investor's risk. The downside is that the counterparty risk is increased, as there as a result are two counterparties to consider. However, in most CDS contracts, requirements on collateral are included, which of course reduces counterparty risk considerably.

Likewise, an investor could speculate in the increase in credit risk on a given reference entity and choose to enter a CDS contract on the deliverable bond of the reference entity as the protection buyer.

CDSs are highly used to increase or reduce credit risk, which can cause the face value of the CDS contract to exceed the reference debt, and this will actually often be the case. Another reason for the high outstanding amounts on the CDS market is the frequent use of reverse swap contracts in the market. They are used when an investor wishes to resign from a contract rather than terminating it.

4.4 Credit Default Swap Spread

The CDS spread is, as defined, the premium which the protection buyer will have to pay to the protection seller in order to be insured against a credit event. The spread is determined so that the protection seller is compensated for the credit risk he takes on when entering the contract.

As the chapter on credit risk examined, the credit risk will depend on the probability of a credit event occurring. The CDS spread will mainly be affected by the markets expectations to the risk that a credit event will happen and the expectations to the subsequent recovery rate. If the market strongly believes that a credit event will occur, then the CDS spread will increase as a result of this anticipation and vice versa.

With reference to the previous chapter on credit risk on bonds, the CDS spread proves to be affected in the same way as the bond spread and thus, the findings in this chapter can be used analogously on the CDS spread. However, it is important to note that the two spreads are not 100% comparable and different factors affect the two. Therefore, a comparison between bond spreads and CDS spread is evident and will be conducted in the following section. But for the illustrative purpose of examining what affects the CDS spread, the two will be used as highly analogue.

The investors' willingness to take on risk will be reviewed, in order to determine if it is a factor that must be considered in the analysis of the CDS spread.

The CDS spread will intuitively be affected by the markets risk-taking approach, as a lower level of risk tolerances in the market would have to result in a higher compensation for taken on risk, and the CDS spread would therefore be higher as a consequence of the markets low willingness to take on risk. The risk tolerance is generally difficult to measure, but investors are in principle assumed to be risk averse.

One of the assumptions of the various risk models is that it operates within a risk neutral world. This assumption is possible to assume due to *The Risk Neutral Valuation* set forth by Cox & Ross in the 1970's (Cox & Ross 1976). The argumentation behind this evidence will not be conducted, but as it represents an established point of view, it will be used in the following argumentation on the investors' risk willingness' impact on the CDS spread.

"Any security dependent on other traded securities can be valued on the assumption that investors are risk neutral." (Hull, 2005)

This statement indicates that the investors' willingness to take on risk does not cause an effect on the value of the derivatives, when it is expressed as a function of the price on the deliverable bond (Hull, 2005).

In the subsequent treatment of the CDSs, it is not necessary to encounter the investors' risk tolerance, as it is shown that it will not have an effect on the analysis on the different variables determining the size of the CDS spread.

Another type of risk, which is incorporated in the CDS contract and was briefly mentioned in the chapter on credit risk, is the counterparty risk. The counterparty risk was described as the risk between the protection buyer and the protection seller. However, Hull & White (2001) conclude that in most cases, the impact of counterparty risk on the CDS spread is very small. This is for example due to the protection buyers possibility to enter into a new contract with a new counterparty, should the first counterparty default, and in doing so regaining the protection for the rest of the contract period if the counterparty defaults. Many similar studies seem to ignore or neglect counterparty risk, and based on this and the small impact it has on the CDS spread, this risk will not be included in the later empirical analysis on the determinants affecting the CDS spread.

CDS spread is the part of the bond spread that can be attributable to credit risk. The previous examination dedicated to credit risk can therefore be used in the study of CDS spreads. As the investors' willingness to take on risk was proven not to be of significance, the CDS spread can be expressed as follows:

$$CDS\ spread \approx Default\ rate * (1 - Recovery\ rate)$$

As examined in the preceding chapter, credit risk can be divided into default risk and recovery risk respectively. The macro and micro economic effects, to which a company is exposed, affect both the default risk and the recovery risk. Furthermore, it was found that risks such as downgrade risk and spread risk are derived from the default rate and recovery risk, and are used as a qualitative and quantitative measurement of risk respectively.

All of the above mentioned risk factors was found to impact the default component of credit risk, but according to Longstaff et al. (2005), credit risk furthermore consists of a non-default component. The study suggests that the non-default component has a close relation to both the idiosyncratic and the market driven liquidity factors. These liquidity effects examined by Longstaff et al. were found to pose an impact on the bond spread, but not to be of significance to the CDS spread, as the latter only is affected by the default component of credit risk. However, it is interesting to disclose liquidity effects in relation to CDS spreads, as it must have some impact on the size of the spread. The degree to which the protection seller is able to trade CDSs on the market will have an effect on the CDS spread. The outstanding amount in the market will have an impact, and a lower liquidity would subsequently lead to an increase in the size of the CDS spread, as a consequence of supply and demand.

The liquidity effect would have to be added to the credit risk, and is now composed by default risk, recovery risk and the liquidity effect. Thus, the CDS spread can be expressed as follows:

$$CDS\ spread \approx Default\ rate * (1 - Recovery\ rate) + liquidity\ risk\ on\ CDS$$

A method of measuring the liquidity risk is to review the bid-ask spread on the CDS traded. A large spread implies a lack of liquidity, whereas a smaller spread is an indication of a high level of liquidity in the CDS market.

To summarize, the following factors will have an impact on the size of the CDS spread:

- Macro economic effects
- Micro economic effects
- The liquidity of the CDS

4.5 Bond Spread vs. CDS Spread

In the previous, both bond spreads and CDS spreads have been reviewed and similarities have arisen, wherefore the two spreads were used analogously in the examination of CDS spreads. In the analysis on credit risk, which is subject to this thesis, CDS spreads are used in preference to bond spreads. This choice will be developed further in the following.

A comparison between bond spreads and CDS spreads is evident, as they are both expressions of credit risk. The similarities between the two spreads have also led the investors to speculate in the differences, and how to exploit these. Despite these similarities, it is important to clarify that the spreads are not 100% comparable, and different circumstances affect the two spreads.

That the bond spread is not considered to be equal the price of credit risk is reviewed in the chapter on credit risk, and the additional non-default component is touched upon briefly. Likewise, the chapter on CDSs finds that the same holds for the CDS spread, and that factors like the CTD-option and liquidity cause the spread not to be a pure measurement of risk. However, according to Hull et al. (2004), it is reasonable to consider the CDS spread to constitute a purer expression of credit compared to the bond spread. The impact of the CTD-option on the CDS spread will typically be very small as discussed in the previous, and further the CDS marked is considered to be very liquid (O'kane, 2011) wherefore the liquidity component also is assumed to have a smaller effect on the CDS spread contrary to the bond spread.

Blanco et al. (2005) argue, in their analysis of the relationship between investment grade bonds and CDSs, that the CDS market is the least complicated place to trade credit risk. There are no short-sale restrictions on this market, and it is possible to trade large amounts. Market participants are more diverse, and those who want to hedge loans and counterparty risk can do it in the CDS market. The variety of market participants causes the market liquidity to increase. Especially this difference in liquidity has resulted in the CDS spread often being used instead of the price of the bond, for instance when a bank's creditworthiness is assessed.

Moreover, Ericsson (2009) suggests that an advantage in using CDS spreads over bond spreads is that CDS spreads seem to reflect changes in credit risk more accurately and quickly than corporate bond yield spreads. He refers to the study by Blanco et al. (2005), who provide evidence that changes in the credit quality of the underlying bond are likely to be reflected more quickly in the CDS spread than in the bond spread. According to Ericsson, this may be due to important non-default components in bond spreads that obscure the impact of changes in credit quality.

In continuation, Blanco et al. (2005) find strong evidence, that CDS spreads lead spreads on bonds. By examining the determinants of changes in credit risk, they find that macro variables have a greater immediate impact on the bonds' bond spreads than on the CDS spread. Furthermore, they find that company-specific returns and implied volatility have a greater immediate impact on the CDS spread than on the bonds. In the long run, the two risk measurements are found to be equally sensitive, but a delayed adjustment on the bond market is observed.

Furthermore, some challenges can arise in the work with bonds. By using CDS spreads, a specification of benchmark risk-free yield curve is not required, as the CDS spreads are already spreads. Thus, any added noise arising from a poorly specified model of risk-free yield curve is avoided (Ericsson 2005).

When dealing with CDS spreads, no coupon effect is to be taken into account, as is the case with bond spreads. Moreover, maturities can be disregarded if CDSs with the same maturity are used. These specific matters can constitute a challenge when working with bonds though. Furthermore, the CDS can be compared to a bond traded at face value every day, as no cash is exchanged at the conclusion of the contract (Benkert 2004).

Lastly, one should be aware that the bond spread contains components that cannot be attributed to credit risk, and are not captured in the general credit risk models as described previously in the chapter on credit risk. For instance in the studies of Longstaff et al. (2005) and Elton et al. (2001), liquidity and taxes, respectively, are found to have an effect on the bond spread and are included in the so-called non-default component of the bond spread.

To conclude, bond spreads and CDS spreads are not completely comparable, but nevertheless accompany each other reasonably close. With a few assumptions, a risk-free portfolio of the two spreads can be arranged (O'Kane 2011). However, it requires some assumptions to be made on the above mentioned issues, and because these differences primarily arise in practice, the thesis will not distinguish between whether a model expects bond spreads or CDS spread, as they are theoretically identical.

All of the above makes the CDS spreads an easier measurement to work with in the analysis of the determinants that have an influence on credit risk, wherefore this approach is chosen in the later analysis.

4.6 Summary

A CDS contract is an "over-the-counter" contract between only two parties, the protection seller and the protection buyer. The contract is a protection against default, and the protection buyer pays a serial of premiums to the protection seller (the premium leg), which is the protection buyer's compensation for taken on risk, and the premium leg corresponds to the present value of the expected loss in the case of a credit event (the protection leg). A CDS contract not only insures against the "pure" default, but can also cover variations of default such as failure to pay or restructuring of debt, wherefore the notion credit event is used.

The derivatives market showed rapid growth from the beginning of the 00's until the financial crisis in 2008, which reflects the development in new financial products – especially the introduction of the CDS has a large explanatory effect of this development. Despite the success of the CDSs, it only made up 12.24% of the OTC derivatives market, when it was at its highest in 2007. The largest financial product in the market in regard to market share, is the interest rate contracts which constitute 77%. The outstanding amount of CDSs was 62,173 trillion USD when it was at its highest in 2007, and this amount has declined ever since the financial crisis, wherefore the notional outstanding amount was 12,294 trillion USD at the end of 2015. As a result of the financial crisis, regulations have been established in order to ensure greater stability in the financial markets. Regulative requirements for clearing derivatives through clearinghouses have been made, in order to reduce private arrangements between buyers and sellers, which is encumbered with higher risk. These same regulations have contributed to a decline in the derivatives market over the past couple of years.

A CDS contract can be used for several purposes. It can be used both for hedging against risk, and taking on more risk. Investing in a CDS contract gives the investor the opportunity to diversify his credit portfolio, as he does not need admission to the deliverable bond when investing in the CDS. Furthermore, it does not require an initial payment to invest in the CDS. The CDS spread can be expressed as the sum of the default risk x (1-recovery rate) and a liquidity risk. Thus, the factors determining the CDS spread are the liquidity on the CDS contract, macroeconomic effects, and the microeconomic effects on the given reference entity. In addition, some contractual circumstances were discussed to cause an impact on the size of the CDS spread, but the significance combined with the difficulties in estimating these effects lead to an exclusion of these effects in the following analysis.

To what extent, the reviewed determinants are able to explain the size of the CDS spread, will be subject to the later empirical analysis. Prior to that analysis, the following chapter will examine the previous empirical studies on the determinative factors of both the bond spread and the CDS spread, and the findings in these studies will be reviewed, in order to decide which specific variables will be included in the empirical analysis.

5 Previous Empirical Studies

In our process of investigating which variables that have an impact on the CDS spread, three previous studies have been selected to form the basis of the empirical analysis by: Collin-Dufresne et al. (2001), Benkert (2004), and Ericsson et al. (2009). Common for these studies is that they are all based on the variables of Merton's structural model, and hence use the structural approach to identify the theoretical determinants of the spread. The highlights from the individual studies are reviewed in this section.

5.1 Collin-Dufresne et al. (2001)

In the study "*The Determinants of Credit Spread changes*" (Collin-Dufresne et al., 2001) the determinants of the credit spread are investigated. The paper examines the changes in the credit spread and the explanatory variables, rather than the levels. Furthermore, it is based on the credit bond spread instead of the credit default swap spread. The data used in the study are monthly data from industrial bonds in the period from July 1988 through December 1997. Many later studies are based on this paper.

The study builds on the assumption that bond spreads originate for two main reasons (1) the risk of default and (2) in the event of default, not all the promised payment is received. Therefore proxies for both changes in the probability of default and changes in the recovery rate are used as explanatory variables. The only firm specific factor used in the original regression is the firm leverage. The firm specific variable is included in order to measure the health of the company. In the second model, the stock return on each bond is included as the firm specific factor instead of the firm leverage. The two models provide very similar results though, and both firm specific variables tend to be statistically significant. The rest of the variables, which are of macroeconomic character, are: the risk free rate, the squared level of the risk free rate, the slope of the yield curve, volatility, S&P 500 index and jump magnitudes of the S&P 500 index. The volatility is measured by the VIX index rather than firm specific volatility. The S&P 500 index is included to reflect the general economy. It is the opinion of Collin-Dufresne et al. that the S&P 500 index captures all the firm specific returns, wherefore this should be included instead of the firm specific returns. The slope of the yield curve is included, in order to investigate if the future expectations to the future short-term interest rates have an impact on the credit spread. The slope of the yield curve reflects both the expectations to the general economy, and the firm's future funding opportunities.

The sample data is first divided by leverage groups or ratings, and then further divided by maturity of the bond. It is found that the model has a quite low explanatory power. In the first case, the adjusted R^2 spans from 19% to 25%, and in the second case it spans from 17% to 34%. The model generally has the lowest explanatory power when explaining the variation in long-term, high-leverage bonds, and highest explanatory power when explaining the variation in short-term low-leverage bonds. The only factors in the model that prove not to be statistically significant are the convexity and the slope of the yield curve. In attempt to achieve a higher explanatory power, a bunch of other variables are included, comprising different liquidity variables, but the variables only add a limited additional explanatory power to the model. It is furthermore concluded, that a significant part of the residuals seems to be driven by a common systematic factor, which is not captured by the theoretical variables.

5.2 Benkert (2004)

The study "*Explaining Credit Default Swap Premia*" (Benktert, 2004) proposes a simple approach for explaining credit default swap premium using regression analysis. The study especially investigates the effects of volatility - comprising historical and option implied volatility. The sample includes panel data on CDS spreads on 120 international firms from various industrial sectors, and spans the period between January 1, 1999 and May 31, 2002. All together 26,478 quotes are used in the regression.

Besides the mentioned two different measurements of volatility, the regression model includes the following variables: the risk free rate, liquidity, credit rating, and three accounting variables comprising profitability, leverage and interest coverage. With all variables included, the model has an explanatory power of 76.8%, measured by R^2. Volatility and credit ratings are the variables that contribute most to the explanatory power, while both the liquidity variable and the three accounting variables seem to have a very limited effect on the credit default swap premium. It shows that the accounting variables are all captured better by the credit rating variable. It was found that both historical and option implied volatility has a statistically significant explanatory influence on the credit default swap premium. By holding all other variables constant and only changing the two different measures of volatility, it can be concluded from the study that option implied volatility has a stronger effect than historical volatility. Using both variables however, improved the explanatory power of the model.

5.3 Ericsson et al. (2009)

The study "*The Determinants of Credit Default Swap Premia*" (Ericson et al., 2009) investigates linear relationship between the three theoretical determinants of default risk and credit default swap spreads; Financial leverage, the risk free rate and volatility as proposed in Merton's structural model.

The data span the period from 1999 to 2002. The quotes are corresponding to swaps on senior debt. The data originate from international companies, but the majority is based on U.S. companies since they dominate the swap market. Utilities and financial companies are excluded from the data. The paper is intimately related to the paper of Collin-Dufresne et al. (2001), but an important distinction is that this paper by Ericsson et al. studies swap spreads rather than corporate bond yield spreads. Both levels and changes in the credit default spread and the explanatory variables are investigated, and therefore two different models are set up.

The model based on spread levels has an explanatory power of approximately 60%, while the model based on spread difference has an explanatory power of 23%. The regression results are also divided by low and high ratings, and it reveals that the R^2 is higher for the lower ratings than the higher ratings. This applies to both the level- and the difference model. The regression is run on both offer and bid quotes, and it shows that the explanatory power of the level model is higher for the regression made on bid quotes rather than offer quotes. It is concluded that, although a substantial amount of the variation in the CDS spread is not captured by the three theoretical determinants, they are all significant and clearly important factors when explaining the variation in the CDS spread. The leverage variable clearly dominates the other two variables by explanatory power. The regression is further extended to include the same variables as the study by Collin-Dufresne et al. (2001) The additional variables increase the explanatory power of the level model by approximately 14% and the difference model by roughly 7.5%, respectively. Thus, the explanatory power of the new models is respectively 74% and 31.5%. In order to investigate the robustness of the regression results, separate regression is run for the individual years, and it is found that the explanatory power of the models increases noticeably over time, which could be due to increasing market liquidity.

5.4 Summary

As mentioned in the introduction to this section, the common factor of all above-mentioned studies is that they all comprise the three variables in Merton's structural model of default as basis for the analysis. The three variables included in Merton's model: firm leverage, volatility and the risk free rate, are all proven to be statistically significant when explaining the credit and CDS spread. [4] However, there is disagreement regarding which measure of volatility that should be used. Collin-Dufresne et al. use implied volatility based on the VIX index, and hence not firm specific. Benkert (2004) uses both historical and option implied volatility, which are both statistically significant. Ericsson et al. (2009)

[4] Collin-Dufresne et al. (2001) is based on bond spread as dependent variable. Benkert (2004) and Ericsson et al. (2009) are based on the CDS spread.

include only historical volatility. The studies all agree that the credit rating is an important variable to include. The studies use different macroeconomic factors, but the S&P 500 index is widely used and proven to have significantly explanatory power. Collin-Dufresne et al. (2001) and Benkert (2004) attempt to include different measures of liquidly in their model, but the variables do not seem to have any significant effect and have very limited explanatory power of the CDS spread.

It is important to notice that the results obtained through the three studies cannot be compared directly, as there are differences in the method, time period and data basis applied in these studies. Furthermore, the study by Collin-Dufresne et al. (2001) is based on bond spread, while the two other studies are based on the credit default swap spread. Consequently, the studies are only used as inspiration to the factors included and the hypothesis setup in the empirical analysis.

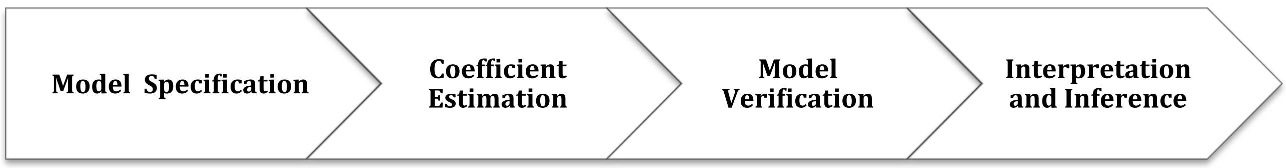
PART II

Newbold et al. (2013) describe the process of building a model as follows:

"The art of model building recognizes the impossibility of representing all the many individual influences on a dependent variable, and tries to pick out the most influential variables"

According to Newbold et al., the model-building methodology consists of 4 steps, which will further form the framework of the empirical analysis conducted in this thesis.
The four stages of statistical model building are described in the figure below:

Figure 6.0 – The Stages of Model Building



Source: Own creation, Newbold et al.(2013)

The first step of model specification includes the selection of dependent and independent variables. As the objective of the thesis is to assess determinants of the CDS spread, the CDS spread was chosen as the dependent variable in the model.

The process of identifying a set of likely predictors should, according to Newbold et al., highly rely on appropriate economic theory, and studies providing a rationale for the model. This selection will be further presented in chapter 6, which gives a presentation of data, the determinants in question, the hypotheses and statistical description of the dataset.

Second step of statistical model building is to estimate a multiple regression model, including an analysis of the regression results and the different variables' individual impact on the dependent variable, the CDS spread. Chapter 7 will conduct this analysis and, moreover, seeks to test the additional determinants suggested by the previous empirical studies, in the attempt to achieve a stronger model for explaining the CDS spread.

Chapter 8 will form the third stage of the model building procedure, where model verification will be conducted. After fitting the regression model, it is important to check the adequacy of the model. In this process, it is valuable to investigate the residuals to determine how the model actually fits the data, and to what degree the regression assumptions are adherent. In addition, chapter 9 will examine additional regression results, and a robustness analysis will be included to examine whether the findings in the regression model stays robust over time.

Lastly, in chapter 10, the fourth stage of the model building process will be carried out. This stage consists of an interpretation and inference that will be carried out as a discussion of the regression results, a comparison to other previous findings.

