The Nordic Credit Spread Puzzle

Assessing the Performance of a Structural Modeling Framework for Credit Risk

Master's Thesis

Master of Science in Business Administration and Economics
(cand.merc. Finance & Strategic Management)

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June 26, 2014

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Number of pages including Appendix
111

Number of characters including blanks
192853

Copenhagen Business School 2014

Executive Summary

The credit spread puzzle alludes to the examination that structural models of credit risk, such as the one presented by Robert Merton (1974), generate credit spreads smaller than the market, when calibrated to observed default frequencies. The purpose of this thesis is to analyze whether the credit spread puzzle exist in the Nordics through the use of a structural model, an extension of Merton's model of default. In contrast to the existing literature, we use CDS as reference data instead of bond data, because of advantages related to liquidity and its contractual nature. We use a sample of 25 individual companies from the Nordic region (Denmark, Finland, Norway and Sweden) and cover the period from 2006-02-14 to 2014-02-14, during which three sub-periods have been assigned with regards to the financial crisis (Pre-Crisis, Crisis and Post-Crisis) in order to determine whether times of economic turbulence influence financial figures. All necessary data is obtained from available data sources such as Bloomberg, Datastream and Moody's.

When contrasting our results against previous studies, we find that this paper contribute to the existing literature on the study of the credit spread puzzle. First, we confirm that our results are qualitatively in line with the existing literature, in that the majority of our model-implied spreads, across all rating categories, tend to underpredict observed market spreads. Second, when contrasting our quantitative figures against existing studies trying to resolve the credit spread puzzle using bond data, our model spreads show a better match with observed spreads compared to what is found in the literature. Possible reasons for this might be related to the approach that we apply, the fact that we look at a different time horizon or that we use Nordic data. Although our model predictions prove to match market spreads fairly well, when comparing the different sub-periods, we find that the accuracy of the predictions differs, where the Post-Crisis period shows the most accurate predictions, the Crisis the least accurate in absolute terms and the Pre-Crisis the worst in relative terms.

We find a credit spread puzzle in the Nordics and that CDS data serve as a better proxy compared to bond data. Hence, our results are qualitatively in line with the existing literature, but not quantitatively, where the predictions errors of our model spreads tend to be less severe compared to previous studies. Overall, our results suggest that the credit spread puzzle is not as eminent in the Nordics compared to what is seen in the U.S.

Preface

We would like to thank our supervisor, Ramona Westermann from Copenhagen Business School, for assisting and providing us with valuable guidance throughout this master thesis process.

Copenhagen, 26^{th} of June 2014

Nicolina Rollof Knudtzon & Victor Thomas Anton Karlsson

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List of Abbreviations

bps:	Basis Points
BIS:	Bank for International Settlements
CCA:	Contingent Claims Analysis
CDS:	Credit Default Swap
CTD:	Cheapest-To-Deliver
DEN:	Denmark
DTCC:	Depository Trust & Clearing Corporation
FIN:	Finland
GDP:	Gross Domestic Product
IMF:	International Monetary Fund
ISDA:	International Swap and Derivative Association
MAE:	Mean Absolute Error
MAPE:	Mean Absolute Percentage Error
ME:	Mean Error
MPE:	Mean Percentage Error
N:	Number
NASD:	National Association of Security Dealers, Inc.
NIB:	Nordic Investment Bank
NOR:	Norway
OTC:	Over-The-Counter
SWE:	Sweden
USD:	United States Dollar
WBG:	World Bank Group

1 Introduction

There exist two different types of approaches that are used within academic literature for the purpose of modeling credit risk – reduced-form models and structural models. Reduced-form models are based on the modeling of the interest rate term structure, and these models are called reduced-form since they do not explicitly state the relation to economic fundamentals. Structural models, on the other hand, look at the fundamental drivers of risk such as companies' capital structures, asset values and asset volatilities. Hence, structural models are given the name due to its explicit link to economic fundamentals and are able to provide intuitive explanations of a company's default risk and its underlying drivers. This is interesting, since the management of a firm or an investor can comprehend how the default risk of a company would change given some change in the firm's corporate structure or volatility and, for an investor, how this can be hedged. In addition, it can be used to assess the riskiness of a publicly traded firm that have no bonds issued on the public markets, as structural models also provide explanations on the pricing of corporate debt. Most structural models are based on the developments of Robert Merton (1974) who show that the intuition behind Black and Scholes' (1973) option pricing model can be applied to price corporate debt, and therefore also to asses a firm's default risk. Nevertheless, due to the scope of this thesis we look into the findings from structural models, as the credit spread puzzle is defined as the inability of structural models to explain why model-implied spreads are too low compared to actual spreads, which is what we base our paper upon. Hence, we will not look into the findings from reduced-form models, however Section 2.2.4 illuminates around the most important conclusions from reduced-form models.

1.1 The Credit Spread Puzzle

The credit spread puzzle alludes to the examination that structural models of credit risk, such as the one presented by Merton (1974) generate credit spreads that are smaller than the ones observed in the data, when calibrated to observed default frequencies. Huang and Huang were the first researches to observe this and state in their working paper, from 2003, that structural models of credit risk, such as the Merton Model, cannot fully explain credit spreads. They claim that credit risk, a feature that structural models try to explain, only make up a fraction of the total spread, and that other effects, such as illiquidity, call and conversion features as well as the asymmetric tax treatment of corporate and Treasury bonds contribute to the spread (Huang & Huang 2012). However, even after controlling for these factors, the observed spreads are still too high compared to those predicted by the models. As a consequence of this, investors earn a credit premium for holding bonds that are issued by reference entities other than governments. Previous and current research aim to resolve and explain the reasons for the historically high excess return received by corporate bondholders; however, there continues to persist unexplained features affecting the credit spread. Although Huang and Huang were the first to highlight this matter in their working paper from 2003, it is actually termed the "credit spread puzzle" by Chen, Collin-Dufresne and Goldstein in 2009. Nevertheless, later sections look into the findings by important researchers who have managed to justify the default components of the credit spreads for investment grade corporate bonds.

Moreover, a recent paper by Feldhütter and Schaefer (2013) point out that those studies finding evidence of the credit spread puzzle suffer from low statistical power. In addition, they highlight the importance of a convexity bias à la Strebulaev (2007), i.e. that the spreads generated by a model using average variables are in general lower than average spreads, since spreads typically are convex in company variables. As the spreads generated when using average values are usually lower than average spreads for individual firms, this consequently leads to biased results. Instead, the authors test U.S. corporate spreads in a so-called bias-free approach, where the spreads are calculated for each bond transaction separately, and find that the model predicts spreads of three-year bonds accurately. Whereas, for long-term bonds, the model does not manage to predict the spreads as precisely as it does for short-maturity spreads, yet more accurately than what is found in previous studies.