6 Empirical Analysis

The previous studies, reviewed in the last chapter, are used as inspiration to the empirical analysis. Even though the studies are not directly comparable, they all have in common that the three variables from Merton's structural model of default are all proven to have a significant effect on the determination of the level of the CDS spread. The approach of this thesis is primarily inspired by the approach of Ericsson et al. (2009) and Benkert (2004). First, we will run a base case multiple linear regression model, with the three theoretical determinants of default risk inspired by Merton's structural model as the explanatory variables of CDS spread. The three variables are: financial leverage, the risk free rate, and historical volatility. Then, to obtain a higher explanatory power, the model is expanded to include additional micro- and macroeconomic variables as a measure of both the financial health of the individual firms and the overall economic condition. The additional variables span: Equity return, price/book value, credit rating, S&P 500 index, GDP growth, and CDS-liquidity. Inspired by Benkert (2004), we will also add option-implied volatility as a variable, since it was concluded to add a higher explanatory power to the model than historical volatility. The regression model is run in several different combinations of the mentioned variables, in order to observe the behaviour of the different variables in various contexts. The data, hypothesis, and variables are presented and reviewed further in the following sections.

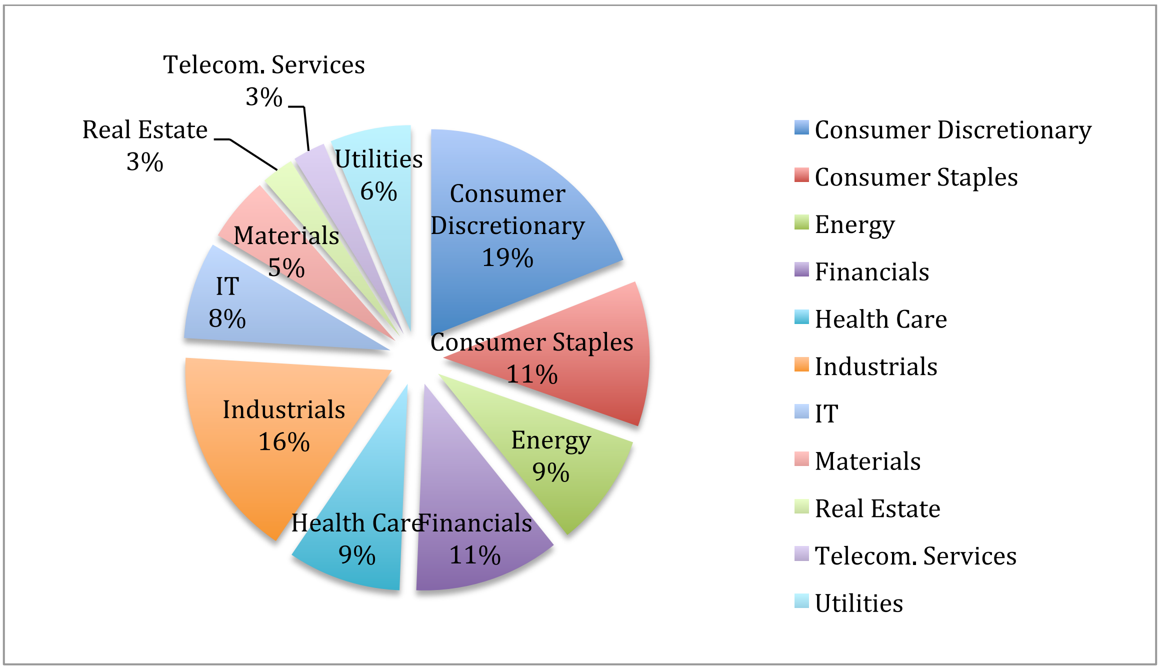
6.1 Data

As proposed, the purpose of the empirical analysis is to investigate which variables that have an impact on the CDS spread. To analyse the relationship between the CDS spread and the included variables, a multiple linear regression model is run. In this section, the applied data are reviewed, and hypotheses based on the data will be presented.

6.1.1 Data Basis

The regression analysis is based on panel data from Markit CDX NA IG index, since it is the most liquid North American CDS index (Markit.com). The CDS index consists of 125 North American single-name CDS contracts on reference entities that are rated in the category investment grade, but 46 of the reference entities have been removed, since there were missing data on some of the variables in some parts of the period. As a consequence, the regression is based on the remaining 79 companies in the index. The period spans from 01/04/2005 to 12/30/2016, and only companies that have been in the index during the entire period are included. All the analysed data are collected from The Bloomberg Terminal and are expressed as daily quotes – excluding weekends and holidays. This implies that only data from trading days are included to obtain the most exact regression without any estimation errors. CDS-contracts on companies from 9 different sectors are represented in the data; the figure below shows the distribution of the companies by sector.

Figure 6.1 – Distribution of Companies in Markit CDX NA IG Index by Sector

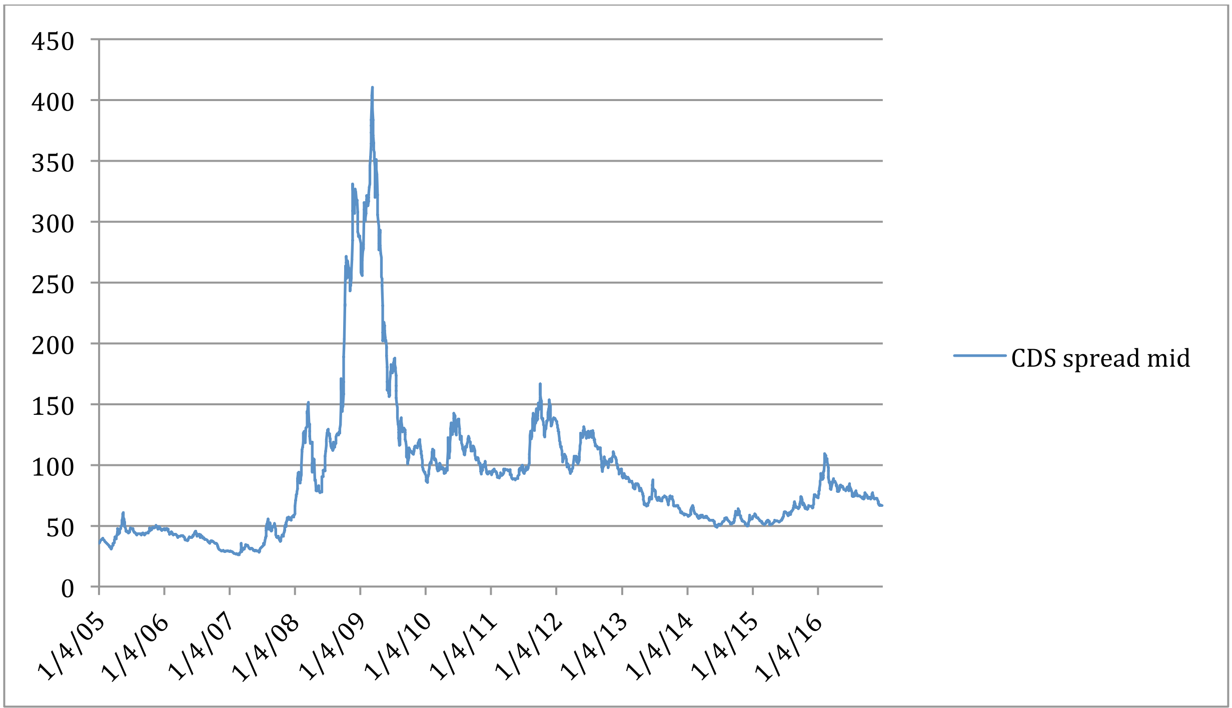


Source: Own creation based on data material

6.1.2 The Dependent Variable: CDS Spread

As the thesis is investigating, which variables that have an impact on the CDS spread, the CDS spread is chosen as the dependent variable in the regression analysis. The CDS spread is included in the analysis as the daily quotes for single-name CDS contracts with 5-years maturity on the included companies. Contracts with 5-years maturity are chosen, since these are the most traded CDS contracts and also predominantly represented in previous studies presented in chapter 5. In the analysed period 238,580 quotes of the CDS spread are represented. The quotes are mid quotes of the CDS spread, which is the simple average of the bid and ask quotes. The CDS spread is reported in basis points. The average value of the CDS spread mid quotes in the analysed period is 86.34 basis points. The development in the average CDS spread for the 79 companies in the analysed period is shown in the figure below. As pointed out by the figure, the spread is relatively stable from 2005 to 2007, but starts increasing heavily at the end of 2007 and reached its top on 9th of March 2009, which reflects the evolution of the financial crisis. Afterwards, the trend turns around and the spread decreases, but is still quite volatile in the following years.

Figure 6.2 – Average CDS spread mid quote in bp



Source: Own creation based on data material

6.1.3 The Independent Variables

Based on Merton's structural model and previous empirical studies, the regression analysis will include the variables mentioned in the beginning of the section. In the following section, each of the independent variables will be presented and examined.

6.1.3.1 Volatility

The volatility is an expression of the fluctuations in the stock price of the underlying company. Both historical and option implied volatility[5] is included in the model, inspired by the empirical study by Benkert (2004), which showed that implied volatility had a stronger effect on the CDS spread than the historical volatility. Option implied volatility reflects the markets future expectations to the future fluctuations, and it is measured by the volatility of an option with maturity of 30 days on the underlying asset. Historical volatility reflects the past actual volatility, and is measured as the standard deviation of the daily stock return during the last 180 calendar days. The data of both variables are collected directly from Bloomberg. According to Merton's structural model of pricing credit risk in chapter 3, the volatility of the underlying asset is a central factor when determining the value of the risky asset. Both volatility measures are included as a percentage measure.

[5] Option implied volatility will throughout the paper be referred to as implied volatility. Historical volatility and option implied volatility combined is referred to, as the volatility measures.

6.1.3.2 *Financial Leverage*

The financial leverage of the companies is included as the debt to equity ratio in %. The D/E ratios are daily quotes, but since the leverage of a firm does not change on daily basis or short-term periods, the variable is constant throughout longer time periods. The D/E ratio is collected from Bloomberg and is defined by:

$$\text{Debt/Equity ratio } (\%) = \frac{\text{book value of debt}}{\text{book value of equity}} * 100$$

The financial leverage of the companies is included to reflect the economic health and stability of the respective companies, and is important when pricing credit risk according to Merton's structural approach.

6.1.3.3 *Price/Book Value*

The price/book ratio, also referred to as P/B value, of the companies is included in the regression as a proxy for the profitability and the market's expectations to the company, since it compares the marked value of the company to its book value, and hence reflects whether the market consider the stock to be more or less worth than the book value. The ratio is defined by:

$$\text{Price / book value} = \frac{\text{Market value of firm}}{\text{Book value of equity}}$$

If the P/B ratio is below 1, the company's share is either undervalued or the company is earning a very poor return. On the other hand, a company with high P/B ratio is either overstated or earning a very high return. It is important to keep in mind that the P/B value varies a lot across different industries.

6.1.3.4 *Stock Return*

Stock return is also included as a proxy for the profitability of the firm, as it measures the profit generated by the company, and also the markets expectations to the company. It is included as a daily measure of the change in the stock price of the underlying asset. The daily stock return is reported in percentage.

6.1.3.5 *Credit Rating*

The credit rating is included as well to reflect the stability and credit worthiness of the individual firm declared by public rating agencies. Only ratings from Standard & Poor's are used in the regression, since there were missing data in the ratings from both Moody's and Fitch. Ratings are used to divide bonds into credit rating classes based on the ability of serving the corresponding debt. The rating scale typically spans from AAA to D, where AAA is the highest possible rating and D the lowest. Credit ratings are reported quarterly, and the average rating of the companies included in the analysis span from BB to AAA.[6] No included company has a rating below BBB in 2016. The ratings are converted into numbers in the regression, corresponding to the rating class as follows:

Figure 6.3 – Ratings converted into numbers corresponding to the rating class

AAA	= 20	BB	= 9
AA+	= 19	BB-	= 8
AA	= 18	B+	= 7
AA-	= 17	B	= 6
A+	= 16	B-	= 5
A	= 15	CCC+	= 4
A-	= 14	CCC	= 3
BBB+	= 13	CCC-	= 2
BBB	= 12	CC	= 1
BBB-	= 11	C	= 0
BB+	= 10	D	= N/A

Source: Own creation

6.1.3.6 Risk Free Rate

The risk free interest rate level is used to reflect the level of the risk free term structure in the period and thereby expresses the economic business cycle. As a proxy for the risk free rate level, the 5-years US Treasury rate is used, which corresponds to the 5-years' maturity of the CDS contracts. The same proxy for the risk free rate is used in the previous empirical studies. Alternatively, and as a more correct proxy, the LIBOR rate could be used, but since the maturity of the LIBOR rate has a maximum of 12 months, the 5-years US Treasury rate is used instead.

6.1.3.7 S&P 500 Index

The S&P 500 index is used as a proxy of the overall market. It reflects the overall economic condition since it contains a wide range of large cap companies representing different sectors. Therefore, this index provides a broad view of the economic health of the US economy, which is expected to have an influence on the CDS spread. The S&P index is reported as the daily return on the index in percentage.

[6] Ford Motors have ratings below BB from 03/31/2006 to 12/31/2012 – but the average rating of Ford Motors in the entire period is BB. The rating based on 12/30/2016 is BBB.

6.1.3.8 GDP Growth

The GDP growth is also included as a proxy for the overall economic state. A high and increasing GDP reflects economic and wealth growth of the nation. GDP growth is reported quarterly and is included as the change in GDP per capita compared to the same quarter last year in percentage.

6.1.3.9 CDS Liquidity

Previous studies did not seem to find liquidity as an important factor in explaining the CDs spread. As a proxy for the liquidity of the individual CDS contracts, the spread between the bid and the ask quotes are included. The bid-ask spread reflects the supply and demand relationship for the particular CDS contract, and hence the liquidity of the contract. A small spread reflects a high demand and therefore a high liquidity of the contract. Bid and ask quotes are collected from Bloomberg, and the spread is calculated as the difference between the quotes.

6.2 Estimated Regression Equation

With all the variables examined, we can now line up the estimated regression equation as below:

$$\begin{aligned}\text{CDS Spread}_{i,t} = {} & \alpha + \beta_1\text{Historical volatility}_{i,t} + \beta_2\text{Implied volatility}_{i,t} + \beta_3\text{Leverage}_{i,t} \\ & + \beta_4\text{Price/book value}_{i,t} + \beta_5\text{Stock return}_{i,t} + \beta_6\text{Credit rating}_{i,t} + \beta_7\text{Risk free rate}_{i,t} \\ & + \beta_8\text{S\&P 500 index}_{i,t} + \beta_9\text{GDP growth}_{i,t} + \beta_{10}\text{CDS Liquidity}_{i,t} + \varepsilon_{i,t}\end{aligned}$$

CDS $\text{Spread}_{i,t}$ denotes the CDS spread at time *t*, for company *i*. The regression model is run in different scenarios and combinations with the purpose of observing the behaviour of the different variables in various contexts. The base case model includes the original theoretical determinants: historical volatility, leverage, and the risk free rate. Historical volatility is then replaced with implied volatility, and also extended to include both volatility variables to examine the contribution and behaviour of the two different volatility measures. The model is also run as a simple linear regression model on the single theoretical variables, highly inspired by Ericsson et al. (2009).

A model only including the macroeconomic variables is run as well to solely examine their impact on the CDS spread level.

To analyse the impact of the firm-specific measures: leverage, price/book value, equity return, and credit rating, a model with different combinations of those will be reviewed. The purpose of this scenario is to investigate, if the accounting variables are significant and contribute to the explanatory power of the model, or if they are better captured by the credit rating variable as proposed by (2004).

The different model combination and regression results will be processed in chapter 7: Regression Results, followed by model verification in chapter 8 and additional results and robustness check in chapter 9.

6.3 Hypotheses

In the following section, the hypotheses and thus the expected relationship between the independent variables and the CDS spread will be presented. The hypotheses are based on the theoretical background, previous empirical studies and the economic intuition. The phrases *negative* and *positive* refer to the mathematical interpretation, and hence a negative impact on the CDS spread indicates a decrease in the CDS spread and vice versa.

Hypothesis 1: Increase in Volatility has a Positive Impact on the CDS Spread

The volatility reflects the fluctuations in the stock value of the company. Higher volatility reflects a higher level of uncertainty and thereby a higher risk of default. Thus, it is expected that a higher level of volatility should result in a higher level of the CDS spread.

Hypothesis 2: Increase in Financial Leverage has a Positive Impact on the CDS Spread

Following the basic idea from Merton's structural model, the event of default occurs when the value of the firm's debt exceeds the firm's assets. Consequently, the risk of default increases as the financial leverage increases, causing an increase in the CDS spread as well. Therefore, a higher level of financial leverage is expected to have a positive impact on the CDS spread.

Hypothesis 3: Increase in the Price/Book Value has a Negative Impact on the CDS Spread

Since an increase in the P/B value is a result of the company generating a higher return or the market having very positive future expectations to the firm, this should intuitively have a negative impact on the CDS spread.

Hypothesis 4: Stock Return is Negatively Correlated with the CDS Spread

Equity return on the individual company is included in the regression to capture and reflect the profitability of the firm. If the equity return is high and increasing due to well performance, profitable results, and high expectations to the company, the risk of default will decrease. Vice versa, if the firm is struggling to perform and deliver profitable results, the risk of a default event will increase and consequently, the compensation for assuming risk will increase. Thus, a higher stock return will have a negative impact and lower the CDS spread.

Hypothesis 5: Increase in Credit Rating has a Negative Impact on the CDS Spread

A higher rating reduces the risk of a default event, since the rating reflects the creditworthiness of the underlying asset. A reduction in the default rate following from a higher rating therefore has a negative impact on the CDS spread.

Hypothesis 6: Increase in the Risk Free Rate has a Negative Impact on the CDS Spread

A higher level of the risk free rate is expected to cause a lower CDS spread. This is due to the fact that a lower rate level is associated with recession, while a high rate level is associated with periods of economic upturn. The default rate is generally higher during recession, and therefore a higher compensation for assuming the risk of default, expressed by the CDS spread, is expected.

Hypothesis 7: The S&P 500 Index is Negatively Correlated with the CDS Spread

The S&P 500 index reflects the overall economic condition, and therefore the index provides a broad view of the economic health of the US. If the index is low, it is associated with recession and higher default risk, and a higher compensation for assuming risk will follow. Therefore, the S&P 500 index is expected to be negatively correlated with the CDS spread.

Hypothesis 8: Growth in GDP is Negatively Correlated with the CDS Spread

Since the growth in GDP reflects economic growth, a higher growth level is expected to decrease the CDS spread. If the GDP growth rate is low, it is associated with economic recession and as mentioned, the default rate is higher during recession and therefore the CDS spread should be affected positively in this case, since the risk of default is higher. If the GDP growth level is high, it is associated with economic boom periods, and the CDS spread is expected to decrease since the event of default is less expected.

Hypothesis 9: CDS Liquidity is Positively Correlated with the CDS Spread

The bid-ask spread of the CDS contract is included to reflect the liquidity of the CDS contract. If many investors are interested and hence the demand is high, it results in a smaller spread and higher liquidity. A higher spread means a lower liquidity of the contract, which means the contract is traded less frequently or is not easily negotiable and hence more risky. Thus, a higher spread is expected to increase the CDS spread.[7]

6.4 Descriptive Statistics

The following section will provide the reader with some descriptive statistics, in order to outline the dataset used in the empirical analysis and to examine the characteristics of the determinants and their relationship.

One way of assessing the data is to compare the standard deviations of each variable to get an idea of the uncertainty encumbered in the different determinants. However, to compare the standard deviations directly would be extremely misleading, as all variables are measured in various units. Due to this variety in the data, the *Coefficient of Variation* is included for each variable in order to get a measure for comparison. The coefficient is a measure of relative dispersion and expresses the standard deviation as a percentage of the mean. The CV thereby adjusts for the scale of units in the population.

Coefficient of Variation:

$$CV = \frac{\sigma}{\mu}$$

From table 6.1 beneath, it emerges that the variable representing return, both company specific return and the return on the S&P500, constitutes the largest dispersion relatively to the mean.
On the other hand, the credit rating represents the smallest dispersion of only 14.5%, which is due to selection of data. The CDX IG NA index only represents Investment graded companies, wherefore a smaller diversion of ratings is represented in the dataset than if all junk-bonds were included as well. The mean of the rating variables is 13.4, which corresponds to a level between BBB+ and A-, using S&P's credit rating scale.

[7] High CDS liquidity is expected to have a negative impact on the CDS spread, but since the liquidity is measured by the bid-ask spread, a higher spread (meaning low liquidity) is then expected to increase the CDS spread, and a lower spread (meaning high liquidity) is expected to decrease the CDS spread.

Table 6.1 – Descriptive Statistics

	Mean	Median	Std dev	CV	Min	Max	5% percentile	95% percentile	N
CDS spread	86.344	54.771	177.554	2.056	5.750	9,183.379	17.329	225.252	238,580
Historical vol	28.834	24.122	18.032	0.625	8.195	241.305	14.686	58.854	238,580
Implied vol	28.298	24.416	15.886	0.561	9.163	478.043	14.797	53.717	238,580
Leverage	169.309	70.683	542.266	3.203	6.077	1,6174.359	26.640	425.897	238,580
Price/Book	4.412	1.882	17.235	3.906	0.041	687.698	0.631	9.818	238,580
Stock return	0.053	0.049	2.108	39.413	-60.791	102.358	-2.833	2.882	238,580
Credit rating	13.430	13.000	1.881	0.140	1.000	20.000	11.000	16.000	238,580
Risk free rate	2.331	1.757	1.342	0.576	0.543	5.231	0.734	4.795	238,580
S&P 500 index	0.037	0.073	1.231	33.695	-9.026	11.581	-1.822	1.686	238,580
GDP Growth	1.613	1.893	1.737	1.077	-4.062	3.620	-3.284	3.333	238,580
CDS Liquidity	6.396	5.000	11.063	1.730	-1,026.17	713.070	2.655	13.777	238,580

Source: Own creation based on data material

From the statistics it further emerges that the CDS spread in the period on average was 86.34 basis points with a standard deviation of 177.55 basis points. This is a relatively high dispersion when comparing the CV to the other variables. The median of the CDS spread is lower than the mean, and it suggests a skewed-right distribution, which can be further supported by reviewing the histogram enclosed in the appendix (figure 14.1), and by calculating the skewness which for the CDS spread is 23.87. The histogram, however, also indicates the presence of outliers in the dataset, which explains the difference between mean and median, as the median is not affected by outliers, whereas the mean is.

The max values across all variables also indicate this presence of outliers in the dataset, wherefore this matter will be developed further as a separate subsection later.

Table 6.1 shows that historical and implied volatility to a high degree possess similar attributes, as they are almost consistent on all statistics. However, this is expected, as both variables are expressions of the same thing, but with differing time perspective.

Likewise, the table could give an indication of which variables are correlated and the relationship between certain pairs of variables. Despite these indications, the table should not be used to jump to conclusions in regard to correlations, thus a correlation matrix is conducted and presented below.

6.4.1 Correlation

Additional to the descriptive statistics just presented, the relationship between the specific pair of variables also needs to be assessed in order to lookout for critical collinearity.

Table 6.2 constitutes a correlation matrix, where the correlations between the variables are presented, and the corresponding p-values are furthermore provided. The p-value indicates the probability that no correlation between two variables exists. Thus, a low p-value indicates a strong linear relationship between two variables. Generally, the p-values indicate that the majority of variables to some extent are correlated with one another, which is only acceptable to some degree. If a pair of variables correlates to a degree where a direct linear interrelation occurs between the two, then multicollinearity will be present, and one should consider excluding one of the variables. However, multicollinearity in the dataset will be further examined as a part of the chapter on model verification later on. This section is merely intended to investigate how the various variables internally influence one another, and thereby help outlining the characteristics of this specific dataset.

Table 6.2 – Correlation matrix

	CDS spread	Historical vol	Implied vol	Leverage	Price/ Book	Stock return	Credit rating	Risk free rate	S&P 500 index	GDP Growth	CDS Liquidity
CDS spread	1.000	0.490	0.551	0.192	-0.032	0.016	-0.266	-0.109	0.001	-0.217	0.079
		< 0.0001	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*0.5799*	*< 0.0001*	*< 0.0001*
Historical vol		1.000	0.808	0.008	-0.068	0.021	-0.140	-0.086	0.006	-0.637	0.158
			< 0.0001	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*0.0020*	*< 0.0001*	*< 0.0001*
Implied vol			1.000	0.023	-0.072	-0.042	-0.149	-0.018	-0.049	-0.563	0.173
				< 0.0001	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*
Leverage				1.000	0.810	0.002	-0.155	-0.058	0.002	-0.028	0.002
					< 0.0001	*0.4697*	*< 0.0001*	*< 0.0001*	*0.3326*	*< 0.0001*	*0.3211*
Price/Book					1.000	0.004	-0.022	-0.082	0.005	0.000	-0.005
						0.0489	*< 0.0001*	*< 0.0001*	*0.0240*	*0.8834*	*0.0093*
Stock return						1.000	-0.008	-0.002	0.616	-0.001	-0.005
							< 0.0001	*0.3277*	*< 0.0001*	*0.6142*	*0.0238*
Credit rating							1.000	0.077	-0.003	0.010	-0.002
								< 0.0001	*0.1176*	*< 0.0001*	*0.4230*
Risk free rate								1.000	-0.003	0.122	-0.042
									0.0920	*< 0.0001*	*< 0.0001*
S&P 500 index									1.000	0.009	-0.010
										< 0.0001	*< 0.0001*
GDP Growth										1.000	-0.191
											< 0.0001
CDS Liquidity											1.000

Source: Own creation based on data material, high correlations are marked.

The correlation between the dependent variables and the independent variables should reflect the hypothesis put forward in the preceeding section. From this it emerges that P/B, credit rating, risk free rate, and the GDP growth are all variables which seem to correlate negatively with the CDS spread, meaning that an increase in the given determinants will lead to a decrease in the CDS spread, and this is in accordance with the hypotheses outlined. However, stock return is according to the correlation matrix positively correlated with CDS spread, which contradicts both the hypothesis and the economic theory. As argued earlier, if the stock return is high and increasing following from well performance and profitable results by the company, the risk of default will decrease which should consequently lead to an decrease in the CDS spread. However the correlation matrix indicates the opposite relationship. Despite the anticipation of a negative correlation, this matter will not be examined further, as the correlation after all is perceived as relatively small.

In general, the correlation matrix indicates that implied volatility, historical volatility, credit rating, GDP growth and leverage correlate highly with the CDS spread, and in the order mentioned.

The table furthermore discloses that some of the independent variables have high correlations with each other. This is further supported by the enclosed correlation matrix in appendix (figure 14.4), which illustrates these extremes by the use of conditional formatting. From this, it is clear that both volatility variables have high negatively correlations with the GDP growth. And an even higher internal correlation of 0.80 between these two volatility variables emerges from the table, which is expected due to the similarities in characteristics as outlined earlier. Stock return and S&P500, and Leverage and Price/Book are two other pairs of variables, which correlate highly with one another. These three pairs of independent variables are all examples of variables, which to a lower or higher degree are measurements of the same thing, and are thereby closely related to one another. The high correlations might lead to an incorrect estimation of the coefficient in the regression model, wherefore one needs to assess the possibility of multicollinearity, and the possibility of excluding one or more variables in order to improve the model. More on this in chapter 8 on model verification, for the present the three pairs will be treated no different, however kept in mind for later analysis.

6.4.2 Outliers

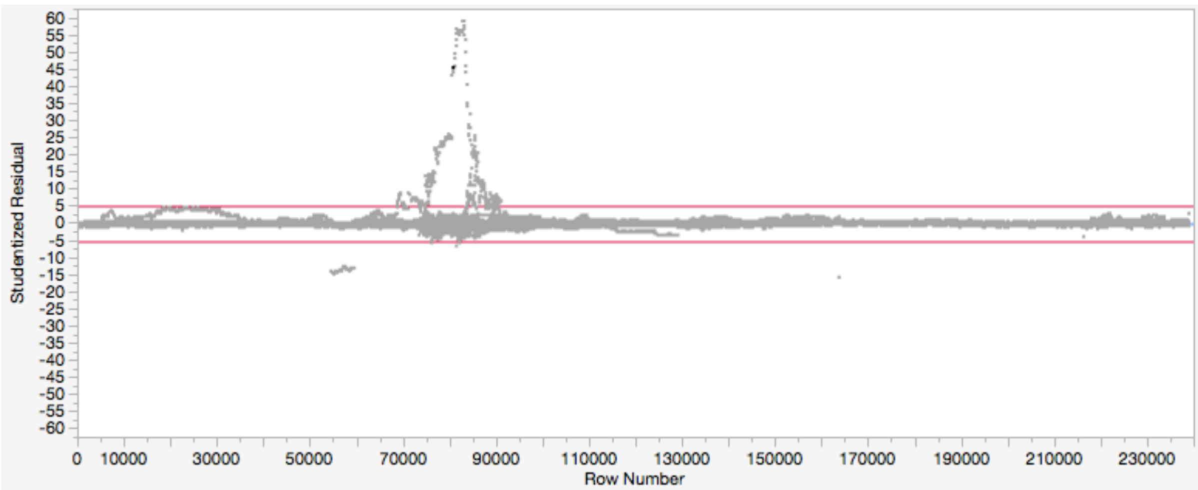
As indicated several times, the data seem to consist of large outliers. When outliers are detected in a dataset, it is important to examine for possible causes, and to distinguish between errors in data and actual observations having an explanatory effect on the model. In the first case, the outliers should of course be removed, but in latter case, the observations must be thoroughly examined before merely removed. If extreme observations represent extensions of the linear relationship, then the estimated model is strengthened by including these. However, if the extreme observations result from unusual conditions or recording errors, the estimated model will be misleading and in that case, the outliers should be removed from the data.

The outlier points can be identified by computing the standardized residuals (Newbold et al 2013):

$$e_{is} = \frac{e_i}{s_e\sqrt{1 - h_i}}$$

It can be helpful to calculate these specific outlier points to allow for a thorough deep dive into the data, and to establish if the points in question are a result of errors in data, or if the divergence for instance is due to unusual circumstances in some specific company that has to be investigated further. Contrary to this method of pointing out the specific outliers, a residual plot can also be useful in detecting potential trends or patterns in the residuals, and a visualization makes this possible.

Figure 6.4 – Standardized Residuals by Row



Source: Own creation based on data material

Above figure is included in order to illustrate the standardized residuals within a 95% confidence interval, and thereby identify the presence of outliers in the data set.
From this, it emerges that the largest part of the observations lies within the limits, however a trend of outliers around row 80,000 is observed.

The examination of this cluster of outlines leads to the conclusion that the financial distress in 2009 explains the deviations. Around 2009, really large fluctuations are observed in the dataset across almost all variables. These fluctuations are the after-effects of the financial crisis in 2007-2008, and the outliers are therefore kept in the dataset. These fluctuations as result of the financial distress can be categorized as unusual circumstances, and some irrationality might exist. However, the distress struck the entire market and affected all variables and companies to various degrees. The outliers detected in the model thus reflect extreme values of the expected relationship between the dependent and the independent variables. Furthermore, the outliers do not occur randomly in the dataset, but causality is observed, wherefore the outliers do not reflect errors in the data, but rather some extreme reactions to events in the market.

Even though the outliers observed in the data set are intentionally included in the modelling process, they should be kept in mind, as it inevitably will affect the estimated model as well as the linearity of the model.

7 Regression Results

The multiple linear regression model, presented in previous chapter, has now been carried out, using ordinary least squares method. In this section, the results obtained from the regression model will be examined, and the hypotheses lined up in the previous section will be evaluated and either rejected or not rejected.

The model is build step-by-step inspired by Benkert (2004) with the purpose of observing the behaviour of the different variables in various contexts, and to investigate the added explanatory power of the different set of variables. The base case model (M0) includes the original theoretical determinants: historical volatility, leverage, and the risk free rate. Historical volatility is then replaced with implied volatility, and also extended to include both volatility variables to examine the contribution and the behaviour of the two different volatility measures (M1-M2). The model is also run as a simple linear regression model on the three single theoretical variables, highly inspired by Ericsson et al. (2009), to examine the contribution of each of the variables (M3-M6).

A model only including the macroeconomic variables is run as well to solely examine their impact on the CDS spread level – both with CDS liquidity and without (M7-M8). The model with the macroeconomic variables and the CDS liquidity variable is then extended to include the volatility variables (M7-M11) to observe their behaviour.

To analyse the impact of the firm-specific variables the three accounting variables: leverage, price/book value and stock return are added to the model, while holding CDS liquidity and the macroeconomic variables constant. (M12) The accounting variables are then replaced with the credit rating variable, and also extended to include both (M13-M14). The purpose of this scenario is to investigate, if the firm specific accounting variables are significant and contribute to the explanatory power of the model, or if they are better captured by the credit rating variable as proposed by Benkert (2004).

The M14 model is then extended to include the volatility variables again in order to observe and examine the behaviour of the variables (M15-M17). The last models include all the 10 variables investigated (M17-18).

The estimated coefficients of the independent variables are lined up in bold, and underneath the corresponding t-statistics are reported. For coefficients being insignificant based on a 5% significance level, the t-test is reported in red. For coefficients being just on the edge of being insignificant based on a 5% significance level, the t-test is reported in blue.

Table 7.1 –Regression Models: M0-M2: The Three Theoretical Variables

	M0	M1	M2
Intercept	**-43.7002**	**-68.5003**	**-74.5431**
t-test	-5.3	-85.2	-91.6
Historical volatility	**4.7615**		**1.5545**
t-test	277.1		41.5
Implied volatility		**6.0973**	**5.0395**
t-test		328.8	160.0
Leverage	**0.0604**	**0.0570**	**0.0576**
t-test	106.0	104.8	106.2
Price/Book			
t-test			
Stock return			
t-test			
Credit rating			
t-test			
Risk free rate	**-7.4986**	**-11.7311**	**-10.6198**
t-test	-32.4	-53.4	-48.1
S&P 500 index			
t-test			
GDP growth			
t-test			
CDS Liquidity			
t-test			
Adj. R^2	**27.85%**	**34.37%**	**34.84%**

Source: Own creation based on data material

In table 7.1, the results from the base case model (M0) including historical volatility, leverage, and the risk free rate are presented. It is clear that all three variables are strongly statistically significant, and the model has an explanatory power of 27.85%, measured by R^2. All variables have the expected algebraic sign as proposed in the hypothesis lined up in the previous section of the thesis. When historical volatility is replaced by the implied volatility variable (M1), the explanatory power of the model increases with 6.52%. It can be derived from the model that if the implied volatility increases by 1%, the CDS spread will increase by 6.0973 basis points, all things being equal. Meanwhile, an increase by 1% in the historical volatility will cause an increase in the CDS spread of 4.7615 basis points. Adding both volatility variables in the model (M2) contributes with a higher explanatory power of 6.99% relatively to the base case model. That is to say, adding both volatility measures only adds 0.47% to the model's explanatory power compared to the model including the implied volatility as the only volatility measure (M1). This indicates the fact that the variation in the CDS spread is, to a greater extent, better captured by implied volatility than by historical volatility. The relatively small change in the R^2 by adding both variables, instead of only a single variable, also confirms the high degree of positive correlation between historical and implied volatility which was identified in the descriptive statistics part.

Table 7.2 shows the contribution in explaining the variation in the CDS spread of each of the variables: historical volatility, implied volatility, leverage, and the risk free rate separately in four different models (M3-M6).

Table 7.2 –Regression Models: M3-M6: Three Theoretical Variables Separate

	M3	M4	M5	M6
Intercept	**-52.7607**	**-87.9737**	**75.7094**	**119.8854**
t-test	-88.3	-142.0	202.6	165.5
Historical volatility	**4.8243**			
t-test	274.5			
Implied volatility		**6.1602**		
t-test		322.6		
Leverage			**0.062811**	
t-test			95.5	
Price/Book				
t-test				
Stock return				
t-test				
Credit rating				
t-test				
Risk free rate				**-14.3877**
t-test				-53.4
S&P 500 index				
t-test				
GDP growth				
t-test				
CDS Liquidity				
t-test				
Adj. R^2	**24.01%**	**30.38%**	**3.68%**	**1.18%**

Source: Own creation based on data material

From table 7.2, it can be derived that all variables are statistically significant, but the volatility variables are clearly accountable for the majority of the model's explanatory power (M3-M4) The table also confirms the fact that implied volatility contributes to a very large part of the explanatory power of the model. The explanatory power of the two other variables, leverage and the risk free rate, constitutes respectively 3.68% and 1.18% (M5-M6), which are obviously much lower values than for the volatility variables.

Table 7.3 shows the contribution in explaining the variation in the CDS spread of the macroeconomic variables solely, and also adding the CDS liquidity variable. The model including the macroeconomic variables and the CDS liquidity variable is then extended to include the volatility variables in turn and at the same time.

Table 7.3 –Regression Models: M7-M11: Macroeconomic variables, CDS Liquidity and Volatility

	M7	M8	M9	M10	M11
Intercept	**150.9276**	**146.6724**	**-66.0721**	**-87.7515**	**-111.5131**
t-test	202.1	182.9	-57.9	-85.1	-100.3
Historical volatility			**5.4271**		**1.7977**
t-test			239.5		59.2
Implied volatility				**6.8057**	**5.4497**
t-test				296.4	168.7
Leverage					
t-test					
Price/Book					
t-test					
Stock return					
t-test					
Credit rating					
t-test					
Risk free rate	**-10.4555**	**-10.3800**	**-9.8405**	**-14.5724**	**-13.5593**
t-test	-39.7	-39.5	-41.7	-64.7	-60.4
S&P 500 index	**0.4553**	**0.4917**	**-0.5090**	**4.2439**	**3.1648**
t-test	1.6	1,7	-2.0	17.4	13.1
GDP growth	**-24.9933**	**-24.3460**	**11.0873**	**10.2321**	**15.0796**
t-test	-122.7	-117.7	46.7	48,3	66.8
CDS Liquidity		**0.4894**	**0.1567**	**-0.1846**	**-0.1605**
t-test		15.2	5.4	-6.7	-5.8
Adj. R^2	**7.04%**	**7.13%**	**25.14%**	**32.13%**	**33.11%**

Source: Own creation based on data material

Including only the macroeconomic variables: Risk free rate, S&P 500 index, and GDP growth, the model can explain 7.04% of the variation in the CDS spread (M7). Adding CDS liquidity (M8) only contributes with 0.09% to the explanatory power of the model. In spite of that, CDS liquidity is still statistically significant in the model. The risk free rate, GDP growth, and CDS liquidity have the expected algebraic sign. However, the S&P 500 index variable is acting differently than expected, since the algebraic sign is positive. In both cases though, the variable is not statistically significant at a 5%

level, meaning that it does not quite make sense to interpret the estimated coefficient of S&P 500 index in M7 and M8.

Adding historical volatility to the model (M9) increases the explanatory power by a notable amount. The algebraic sign of both the S&P 500 index and the GDP growth now shifts to the opposite sign. The S&P 500 index is still on the edge of being significant though. Including the historical volatility variable then indicates a positive correlation between this variable and the S&P 500 index, and a highly negative correlation between historical volatility and GDP growth, as it was also pointed out in the correlation matrix in the descriptive statistics. Replacing historical volatility with implied volatility (M10) increases the explanatory power of the model, as it was the case in M0-M2. GDP growth still has a positive algebraic sign, and S&P 500 now has a positive algebraic sign again and also becomes statistically significant. This indicates a negative correlation between both the implied volatility and the GDP growth, and the implied volatility and the S&P 500 index. The CDS liquidity variable, measured by the bid-ask spread, also shifts algebraic sign from positive, as expected, to negative. Including both the volatility measures (M11) implies a positive algebraic sign of both the S&P 500 index and the GDP growth, and a negative algebraic sign of the CDS liquidity variable. From this it can be derived that an increase in the GDP growth and the S&P 500 index will cause an increase in the CDS spread, which is not expected. Also a higher bid-ask spread meaning a low liquidity on the CDS contract will cause a decrease in the CDS spread, which should not be expected either. The reason for the unexpected behaviour of these variables can be found in the fact that the correlation between CDS liquidity and the volatility variables is higher than between the CDS liquidity and the CDS spread. The same applies for S&P 500 and GDP growth. This means that by adding the volatility variables, this correlation dominates and outdoes the correlation between the CDS spread and the three variables: S&P 500 index, GDP growth, and CDS liquidity.

Table 7.4 is set up to examine the impact of respectively the accounting variables and the credit rating variable on the CDS spread. The macroeconomic variables and the CDS liquidity are held constant throughout the models M12-M14.

Table 7.4 – Regression Models: M12-M14: Macroeconomic Variables, CDS liquidity and Firm-specific Variables

	M12	M13	M14
Intercept	**137.3486**	**468.3245**	**367.9110**
t-test	182.7	187.9	151.5
Historical volatility			
t-test			
Implied volatility			
t-test			
Leverage	**0.2024**		**0.1783**
t-test	198.1		173.1
Price/Book	**-5.5637**		-4.9789
t-test	-172.9		-155,2
Stock return	**2.0065**		**1.8471**
t-test	10.3		9,7
Credit rating		**-24.4118**	**-17.3737**
t-test		-135.7	-99.7
Risk free rate	**-11.7969**	**-7.7607**	**-9.8471**
t-test	-48.3	-30.5	-41.0
S&P 500 index	**-1.4871**	**0.3832**	**-1.4088**
t-test	-4.5	1,4	-4.3
GDP growth	**-22.4907**	**-24.3200**	**-22.6862**
t-test	-117.3	-122.0	-120.8
CDS Liquidity	**0.4712**	**0.4965**	**0.4775**
t-test	15.8	16.0	16.3
Adj. R^2	**20.41%**	**13.79%**	**23.59%**

Source: Own creation based on data material

First of all, the macroeconomic factors and the CDS liquidity now all have the expected algebraic sign throughout M12 to M14. This confirms the fact that the unexpected behaviour identified before, is due to the high degree of correlation between the macroeconomic variables and the volatility variables, as concluded. Looking at the accounting variables, leverage, and the P/B value, they all put on the expected algebraic sign. Stock return puts on a positive algebraic sign, implying that an increase in the return will be followed by an increase in the CDS spread. This is not expected, considering economic intuition. The model (M12) has an explanatory power of 20.41%, which means replacing the accounting variables with the credit rating variable (M13) actually decreases the explanatory power of the model by 6.62%, compared to the model including the accounting variables. However, the credit rating variable undertakes the assumed algebraic sign, meaning that an increase in the credit rating decreases the CDS spread. Furthermore, the S&P 500 index variable shifts algebraic sign, and again it becomes statistically insignificant in the model. Including both all the accounting variables and the credit rating (M14) increases the explanatory power by 3.18% compared to the model only including the accounting variables.