Further, the majority of all literature examining the credit spread puzzle, including Feldhütter and Schaefer (2013), scrutinize this issue in regards to data based on the U.S. marked and U.S. companies, while very low emphasis is placed on the European credit markets. Consequently, we wish to test the accuracy with which Merton's model can predict credit spreads in the Nordic market.

1.2 Credit Default Swaps

When looking into previous research testing structural models of default, it is most common to use corporate bond data as the reference. By contrast, we use Credit Default Swaps (CDSs), because this type of instrument has several advantages that are of high importance when testing whether the credit spread puzzle persists in the Nordics. First, Longstaff, Mithal and Neis (2005) compare corporate bond spreads and CDS premiums (i.e. spreads) and discover that the price differences between bonds and CDSs can mainly be explained by individual corporate bonds' illiquidity. They further emphasize that CDSs are not securities, but contracts, and that this contractual nature make them much less responsive to liquidity or convenience yield effects. As stated in their paper, "illiquidity is seen as a factor that have a larger impact on yield spreads of shorter-maturity bonds simply because trading costs have to be amortized over a shorter holding horizon" (2012: 170). Moreover, they argue that CDSs provide researchers with "a near-ideal way of directly measuring the size of the default component in corporate spread" (Longstaff, Mithal & Neis, 2005: 2214). Second, Blanco, Brennan and Marsh (2005) and Zhu (2006) demonstrate and support that the CDS and bond markets are relatively aligned in the long run, but substantial deviations can arise between the two instruments' credit spreads in the short run. Also, and as latterly emphasized, due to contractual arrangements, bond spreads may be influenced by alterations, such as seniority, coupon rates, embedded options and guarantees. This is stressed by Blanco, Brennan and Marsh (2005) who underline that the deviations relate to "imperfections in contract specifications or due to a clear lead for CDS spreads over bond spreads", whereas Zhu (2006: 213-214) assume it is "largely owing to their different responses to changes in the credit quality of reference entities". Finally, because a CDS contract is usually traded on standardized terms, its price can be regarded as fairly flawless of the default risk of the underlying unit. Hence, these arguments indicate that the CDS market is potentially more efficient than the bond market and, naturally, more appropriate when testing standard structural models [1]. Thus, we rely on these arguments and use CDS data when testing whether the credit spread puzzle persists in the Nordics.

[1] A more detailed discussion regarding the differences between CDS and corporate bond spreads can be found in Longstaff, Mithal & Nies (2005) and Lando (2004).

1.3 Models & Data Collection

As latterly mentioned and which will be further illuminated in later sections, this paper is examining a structural model – an extended version of Merton's model of default. The data for this paper is collected on 25 non-financial Nordic publicly listed corporations collected using two main sources – Bloomberg and Datastream. A firm is included in our sample if we obtain adequate observations on (i) its 5-year CDS spread, (ii) its stock price, (iii) the number of outstanding shares, (iv) balance sheet data on long-term and short-term debt and (v) data on dividend and interest payments.

1.4 Purpose and Problem Statement

The purpose of this thesis is to examine the credit spread puzzle using Merton's model with firm-specific parameter inputs on Nordic companies. To our knowledge, this is the first paper studying this relationship. Although Huang and Huang, as previously stated, did not name the puzzle, the topic was first emphasized in their working paper from 2003. Their paper was not published until 2012 and refers to the finding that, when calibrated to observed default rates and recovery rates, traditional structural models are not able to fully explain the credit spreads for bonds regarded as investment grade. Many researchers aim to resolve the puzzle, but it was not until structural models incorporated time varying macroeconomic risks, that Chen, Collin-Dufresne and Goldstein (2009), Bhamra, Kuehn and Strebualev (2010a; 2010b) and Chen (2010) were able to justify the default components of the credit spreads for investment grade bonds.

Furthermore, there are several reasons why this is an interesting topic to investigate. First of all, and as mentioned, structural models may provide a useful tool to assess the riskiness of a company without any bonds issued on public markets, or to find the underlying drivers behind the pricing of corporate debt. The accuracy of the structural models is therefore crucial. Second, the credit spread puzzle has mainly been researched upon using U.S. data and since less weight has been placed on the European credit markets, we wish to test the accuracy with which Merton's model can predict credit spreads in the Nordics. Hence, our study differentiates itself from previous research in that we examine 25 companies within Sweden, Norway, Denmark and Finland over the time period 2006-02-14 to 2014-02-14. Although our sample is rather small, this is due to certain factors. First, we use CDS market data instead of corporate bond transactions. Second, we keep a strict sample by only focusing on non-financial firms, following the standard in the literature. Hence, when incorporating these elements we are consequently left with a smaller sample, which is also why there is room for further research on the subject.

We aspire to examine the performance exploiting the bias-free approach[2] that is documented in Feldhütter and Schaefer's paper from 2013, by using CDS market data instead of focusing explicitly and only on corporate bond transaction data. Calculated model spreads are then compared to the observed (i.e. actual and real) CDS spreads, for the same time period, in order to see whether there persist any underpredictions.

The main question this thesis seeks to answer is:

- **Does the "Credit Spread Puzzle" exist in the Nordics?**

If that is the case, this will be scrutinized further into by trying to answer the following:

- Is the puzzle more evident in some time periods than in others?
- Are there any company-specific traits that magnify or condemn the effect of the puzzle?
- How do the results from our study compare to the existing literature?

1.5 Limitations

A disadvantage when choosing to examine companies from various countries relates to the fact that the analysis will incorporate data from different states and there is a risk that these firms might be subject to diverse laws and regulations, which can make the studies less comparable and it might lose explanatory power. However, to our favor the laws and regulations within the Nordics are fairly similar and therefore we do not believe this will affect our examination to a very large extent, still it is important to keep this is in mind when making comparisons.

[2] This biased-free approach consists of calculating the spread for each individual company using the Merton model, computing an average, and then comparing the result with the average actual spread.

Furthermore, because the study sample is rather small (25 companies) we might not be able to draw any general conclusions. However, due to the incorporated elements we are left with this representative sample of non-financial Nordic firms whom have documented CDS data. Although we could have included data from other European countries, we have not done so because of the specific consciousness of focusing primarily on the Nordics.

Finally, the main and real limitation of our paper relates to the lack of comparability. In other words, we cannot directly compare our results to studies using U.S. data, as the literature has never tested whether there persists a credit spread puzzle in the U.S. when using CDS data. Most current literature instead examines the phenomenon using bond data. We could alternatively use bond data to see whether there exists a credit spread puzzle in the Nordics. Nevertheless, as previously argued and which will be further discussed in later sections, we decided to use CDS data. However, a robustness check using bond data can be found in Section 8.1.