In table 7.5 below, all the variables, except the volatility variables, are held constant. The table shows how respectively historical volatility and implied volatility impacts the model[8]. In M17 both variables are included, and hence it reflects the entire model with all 10 variables.

Table 7.5 –Regression Models: M14-M17: Macroeconomic Variables, CDS Liquidity, Firm-specific Variables and Volatility

	M14	M15	M16	M17
Intercept	**367.9110**	**16.0446**	**71.8498**	**71.8498**
t-test	151.5	42.4	30.4	30.4
Historical volatility		**4.7533**		**1.6024**
t-test		223.4		56.9
Implied volatility			**6,0236**	**4.8322**
t-test			277,2	160.7
Leverage	**0.1783**	**0.1647**	**0.1538**	**0.1541**
t-test	173.1	175.5	170.9	172.3
Price/Book	**-4.9789**	**-4.2765**	**-3.9655**	**-3.9292**
t-test	-155.2	-145,7	-140.9	-140.5
Stock return	**1.8471**	**1,0632**	**3.0473**	**2.5456**
t-test	9,7	6,1	18.3	15.4
Credit rating	**-17.3737**	**-11.7628**	**-10.7453**	**-10.1649**
t-test	-99.7	-73.3	-70.0	-66.5
Risk free rate	**-9.8476**	**-9.5299**	**-13.7364**	**-12.8601**
t-test	-41.0	-43.6	-65.6	-61,6
S&P 500 index	**-1.4088**	**-1.4607**	**0.6394**	**0.2168**
t-test	-4.3	-4.9	2.2	0.8
GDP growth	**-11.6862**	**8.1845**	**7.6708**	**12.0732**
t-test	-120.8	37.3	39,0	57,5
CDS Liquidity	**0.4775**	**0.1893**	**-0.1151**	**-0.0950**
t-test	16.3	7,1	-4.5	-3.7
Adj. R^2	**23.59%**	**36.80%**	**42.20%**	**4.98%**

Source: Own creation based on data material

[8] M14 in this this table is identical with M14 in previous table. It is copied to this table as a benchmark to M15-M17 for usability.

Adding historical volatility to the model (M15) including all the accounting variables, credit rating variable, the macroeconomic variables, and the CDS liquidity variable contributes with 13.22% to the explanatory power of the model. Replacing the historical volatility with implied volatility (M16) in comparison adds 18.61% to the explanatory power, and results in the S&P 500 index variable to become on the edge of being statistically significant. Adding both volatility variables (M17) contributes with 19.39%.

The model, including all the 10 independent variables (M17), has an explanatory power of approximately 43%, which means that the 10 variables only explain 43% of the variation in the CDS spread. More than half of the variation in the CDS spread is not captured by the model, and must be due to some other factors not included in the model.

In the model including all the 10 independent variables, the S&P 500 index variable turns out to be statistically insignificant and therefore, it does not contribute to the explanatory power of the model. Again, the stock return, the GDP growth, and the CDS liquidity have the opposite algebraic sign than expected. Again, this is most likely due to the high degree of correlation between these variables and the volatility variables, and the fact that the volatility variables dominate the other variables.

Removing the S&P 500 index from the model because of its lack of statistical significance results in the final model in table 7.6.

Table 7.6 –Regression Models: M18: Without S&P 500 Index

	M18
Intercept	**42.1414**
t-test	17.5
Historical volatility	**1.6030**
t-test	56.9
Implied volatility	**4.8313**
t-test	160.8
Leverage	**0.1541**
t-test	172.4
Price/Book	**-3.9292**
t-test	-140.5
Stock return	**2.6232**
t-test	-66.5
Credit rating	**-10.1649**
t-test	-66.5
Risk free rate	**-12.8602**
t-test	-61.6
S&P 500 index	
t-test	
GDP growth	**12.0741**
t-test	57.5
CDS Liquidity	**-0.0951**
t-test	-3.8
Adj. R^2	**42.98%**
F ratio	**19,978.80**

Source: Own creation based on data material

From the model (M18) in table 7.6 it can be concluded that all the rest of the independent variables are statistically significant, and therefore have and explanatory effect on the variation in the CDS spread. By observing the F ratio for the full model (M18) it appears that the model is strongly significant, indicating a linear relationship between the CDS spread and the independent variables.

7.1 Hypotheses

In the following part, the hypotheses lined up in the empirical analysis concerning the relationship between the CDS spread and the independent variables will be examined. The hypothesis will be investigated with univariate regression analysis on each of the 10 independent variables included in the multiple regression models. As pointed out earlier, the phrases *negative* and *positive* refer to the mathematical interpretation, and hence a negative impact on the CDS spread indicates a decrease in the CDS spread and vice versa.

Hypothesis 1: Increase in Volatility has a Positive Impact on the CDS Spread

The regression results clearly showed that the volatility variables have a large impact on the CDS spread, and they actually dominate all other variables in the multiple regression models. As expressed by table 7.7, both volatility variables put on the expected signs, and therefore the hypothesis cannot be rejected[9]. An increase in the volatility causes the CDS spread to increase as well and indicates the positive correlation between them. It can also be derived that both volatility measures are statistically significant, and are actually accountable for the majority of the explanatory power, measured by the adjusted R^2.

Table 7.7 – Univariate Regression: Volatility

Intercept	**-52.7607**
t-test	-88.3
Historical volatility	**4.8243**
t-test	274.5
Adj. R^2	**24.01%**

Intercept	**-87.9737**
t-test	-142.0
Implied volatility	**6.1602**
t-test	322.6
Adj. R^2	**30.38%**

Source: Own creation based on data material

Hypothesis 2: Increase in Financial Leverage has a Positive Impact on the CDS Spread

Table 7.8 shows that the financial leverage of the company, measured by the D/E ratio, behaves as expected and is statistically significant. From the table it can be derived that an increase in the D/E ratio by 1%, all other things being equal, corresponds to an increase in the CDS spread by 0.0628 basis points. Thus, hypothesis 2 also holds water and cannot be rejected.

Table 7.8 – Univariate Regression: Leverage

Intercept	**75.7094**
t-test	202.6
Leverage	**0.0628**
t-test	95.5
Adj. R^2	**3.68%**

Source: Own creation based on data material

[9] When the hypothesis is not rejected it is indicated that the hypothesis can be perceived as correct. But since statistical hypothesis is rather not rejected than accepted, the hypothesis is referred to as not rejected.

Hypothesis 3: Increase in the Price/Book Value has Negative Impact on the CDS Spread

It can be derived from table 7.9 that an increase in the P/B ratio by 1 decreases the CDS spread by 0.3307 basis points. Even if the variable only contributes by a limited amount to the explanation of the variation in the CDS spread, it is still statistically significant and puts on the expected algebraic sign as mentioned. Thus, the hypothesis can be assumed as correct and therefore, it cannot be rejected.

Table 7.9 – Univariate Regression: Price/Book value

Intercept	**87.8030**
t-test	234.1
Price/Book	**-0.3307**
t-test	-15.7
Adj. R^2	**0.10%**

Source: Own creation based on data material

Hypothesis 4: Stock Return is Negatively Correlated with the CDS Spread

As derived from the regression models M12-M19 and table 7.10, the stock return puts on the opposite algebraic sign than expected before the analysis. From the univariate regression it can be derived that an increase in the stock return by 1% will cause an increase in the CDS spread by 1.3878 basis points. The variable proves to be statistically significant, but not as strongly as many of the other variables though, and it explains only 0.03% of the variation in the CDS spread. The hypothesis expecting negative correlation between the stock return and the CDS spread thus should be questioned and initially rejected. The stock return variable and the correlation with the CDS spread will be investigating further in the next chapter.

Table 7.10 – Univariate Regression: Stock Return

Intercept	**86.2695**
t-test	237.3
Stock return	**1.3878**
t-test	9.0
Adj. R^2	**0.03%**

Source: Own creation based on data material

Hypothesis 5: Increase in Credit Rating has a Negative Impact on the CDS Spread

As expected and derived from table 7.11, the credit rating variable is strongly statistically significant and puts on a negative algebraic sign. This means that a higher rating will decrease the CDS spread, which the hypothesis also implies and therefore, it cannot be rejected.

Table 7.11 – Univariate Regression: Credit Rating

Intercept	**422.9550**
t-test	167.4
Credit rating	**-25.0648**
t-test	-134.5
Adj. R^2	**7.05%**

Source: Own creation based on data material

Hypothesis 6: Increase in the Risk Free Rate Level has Negative Impact on the CDS Spread

Throughout all the multiple regression models and table 7.12, it can be concluded that the risk free rate affects the CDS spread negatively. If the risk free rate increases, the CDS spread will decrease. This implies that the hypothesis holds water at expected, and cannot be rejected. The variable also proves to be statistically significant.

Table 7.12 – Univariate Regression: Risk Free Rate

Intercept	**119.8854**
t-test	165.5
Risk free rate	**-14.3877**
t-test	-53.4
Adj. R^2	**1.18%**

Source: Own creation based on data material

Hypothesis 7: The S&P 500 Index is Negatively Correlated with the CDS Spread

The S&P 500 index variable showed some interesting behaviour throughout the models. The variable was eventually removed from the model, since it turned out to be statistically insignificant. The univariate regression in table 7.13 confirms this. The variable puts on the opposite algebraic sign in the table, but since it is not significant, it does not make sense to interpret the algebraic sign, and the hypothesis must be rejected after all. As with stock return, this variable is investigated further in the next chapter.

Table 7.13 – Univariate Regression: S&P 500 Index

Intercept	**86.3378**
t-test	237.4
S&P 500 index	**0.1634**
t-test	0.6
Adj. R^2	**0.00%**

Source: Own creation based on data material

Hypothesis 8: Growth in GDP is Negatively Correlated with the CDS Spread

The GDP growth variable also showed a very interesting pattern of behaviour in the regression models, which was mostly due to the high degree of correlation with the volatility variables, which are dominating the models. In the univariate regression in table 7.14, the variable after all puts on the expected algebraic sign indicating a negative relationship with the CDS spread, and the variable is strongly statistical significant. An increase in the GDP growth is therefore proved to decrease the CDS spread as expected by the lined up hypothesis, and thus the hypothesis cannot be rejected.

Table 7.14 – Univariate Regression: GDP Growth

Intercept	**128.1512**
t-test	267.1
GDP growth	**-25.9136**
t-test	-128.0
Adj. R^2	**6.43%**

Source: Own creation based on data material

Hypothesis 9: CDS Liquidity is Positively Correlated with the CDS Spread

The CDS liquidity in the model is measured by the bid-ask spread on the CDS contracts. A higher spread, meaning a lower liquidity, would be expected to increase the CDS spread. The results from the univariate regression presented in table 7.15 implies that the CDS liquidity is statistically significant, and a higher spread and hence lower liquidity will cause the CDS spread to increase as excepted. This last hypothesis turns out to be plausible as well, and cannot be rejected.

Table 7.15 – Univariate Regression: CDS Liquidity

Intercept	**78.2163**
t-test	186.9
CDS Liquidity	**1.2708**
t-test	38.8
Adj. R^2	**0.63%**

Source: Own creation based on data material

7.2 Summary

The base case model (M0) includes the theoretical determinants, based on the structural model by Merton: historical volatility, leverage, and the risk free rate. The model has an explanatory power of 27.85%, and it is clear that all three variables are strongly statistically significant. However, replacing historical volatility with implied volatility increases the explanatory power of the model to 34.37%. Including both volatility variables, however, increases the explanatory power to 34.84%. By examined regression models on each of the independent variables, it becomes obvious that the volatility variables are responsible for the majority of the explanatory power of the model. By investigating a regression model solely based on the macroeconomic variables and the CDS liquidity, it was found that together they had an explanatory power of 7.13%. The macroeconomic variables generally showed some different behaviour in the classified models, but it was mostly due to the high degree of correlation with the volatility variables. To examine the impact of the accounting variables and credit rating, three models (M12-M14) were set up to compare the contribution of each and also in combination, holding the macroeconomic variables and CDS liquidity constant. From this it appeared that all the variables turned out to be statistically significant, and that the accounting variables added a higher explanatory power to the model than the credit rating solely. Thus, it appears that the firm specific accounting variables are not better captured by the credit rating. However, adding both the accounting variables and credit rating contributes to a higher explanatory power.

The model, including all the 10 independent variables (M17), has an explanatory power of approximately 43%, which means that the variation in the included variables explains approximately 43% of the variation in the CDS spread. It can furthermore be derived that the volatility variables clearly dominate the other variables, and that they are accountable for the majority of the explanatory power of the model. More than half of the variation in the CDS spread is not captured by the model, and must be due to some other factors not reflected by the included variables. In the complete model, the S&P 500 index variable turns out to be statistically insignificant and therefore, stock return, GDP growth, and CDS liquidity have the opposite algebraic sign than expected, which is mostly due to the high degree of correlation between the included variables, and the fact that the volatility variables dominate the other variables.

Hypotheses 1-9 concerning the independent variables' impact on the CDS spread were tested using univariate regression analysis, and it was found that none of the hypotheses lined up in chapter 6 could be rejected, except for hypotheses 4 and 7 concerning the stock return and S&P 500 index. Both variables turned out to be positively correlated with the CDS spread, which was not expected. Also S&P 500 turned out to be statistically insignificant. Because of this, both variables will be investigated further in the following chapter. Volatility, leverage, and CDS liquidity turned out to be positively correlated with the CDS spread, while price/book value, credit rating, risk free rate, and GDP growth turned out to be negatively correlated with the CDS spread, as expected.

8 Model Verification

The fourth stage of the model building process consists in a verification of the fitted model. In order to perform this, the 5 Standard Multiple Regression Assumptions set forward by Newbold et al. (2013) are examined in the chronological order in which they are listed.

8.1 Model Assumptions

After fitting the regression model, it is valuable to examine the residuals to determine, how the model actually fits the data, and if the regression assumptions are met.

Standard Multiple Regression Assumptions:

1. The $x_i$terms are fixed numbers, which are independent of the error terms, ε_i.
2. The dependent variable Y is a linear function of the independent variables, x_i.
3. The error terms are normally distributed random variables with a mean of zero and the same variance, σ^2. The latter is referred to as homoscedasticity.
$$E[\varepsilon_i] = 0 \quad and \quad E[\varepsilon_i{}^2] = \sigma^2 \qquad for(i = 1, \dots, n)$$
4. The error terms, ε_i, are not correlated with one another, so that the following applies:
$$E[\varepsilon_i, \varepsilon_l] = 0 \quad for\ all\ i \neq l$$
5. It is not possible to find a direct linear relationship between the independent variables, x_i. This is also referred to as multicollinearity.

Source: Newbold et al. (2013)

1. The Determinants must be Independent of the Residuals

To verify the first assumption, one must examine the correlation between the residuals and the independent variables. A residual plot by row can help giving an indication of this correlation, as a trend in the residuals observed might suggest a pattern.

However, according to Newbold et al (2013), this assumption is most often taken for given, as it only fails to hold in some advanced econometric work, where the independent variables cannot be measured precisely. This will typically not be the case, which also applies in the modelling of CDS spread.

With that in mind and with the support from the later residual plot presented, the first assumption is said to hold for the specific model.

2. The Dependent Variable Must be a Linear Function of the Determinants

In order to test this assumption, the top section of the earlier presented correlation matrix is revisited, as this indicates how CDS spread is correlated with the independent variables in the model. The correlation between CDS spread and the given determinant should be significant in order to claim a linear relation.

Table 8.1 – Extraction of Correlation Matrix

	CDS spread	Historical vol	Implied vol	Leverage	Price/ Book	Equity return	Credit rating	Risk free rate	S&P 500 index	GDP Growth	CDS Liquidity
CDS spread	**1.000**	**0.490**	**0.551**	**0.192**	**-0.032**	**0.016**	**-0.266**	**-0.109**	**0.001**	**-0.217**	**0.079**
		< 0.0001	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*0.5799*	*< 0.0001*	*< 0.0001*

Source: own contribution based on data material

From the table, it emerges that all variables, except S&P 500, have a high degree of correlation with the dependent variable. This is further supported by the p-values provided beneath the correlations. The p-values <0,0001 indicates that the hypothesis of zero correlation between two variables cannot be rejected.

The variable S&P500, however, suggests a 57.99% probability that no direct linear relationship between the determinant and the CDS spread exist. This same relationship was found in the model in the preceding chapter. The coefficient statistics turned out to have no statistical significance, indicating the variable should be removed from the model.

The strength of the linear relationship between the dependent and the independent variables can also be assessed visually through a scatterplot, and numerically through the R^2 and the F-statistic. The two latter should both take on large values in order to meet the assumption of linearity. From the linear regression conducted in the previous chapter, the adjusted R^2 of the model was 42.98 % and the F-statistic was found to be 19,9978.80 for the full model. These figures both indicate evidence to support a linear model.

The above examination suggests some degree of linear relationship between the CDS spread and the determinants, wherefore the second assumption is considered met.

3. The Residuals Must be Normally Distributed with a Mean of Zero and Homoscedastic

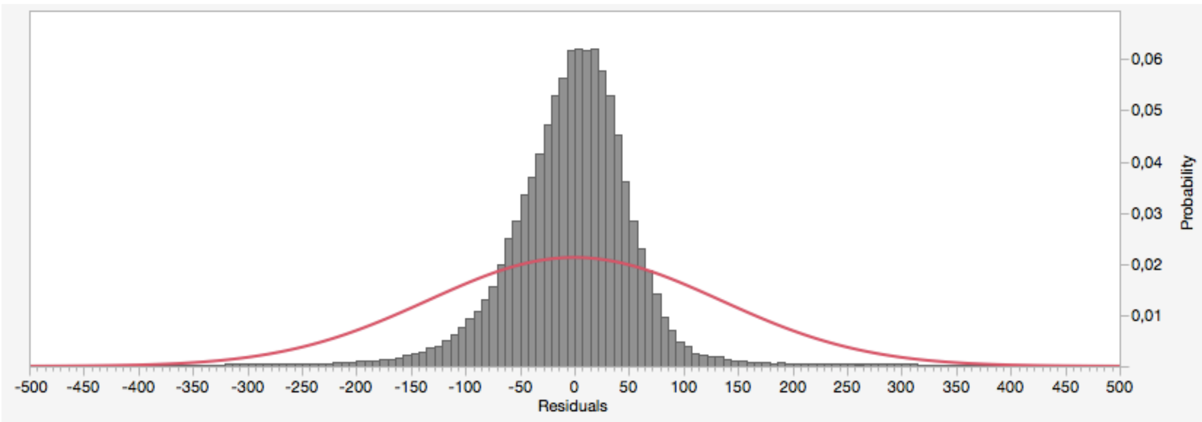
For the third assumption to hold, the residuals must be both normally distributed with a mean of zero, and simultaneously the residuals must be homoscedastic.

Normality

The first part of the assumption regarding the normality in the residuals can be examined, both by a histogram plotting the distribution of the residuals, and by assessing a normal quantile plot of the residuals.

The horizontal axis of the histogram below is cropped to further assess the observations with higher density. Thus, the outliers are not shown in the figure. The normal fit is however based on the entire data set, so the crop is only made for illustrative purposes.

Figure 8.1 – Histogram of Residuals



Source: own contribution based on data material

From the histogram above, the residuals seem to be both normally distributed as well as constituting a mean of zero. Thus based on this illustration, the assumption of normality in the residuals seems to hold.

However, a numerical examination is conducted to further test the assumption. This is conducted through a Goodness-of-Fit test, which in JMP consists in a Kolmogorov-Smirnov test (KSL test) for larger sample sizes than 2000. From this test, it appears that the null hypothesis of normality in residuals cannot be rejected at a 1% significance level, but is, however, rejected at a 5% significance level (figure 14. 2 in appendix).

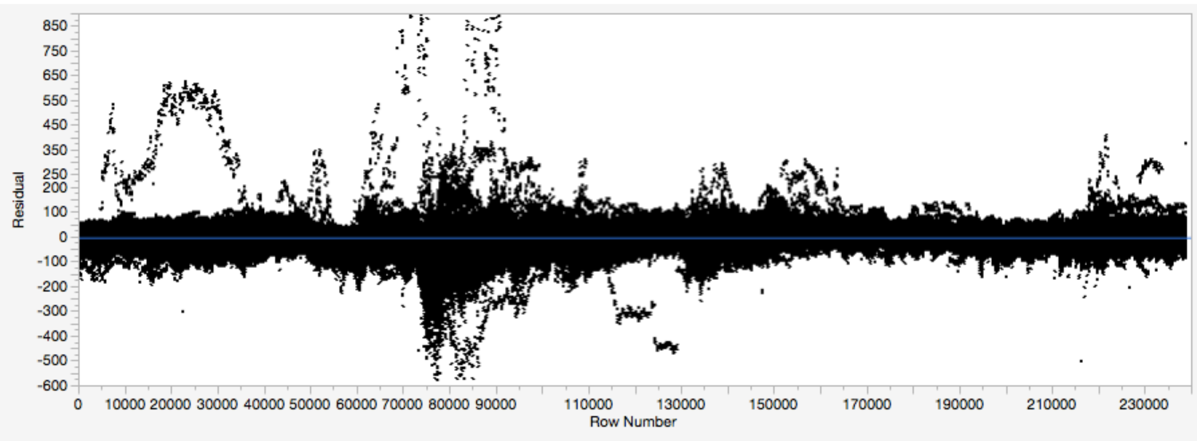
The Central Limit Theorem allows one, according to Newbold et al (2013), to relax this assumption if the sample size is large enough, which would be the case with this data set. However, the presence of outliers might cause some issues to this consideration.

With large reservations, the assumption of normality in the residuals are said to be met, supported by the histogram and The Central Limit Theorem, but due to outliers, the Goodness-of-fit test can only accept the null hypothesis of normality on a 1% significance level.

Homoscedasticity

The second part of this model assumption is related to homoscedasticity in the residuals. This requests a random and constant variance in the residuals, and can be assessed by plotting the residuals against row, as the figure below shows.

Figure 8.2 – Residuals plotted against Row Number



Source: own contribution based on data material

The observations must be randomly spread, and no tendency or pattern relative to row should be observed. However, some tendency appears from the plot, wherefore an unambiguous conclusion cannot be made from this illustration, and a numerical test is needed in order to fully reject or accept the assumption of homoscedastic residuals.

To test for homo- or heteroscedasticity in the residuals, one can perform a White test or the Breusch–Pagan test. However, a median split is conducted, in order to test if the variances above the median are the same as those below the median. If the latter would be the case, then the assumption of homoscedasticity in the variance is said to hold.

The tests mentioned above are conducted, and both the Brown-Forsythe test and the Welch test reject the null hypothesis of equal variance in the residuals. The estimated test statistics and further details can be found as enclosed appendix, figure 14.3. The tests thereby indicate that the variance in the residuals is not constant and thus, the assumption of homoscedastic residuals is not met. However, this is often the case when regressing economical and financial panel data.

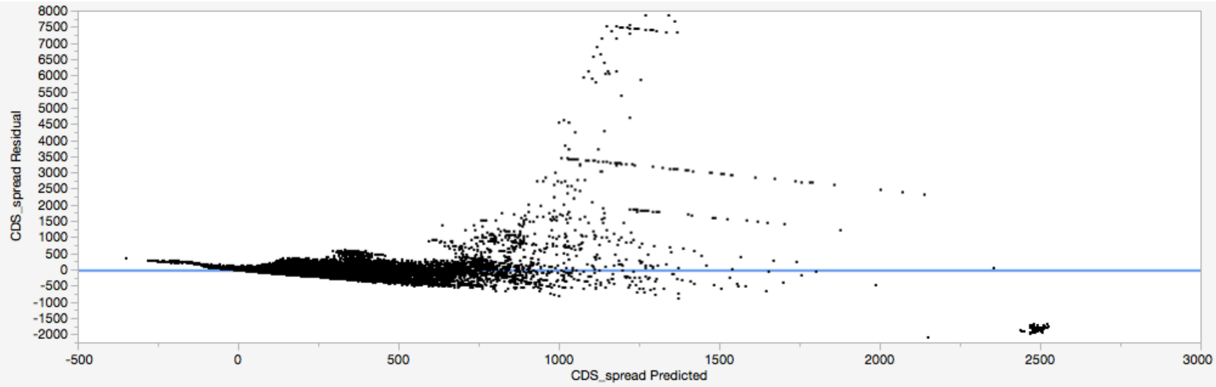
From the above examination of the residuals, it is concluded that the third assumption for the multiple regression is only partly met. Normality in the residuals is with some reservations considered met, however, homoscedasticity in the residuals is rejected.

4. The Residuals Must be Non-Correlated with one another

The fourth assumption for multiple regression models requires the residuals to be independent of one another. Again, this can be addressed both visually and numerically by residual plots and tests respectively.

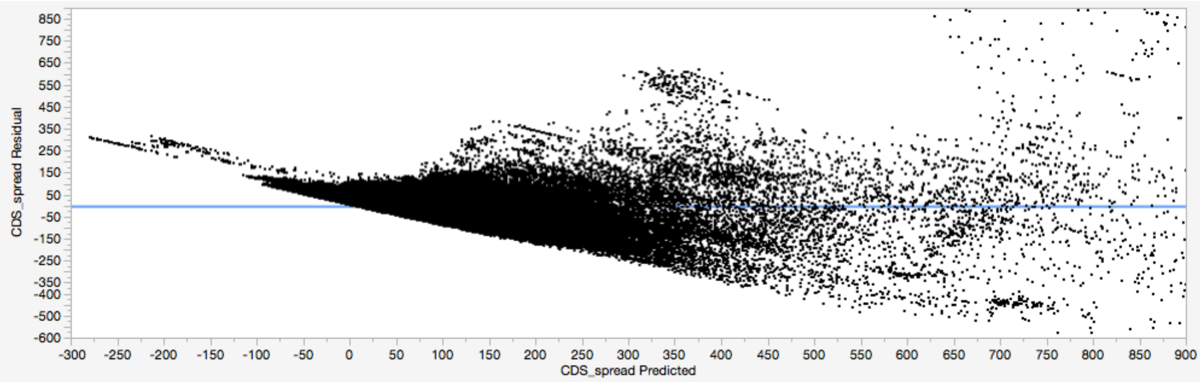
Figure 8.3 and 8.4 are identical residual plots, where the predicted CDS spread is plotted against the residuals. However, figure 8.4 is cropped in order to get a closer look into the larger concentrations of observations.

Figure 8.3 – Residuals plotted against Predicted CDS Spread



Source: own contribution based on data material

Figure 8.4 – Residuals plotted against Predicted CDS Spread (Cropped)



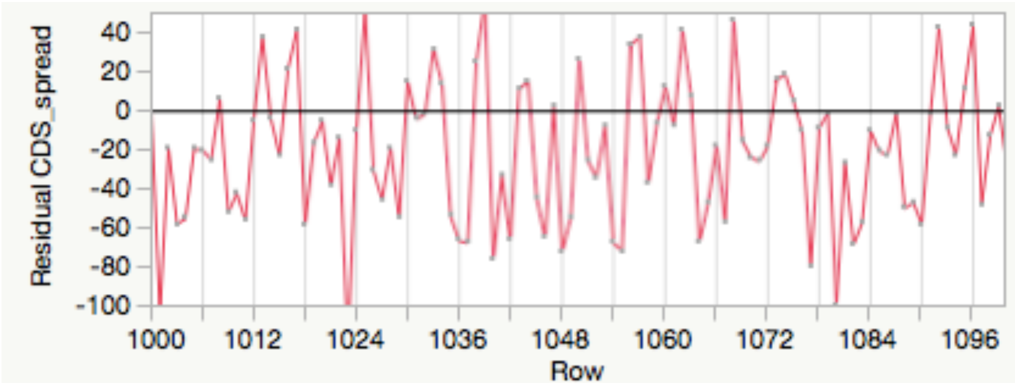
Source: own contribution based on data material

In order to meet the assumption of no correlation between the residuals, the observations in above plot should spread randomly around zero for all values of predicted CDS spread. The observations should furthermore not take on any trend nor follow a curve. However, a trend is spotted as the residuals seem to increase with an increase in the predicted CDS spread, and therefore the conclusion regarding the correlation is a bit ambiguous.

A correlation between residuals over several time periods could indicate that some factors are not included in the model. Thus these effects would be included in the residuals in the form of correlation from adjacent time periods. This further emphasizes the importance of testing the hypothesis that the residuals are not correlated when performing regression with time-series data. Correlation between first-order residuals are defined as autocorrelated, meaning that the residual has a higher correlation with the previous time period contrary to residuals two or more periods previous in the time series (Newbold et al. 2013).

Again graphical methods might be useful in detecting the presence of such autocorrelation, and figure 8.2 provides this graphical description. However the correlation in the residuals from one period to another does not show clearly from this figure, because of the density and high number of observations. Instead a close up of the residuals plotted against time is provided in figure 8.5, in order to investigate this matter further.

Figure 8.5 – Time-series plot of residuals (cropped)



Source: Own creation based on data material, JMP 13

Examining the time series plot of the residuals above no apparent pattern in the progression through time is observed, however the plot does not provide strong evidence for autocorrelation in the residuals.

Hence a more formal test is desirable, wherefore a Durbin Watson test is conducted. The Durbin Watson test examines for first order autocorrelation, and thereby seeks to test the null hypothesis of no autocorrelation.

Table 8.2 – Durbin-Watson test

Durbin-Watson	Number of Obs.	AutoCorrelation	Prob<DW
1.898	238,580	0.051	<0.0001*

Source: own contribution based on data material, test conducted in JMP 13

According to Newbold et al (2013), the test statistic (d) always lies between 0 and 4, positive correlations being reflected by a small value of d, and negative correlations are indicated by a test statistic closer to the upper level of 4. If the residuals are not autocorrelated, then d is approximately 2.

When conducting the Durbin Watson test, it is found that the test statistic equals 1.898, being very close to 2, which implies no autocorrelation. The p-value further indicates that the null hypothesis cannot be rejected, and it is therefore concluded that the residuals are not autocorrelated.

5. Multicollinearity between the Determinants should not Exist

The relationship between the different independent variables was briefly examined in the correlation matrix in the chapter presenting the data set and also commented in the regression results. However, a more thorough examination needs to be conducted in order to test, whether or not the fifth and last assumption of the multiple model regression holds.

It is inevitable that the independent variables will have no collinearity when working with empirical data, as the correlation matrix below also reveals. Thus, some degree of collinearity is generally accepted, as long as no perfect multicollinearity appears. The presence of multicollinearity in a dataset leads to difficulties knowing to which variables specific changes are related.

The correlation matrix is revisited, and shows the correlation between all the explanatory variables reviewed in the analysis so far. It emerges from the matrix that no perfect multicollinearity between any variables is observed.

Table 8.3 – Correlation Matrix

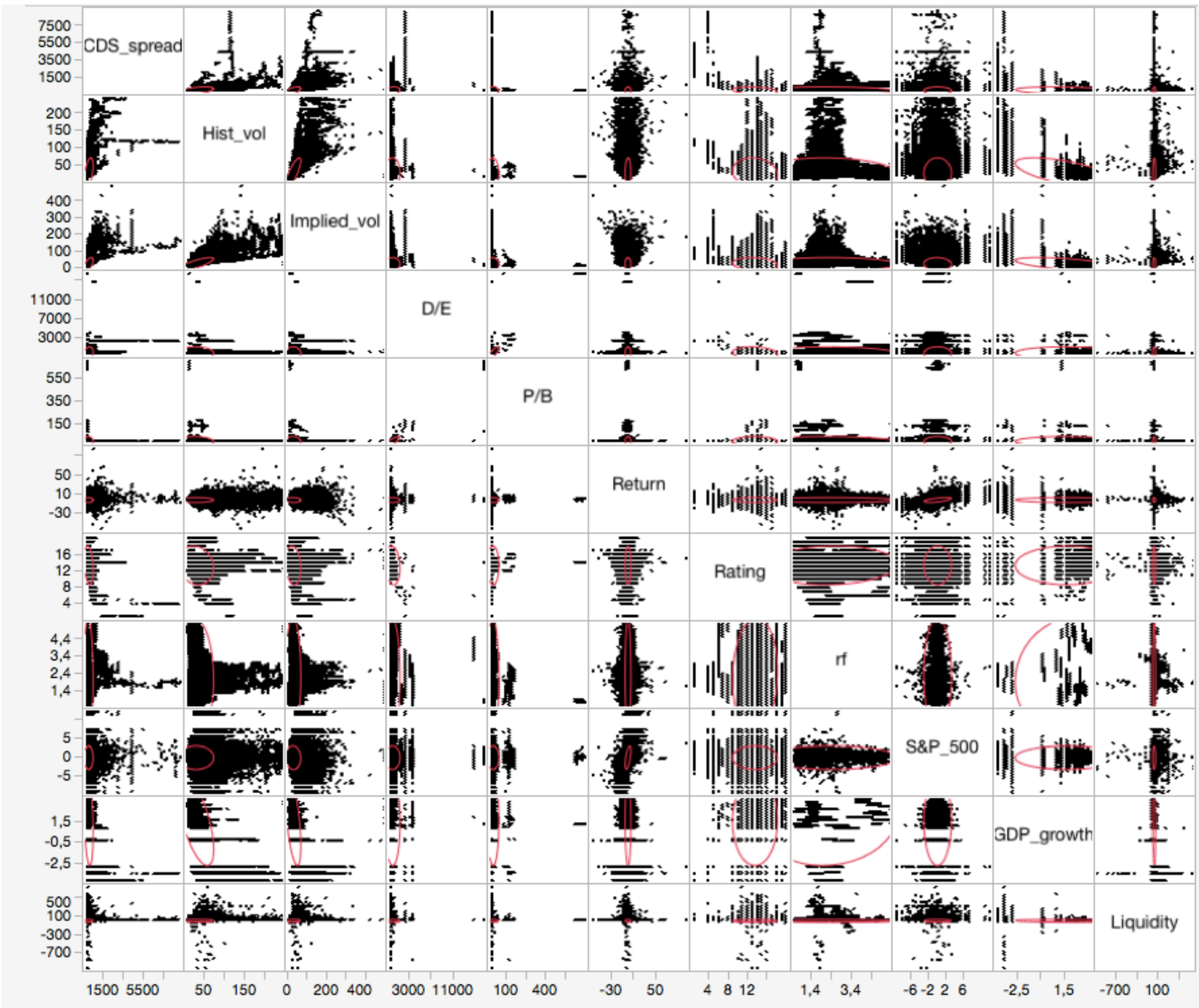
	CDS spread	Historical vol	Implied vol	Leverage	Price/ Book	Stock return	Credit rating	Risk free rate	S&P 500 index	GDP Growth	CDS Liquidity
CDS spread	1.000	0.490	0.551	0.192	-0.032	0.016	-0.266	-0.109	0.001	-0.217	0.079
		< 0.0001	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*0.5799*	*< 0.0001*	*< 0.0001*
Historical vol		1.000	0.808	0.008	-0.068	0.021	-0.140	-0.086	0.006	-0.637	0.158
			< 0.0001	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*0.0020*	*< 0.0001*	*< 0.0001*
Implied vol			1.000	0.023	-0.072	-0.042	-0.149	-0.018	-0.049	-0.563	0.173
				< 0.0001	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*	*< 0.0001*
Leverage				1.000	0.810	0.002	-0.155	-0.058	0.002	-0.028	0.002
					< 0.0001	*0.4697*	*< 0.0001*	*< 0.0001*	*0.3326*	*< 0.0001*	*0.3211*
Price/Book					1.000	0.004	-0.022	-0.082	0.005	0.000	-0.005
						0.0489	*< 0.0001*	*< 0.0001*	*0.0240*	*0.8834*	*0.0093*
Stock return						1.000	-0.008	-0.002	0.616	-0.001	-0.005
							< 0.0001	*0.3277*	*< 0.0001*	*0.6142*	*0.0238*
Credit rating							1.000	0.077	-0.003	0.010	-0.002
								< 0.0001	*0.1176*	*< 0.0001*	*0.4230*
Risk free rate								1.000	-0.003	0.122	-0.042
									0.0920	*< 0.0001*	*< 0.0001*
S&P 500 index									1.000	0.009	-0.010
										< 0.0001	*< 0.0001*
GDP Growth										1.000	-0.191
											< 0.0001
CDS Liquidity											1.000

Source: own contribution based on data material

The correlation between historical volatility and implied volatility is very high, and the same level of correlations is seen between the variables price/book and leverage. However, there must be a very high level of collinearity before the regression estimates are affected.

Another way of examining the relationship between the variables is by the use of a matrix plot, like the one presented below. This matrix provides a display format, which is similar to the correlation matrix above, however, the advantage of this scatter plot is that all observations are included, and any potential linear relationship is visualized providing a clearer overview.

Figure 8.6 – Scatterplot matrix



Source: own contribution based on data material, JMP 13

This presentation enables one to see, if a linear relationship exists, or if there is some strange grouping between two variables. The red lines indicate the density of observations, and further assists the examination of patterns. The assessment of the scatter plot matrix leads to the same conclusion as to no perfect multicollinearity.

The above examination of the relationship between the various independent variables leads to the conclusion that correlation between the variables is present to some varying degree, however, no direct linear relationship is found, and the fifth assumption is therefore met.

The model verification has now been completed, assessing the five assumptions of multiple regression put forward by Newbold et al (2013). From this examination, it appears that there might be some problems in using the dataset for regression purposes. Especially the third assumption regarding normality and homoscedasticity in the residuals was not found adequate.

According to Newbold et al (2013), the least square procedure can in some cases still be used, despite of some violations of the assumptions put forward. The previous empirical studies' similar handling of these contradictions further justifies the model selection conducted in the thesis. However, it should of course be kept in mind that major breaches in the assumptions may affect the results of the regression.

9 Additional Regression Results and Robustness Check

In chapter 7, the results from the regression analysis were examined. The regression model primarily showed, what was expected for most of the hypotheses lined up. However, some of the variables had an unexpected behaviour, and the entire model only obtained an explanatory power of approximately 43%, meaning that slightly more than half of the variation in the CDS spread cannot be explained by the included variables, and therefore should be explained by other factors. Since the analysed period spans 2005 to 2016, it includes some very different states of the American economy, comprising the financial crisis that escalated in 2008. As presented in the second chapter, the number of defaults varies a lot in the included time period, reaching its absolute top in 2009.

All previous empirical studies are based on data from the late 90's and early 00's, and hence several years prior to the crisis. And even though we cannot directly compare the results, the large deviation in the results from the previous studies and this paper could be due to the fact that this paper includes a period with a very comprehensive financial crisis and, not to forget, the fact that the CDS marked has developed and increased a lot since then. Based on this, the regression results are divided into shorter periods to investigate, how the results vary during the different periods.

Since the two variables stock return and S&P 500 index turned out to have a positive but very limited impact on the CDS spread, with the latter being insignificant, a simple moving average of the variables are calculated. The new variable measurements will be examined to investigate their behaviour and thus the two rejected hypotheses 4 and 7 further.

Furthermore, to test the robustness of the volatility variables, VIX will be included as the measurement of volatility and compared to historical and implied volatility. To test the robustness of the response variable, CDS spread mid, the regression model is build up with respectively the CDS bid spread and the CDS ask spread as independent variables.

9.1 Time Factor

To find out if the time factor plays a considerable role in the analysis, the data and regression is split up into 4 minor periods. The first period spans from 2005 to 2006, and represent a period of economic boom and very low number of defaults. The second period spans from 2007 to 2009, and is characterised by the culmination of the financial crisis and a very high level of the CDS spreads combined with a very high number of defaults. The third period spans from 2010-2012, and is the period just after the crisis, where the American economy was still bothered by high volatility as well as low interest rates. The last period spans 2013 to 2016. Since the periods span different years, the number of total observations differs across the periods. However, this is not estimated to affect the results from the regression. Below in table 9.1 the mean values for each variable in the different periods are reported.

Table 9.1 – Mean Values of the Variables in Different Periods

Mean Values	2005-2006	2007-2009	2010-2012	2013-2016
CDS Spread	41.9804	128.2003	103.3954	64.2902
Historical volatility	22.0927	41.9126	28.3880	22.7170
Implied volatility	23.5794	40.0962	27.5409	22.3618
Leverage	101.3743	169.5509	174.8700	198.7993
Price/book	2.2227	3.1614	4.1526	6.6347
Stock return	0.0599	0.0281	0.0560	0.0675
Credit rating	13.6599	13.5534	13.2881	13.3280
Risk free rate	4.3913	3.1294	1.3889	1.4117
S&P 500 index	0.0424	-0.0051	0.0479	0.0564
GDP growth	3.0057	-0.4239	2.1234	2.0664
CDS liquidity	5.0067	8.6049	5.6897	5.9587

Source: Own creation based on data material

Table 9.1 shows that the average CDS spread tops in the second period, and decreases in the periods after the crisis. In the fourth period, the average level is still somewhat higher than in the first period. The volatility, both historical and implied, also reaches very high values in the second period, and slowly returns to approximately the same level as in the first period. The financial leverage and the P/B value have increased continually during the entire timeline, while the risk free rate is decreasing considerably over the periods. Converted back into credit rating classes (figure 6.3) and rounded up to nearest whole number, the average credit rating decreases from A- to BBB+ from the second period to third period. The stock return and the S&P 500 index both reach the bottom in the second period. In the first, third, and fourth periods they are almost at identical average levels. The average GDP growth is negative in the second period, and the bid-ask spread is notably high in the same period, indicating a very low liquidity on the CDS contracts. The liquidity is lower in the following period, but increases again in the fourth period. Thus, it can be observed that the majority of the independent variables are quite volatile and unstable in the entire period analysed, which most likely affects the results and the explanatory power of the model.

The regression results based on each period are reported below in table 9.2. The composition is the same as in the last chapter with the t-test value reported below the coefficient estimates. The t-test is marked in red if it is insignificant, and in blue if it is just on the edge of being insignificant. The significance level is 5%, identical with the last chapter.