1.6 Thesis Structure

Having introduced the idea behind what this thesis will delve around, the paper proceeds as follows: In Section 2, we give a thorough background overview of the main concepts that will be discussed in addition to highlighting the main findings related to structural models of credit risk. The following section (Section 3), explains Merton's Structural Model of Credit Risk as well as outlining the extended Merton model, which is the model we base our paper on. Section 4 describes and discusses the methodology. Section 5 looks into the data collection by illuminating the differences between CDS and bond data as well as covering descriptive data. The next section (Section 6) outlines the empirical results of our model, whereas Section 7 examines and analyzes these results in relation to the existing literature. Section 8 includes the different robustness tests and Section 9 suggests directions for further research while Section 10 concludes.

2 Background

Section 2.1 looks into the credit derivative market, by explicitly focusing on CDSs through explaining its nature and function as well as how this derivative instrument is seen to have influenced and impacted the global financial crisis. This is followed by Section 2.2, which emphasizes key findings from previous research by highlighting the topics that are essential to our paper.

2.1 Credit Derivatives

Despite the criticism facing credit derivatives after the global financial crisis, these instruments have become fundamental to the current financial markets. They comprise one of the most important expansions of the derivative markets permitting participants to trade and manage credit risk in much the same way as market risk. Exploiting credit derivatives have led to new opportunities for financial institutions on how to dynamically manage their credit risk, through strategically position themselves within the derivative market in order to gain protection from credit events in their loan portfolio. Appropriately, the largest market participants constitute banks that mainly place themselves on the buy- or long side of the derivative contract, whereas insurance companies comprising the other major part entering the short positions in the CDS market. According to Depository Trust and Clearing Corporation (DTCC), CDSs is the derivative 'instrument' making up more than half of the total gross national value of outstanding credit derivatives, as of 2010. The following quote by Alan Greenspan (2004) emphasizes the importance and the possibilities created by credit derivatives:

"The new instruments of risk dispersion have enabled the largest and most sophisticated banks in their credit-granting role to divest themselves of much credit risk by passing it to institutions with far less leverage. These increasingly complex financial instruments have contributed, especially over the recent stressful period, to the development of a far more flexible, efficient, and hence resilient financial systems than existed just a quarter-century ago".[3]

[3] This quote is from Alan Greenspan's speech "Economic Flexibility" before Her Majestys Treasure Enterprise Conference (London, 26 January 2004).

As have been documented, and that can be drawn from Figure 2.1, which is based on data from the International Swaps and Derivative Association (ISDA) market survey, is related to the fact that the CDS markets have faced volatile periods. According to the survey, the fiscal year of 2001 to the end of 2007, just before the financial crisis, face a dramatic increase in the outstanding amount of CDSs from USD 0.9 trillion to USD 62.2 trillion. Thereon, it consistently decreased to USD 26.3 trillion at the end of the first half of 2010, which is when the latest ISDA market survey was issued.

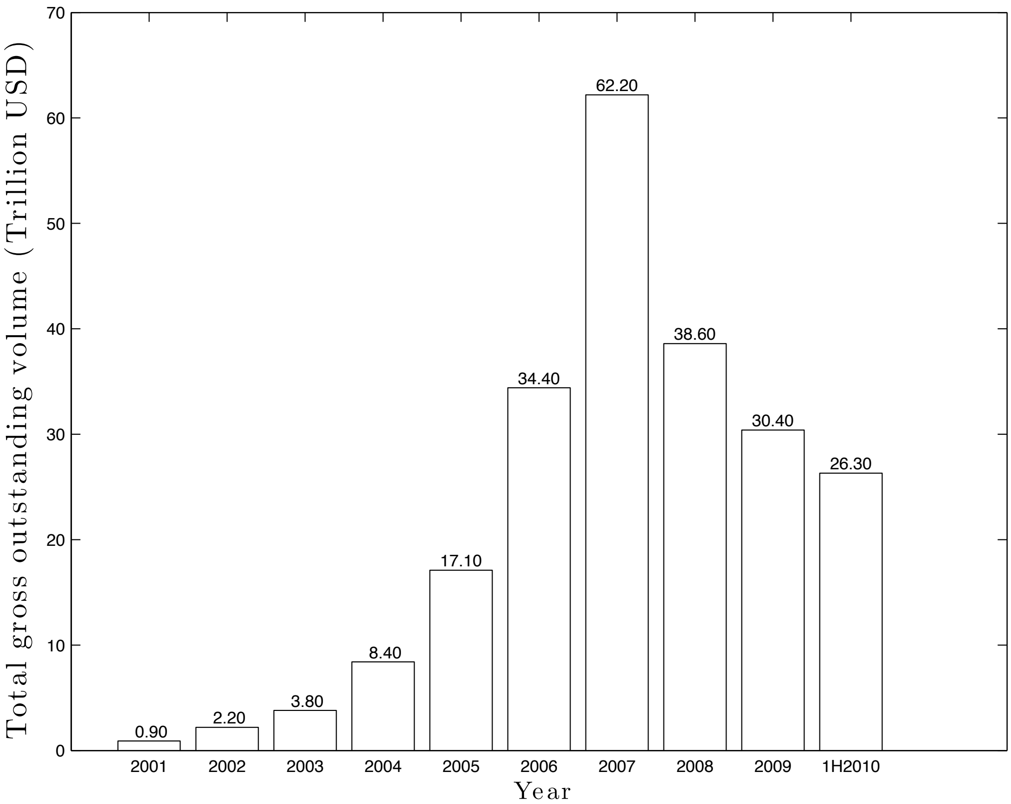

Figure 2.1. Total Gross Notional Outstanding CDS. Source: ISDA Market Survey 1987-2010.

2.1.1 Credit Default Swaps

A credit default swap (CDS) is considered to be the most popular single-name credit derivative instrument. It constitutes a protection contract providing insurance against potential losses that might arise from a certain type of pre-defined credit event. A CDS contract constitutes two parties entering an agreement: a long (buyer) and a short (seller) position. The buyer of protection agrees to make periodic payments to the seller during the specified life of the agreement in the form of an insurance premium, namely the CDS spread[4]. The CDS spread is the rate of payments made per year by the derivative buyer and is a direct market-based measure of the reference entity's credit risk. Hence, the CDS spread is equivalent to the spread between the yield on a defaulting bond and the risk-free interest rate. Unless a specified credit event occurs (e.g. the reference entity defaults before maturity), the seller of protection makes no payment, and the relationship between the two parties ends without any obligation. However, in case the reference entity faces a credit event (e.g. defaults on its obligation), the buyer of a CDS contract is compensated for the loss incurred as a result of the credit event, which is equal to the difference between the par value of the bond or loan and its market value after default. In other words, one could say that a CDS transfer risk to the part most willing to bear it. The following sections will explain these processes in detail.

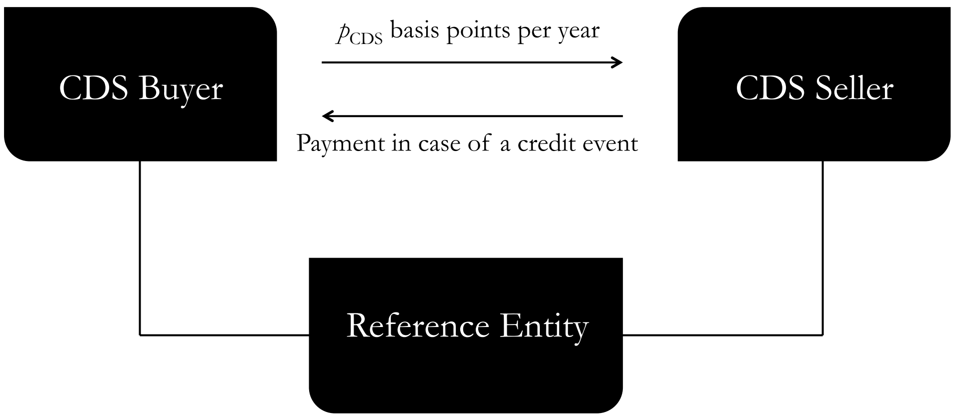

Figure 2.2. The structure of a Credit Default Swap agreement.

Figure 2.2 demonstrates the connection between the two bodies of the CDS contract. The contract offers the long position (CDS buyer) insurance against the risk of default by a specific corporation or sovereign entity; identified as the so-called reference entity and default is referred to as the credit event[5]. If a credit event takes place, the buy (long) side of the CDS contract gains the rights to sell a pre-determined quantity of bonds issued by the reference entity at face value, that is to say the principal amount of the bond that is required at maturity. The seller on the other hand approves to buy the bonds at face

4 The CDS spread is expressed as a percentage of the notional principal.

5 Credit events are usually defined to either involve a material default, bankruptcy or debt restructuring for a specified reference asset.

value if stroke by a credit event. The bonds total nominal value that can be sold is referred to as the notional principal. In return of the right to sell the bond in case of a credit occurrence, the contract buyer agrees to make payments periodically to the seller until maturity or default, whichever is first. Usually, these payments are to be paid in arrear each quarter; however this might differ between contracts. Furthermore, in occurrence of a credit event, the payment on default is either physical or in cash. Cash settlement, the dominant method, is conducted by setting the recovery price (mid-market value of the bond) in an auction handled by ISDA, and the compensation received by the protection buyer is the notional principal less the post-default market value of the reference obligation. In a physical settlement procedure, the protection buyer has to deliver a bond of seniority at least equal to that of the reference obligation, and in return, receives the full notional principal from protection seller – in case of multiple bond deliverables; the protection buyer will optimally deliver the cheapest bond to the protection seller (the so-called cheapest-to-deliver (CTD) option. Either way, the value of the buyer's portfolio is restored to the initial notional principal. For bonds or loans it is important that the CDS contract precisely specify which reference obligations that can be delivered to satisfy the protection seller's obligation. The insurance premium paid to the protection sellers will also terminate in case of a credit event, however, as contracts usually contain in arrear payments, the protection buyer makes the final accrual payment. As previously stated, the total insurance premium per year is the so-called CDS spread and is estimated in proportion of the notional principal of the CDS contract. The length of a CDS contract (maturity) can range from 1-10 years, however maturities of 5 years are most common, because it is the most liquid in the credit derivative market and is the commonly used in the literature (Hull, 2012; Bai & Collin-Dufresne, 2013).

Despite the fact that CDSs are defined as over-the-counter (OTC) financial instruments, they are controlled by ISDA. ISDA is a trade organization of financial participants in the market for OTC derivatives and proposes classifications of terms and conditions for CDS contracts. The association has more than 800 member institutions from 62 countries, ranging from corporations, investment managers, insurance companies, international and regional banks. There are primarily three areas in which ISDA is specialized in order to regulate the OTC derivatives – reduce counterparty credit risk, increase transparency and improve the market's operational infrastructure.

Furthermore, a CDS contract permit participants to trade credit risk of the reference entity despite having to enter positions in securities distributed by the reference entity. Market participants taking a long (short) position speculate that the financial stability of a particular reference entity is going to decrease (increase) the credit conditions – this strategy is mainly seen amongst hedge funds. However, it is common for bondholders, such as pension funds or insurance companies, to buy protection in order to reduce their credit exposure in bond investment of the reference entities. This is specifically seen when bonds have been downgraded and buyers lack interest or call for larger discounts. Whereas banks tend to long CDSs to diminish credit exposure of their loans as an alternative of securitizing loans to lessen their capital requirements.

In addition to the abovementioned examples, CDS contracts can be used as a way to protect positions in bonds of the reference unit. As an example, you buy a 5-year bond with nominal value equal to USD 10 million proposing a yield of 7% as well as taking a long position in a 5-year CDS contract having the bond issuer as reference unit, a notional principal of USD 10 million and a credit spread of 2% or 200 bps. The CDS change the function of the corporate bond to a nearly risk-free bond with a yield of 5%. Therefore, in the occurrence of a credit event, you will earn 5% interest till the event and thereafter obtain the par value in exchange for the bond. In order to avert any arbitrage opportunities, it is vital that the additional rate of an *n*-year bond over the particular *n*-year CDS contract matches the risk-free rate. In case the spread is considerably higher than the risk-free rate, investors see the opportunity of earning an arbitrage profit through borrowing the risk-free rate and buy the outlined portfolio. If the spread instead were considerably less than the risk-free rate, an arbitrageur would short-sell the bond, sell CDS protection and invest the accessible funds at the risk-free rate in return of an arbitrage profit. This highlights the importance of having an additional rate of an *n*-year rate over the risk-free rate that equals the *n*-year CDS spread. Based on these arguments, the variance between the additional rate and the CDS spread, the so-called CDS-bond basis, should be close to zero. However, although the basis is predicted to be equal to zero, this link does not always hold in practice. Hence, market data have shown that the basis can either be negative or positive; in addition, the value is both firm specific and time-dependent (Wit, 2006).

2.1.2 Financial crisis impact on CDSs

Many observers, comprising financial market participants, economists and media agents, claim that the CDS market contributed significantly to the evolvement of the credit crisis. They are predominantly concerned about CDSs being traded in the large unregulated OTC market as bilateral contracts that involve counterparty risk and that they facilitate speculation concerning a reference entity's financial strength. There are various statements by observers whom identify CDSs to be a prominent villain of the credit crisis. As with all derivatives, a CDS take many forms. They could be purchased to protect portfolios of subprime mortgages and, in securitizations, portions of such portfolios. Swaps offering insurance against credit events on portfolios of subprime mortgages made it feasible for investors to take exposure to subprime mortgages without having to position themselves in the mortgages. Throughout the boom preceding the credit crisis, the request for exposure to subprime mortgages cultivated so rapidly and severely that there were lack of subprime mortgages to fulfill that request. Ultimately, investors obtained such exposure synthetically through CDS contracts.