Table 9.2 –Regression Models 2005-2006, 2007-2009, 2010-2012, and 2013-2016

	2005-2006	2007-2009	2010-2012	2013-2016
Intercept	**22.3292**	**151.4923**	**99.3481**	**34.4947**
t-test	4.4	15.9	48.5	25.38
Historical volatility	**-0.7992**	**1.7481**	**1.9810**	**2.7091**
t-test	-15.1	27.9	65.6	109.35
Implied volatility	**3.1061**	**5.8930**	**2.2436**	**2.1983**
t-test	60.4	89.8	69.8	88.0
Leverage	**0.3873**	**0.1474**	**0.1005**	**0.0424**
t-test	258.6	75.6	111.5	49.72
Price/Book	**-8.7036**	**-3.1986**	**-2.9548**	**-1.0955**
t-test	-84.1	-32.6	-105.5	-49.53
Stock return	**0.7351**	**3.7386**	**0.8264**	**0.525**
t-test	4,5	9.1	5.3	5.59
Credit rating	**-6.2137**	**-26.0515**	**-7.4392**	**-4.7015**
t-test	-52.8	-50.8	-62.4	-63.8
Risk free rate	**1.2255**	**3.6810**	**-12.9551**	**-8.6657**
t-test	1.8	2.3	-39.8	-17.87
S&P 500 index	**0.5460**	**-0.8483**	**0.8711**	**0.7923**
t-test	1.5	-1.2	3.6	4.6
GDP growth	**7.5343**	**14.0025**	**-6.2560**	**-1.8345**
t-test	11.6	17.3	-1.8	-8.39
CDS Liquidity	**0.1608**	**-0.0388**	**-0.2116**	**-0.5818**
t-test	1.8	-0.8	-3.8	-19.24
Adj. R^2	**71.24%**	**43.25%**	**57.14%**	**56.01%**

Source: Own creation based on data material

From table 9.2, it can be derived that the model covering the years prior to the financial crisis has an explanatory power of 71.24%, whereas the model covering the crisis has an explanatory power of only 43.25%. The two models covering periods after the peak of the crisis have an explanatory power of approximately 57% and 56%. The evolution in the explanatory power of the model indicates a substantially better explanation of the variation in the CDS spread prior to the crisis. The model from 2005-2006, prior to the crisis though shows some other interesting factors. In the full model, the historical volatility has the opposite sign than expected, indicating that an increase in the historical volatility would cause a decrease in the CDS spread. The reason for this behaviour is found in the high correlation between both the historical volatility and implied volatility, and the historical volatility and credit rating. Thus, historical volatility is positively correlated with the CDS spread, but is dominated by both credit rating and implied volatility (see table 14.5 in appendix for correlation matrix). The risk free rate, S&P 500 index, and CDS volatility are statistically insignificant in the model prior to the crisis.

In the 2007-2009 model, the S&P 500 index and the CDS liquidity variables are also statistically insignificant. The risk free rate is just on the edge of being significant, and is highly negatively correlated with and dominated by the volatility variables, which explains the unexpected algebraic sign (see table 14.6 in appendix for correlation matrix).

The models 2010-2012 and 2013-2016 show more expected results with all the variables being significant, even though the explanatory power is 57.14% and 56.01% respectively. Again, the stock return, the S&P500 index, and the CDS liquidity put on opposite algebraic signs than expected in both models, which has been a common issue in many of the models examined in this thesis. Some of the unexpected behaviour of the variables is due to the high degree of correlation between the independent variables. The variables stock return and S&P500 index also showed unexpected results in the univariate regression in the last chapter, and hence, these variables will be investigated further later in this chapter.

Table 9.3 below shows the correlation between the CDS spread and the independent variables corresponding to the regression models during the different time periods.

Table 9.3 – Correlation between the Independent Variables and CDS spread in Different Periods

	2005-2006	2007-2008	2010-2012	2013-2016
Historical volatility	0.2516	0.4685	0.5923	0.6782
Implied volatility	0.3710	0.5565	0.5891	0.6541
Leverage	0.4907	0.3134	0.1462	-0.0446
Price/Book	-0.0598	-0.0265	-0.0860	-0.0784
Stock return	-0.0071	0.0227	0.0111	0,0119
Credit rating	-0.4211	-0.3122	-0.4274	-0.3639
Risk free rate	-0.0512	-0.2346	-0.0685	-0.1382
S&P 500 index	0.0014	0.0033	0.0081	0.0075
GDP growth	0.0416	-0.2376	0.0186	-0.1800
CDS Liquidity	0.0207	0.0676	0.0263	0.0290

Source: Own creation based on data material. Dark green and red colours indicate respectively, strong positive and strong negative correlation. Light green and red colours indicate respectively, less strong positive and less negative correlation

Table 9.3 clearly shows how the correlation between the CDS spread and the two volatility variables has increased significantly during the periods. In the first two periods, implied volatility is higher correlated with the CDS spread, but in the last two periods, the correlation between the CDS spread and respectively historical and implied volatility is almost at the same level. On the other hand, it can be derived from the table that the correlation between the CDS spread and financial leverage has decreased continually from the first to the fourth period. The correlation actually goes from positive to negative in the last period. Credit rating and price/book value seem to have nearly the same correlation with the CDS spread in all periods. The same thing applies for the risk free rate, however, it is more strongly negatively correlated with the CDS spread in the second and fourth period. GDP growth varies a bit during the periods. It goes from being slightly positive correlated with the CDS spread to strongly negative correlated in the second period. This pattern is repeated again from third to fourth period. CDS liquidity is slightly positively correlated with the CDS spread in all the periods, except for the second period, representing the financial crisis. Stock return and the S&P 500 index are positively correlated with the CDS spread to the same extent in almost all the four periods, except for stock return in the first period. Thus, the issue with the unexpected behaviour of these variables does not seem to be dependent on the period and therefore, these variables will be examined further in a following section.

By running the full regression model on each single year of the entire period, we obtain an explanatory power ranging between 49.4% as the lowest in 2014, and 73.4% as the highest in 2006. In general, the model tends to explain the variation in the CDS spread better when based on individual years rather than on longer periods. This could indicate a lack of robustness fit of the model during the years since the explanatory power and the estimated coefficients vary over the years. This will not be investigated further due to the constraints of the thesis (see figure 14.8-14.19 in appendix for the regression results of each of the years). In table 9.4 below, the explanatory power is reported on single years for both the base case model, including only the theoretical variables inspired by the structural model, and the full model including all 10 independent variables.

Table 9.9.4 – Adjusted R^2 based on Regression Models on Individual Years in the entire Period

Adj. R^2 - M0 model	
2005	54.5%
2006	61.8%
2007	48.3%
2008	58.2%
2009	29.7%
2010	42.8%
2011	44.0%
2012	42.0%
2013	52.5%
2014	36.3%
2015	34.0%
2016	53.3%

Adj. R^2 - M17 model	
2005	69.8%
2006	73.4%
2007	59.9%
2008	71.8%
2009	54.8%
2010	65.8%
2011	55.3%
2012	55.5%
2013	59.9%
2014	49.4%
2015	49.7%
2016	65.6%

Source: Own creation based on data material

9.2 Stock Return and S&P 500 Index based on Simple Moving Average

Since the measurements of the variables: stock return and the S&P 500 index, acted unexpectedly in the regression analysis, another calculation of the variables will be examined. The included variables were based on raw daily stock return with a lot of noise in the data. To adjust for the daily fluctuations in the variables, we calculated a simple moving average based on the last 180 days on both the stock return and the S&P 500 index, and included both in the final model instead of the original variables. The results are reported in table 9.5 below.

Table 9.5 – Regression Models: M17 and SMA (180) based on Simple Moving Avarage of the variables: Stock Return and S&P 500 Index

	M17	SMA (180)
Intercept	**71.8498**	**46.1014**
t-test	30.4	18.7
Historical volatility	**1.6024**	**1.7966**
t-test	56.9	62.2
Implied volatility	**4.8322**	**4.6999**
t-test	160.7	141.9
Leverage	**0.1541**	**0.1533**
t-test	172.3	172.3
Price/Book	**-3.9292**	**-3.8871**
t-test	-140.5	-139.6
Stock return	**2.5456**	**-127.9087**
t-test	15.4	-47.2
Credit rating	**-10.1649**	**-10.6599**
t-test	-66.5	-69.4
Risk free rate	**-12.8601**	**-11.8285**
t-test	-61.6	-56.7
S&P 500 index	**0.2168**	**225.4587**
t-test	0.8	41.4
GDP growth	**12.0732**	**10.0511**
t-test	57.5	46.0
CDS Liquidity	**-0.095**	**-0.0475**
t-test	-3.7	-1.9
Adj. R^2	**42.98%**	**43.49%**

Source: Own creation based on data material

From table 9.5, it can be derived that by adding stock return and S&P 500 index, based on simple moving average, the explanatory power of the model increases by only 0.5%. Both variables are now statistically significant, but S&P 500 still puts on the opposite algebraic sign. This is due to the high degree of correlation with the other independent variables that are dominating in the model, especially the volatility variables and the stock return (see table 14.9 in appendix for the correlation matrix).

We also did a univariate regression on both of the variables with a view to retest hypotheses 4 and 7 regarding negative correlation between the CDS spread and the two variables. The results are reported in table 9.6 below.

Table 9.6 –Univariate Regression: Stock Return and S&P 500 Index based on Simple Moving Avarage

	SMA (180)
Intercept	**98.7244**
t-test	259.4
Stock return	**-249.6529**
t-test	-93.8
Adj. R^2	**3.56%**

	SMA (180)
Intercept	**104.1698**
t-test	266.9
S&P 500 index	**-515.3022**
t-test	-109.5
Adj. R^2	**4.73%**

Source: Own creation based on data material

From the univariate regression analysis, it now shows that both the variables assume the expected algebraic sign, indicating both variables having a negative impact on the CDS spread. Thus, an increase in stock return and the S&P 500 index will cause a decrease in the CDS spread, and based on this, hypotheses 4 and 7 outlined in chapter 6 cannot be rejected, with the variables calculated as the simple moving average. Solely, the variation in the stock return and the S&P 500 index explains respectively 3.56% and 4.73% of the variation in the CDS spread, compared to 0.03% and 0.0% before the variables were adjusted for the noise by calculating the simple moving average.

9.3 VIX

The volatility measures included in this paper are based on each company in the regression. Both historical and implied volatility turned out to be accountable for the majority of the explanatory power of the model. To investigate the volatility measures included in the regression, the model is build up again with VIX as the only volatility variable, and combined with historical and implied volatility. VIX represent option-implied volatility based on a wide range of S&P 500 options. The results from the models are reported in table 9.7 below.

Table 9.7 – Regression Models: M17 including VIX as Volatility Variable

	Only VIX	M17	M17 + VIX
Intercept	**284.6906**	**71.8498**	**92.6049**
t-test	106.6	30.4	37.0
Historical volatility		**1.6024**	**0.8861**
t-test		56.9	29.6
Implied volatility		**4.8322**	6.3
t-test		160.7	169.0
VIX	**3.3326**		**-3.3900**
t-test	71.4		-66.2
Leverage	**0.1751**	**0.1541**	**0.1532**
t-test	171.7	172.3	173.0
Price/Book	**-4.8388**	**-3.9292**	**-3.9248**
t-test	-152.2	-140.5	-141.7
Equity return	**1.9329**	**2.5456**	**2.8761**
t-test	10.2	15.4	17.5
Credit rating	**-17.6826**	**-10.1649**	**-9.0377**
t-test	10.2	-66.5	-59.3
Risk free rate	**-7.4381**	**-12.8601**	**-16.3420**
t-test	-31.0	-61.6	-76.6
S&P 500 index	**1.5068**	**0.2168**	**-2.2422**
t-test	4.6	0.8	-7.9
GDP growth	**-11.2157**	**12.0732**	**3.2910**
t-test	-45.7	57.5	13.3
CDS Liquidity	**0.2442**	**-0.095**	**0.0386**
t-test	8.4	-3.7	1,5
Adj. R^2	**25.19%**	**42.98%**	**44.01%**

Source: Own creation based on data material

As it can be derived from table 9.7 including VIX in the entire model only adds approximately 1% to the explanatory power compared to M17. Including VIX as the single measure of volatility only brings up the explanatory power of the model to 25.19%. Thus, both historical and implied volatility contribute to a considerably better explanatory power of the model than VIX.

9.4 CDS Bid and Ask Spreads

To investigate the robustness of the response variable, CDS spread mid, which is the simple average of the bid and ask quotes, the regression is run again with respectively the CDS bid spread and the CDS ask spread as response variables instead. The new estimated models based on the bid and ask spreads are reported in the table below.

Table 9.8 – Regression Models: M17 and CDS Bid and Ask spread as Independent Variables

	M17	M17 - Bid	M17 - Ask
Intercept	**71.8498**	**41.4387**	**41.8762**
t-test	30.4	17.6	17.0
Historical volatility	**1.6024**	**1.5339**	**1.6565**
t-test	56.9	54.5	57.5
Implied vol	**4.8322**	**4.7452**	**4.9537**
t-test	160.7	157.9	161.1
Leverage	**0.1541**	**0.1524**	**0.1569**
t-test	172.3	170.6	171.6
Price/Book	**-3.9292**	**-3.8890**	**-3.9987**
t-test	-140.5	-139.2	-139.9
Stock return	**2.5456**	**2.4987**	**2.6178**
t-test	15.4	15.1	15.5
Credit rating	**-10.1649**	**-10.0702**	**-10.3106**
t-test	-66,5	-65.9	-66.0
Risk free rate	**-12.8601**	**-12.7063**	**-12.9920**
t-test	-61.6	-60.9	-60.9
S&P 500 index	**0.2168**	**0.1400**	**0.2192**
t-test	0.8	0.5	0.8
GDP growth	**12.0732**	**11.7267**	**12.4289**
t-test	57.5	55.8	57.8
CDS Liquidity	**-0.095**	**-0.0939**	**-0.0923**
t-test	-3.7	-3.7	-3.6
Adj. R^2	**42.98%**	**42.04%**	**43.03%**

Source: Own creation based on data material

From table 9.8 it can be derived that running the regression with respectively CDS bid quotes and CDS ask quotes as the dependent variable does not alter the model substantially. It seems that the independent variables are slightly better at explaining the CDS ask quotes than the CDS bid quotes. The obtained explanatory power is 1% higher for CDS ask quotes as the dependent variable, than for CDS bid quotes as the dependent variable. However, this does not seem to affect the results in a significantly way.

9.5 Summary

This chapter dived a bit deeper into the analysed period and the included variables, in order to investigate the unexpected behaviour and the lack of explanatory power of the model, and to check the robustness of the model. It can be concluded that by dividing the model into smaller time periods referring to different stages of the economy, the explanatory power of the model and the variables' behaviour vary. In general, many of the variables are very volatile in the period, when looking at the development in the mean values. The leverage seems to have a deceasing significant influence on the CDS spread during the years, while both the volatility measures have a increasing influence on the CDS spread during the same period. Dividing the model further into individual years, questions the robustness of the model, as it can be concluded that the explanatory power varies a lot over the years and generally, the model is a lot better at explaining the variation in the CDS spread in single years. It was also found that by including both the stock return and S&P 500 return, calculated as the simple moving average based on the last 180 days, it increased the model's explanatory power by a very small amount. By running univariate regression analysis again on the new variables, it was concluded that they were both statistically significant and assumed the excepted algebraic sign. Thus, the initially rejected hypotheses 4 and 7 concerning the stock return and the S&P 500 return actually turned out to be consistent, and thus not rejected. By running the model based on VIX as the volatility variable, and by adding it to the complete model (M17), it did not seem to have a significant effect on the explanatory power of the model. By running the model on both the CDS bid spread and the CDS ask spread as the independent variables, it showed that the included variables are slightly better at explaining the variation in the CDS ask spread than the CDS bid- and mid spread. However, this did not seem to affect the results in a significant way.

10 Discussion

In previous chapters, hypotheses about determinants of the CDS spread were lined up, and a multiple linear regression model, including 10 different independent variables, has been carried out, using least squares method. The investigated independent variables comprise: historical volatility, option implied volatility, financial leverage, price/book value, stock return, credit rating, risk free rate, S&P 500 index, GDP growth, and CDS liquidity. All variables except for S&P 500 index turned out to be statistically significant in explaining the CDS spread. Both the coefficients of the variables: S&P 500 index and stock return, undertook the opposite algebraic sign than expected, indicating a positive correlation with the CDS spread. Later, a simple moving average on the variables were calculated, and turned out to have a higher explanatory power, whilst being negatively correlated with the CDS spread as expected. In this chapter, all the regression results will be discussed, and compared to the previous empirical studies presented in chapter 5. However, it is important to keep in mind that the previous studies cannot be compared directly to the findings of this thesis, since they are different in time period, data basis and to some extent the applied methods.

The base case model included the three theoretical determinants of credit risk stated by Merton's structural model: historical volatility, leverage, and the risk free rate. All the variables turned out to be statistically significant. Implied volatility turned out to be a more important factor than historical volatility in explaining the variation in the CDS spread. However, the two volatility variables combined contributed to a higher explanatory power of the model. This pattern is very similar to the one observed by Benkert (2004).

Among the variables in the base case model, the volatility clearly tends to contribute to a majority of the explanatory power. The model including only leverage has a quite lower explanatory power, than expected. The risk free rate solely has a limited explanatory power. In the study by Ericsson et al. (2009), leverage clearly dominated the two other variables, wherefore we find this development quite interesting. The additional regression results further showed that the correlation between leverage and the CDS spread had decreased continually throughout the period from being strongly positive to being slightly positive. In the same period, the average leverage has increased continually. This relationship indicates that leverage and the CDS spread are stronger correlated when the leverage level is low. To investigate this relationship further, another measure of the leverage than D/E could be included instead.

Furthermore, the firm specific accounting variables and the credit rating were examined. All the variables turned out to be statistically significant, but the accounting variables together added more explanatory power to the model than credit rating. Thus, the fact that the accounting variables should be better captured by credit rating, as proposed by Benkert (2003), does not seem to be the case in our regression analysis. This differing finding could be due to the different accounting variables included. Benkert (2003) included past profitability, leverage, and interest coverage as firm specific accounting variables, while our regression model included stock return, leverage, and price/book value. Thus, the included firm specific accounting variables in our regression are more marked-oriented than accounting-oriented, which could be the explanation of the different findings.

The previous empirical studies all include various liquidity variables, but did not seem to find any significant relationship between liquidity and the CDS spread. In our regression, we included the liquidity on the individual CDS contracts instead, with a view to investigate the impact on the CDS spread. The variable was included as the bid-ask spread. This variable only added a small portion of explanatory power to the model, however, it turned out to be statistically significant, and a higher bid-ask spread and consequently a lower liquidity on the CDS contract, seemed to increase the CDS spread. The variable, though, appears to have the opposite outcome, when including the volatility measures in the model, which is due to the high degree of correlation between the bid-ask spread and the volatility variables. When dividing the model into shorter periods, the bid-ask spread turns out to be statistically insignificant in the first two periods from respectively 2006-2007 and 2008-2009, but statistically significant in the last two periods from 2010-2012 and 2013-2016. This could indicate the liquidity component having an increasingly explanatory power during the years.

GDP growth also turned out to be statistically significant. In our regression, we used the GDP growth per capita compared to same quarter the previous year. To investigate this variable further, different measures could be included. None of the previous empirical studies, used as inspiration, included the growth in the GDP. The GDP growth coefficient did behave a bit different shifting algebraic sign when including the volatility variables. This behaviour was caused by the high degree of negative correlation between the GDP growth and the volatility.

The risk free rate level in the regression is based on the 5-years US treasury interest rate, which corresponds to the 5-years maturity of the CDS contract. This is identical to the proxy used in previous studies. However, the risk free rate variable did not seem to be such an important factor as expected, when it came to explaining the variation in the CDS spread. This could be due to the fact that the level of the risk free rate has been almost continually decreasing in an extensive part of the period, while the CDS spread has also been decreasing. Thus, the risk free rate and the CDS spread have not been that strongly correlated during the entire period. Another proxy for the risk free rate level could be included instead, or the slope of the yield curve. However, the latter would most likely be excluded from the regression due to multiculinarity with the risk free rate variable.

The S&P 500 index turned out to be statistically insignificant in the regression. Furthermore, the stock return was statistically significant, but with the opposite algebraic sign than expected. The regression indicated a positive correlation between the stock return and the CDS spread, which was not expected and does not really make sense. The two variables were then included in the regression as the simple moving average based on the last 180 days instead. By running a univariate regression on both variables, they both turn out to have some explanatory power of the variation in the CDS spread. Moreover, they both undertake the expected algebraic sign, indicating a negatively correlated relationship with the CDS spread.

Replacing the variables based on the simple moving average makes both variables statistically significant in the model and increase the explanatory power of the model by a small portion. However, in the full model, the S&P 500 index variable based on the simple moving average still undertakes the opposite algebraic sign. This is due to the high degree of correlation with both stock return and volatility, which dominates the variable.

Since the full model only obtained an explanatory power of approximately 43%, the full period was divided into shorter periods, and the regression was also run on each year. This actually questioned the robustness of the model a bit, since the explanatory power of the model varies though the years. Generally, the explanatory power of the single years is at a higher level, indicating the model is better at explaining the variation in the CDS spread based on single years, rather than longer periods. The model seems to lack explanatory power during the period comprising the financial crisis, indicating that the model is not very suitable of explaining the variation in the CDS spread during periods characterized by financial distress and high default rates. In the years prior to the financial crisis, the model reaches highest explanatory power. Divided into single years, the model has lowest explanatory power in 2014 and 2015. This could somehow be connected with the increasing number of defaults in this period, as presented in figure 2.1, chapter 2.

Ericisson et al. (2009) found, by running the regression on each individual year that the explanatory power of the model increases noticeably over time, which was concluded could be due to increasing market liquidity. We do not experience the same behaviour in the time period we selected for the regression. Even though the explanatory power of the models based on single years do increase from 69.8% in 2005 to 71.9% in 2008, it varies lot in the following years. This behaviour could be due to the consequences of the financial crisis and general changes in the CDS marked, comprising different regulations implemented.