The latter observations have focused on three central issues of the CDSs with which they believe augmented if not event instigated the credit crisis. The first reason, as previously outlined, is that CDSs made the credit boom feasible, which ultimately led to the economic crisis. This is due to the fact that financial institutions were capable of increasing lending without raising capital, as they entered CDS contracts concurrently. It has been discussed as to whether this led to a departure of risk-bearing and funding indicating that banks were unwilling to handle the essential credit analysis when distributing loans to borrowers, as they were enable to hedge the involved risk through CDSs. The second argument relates to the creation of systemic risk, having been fostered by financial institutions holding CDSs for trillions of dollar of notional principal. These massive exposures are expected, by some observes, to have caused a crisis of confidence in financial institutions following the bankruptcy of Lehman Brothers during the autumn of 2008, as market participants were left with the notion of what banks are paying on CDS contracts. The final reason relates to the absence of transparency in the CDS market, where banks are not required to report the amount of CDSs they buy or sell on their balance sheet, permitting market participants to manipulate the outlook about the financial conditions of institutions. Conversely, these reasons are claimed by critics to have been partially accountable for the failure of Bear Stearns and Lehman Brothers. Following this argument, the problem with CDSs relates to how they are traded and it is argued that these derivatives should be traded on exchange and not OTC. (Stulz, 2009).

Nevertheless, although it is common to hear how the CDS market contributed significantly to the crisis, it is vital to reflect and also understand how well the market worked during in the financial crisis. First, financial institutions ability to protect their loans, through the use of CDS contracts has a beneficial consequence, by making them capable of supplying access to debt outside their own required levels of exposure as well as leading to improved credit availability for debtors. Based on research, just a small portion of the unsettled CDS contracts was used to protect loans by banks (Minton, Stulz & Williamson, 2009). Moreover, CDSs are seen to provide more liquid markets for trading credit risk than the underlying bond markets, because they do not demand sizable volumes of capital to be subsidized and CDSs are generally regulated by ISDA. Consequently a CDS contract can be used to protect diverse forms of distributed bonds or receivables of the reference unit. Typically, it is more challenging and pricy to enter a short position in the bond of a reference unit than entering a long position in a CDS. Hence, the accessibility of CDSs should advance the capital distribution in the market. A noteworthy fact is that the CDS market actually functioned outstandingly well through the beginning of the credit crisis, and a good example is how well it handled the default on Lehman. The DTCC recorded contracts on Lehman Brothers for a notional principal of USD 72 billion, which meant that on the day of its bankruptcy, CDS sellers were bound to pay 91.375 % of the par value to insurance buyers. The settlement of these contracts was effectively finalized since the net position was reasonably small, as many institutions were both sellers and buyers of protection of Lehman, only USD 5.2 billion were exchanged through the DTCC. Lastly, it is important to understand that CDS contracts are not the reason behind the financial suffering at Bear Stearns, Lehman and AIG. The great losses were suffered due to investors and financial institutions incorrect belief that AAA-tranches or securitized loan portfolios had low likelihoods of default. However, these portions were kept in large amounts by leveraged institutions, which successfully led to a lack of confidence in the financial system, as the losses on these tranches led to knock-on losses. While the exposure of derivatives by market participants was not recognized during this period, which might also be the reason for the increased uncertainty about them, the CDS instrument enabled financial institutions to protect and limit the risk associated with their investment, which consequently led to more secure and protected institutions. (Stulz, 2009; Minton, Stulz & Williamson, 2009).

2.2 Previous Research

Pricing models of CDSs and corporate debt, as well as the credit spread puzzle have been and continue to be a widespread discussed topic. Although the results from Huang and Huang's working paper (2003), which show that for investment-grade bonds of all maturities, credit risk only account for a small fraction of the observed corporate-treasury yield spread, it was, as previously stated, actually Chen, Collin-Dufresne and Goldstein whom in 2009 referred to this finding at the "credit spread puzzle". However, when looking at the existing literature documenting this topic, the authors are not unanimous to the underlying reason behind the puzzle. The following section start by illuminating what is actually meant by the puzzle. The second part briefly looks into the structural models that are considered fundamental to the studies on this topic. The third part concisely explains and emphasizes the most important empirical findings that base its work on testing structural models. Although this paper is focusing on structural models, the final section gives an overview of the main findings from reduced-form models.

2.2.1 The Credit Spread Puzzle

The credit spread puzzle is very complex and has been a frequent theme in empirical research. Instead of looking into every paper having studied and attempted to resolve the puzzle, the following section highlights the main findings of the most revolutionary and recent papers.

Merton's model (1974) as well as extended versions of the model have been unsuccessful in explaining the historically high credit premium obtained by corporate investors. As mentioned, even when calibrated to observed default frequencies, the models typically generate credit spreads smaller than what is observed in the market. The credit spread is seen as a compensation for two main risk types – default risk and recovery risk. Default risk refers to the risk that an issuer will default, whereas the recovery risk is the possibility of obtaining less than the guaranteed payment in case the issuer defaults. However, it has been found that the credit spread between BBB-rated (3-5 year maturity) corporate bonds and treasuries averaged to about 170 bps per annum throughout 1997-2003, whereas the expected total loss from default for the same bonds was about 20 bps per annum. In this case, the spread was more than eight times the expected loss from default, which demonstrates that the credit spread has compensated a lot more than the anticipated loss from default (Amato & Remolona, 2003). Reduced-form and structural models are the two approaches having been used within academic literature attempting to explain the differences in credit spreads. Reduced-form models make use of statistical analysis when identifying the elements, including non-default-related element, that might explain the observed credit spreads, such as liquidity, tax, equity volatility and interest rate structure, using a factor model regression. Structural models on the other hand syndicate economic theory, measurements and identification to quantitatively account for observed credit spreads. Although both models have been used with the aim to resolve the credit spread puzzle, and many studies have managed to find elements accounting for a significant portion of the credit spread, there is a sizeable portion of the variation that is still left unidentified. This thesis looks into the findings from structural models, as the credit spread puzzle is defined as the inability of structural models to explain why the spreads are too low compared to actual spreads. Thus, we will not look into the findings from reduced-form models, however Section 2.2.4 illuminate around the most important findings from reduced-form models.