Furthermore, the model verification showed that the residuals were normally distributed, with a mean of zero and non-correlated, but the assumption about homoscedastic residuals was not met. Thus, the residuals did not seem to have a random and constant variance and there seemed to be a tendency in the residuals. However, this is often the case when analysing economical and financial panel data. When the CDS spread increased, the variance in the residuals also increased. From this it can be derived that the model is poorer at explaining the variation in the CDS spread, as the spread increases. This is also reflected in the fact that the explanatory power of the model tends to be much higher, when the mean value of the CDS spread is lower prior to the financial crisis. During the crisis with volatile mean values and increasing CDS spread, the model's explanatory power is decreasing.

The section on model verification furthermore tested the presence of autocorrelated residuals in the regression. Such a correlation between residuals over time periods could indicate that one or more important factors are not included in the model. This hypothesis was rejected in the model verification, as the Durbin-Watson test indicated no autocorrelation in the regression residuals. However, this was not found to be the case in the study conducted by Collin-Dufrense et al. (2001), who concluded that a significant part of the residuals was driven by a common systematic factor, which was not captured by the theoretical variables. Despite the curiosity to investigate further these findings of Collin-Dufresne et al., the combination of no found autocorrelation and the limited extent of this thesis prevents a deeper examination. Such an investigation would require a thorough analysis of cross-correlations in the residuals and a principal components analysis, in order to determine if the remaining part of the residuals could be explained by some systematic factor.

11 Conclusion

This thesis has investigated which factors of credit risk that are crucial, when determining the CDS spread by using multiple linear regression analysis.

From economic theory on credit risk and credit default swap contracts, it was derived that the size of the CDS spread should be affected by firm-specific factors, macroeconomic factors, and the liquidity of the CDS contract.

According to theory of structural models originally developed by Merton (1974), it can be derived that the event of default depends on three factors: firm leverage, volatility, and the risk free rate. A majority of the previous studies concerning determinants of credit default swap spreads are based on this structural approach. Earlier studies by Collin-Dufresne et al. (2001), Benkert (2003), and Ericsson et al. (2009) all find the three theoretical factors proposed by Merton (1974) to be the key determinants of the CDS spread. Furthermore, credit rating tends to have a significant influence, while liquidity factors were found to have a limited impact on the CDS spread.

The empirical analysis conducted in this thesis was based on data from 79 American companies from the Markit CDX NA IG index in the period January 4th 2005 to December 30th 2016. The investigated factors included in the drawn up model span: historical volatility, option-implied volatility, leverage, price/book value, stock return, credit rating, the risk free rate level, S&P 500 index return, GDP growth, and CDS liquidity. The latter measured by the bid-ask spread.

The base case model including the three theoretical factors: leverage, historical volatility, and the risk free rate obtained an explanatory power of the variation in the CDS spread of approximately 28%, with historical volatility being responsible for the majority. The three theoretical factors were all found to have a significant impact on the CDS spread.

By adding option-implied volatility to the model, the explanatory power increases to approximately 35%, and by adding the rest of the variables, the model's explanatory power is approximately 44%. Furthermore, it was found that volatility factors, especially option-implied volatility, clearly dominated all other factors in the model.

Volatility, leverage, and the CDS bid-ask spread all proved to be positively correlated with the CDS spread and hence, higher values of the factors will cause an increase in the CDS spread. Price/book value, credit rating, the risk free rate, and GDP growth all showed to be negatively correlated with the CDS spread and hence, higher value of these factors will cause a decrease in the CDS spread. Some of the macroeconomic variables displayed some varying behaviour due to the high degree of correlation with the volatility factors that dominated the model. By univariate regression, not only the three theoretical variables, but also the CDS bid-ask spread, price/book value, credit rating, and GDP growth all turned out to be statistically significant.

Since daily stock return on the underlying assets showed a limited impact but a peculiar behaviour, indicating that higher stock return would cause the CDS spread to increase, and a linear relationship did not seem to appear between the daily return of the S&P 500 index and the CDS spread, the two variables were investigated further. Based on this, a 180 days simple moving average was calculated. Both variables then turned out to be negatively correlated with- and to have a significant influence on the CDS spread. However, adding these to the model only increased the explanatory power by approximately 1%.

Since the obtained explanatory power of the model, amounting to approximately 43%, was somewhat lower than those obtained by previous studies, and consequently, more than half of the variation in the CDS spread is not captured by the model, the model was divided into shorter time periods, representing different stages of the economy. It was found that the explanatory power of the model and the variables' behaviour vary, depending on the respective periods. The impact of the leverage on the CDS spread seemed to decrease over the years, while both of the volatility measures had an increasing impact on the CDS spread in the same period. By running the regression model on the individual years, it was found that this model, in generally, is better at explaining the variation in the CDS spread in single years. The model and hence the included determinants proved to be much better at explaining the variation in the years prior to the financial crisis, with an explanatory power of approximately 71%.

To summarize, all the investigated firm specific and macroeconomic factors (historical volatility, option-implied volatility, leverage, price/book value, stock return, credit rating, the risk free rate, S&P 500 index return, GDP growth and CDS liquidity,) seem to be important determinants of the CDS spread. Volatility is clearly the most central factor, and especially implied volatility is found to be a key factor when determining the CDS spread, while leverage seems to be of less significance than previously thought. However, the determinants are found to be better in explaining the CDS spread prior to the crisis, and thus, the determinants seem to have a weaker influence on the CDS spread in periods of financial distress and when the values of the factors and the CDS spread are volatile.

12 Future implications

In the following part, other potential determinants of the CDS spread, which have not been subject to this paper, are presented. This part should not be perceived as a comprehensive review of other studies and potential determinants, but rather as a reference to other potential determinants of the CDS spread and factors which could be interesting to investigate further.

The data included in this thesis are based on single-name CDS contracts on reference entities characterized by investment grade, and thus, no data on companies with lower ratings than BBB are represented in the data set. Therefore, it could be interesting to include data from CDS contracts on reference entities with lower ratings. This could be combined with a detailed examination of the impact of different categories of leverage level and credit ratings, with the purpose of investigating whether the model is better at explaining the variation in the CDS spread for low leveraged, low rated firms or vice versa, as it was also proposed by Colling-Dufresne et al. (2001) and Ericsson et al. (2009). This is especially interesting due to our finding that the leverage variable, measured by the debt to equity ratio, in the regression model seemed to have less impact on the CDS spread during the years, whereas the average leverage increased.

Since the variables and default numbers vary a lot in different sectors, it would be interesting to examine whether the proposed model in this thesis is better at explaining the variation in the CDS spread for some sectors than others. To investigate this, the regression data could be divided into sectors and the model should then be implemented on the different sectors.

Furthermore, Zhang et al. discovered a strong relationship between jump magnitudes in the equity return and the credit risk measured by the CDS spread, as presented in their paper "*Explaining Credit Default Swap Spreads with Equity Volatility and Jump Risk of Individual Firms*" (Zhang et al., 2005). Since the stock return variable in the regression model carried out in this thesis showed some varying behaviour, depending on the how it was measured and calculated, it would be interesting to include jump magnitudes in the return as a variable in a more detailed study of the determinants of the CDS spread.

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14 Appendix

Table 14.1 – Companies used in the Analysis

COMPANY	SECTOR
21st Century Fox America Inc	Consumer Discretionary
Aetna Inc	Health Care
Allstate Corp/The	Financials
Altria Group Inc	Consumer Staples
American Electric Power Co Inc	Utilities
American Express Co	Financials
American International Group Inc	Financials
Amgen Inc	Health Care
Anadarko Petroleum Corp	Energy
Apache Corp	Energy
Arrow Electronics Inc	Information Technology
AT&T Inc	Telecommunication Services
AutoZone Inc	Consumer Discretionary
Avnet Inc	Information Technology
Baxter International Inc	Health Care
Boeing Co/The	Industrials
Boston Scientific Corp	Health Care
Bristol-Myers Squibb Co	Health Care
Campbell Soup Co	Consumer Staples
Capital One Bank USA NA	Financials
Cardinal Health Inc	Health Care
Carnival Corp	Consumer Discretionary
Caterpillar Inc	Industrials
Computer Sciences Corp	Information Technology
Conagra Brands Inc	Consumer Staples
ConocoPhillips	Energy
CSX Corp	Industrials
CVS Health Corp	Consumer Staples
Deere & Co	Industrials
Devon Energy Corp	Energy
Dominion Resources Inc/VA	Utilities
Dow Chemical Co/The	Materials
Eastman Chemical Co	Materials
EI du Pont de Nemours & Co	Materials
Exelon Corp	Utilities
FirstEnergy Corp	Utilities
Ford Motor Co	Consumer Discretionary
General Electric Co	Industrials
General Mills Inc	Consumer Staples

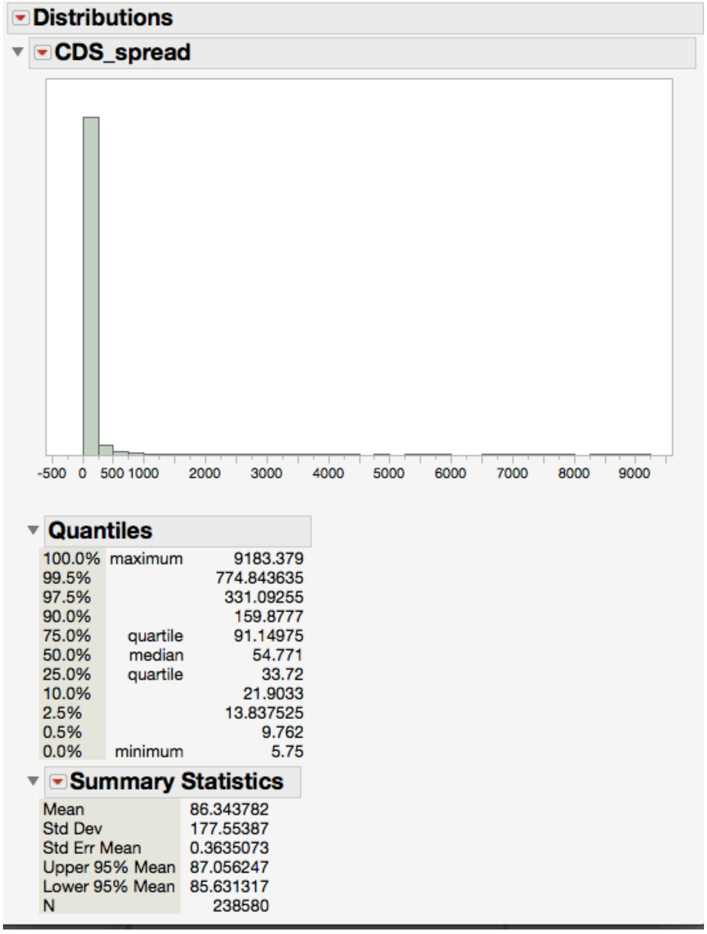
Halliburton Co	Energy
Hartford Financial Services Group Inc/The	Financials
Hess Corp	Energy
Home Depot Inc/The	Consumer Discretionary
Honeywell International Inc	Industrials
HP Inc	Information Technology
International Business Machines Corp	Information Technology
International Paper Co	Materials
Johnson Controls International plc	Industrials
Kroger Co/The	Consumer Staples
Lincoln National Corp	Financials
Lockheed Martin Corp	Industrials
Loews Corp	Financials
Lowe's Cos Inc	Consumer Discretionary
Marriott International Inc/MD	Consumer Discretionary
McDonald's Corp	Consumer Discretionary
McKesson Corp	Health Care
MetLife Inc	Financials
Mondelez International Inc	Consumer Staples
Motorola Solutions Inc	Information Technology
Newell Brands Inc	Consumer Discretionary
Nordstrom Inc	Consumer Discretionary
Norfolk Southern Corp	Industrials
Northrop Grumman Corp	Industrials
Prudential Financial Inc	Financials
Raytheon Co	Industrials
Sempra Energy	Utilities
Simon Property Group LP	Real Estate
Southwest Airlines Co	Industrials
Staples Inc	Consumer Discretionary
Target Corp	Consumer Discretionary
Time Warner Inc	Consumer Discretionary
Tyson Foods Inc	Consumer Staples
Union Pacific Corp	Industrials
Valero Energy Corp	Energy
Verizon Communications Inc	Telecommunication Services
Wal-Mart Stores Inc	Consumer Staples
Walt Disney Co/The	Consumer Discretionary
Weyerhaeuser Co	Real Estate
Whirlpool Corp	Consumer Discretionary

Table 14.2 – Rating Agency Credit Scale

Standard & Poor's	Moody's	Fitch IBCA	
AAA	Aaa	AAA	Investment Grade
AA+	Aa1	AA+	
AA	Aa2	AA	
AA-	Aa3	AA-	
A+	A1	A+	
A	A2	A	
A-	A3	A-	
BBB+	Baa1	BBB+	
BBB	Baa2	BBB	
BBB-	Baa3	BBB-	
BB+	Ba1	BB+	Non-investment Grade
BB	Ba2	BB	
BB-	Ba3	BB-	
B+	B1	B+	
B	B2	B	
B-	B3	B-	
CCC+	Caa1	CCC+	
CCC	Caa2	CCC	
CCC-	Caa3	CCC-	
CC	Ca	CC	
C	C	C	
D		D	

Source: Own creation, Bank of International Settlement (BIS.org)

Figure 14.1 – Distribution of DCS spread



Source: own creation, JMP 13

Table 14.3 – Correlation matrix formatted in accordance with extremes

	CDS spread	Historical vol	Implied vol	Leverage	Price/ Book	Equity return	Credit rating	Risk free rate	S&P 500 index	GDP Growth	CDS Liquidity
CDS spread		0.490	0.551	0.192	-0.032	0.016	-0.266	-0.109	0.001	-0.217	0.079
Historical vol			0.808	0.008	-0.068	0.021	-0.140	-0.086	0.006	-0.637	0.158
Implied vol				0.023	-0.072	-0.042	-0.149	-0.018	-0.049	-0.563	0.173
Leverage					0.810	0.002	-0.155	-0.058	0.002	-0.028	0.002
Price/Book						0.004	-0.022	-0.082	0.005	0.000	-0.005
Equity return							-0.008	-0.002	0.616	-0.001	-0.005
Credit rating								0.077	-0.003	0.010	-0.002
Risk free rate									-0.003	0.122	-0.042
S&P 500 index										0.009	-0.010
GDP Growth											-0.191

Source: own creation based on data material

Figure 14.2 – Goodness-of-Fit test on residuals of full model

Goodness-of-Fit Test

KSL Test

D		Prob>D
0.238065	<	0.0100*

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Source: own creation, JMP 13

Figure 14.3 – Brown-Forsythe and Welch's Test

Tests that the Variances are Equal

Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
0	119287	30.9981	23.83849	23.77103
1	119293	184.4853	56.23116	55.39479

Test	F Ratio	DFNum	DFDen	p-Value
O'Brien[.5]	140.5142	1	238578	<.0001*
Brown-Forsythe	3791.8566	1	238578	<.0001*
Levene	4003.3346	1	238578	<.0001*
Bartlett	266804.62	1	.	<.0001*
F Test 2-sided	35.4204	119292	119286	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
6521.6344	1	126023	<.0001*

t Test
80.7566

Source: own creation, JMP 13

Figure 14.4 – Regression model year 2005-2006

Summary of Fit

RSquare	0,712496
RSquare Adj	0,712424
Root Mean Square Error	41,24246
Mean of Response	41,98037
Observations (or Sum Wgts)	39658

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	167123846	16712385	9825,378
Error	39647	67437192	1700,9406	**Prob > F**
C. Total	39657	234561039		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	22,329155	5,136207	4,35	<,0001*
Hist_vol	-0,799233	0,053024	-15,07	<,0001*
Implied_vol	3,1061151	0,051439	60,38	<,0001*
D/E	0,3872951	0,001498	258,61	<,0001*
P/B	-8,703551	0,103459	-84,13	<,0001*
Return	0,7350831	0,164376	4,47	<,0001*
Rating	-6,213711	0,117696	-52,79	<,0001*
CDS liquidity	0,1608166	0,089773	1,79	0,0732
rf	1,2551708	0,708279	1,77	0,0764
S&P 500	0,5459652	0,364859	1,50	0,1346
GDP Growth	7,5343219	0,648618	11,62	<,0001*

Effect Tests

Source: own creation, JMP 13

Table 14.4 – Correlation Matrix, Regression model year 2005-2006

Multivariate

Correlations

	CDS spread	Hist_vol	Implied_vol	D/E	P/B	Return	Rating	CDS liquidity	rf	S&P 500	GDP Grow
CDS spread	1,0000	0,2516	0,3710	0,4907	-0,0598	-0,0071	-0,4211	0,0207	-0,0512	0,0014	0,04
Hist_vol	0,2516	1,0000	0,7652	0,0934	0,0065	0,0067	-0,3468	0,0082	-0,0855	0,0017	-0,03
Implied_vol	0,3710	0,7652	1,0000	0,1466	0,0020	-0,0546	-0,3316	0,0047	-0,0951	-0,0438	-0,09
D/E	0,4907	0,0934	0,1466	1,0000	0,0895	-0,0100	-0,1752	-0,0024	-0,0438	-0,0027	-0,03
P/B	-0,0598	0,0065	0,0020	0,0895	1,0000	0,0075	0,1214	-0,0105	-0,0125	0,0032	-0,04
Return	-0,0071	0,0067	-0,0546	-0,0100	0,0075	1,0000	-0,0085	0,0042	0,0046	0,5180	-0,00
Rating	-0,4211	-0,3468	-0,3316	-0,1752	0,1214	-0,0085	1,0000	-0,0029	0,0046	0,0002	-0,00
CDS liquidity	0,0207	0,0082	0,0047	-0,0024	-0,0105	0,0042	-0,0029	1,0000	-0,1088	-0,0093	0,18
rf	-0,0512	-0,0855	-0,0951	-0,0438	-0,0125	0,0046	0,0046	-0,1088	1,0000	0,0227	-0,36
S&P 500	0,0014	0,0017	-0,0438	-0,0027	0,0032	0,5180	0,0002	-0,0093	0,0227	1,0000	-0,00
GDP Growth	0,0416	-0,0380	-0,0939	-0,0352	-0,0481	-0,0002	-0,0058	0,1881	-0,3658	-0,0082	1,00

Source: own creation, JMP 13

Figure 14.5 - Regression model year 2007-2009

Summary of Fit

RSquare	0,432569
RSquare Adj	0,432474
Root Mean Square Error	248,6987
Mean of Response	128,2003
Observations (or Sum Wgts)	59724

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	2815516584	281551658	4552,093
Error	59713	3693311011	61851,038	Prob > F
C. Total	59723	6508827595		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	151,49225	9,501927	15,94	<,0001*
Hist_vol	1,7480741	0,062672	27,89	<,0001*
Implied_vol	5,8930462	0,065595	89,84	<,0001*
D/E	0,1474006	0,001949	75,61	<,0001*
P/B	-3,198569	0,098172	-32,58	<,0001*
Return	3,7385894	0,40904	9,14	<,0001*
Rating	-26,05149	0,513197	-50,76	<,0001*
CDS liquidity	-0,038805	0,049321	-0,79	0,4314
rf	3,6809746	1,603758	2,30	0,0217*
S&P 500	-0,848334	0,695868	-1,22	0,2228
GDP Growth	14,002548	0,811902	17,25	<,0001*

Source: own creation, JMP 13

Table 14.5 – Correlation Matrix, Regression model year 2007-2009

Multivariate

Correlations

	CDS spread	Hist_vol	Implied_vol	D/E	P/B	Return	Rating	CDS liquidity	rf	S&P 500	GDP Growth
CDS spread	1,0000	0,4685	0,5565	0,3134	-0,0265	0,0227	-0,3122	0,0676	-0,2346	0,0033	-0,2376
Hist_vol	0,4685	1,0000	0,7664	0,0662	-0,0359	0,0332	-0,1422	0,1319	-0,5712	0,0193	-0,6551
Implied_vol	0,5565	0,7664	1,0000	0,0950	-0,0513	-0,0371	-0,1384	0,1524	-0,4958	-0,0401	-0,5148
D/E	0,3134	0,0662	0,0950	1,0000	0,4439	0,0015	-0,2553	0,0006	-0,0421	0,0024	-0,0315
P/B	-0,0265	-0,0359	-0,0513	0,4439	1,0000	0,0060	0,0085	-0,0077	-0,0441	0,0075	-0,0396
Return	0,0227	0,0332	-0,0371	0,0015	0,0060	1,0000	-0,0124	-0,0042	0,0010	0,6293	-0,0123
Rating	-0,3122	-0,1422	-0,1384	-0,2553	0,0085	-0,0124	1,0000	-0,0068	0,0535	-0,0050	0,0626
CDS liquidity	0,0676	0,1319	0,1524	0,0006	-0,0077	-0,0042	-0,0068	1,0000	-0,1749	-0,0078	-0,1821
rf	-0,2346	-0,5712	-0,4958	-0,0421	-0,0441	0,0010	0,0535	-0,1749	1,0000	0,0152	0,7865
S&P 500	0,0033	0,0193	-0,0401	0,0024	0,0075	0,6293	-0,0050	-0,0078	0,0152	1,0000	-0,0087
GDP Growth	-0,2376	-0,6551	-0,5148	-0,0315	-0,0396	-0,0123	0,0626	-0,1821	0,7865	-0,0087	1,0000

Source: own creation, JMP 13

Figure 14.6 – Regression model year 2010-2012

Summary of Fit

RSquare	0,5715
RSquare Adj	0,571428
Root Mean Square Error	49,72704
Mean of Response	103,3954
Observations (or Sum Wgts)	59566

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	196412353	19641235	7942,982
Error	59555	147266321	2472,7785	Prob > F
C. Total	59565	343678674		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	99,348072	2,046608	48,54	<,0001*
Hist_vol	1,9810131	0,030186	65,63	<,0001*
Implied_vol	2,243587	0,032142	69,80	<,0001*
D/E	0,1005344	0,000886	113,46	<,0001*
P/B	-2,954772	0,028136	-105,0	<,0001*
Return	0,8263525	0,157294	5,25	<,0001*
Rating	-7,43921	0,119314	-62,35	<,0001*
CDS liquidity	-0,211649	0,055736	-3,80	0,0001*
rf	-12,95505	0,325194	-39,84	<,0001*
S&P 500	0,8711195	0,240678	3,62	0,0003*
GDP Growth	-0,625595	0,345384	-1,81	0,0701

Source: own creation, JMP 13

Table 14.6 – Correlation Matrix, Regression model year 2010-2012

Correlations

	CDS spread	Hist_vol	Implied_vol	D/E	P/B	Return	Rating	CDS liquidity	rf	S&P 500	GDP Growth
CDS spread	1,0000	0,5923	0,5891	0,1462	-0,0860	0,0111	-0,4274	0,0263	-0,0685	0,0081	0,0186
Hist_vol	0,5923	1,0000	0,7500	-0,0509	-0,1342	0,0174	-0,2538	0,0587	0,0200	0,0161	0,1284
Implied_vol	0,5891	0,7500	1,0000	-0,0292	-0,1034	-0,0684	-0,2629	0,1041	0,0457	-0,0680	-0,0485
D/E	0,1462	-0,0509	-0,0292	1,0000	0,8682	0,0047	-0,2027	-0,0000	0,0179	0,0008	0,0025
P/B	-0,0860	-0,1342	-0,1034	0,8682	1,0000	0,0060	-0,0558	-0,0058	-0,0097	0,0021	-0,0020
Return	0,0111	0,0174	-0,0684	0,0047	0,0060	1,0000	-0,0017	-0,0075	0,0169	0,6868	0,0244
Rating	-0,4274	-0,2538	-0,2629	-0,2027	-0,0558	-0,0017	1,0000	-0,0055	-0,0216	-0,0001	-0,0124
CDS liquidity	0,0263	0,0587	0,1041	-0,0000	-0,0058	-0,0075	-0,0055	1,0000	0,1290	-0,0101	0,1496
rf	-0,0685	0,0200	0,0457	0,0179	-0,0097	0,0169	-0,0216	0,1290	1,0000	0,0191	0,0214
S&P 500	0,0081	0,0161	-0,0680	0,0008	0,0021	0,6868	-0,0001	-0,0101	0,0191	1,0000	0,0398
GDP Growth	0,0186	0,1284	-0,0485	0,0025	-0,0020	0,0244	-0,0124	0,1496	0,0214	0,0398	1,0000

Source: own creation, JMP 13

Figure 14.7 – Regression model year 2013-2016

Summary of Fit

RSquare	0,560121
RSquare Adj	0,560066
Root Mean Square Error	32,86357
Mean of Response	64,29016
Observations (or Sum Wgts)	79632

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	109498099	10949810	10138,58
Error	79621	85991830	1080,0144	Prob > F
C. Total	79631	195489929		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	34,494658	1,359127	25,38	<,0001*
Hist_vol	2,7090718	0,024774	109,35	<,0001*
Implied_vol	2,1983242	0,024982	88,00	<,0001*
D/E	0,0424087	0,000853	49,72	<,0001*
P/B	-1,095501	0,022118	-49,53	<,0001*
Return	0,5250162	0,094001	5,59	<,0001*
Rating	-4,701515	0,07369	-63,80	<,0001*
CDS liquidity	-0,581797	0,030237	-19,24	<,0001*
rf	-8,665683	0,484799	-17,87	<,0001*
S&P 500	0,7923042	0,172215	4,60	<,0001*
GDP Growth	-1,834496	0,218752	-8,39	<,0001*

Source: own creation, JMP 13

Table 14.7 – Correlation Matrix, Regression model year 2013-2016

Multivariate

Correlations

	CDS spread	Hist_vol	Implied_vol	D/E	P/B	Return	Rating	CDS liquidity	rf	S&P 500	GDP Growth
CDS spread	1,0000	0,6782	0,6541	-0,0446	-0,0784	0,0119	-0,3639	0,0290	-0,1382	0,0075	-0,1800
Hist_vol	0,6782	1,0000	0,7451	-0,1086	-0,1112	0,0115	-0,2578	0,1087	-0,1228	0,0039	-0,2084
Implied_vol	0,6541	0,7451	1,0000	-0,0936	-0,0985	-0,0542	-0,2688	0,1091	-0,0632	-0,0571	-0,1364
D/E	-0,0446	-0,1086	-0,0936	1,0000	0,9762	0,0007	-0,0524	-0,0007	-0,0479	0,0022	-0,0346
P/B	-0,0784	-0,1112	-0,0985	0,9762	1,0000	0,0024	-0,0203	0,0004	-0,0463	0,0027	-0,0336
Return	0,0119	0,0115	-0,0542	0,0007	0,0024	1,0000	-0,0061	-0,0047	-0,0180	0,5498	-0,0141
Rating	-0,3639	-0,2578	-0,2688	-0,0524	-0,0203	-0,0061	1,0000	-0,0007	0,0112	-0,0007	0,0187
CDS liquidity	0,0290	0,1087	0,1091	-0,0007	0,0004	-0,0047	-0,0007	1,0000	0,0504	-0,0151	-0,0334
rf	-0,1382	-0,1228	-0,0632	-0,0479	-0,0463	-0,0180	0,0112	0,0504	1,0000	-0,0273	0,5543
S&P 500	0,0075	0,0039	-0,0571	0,0022	0,0027	0,5498	-0,0007	-0,0151	-0,0273	1,0000	-0,0151
GDP Growth	-0,1800	-0,2084	-0,1364	-0,0346	-0,0336	-0,0141	0,0187	-0,0334	0,5543	-0,0151	1,0000

Source: own creation, JMP 13

Figure 14.8 – Regression model year 2005

Summary of Fit

RSquare	0,697699
RSquare Adj	0,697547
Root Mean Square Error	35,70948
Mean of Response	44,26662
Observations (or Sum Wgts)	19829

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	58325136	5832514	4573,921
Error	19818	25271263	1275	Prob > F
C. Total	19828	83596399		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>ltl
Intercept	206,63151	11,79695	17,52	<,0001*
Hist_vol	-0,30909	0,067403	-4,59	<,0001*
Implied_vol	2,7630652	0,063325	43,63	<,0001*
D/E	0,3490023	0,001969	177,26	<,0001*
P/B	-7,529186	0,116261	-64,76	<,0001*
Return	0,4339465	0,204399	2,12	0,0338*
Rating	-5,109692	0,142013	-35,98	<,0001*
CDS liquidity	-0,053793	0,171711	-0,31	0,7541
rf	-18,29806	1,50953	-12,12	<,0001*
S&P 500	0,9452019	0,447116	2,11	0,0345*
GDP Growth	-28,49671	1,841561	-15,47	<,0001*

Source: own creation, JMP 13

Figure 14.9 – Regression model year 2006

Summary of Fit

RSquare	0,734084
RSquare Adj	0,73395
Root Mean Square Error	44,97606
Mean of Response	39,69412
Observations (or Sum Wgts)	19829

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	110668588	11066859	5470,935
Error	19818	40088761	2022,8459	Prob > F
C. Total	19828	150757349		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>ltl
Intercept	32,503642	7,949295	4,09	<,0001*
Hist_vol	-1,330453	0,080545	-16,52	<,0001*
Implied_vol	3,4293449	0,080768	42,46	<,0001*
D/E	0,417123	0,002185	190,92	<,0001*
P/B	-10,03532	0,181783	-55,20	<,0001*
Return	0,9120546	0,249966	3,65	0,0003*
Rating	-7,130131	0,185256	-38,49	<,0001*
CDS liquidity	0,0975343	0,110127	0,89	0,3758
rf	0,2267724	1,436525	0,16	0,8746
S&P 500	0,1140216	0,563374	0,20	0,8396
GDP Growth	11,858701	0,806488	14,70	<,0001*

Source: own creation, JMP 13

Figure 14.10 – Regression model year 2007

Summary of Fit

RSquare	0,599051
RSquare Adj	0,598849
Root Mean Square Error	44,00191
Mean of Response	39,40127
Observations (or Sum Wgts)	19829

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	57329472	5732947	2960,977
Error	19818	38370972	1936	Prob > F
C. Total	19828	95700443		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	139,40006	5,65852	24,64	<,0001*
Hist_vol	-0,690247	0,091344	-7,56	<,0001*
Implied_vol	2,3055957	0,076862	30,00	<,0001*
D/E	0,0444761	0,000392	113,49	<,0001*
P/B	-1,475177	0,111562	-13,22	<,0001*
Return	0,0289281	0,243032	0,12	0,9053
Rating	-11,07131	0,176836	-62,61	<,0001*
CDS liquidity	0,2014434	0,168804	1,19	0,2327
rf	-0,002128	0,75947	-0,00	0,9978
S&P 500	1,272712	0,389891	3,26	0,0011*
GDP Growth	1,6590926	0,95814	1,73	0,0834

Source: own creation, JMP 13

Figure 14.11 – Regression model year 2008

Summary of Fit

RSquare	0,718166
RSquare Adj	0,718024
Root Mean Square Error	150,6604
Mean of Response	151,0929
Observations (or Sum Wgts)	19987

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	1155412754	115541275	5090,249
Error	19976	453426210	22698,549	Prob > F
C. Total	19986	1608838963		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	27,752021	11,52206	2,41	0,0160*
Hist_vol	1,7427713	0,097151	17,94	<,0001*
Implied_vol	4,6653656	0,076826	60,73	<,0001*
D/E	0,4707129	0,003691	127,53	<,0001*
P/B	-14,4612	0,234992	-61,54	<,0001*
Return	3,2504376	0,35525	9,15	<,0001*
Rating	-10,82662	0,557852	-19,41	<,0001*
CDS liquidity	-0,071442	0,053721	-1,33	0,1836
rf	-14,63881	2,565703	-5,71	<,0001*
S&P 500	-1,21608	0,551287	-2,21	0,0274*
GDP Growth	27,769184	1,034432	26,84	<,0001*

Source: own creation, JMP 13

Figure 14.12 – Regression model year 2009

Summary of Fit

RSquare	0,548086
RSquare Adj	0,547859
Root Mean Square Error	321,5453
Mean of Response	193,6635
Observations (or Sum Wgts)	19908

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	2494964340	249496434	2413,127
Error	19897	2057177757	103391,35	Prob > F
C. Total	19907	4552142097		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-144,1037	25,91673	-5,56	<,0001*
Hist_vol	-0,355013	0,121327	-2,93	0,0034*
Implied_vol	8,2995426	0,17252	48,11	<,0001*
D/E	0,7387631	0,00808	91,43	<,0001*
P/B	-16,75568	0,220009	-76,16	<,0001*
Return	3,6844712	0,82047	4,49	<,0001*
Rating	-13,33769	1,175408	-11,35	<,0001*
CDS liquidity	0,0498335	0,077149	0,65	0,5183
rf	47,595573	7,835549	6,07	<,0001*
S&P 500	0,2885922	1,658933	0,17	0,8619
GDP Growth	13,672342	1,635259	8,36	<,0001*

Source: own creation, JMP 13

Figure 14.13 – Regression model year 2010

Summary of Fit

RSquare	0,658213
RSquare Adj	0,658041
Root Mean Square Error	49,19455
Mean of Response	103,8322
Observations (or Sum Wgts)	19908

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	92732568	9273257	3831,760
Error	19897	48152799	2420	Prob > F
C. Total	19907	140885367		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	28,440985	4,766175	5,97	<,0001*
Hist_vol	2,1339801	0,050778	42,03	<,0001*
Implied_vol	1,8118436	0,062291	29,09	<,0001*
D/E	0,1341409	0,001282	104,67	<,0001*
P/B	-3,791489	0,042437	-89,34	<,0001*
Return	0,8960465	0,2655	3,37	0,0007*
Rating	-5,965413	0,195507	-30,51	<,0001*
CDS liquidity	-0,009628	0,086525	-0,11	0,9114
rf	-1,415633	0,970258	-1,46	0,1446
S&P 500	0,3996065	0,41994	0,95	0,3413
GDP Growth	11,76792	0,88103	13,36	<,0001*

Source: own creation, JMP 13

Figure 14.14 – Regression model year 2011

Summary of Fit

RSquare	0,553199
RSquare Adj	0,552975
Root Mean Square Error	47,26104
Mean of Response	105,2315
Observations (or Sum Wgts)	19908

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	55025257	5502526	2463,516
Error	19897	44442063	2234	Prob > F
C. Total	19907	99467320		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	97,666416	4,103236	23,80	<,0001*
Hist_vol	2,3647257	0,06751	35,03	<,0001*
Implied_vol	1,7884213	0,058361	30,64	<,0001*
D/E	0,0616324	0,001253	49,18	<,0001*
P/B	-1,801296	0,042385	-42,50	<,0001*
Return	0,2644113	0,24372	1,08	0,2780
Rating	-7,348808	0,20163	-36,45	<,0001*
CDS liquidity	-0,234727	0,095357	-2,46	0,0138*
rf	-6,244217	0,856548	-7,29	<,0001*
S&P 500	1,1027679	0,343306	3,21	0,0013*
GDP Growth	-3,271885	1,726504	-1,90	0,0581

Source: own creation, JMP 13

Figure 14.15 – Regression model year 2012

Summary of Fit

RSquare	0,554956
RSquare Adj	0,554731
Root Mean Square Error	48,22545
Mean of Response	101,1044
Observations (or Sum Wgts)	19750

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	57244539	5724454	2461,396
Error	19739	45906865	2326	Prob > F
C. Total	19749	103151404		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	112,03109	4,409433	25,41	<,0001*
Hist_vol	1,8059296	0,069823	25,86	<,0001*
Implied_vol	3,4899326	0,08738	39,94	<,0001*
D/E	0,1679272	0,003945	42,57	<,0001*
P/B	-4,892772	0,111088	-44,04	<,0001*
Return	0,9439072	0,28944	3,26	0,0011*
Rating	-7,325398	0,212461	-34,48	<,0001*
CDS liquidity	-0,05207	0,110673	-0,47	0,6380
rf	-66,12216	3,586819	-18,43	<,0001*
S&P 500	1,8173701	0,519243	3,50	0,0005*
GDP Growth	-0,857397	0,720596	-1,19	0,2341

Source: own creation, JMP 13

Figure 14.16 – Regression model year 2013

Summary of Fit

RSquare	0,598529
RSquare Adj	0,598327
Root Mean Square Error	26,59384
Mean of Response	69,69794
Observations (or Sum Wgts)	19908

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	20978801	2097880	2966,324
Error	19897	14071799	707	Prob > F
C. Total	19907	35050600		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	64,11155	2,181636	29,39	<,0001*
Hist_vol	4,4251099	0,055603	79,58	<,0001*
Implied_vol	0,2456821	0,05774	4,25	<,0001*
D/E	0,0276673	0,001299	21,31	<,0001*
P/B	-0,667294	0,032978	-20,23	<,0001*
Return	0,11783	0,17141	0,69	0,4918
Rating	-5,985307	0,118779	-50,39	<,0001*
CDS liquidity	-0,21791	0,092998	-2,34	0,0191*
rf	-3,860095	0,753222	-5,12	<,0001*
S&P 500	0,047636	0,325016	0,15	0,8835
GDP Growth	-6,235342	0,417451	-14,94	<,0001*

Source: own creation, JMP 13

Figure 14.17 – Regression model year 2014

Summary of Fit

RSquare	0,494006
RSquare Adj	0,493752
Root Mean Square Error	22,02542
Mean of Response	52,98022
Observations (or Sum Wgts)	19908

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	9423735	942374	1942,561
Error	19897	9652413	485	Prob > F
C. Total	19907	19076148		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	52,472847	3,491485	15,03	<,0001*
Hist_vol	2,5202451	0,050008	50,40	<,0001*
Implied_vol	0,9258972	0,041899	22,10	<,0001*
D/E	0,0707001	0,001815	38,94	<,0001*
P/B	-2,046987	0,051511	-39,74	<,0001*
Return	0,0368514	0,143501	0,26	0,7973
Rating	-4,918195	0,102377	-48,04	<,0001*
CDS liquidity	-0,03666	0,067806	-0,54	0,5887
rf	-1,518413	1,849902	-0,82	0,4118
S&P 500	0,2693421	0,260131	1,04	0,3005
GDP Growth	-0,057778	0,373488	-0,15	0,8771

Source: own creation, JMP 13

Figure 14.18 – Regression model year 2015

Summary of Fit

RSquare	0,497539
RSquare Adj	0,497286
Root Mean Square Error	29,08304
Mean of Response	57,71685
Observations (or Sum Wgts)	19908

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	16664466	1666447	1970,207
Error	19897	16829339	846	Prob > F
C. Total	19907	33493805		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	4,7147281	3,945926	1,19	0,2322
Hist_vol	2,0967955	0,052999	39,56	<,0001*
Implied_vol	2,0532813	0,044383	46,26	<,0001*
D/E	0,0605434	0,001689	35,84	<,0001*
P/B	-1,751396	0,047165	-37,13	<,0001*
Return	0,2862164	0,166974	1,71	0,0865
Rating	-5,230199	0,131389	-39,81	<,0001*
CDS liquidity	-0,022935	0,048128	-0,48	0,6337
rf	14,501045	1,651732	8,78	<,0001*
S&P 500	0,5949833	0,267267	2,23	0,0260*
GDP Growth	2,0658461	0,410789	5,03	<,0001*

Source: own creation, JMP 13

Figure 14.19 – Regression model year 2016

Summary of Fit

RSquare	0,655934
RSquare Adj	0,655761
Root Mean Square Error	41,74635
Mean of Response	76,76562
Observations (or Sum Wgts)	19908

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	66106402	6610640	3793,207
Error	19897	34675643	1743	Prob > F
C. Total	19907	100782044		<,0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-64,21912	3,886434	-16,52	<,0001*
Hist_vol	2,6653469	0,048239	55,25	<,0001*
Implied_vol	3,9696758	0,051776	76,67	<,0001*
D/E	0,0287601	0,001767	16,28	<,0001*
P/B	-0,690543	0,044898	-15,38	<,0001*
Return	0,9970157	0,198864	5,01	<,0001*
Rating	-2,97522	0,191838	-15,51	<,0001*
CDS liquidity	-0,250302	0,05771	-4,34	<,0001*
rf	-4,174481	1,31753	-3,17	0,0015*
S&P 500	1,9915891	0,415666	4,79	<,0001*
GDP Growth	9,5282014	1,403554	6,79	<,0001*

Source: own creation, JMP 13

Table 14.7 – Correlation Matrix, Regression model based on Simple Moving Avarage of Stock Return and S&P 500 Index

Multivariate

Correlations

	CDS spread	Hist_vol	Implied_vol	D/E	P/B	Rating	CDS liquidity	rf	GDP Growth	SMA180(return)	SMA180(S&P500)
CDS spread	1,0000	0,4900	0,5512	0,1918	-0,0321	-0,2656	0,0792	-0,1087	-0,2536	-0,1886	-0,2187
Hist_vol	0,4900	1,0000	0,8081	0,0083	-0,0684	-0,1401	0,1578	-0,0856	-0,6370	-0,1575	-0,3928
Implied_vol	0,5512	0,8081	1,0000	0,0230	-0,0722	-0,1488	0,1732	-0,0183	-0,5628	-0,3552	-0,5405
D/E	0,1918	0,0083	0,0230	1,0000	0,8101	-0,1547	0,0020	-0,0578	-0,0276	0,0290	0,0105
P/B	-0,0321	-0,0684	-0,0722	0,8101	1,0000	-0,0224	-0,0053	-0,0818	-0,0003	0,0474	0,0364
Rating	-0,2656	-0,1401	-0,1488	-0,1547	-0,0224	1,0000	-0,0016	0,0766	0,0100	-0,0878	-0,0328
CDS liquidity	0,0792	0,1578	0,1732	0,0020	-0,0053	-0,0016	1,0000	-0,0416	-0,1908	-0,1079	-0,1885
rf	-0,1087	-0,0856	-0,0183	-0,0578	-0,0818	0,0766	-0,0416	1,0000	0,1218	-0,0046	-0,0386
GDP Growth	-0,2536	-0,6370	-0,5628	-0,0276	-0,0003	0,0100	-0,1908	0,1218	1,0000	0,2027	0,4689
SMA180(return)	-0,1886	-0,1575	-0,3552	0,0290	0,0474	-0,0878	-0,1079	-0,0046	0,2027	1,0000	0,6256
SMA180(S&P500)	-0,2187	-0,3928	-0,5405	0,0105	0,0364	-0,0328	-0,1885	-0,0386	0,4689	0,6256	1,0000

Source: own creation, JMP 13