2.2.2 Structural Models

Merton's (1974) model builds on the option-pricing framework as developed by Black and Scholes (1973) in that it treats a company's equity as a call option on its assets. The model assumes that the firm has issued a certain amount of debt in the form of a zero-coupon bond with a set maturity. The firm defaults at maturity if the value of the company's assets is below the face value of the debt. Hence, the strike price of the implied call option that the equity embodies equals the face value of the debt.

Geske's (1977) model differs from the Merton model in that it treats the coupon on the bond (e.g. liability claims) as a compound option. He explains that risky securities with serial payouts can be valued as compound options. In this framework, on each coupon date, if the shareholders agree to pay the coupon (service debt) by issuing new equity, the firm will continue to operate; however if a default happens, bondholders will receive 100% of the firm's value. The endogenous default boundary of Geske's model is a key enhancement.

Longstaff and Schwartz (1995) suggest a first-time passage model with an exogenous and constant default boundary and recovery rate as well as describing the interest rate dynamics using the Vasicek (1977) model. They assume that the firm value process follows a diffusion process, a Brownian motion, and allow default before the maturity of risky debt. In the event of default, bondholders are assumed to recover a constant fraction of the principal and coupon payment. With help of the closed form solution for a zero-coupon bond derived in the Vasicek model, the authors find a solution for the price of risky zero-coupon bonds and floating rate bonds. A key finding from their model is that the credit spread decreases when the risk-free treasury rate increases; hence credit spreads are a decreasing function of interest rates.

Leland and Toft (1996) develop Leland's (1994) and Black and Cox's (1976) model by assuming that the firm continuously issues a constant amount of debt with finite maturity as well as paying continuous coupons. They examine an explicit stationary debt structure allowing their model to be applied to a finite maturity debt. They assume that to serve the debt or default, equity holders have the option to issue new equity. However, when new equity cannot be raised (negative net equity), which commonly follows when debt service cost match the expected equity return, equity holders receive nothing whereas bondholders will obtain a fraction of the firm asset value. Fundamental from their findings is that debt maturity is shown to be crucial to the leverage ratio and credit spreads.

Collin-Dufresne and Goldstein (2001) build on the Longstaff and Schwartz (1995) model by developing a structural model of default with stochastic interest rates that assumes target leverage ratio. They develop an efficient method for pricing corporate debt within a multi-factor framework that is applicable to both their model and the original Longstaff and Schwartz (1995) model. In addition, they show that taking account of a firm's ability to control its outstanding debt has important influence on credit spread predictions, as well as proposing that the optimal capital structure is very sensitive to the input level of the interest rate.

Chen (2010) focuses on how business cycle risks affect firms' financing decisions and emphasizes the importance of having the possibility to dynamically re-structure, despite being a costly process. He demonstrates through his developed dynamic capital structural model how the impact of business-cycle differences in expected growth rates, economic uncertainty, and risk premium affect financing and default policies. He highlights that the macroeconomic condition of the world will influence countercyclical variations in risk prices, default probabilities, and default losses depending on the firm's reaction, which then will affect the riskiness of the firm. These correlated movements tend to create large credit risk premia for investment-grade firms, which is why better knowledge of business decisions and frictions in a realistic macroeconomic environment can assist to better evaluate the risks that are linked with different corporate securities.

Bhamra, Kuehn and Strebulaev (2010a; 2010b) derive a structural multi-regime model where they explore how the time evolution of the cross-sectional distribution of firms with various leverage ratios will influence credit spreads and default probabilities. With Chen (2010), they have prolonged the framework of state dependent risk premia to the case that allow corporations to dynamically regulate their capital structure by issuing new debt (e.g. re-financing), whilst the asset is following an exogenous stochastic process.

In a recent paper, Arnold, Wagner and Westermann (2013) aim to solve the credit spread puzzle by looking at the impact of business cycle and aggregate investment (invested assets and growth opportunities). They exemplify that by incorporating the combination of a firm's expansion policy and financial leverage in the presence of macroeconomic risk, research has come a long way towards explaining the empirically observed cross-sectional variation in cost of debt, leverage and equity risk premium, which have been ignored by previous models that only consider firms with invested assets. A summary of the previous studies can be found in Table 2.1.

Table 2.1. Results from theoretical models.

Name (Year)	Based on what Model	Developments of Author(s)	Results
Merton (1974)	Black and Scholes (1973)	Examines the valuation of corporate debt in three possible manifestos: zero-coupon debt, coupon-bearing debt and callable debt.	Models a firm's asset as a lognormal process and assumes that the firm will default if the asset value falls below a certain default boundary. He shows that the equity and debt of a firm can be viewed as contingent claims on some underlying firm value.
Geske (1977)	Merton (1974)	Treats the liability claims as compound options and assume companies have the option to issue new equity to service debt. It treats default as the inability of the company to fulfill its debt obligations.	Assumes the default point to be the market value of debt that is endogenously computed and the firm value to be the recovery. The compound option model provides an exact match between a compound option and the equity value of a company with multiple debts.
Longstaff and Schwartz (1995)	Merton (1974), Black and Cox (1976) and Vasicek (1977)	Develop a simple approach to valuing risky corporate debt that incorporates both default and interest rate risk. Assume the default barrier is exogenously fixed and act as a safety covenant in order to protect bondholders as well as allowing interest rates to be stochastic.	The correlation between default risk and the interest rate has a significant effect on the properties of the credit spread.
Leland and Toft (1996)	Leland (1994)	Consider the impact of bankruptcy costs and taxes on structural model output. They assume the firm issues a continuously amount of constant debt with fixed maturity and continuous coupon payments. They assume the default barrier is endogenously fixed as a result of the stockholders' attempt to choose the default threshold, which maximizes the value of the firm.	Debt maturity is shown to be crucial to the leverage ratio and credit spreads.
Collin-Dufresne and Goldstein (2001)	Longstaff and Schwartz (1995)	Introduce a target leverage ratio, allowing firms to deviate from their target leverage ratio in the short run, only.	Develop an efficient method for pricing corporate debt within a multi-factor framework. Emphasize the importance of taking account of the expected trajectory of leverage when computing credit spreads.
Chen (2010)	Shleifer and Vishny (1992), Bansal and Yaron (2004), Longstaff, Mithal and Neis (2005), Hackbarth, Miao and Morellec (2006), Jobert and Rogers (2006).	Builds a dynamic capital structural model of default with explicit linkages to business cycle conditions in the economy as well as re-financing, in order to examine how firms make financing decisions over the business cycle.	Macroeconomic conditions/fluctuations and risk premia influence firm's financing and corporate decisions – defaults are more likely to occur during recessions.
Bhamra, Kuehn and Strebulaev (2010a; 2010b)	Merton (1974), Lucas (1978), Fischer, Heinkel and Zechner (1989), Leland (1994), Goldstein, Ju and Leland (2001), Korajczyk and Levy (2003), Bansal and Yaron (2004), Hackbarth, Miao and Morellec (2006), Strebulaev (2007), Calvet and Fisher 2008)	Examine the impact of business cycle and financial restructuring. They focus on how the time evolution of the cross-sectional distribution of firms with various leverage ratios will influence term structures of credit spreads and default probabilities.	They show that: (1) the ideal financing decision are more conventional in bad times when firms refinance their obligations, (2) default boundary and the aggregate dynamics of the capital structure are countercyclical.
Arnold, Wagner and Westermann (2013)	Mello & Parsons (1992), Bhamra, Kuehn and Strebulaev (2010) and Chen (2010)	Develop a structural equilibrium model with inter-temporal macroeconomic risk, incorporating the element that firms are varied in their asset structure.	Heterogeneity in the composition of assets help to explain cross-sectional variations of credit spread and leverage.

2.2.3 Empirical Findings from Structural Models

The structural approached pioneered by Black and Scholes (1973) and Merton's model of default that was put forward by Merton (1974) is probably the most cited versions of all structural credit risk models. According to Ferry (2003: 23) "…Merton models are now so frequently used that they are actually driving the credit market". Although this part is not going to cover the discussion of his contributions, as it will be enlightened later, it is vital to highlight that this model assume to be served as a basis for all empirical research that is linked to resolving the credit spread puzzle. Structural models propose an economically instinctive set-up for credit risk pricing and is widely used to analyze corporate bond spreads. Within the framework of the structural model, Huang and Huang (2012) study how much of the excess return that can be attributed to credit risk and find robust evidence that credit risk is a factor only accounting for a small portion of the observed credit spread for investment-grade than for non-investment-grade bonds, for all maturities. Their work is fundamental to the research conducted on the puzzle, as they provide evidence that "the puzzle is not simply due to features such as jumps in the firm value process, time-varying asset risk premia, endogenous default boundaries, or recovery risk" (Huang & Huang, 2012: p. 190). They demonstrate that structural models linking some of these factors together with stochastic volatility show potential to resolutions, but that there persist certain unidentified features that can explain the reason behind the puzzle. Existing literature have employed various methods and data with the aim of decomposing the spreads. Moreover, they have examined and explored the role played by different features such as; taxes (asymmetric tax treatment) call and conversion, idiosyncratic-risk factors, risk premium (time-varying risk premia), liquidity premium as well as endogenous investment decisions[6], and found that they do contribute to spreads. However, it was not until 2010, when Chen (2010) and Bhamra, Kuehn and Strebulaev (2010a and 2010b) managed to employ different methods and data that enabled them to explain parts of the credit spread puzzle. These latter papers are the most recent advancements on the credit spread puzzle. However, as outlined above, the next section will briefly look into the empirical literature that have found evidence based on the

[6] See, e.g., Gemmill and Keswani, 2011; Chen, Collin-Dufresne and Goldstein, 2009; Huang and Huang, 2003; Saretto and Gamba, 2012.

grounds that structural models over and undervalue corporate bond spreads, but which have also shown significantly progress with regards to solving the credit spread puzzle. Jones, Mason and Rosenfeld (1984) were amongst the first econometricians to present that the Merton (1974) model with non-stochastic interest rates is not able to generate corporate spreads compatible with those actually observed. They emphasize that given the models simplified nature, they fail to explain the large credit market spreads. Based on their study of testing the predictive power of a Contingent Claims Analysis (CCA) model of typical capital structures, they find that incorporating stochastic (default-free) interest rates, as well as tax effects, would improve the model's performance. Hence, they contribute with identifying and resolving various analytical issues in the formulation of the CCA valuation problem for typical capital structures, and also determine empirical results, which have been crucial in establishing future research priorities.

Lyden and Saraniti (2000) were the first to implement and compare the Merton and Longstaff-Schwartz models using individual bond prices. Through Bridge Information Systems' corporate bond database for historical pricing and bond attributes, they use prices of 56 firms' non-callable bonds and find that the two models underestimate yield spreads; the assumption of stochastic interest rates does not appear to alter the qualitative nature of the finding. They use a sample of firms that may not altogether be representative of the larger corporate world; hence there is a need to further explore the power and the limitations of the classical model in explaining asset prices. Although their analysis confirms prior findings regarding the performance of the Merton model, they are unable to distinguish between the two hypotheses – (1) either the model is rejected or (2) expected future asset volatility differs significantly from past volatility.

Eom, Helwege and Huang (2004) compare the Merton model and four newer models (Geske, 1977; Longstaff & Schwartz, 1995; Leland & Toft, 1996 and Collin-Dufresne & Goldstein, 2001) by controlling the extent to which improvements in structural bond pricing models have enhanced the pricing of risky bonds. They find evidence that the models by Merton and Geske generate spreads that are too small on average, and claim that the spread underestimation tends to originate from the fact that the main means for default are related to high current leverage ratios, high asset volatility, or high payout ratio. The models by Longstaff and Schwartz, Leland and Toft as well as Collin-Dufresne and Goldstein on the other hand clearly manage to evade this problem. However, these latter models share the same problem of incorrectness, as they all have a considerable dispersion of predicted spreads being too high on average. In contrast, Leland and Toft's model is unusual in that it overestimates spreads on most bonds, predominantly those with high coupons, which is mainly due to the affectation of a continuous coupon. As a result of this, their model tends to overpredict credit risk on short-term bonds.

Chen, Collin-Dufresne and Goldstein (2009) examine whether a structural model of default embedded within a habit-formation economy of Campbell and Cochrane (1999) can capture historical credit spreads. They show that combining the Campbell and Cochrane pricing kernel with some instruments to match the countercyclical nature of defaults (either countercyclical default boundaries or idiosyncratic volatility) does an excellent job in apprehending the level and time variation of Baa-Aaa spreads.

Feldhütter and Schaefer (2013) question whether the credit spread puzzle is either a myth or reality. They study the existing literature documenting that spreads obtained from standard structural models are too low compared with actual spreads and discover that standard methods to testing structural models are subject to strong prejudices and low statistical power. Instead of introducing a convexity bias and statistical uncertainty, which they find to be strong when testing structural models using average firm variables (e.g. asset volatility and leverage ratio) and/or to historical default frequencies, these researchers use a bias-free approach when testing the Merton model. Through testing structural models by comparing model-implied and actual spreads on a transaction-by-transaction basis, they find *almost* no evidence of any credit spread puzzle. However, they emphasize that although having found a puzzle for high-quality long-term spreads, this puzzle is less prominent when related to previous findings in terms of spread size and how far down in the credit quality the puzzle extents.

For the sake of brevity, henceforth, we refer Huang and Huang as HH; Feldhütter and Schaefer as FS and Eom, Helwege and Huang as EHH. A summary of the empirical findings from previous studies is found in Table 2.2.

Table 2.2. Empirical findings from previous research.

Name (Year)	Based on what Model	Data	Findings
Jones, Mason and Rosenfeld (1984)	Black and Scholes (1973) and Merton (1974)	Using an example of 27 firms with modest capital structure that is observed monthly during the period 1977-1981 and tested the predictive power of a Contingent Claims Analysis (CCA) model of typical capital structures.	Incorporating stochastic (default-free) interest rates, as well as tax effects, would improve the model's performance and generate a spread of only a few basis points
Lyden and Saraniti (2000)	Merton (1974) and Longstaff and Schwartz (1995)	Compare the Merton and the Longstaff-Schwartz model using 56 firms' prices on non-callable bonds.	Both models underestimate spreads; the assumption of stochastic interest rates did not seem to change the qualitative nature of the finding.
Huang and Huang (2003)	Longstaff and Schwartz, Leland and Toft (1996), Anderson, Sundaresan and Tychon (1996), Mella-Barral and Perraudin (1997) and Collin-Dufresne and Goldstein (2001),	Calibrate these five structural models to match historical default rates, recovery rates, equity risk premia and leverage ratios of investment grade firms based on the availability of default experience data from the period 1973-1998. The data is derived from Moody's and Standard and Poor's where they focus their analysis on all companies with the same credit rating at a given point in time, rather than on any individual company.	All models are consistently incapable of simultaneously matching credit spreads while calibrated to these four moments. They find that credit risk only accounts for a small fraction of the observed yield spreads for investment-grade bonds despite maturity.
Eom, Helwege and Huang (2004)	Merton (1974), Geske (1977), Longstaff and Schwartz (1995), Leland and Toft (1996) and Collin-Dufresne and Goldstein (2001).	Implement these four models and compare the pricing errors generated by using a sample of 182 trader quotes from 48 firms with simple capital structures during the period 1986-1997.	Structural models departing from Merton's framework overestimate spreads for riskier bonds and underestimate spreads for safer bonds.
Chen, Collin-Dufresne and Goldstein (2009)	Merton (1974) and Campbell and Cochrane (1999	Examine whether a structural model of default embedded within a habit-formation economy of Campbell and Cochrane (1999) can capture historical credit spreads using equity returns and historical aggregate consumption data during the period 1974-1998.	Combining the Campbell and Cochrane pricing kernel with some exogenously imposed countercyclical asset value default boundaries, does an excellent job in apprehending the level and time variation of Baa-Aaa spreads. To resolve the puzzle, it is important to bear in mind the significant covariance between default rates and Sharpe ratios – both need to be high during recessions and low during booms.
Feldhütter and Schaefer (2013)	Merton (1974)	Test the Merton model in a bias-free approach using a data set of 534,660 U.S. corporate bond transactions between 2002-2012.	Spreads are typically convex in firm variables, so average spreads are higher than spreads of average firm variables. Historical default frequencies do not proxy well for expected default probabilities. In contrast with previous models, they find almost no evidence that the model under predict credit spreads, apart from a small over prediction of spreads in periods with high-quality long-term spreads.

2.2.4 Reduced-Form Models

As previously mentioned, there are two major theoretical approaches to valuing risky debt – structural models and reduced-form models. Structural models, as formerly highlighted, use fundamental economic inputs, such as leverage ratio and asset volatility, and assume that default is triggered when the value of the assets go below a certain barrier. Reduced-form models on the other hand, do not take firm-specific fundamentals into consideration and therefore do not make any assumptions regarding the causes for default. Hence, they assume there is no relationship between the instantaneous default rate process and firm value. Instead, reduced-form models assume default to be a random event that cannot be known ex-ante, where the default follows some given intensity probability distribution. In continuous time, default is directly predictable and hence will certainly not be a surprise.

Jarrow and Turnbull (1995) present what is considered, amongst the majority of most academics, to be the fist reduced-form model. The authors highlight the fact that structural models use the asset value as underlying in order to price the contingent claims, which can lead to problems, as assets' market values are not directly observable. Instead, the authors' approach on credit risk modeling incorporates a stochastic term structure of risk-free interest rates as well as stochastic credit-risk spreads for specified maturities. Lando (1998) develops this model further to allow for changes between rating classes. Duffie and Singleton (1999) develop a reduced-form model focusing on corporate or sovereign bonds term structures. This approach has since been developed further by Hull and White (2000), Duffie and Lando (2001), where the latter present a framework that attempts to combine the structural with the reduced form approach. Their model assumes a company's management set the default time deliberately in order to maximize the firm value. Even though this study resembles that of Leland and Toft (1996), in the model by Duffie and Lando (2001) investors cannot observe the true asset value and are left with incomplete quarterly reports, i.e. the assumption of complete information is abandoned. Shumway (2001) and Chava and Jarrow (2004) demonstrate a reduced-form approach that can incorporate industry-specific factors, which has an impact on both the probability of default and the recovery rate. Giesecke and Weber (2006) present a model that considers contagion of financial distress between interacting companies. The approach of Guo, Jarrow and Zeng (2009) builds on a structural framework, where a firm's assets and liabilities are used to obtain the recovery rate, but where the information is reduced in order to retain the reduced-form structure. In contrast to other reduced-form models, this approach models the recovery rate at various stages of a company's condition and can thus be used to price risky debt prior to and after a default.

The reduced-form model approach has gained popularity among credit traders because of its mathematical tractability (Arora, Bohn & Zhu, 2005). Furthermore, Jarrow and Protter (2004) claim that reduced-form models are more useful in trading circumstances, since its assumes that the modeler has the same information as the market, while structural models assume that no information asymmetries exist at all, i.e. a credit trading practitioner know as much about some firm's liabilities as the management of that company. Reduced-form models are relatively flexible and can thereby be modified to fit various samples of data. This may however lead to relatively bad out-of-sample fitting, as the models are calibrated to a given historical dataset. This may also cause dubiousness regarding what share of the model's performance that can be related to the quality of the data and what share that can be assessed to the actual features of the model. Another issue with reduced-form models is that empirical testing is relatively sparse, at least in comparison with structural models.

Even though empirical investigations of reduced-form models are relatively thin, some studies examine the performance of these models in a real-world setting. Bakshi, Madan and Zhang (2006) test two reduced-form models developed from the approach of Jarrow and Turnbull (1995) and Duffie and Singleton (1999) and obtain out-of-sample pricing errors of 24.10 and 28.88 bps, using a sample of BBB-rated bonds from 25 U.S. companies. Chen, Cheng, Fabozzi and Liu (2008) test a three-factor reduced-form model on five-year CDS data from 60 global companies and find that the model underpredicts the actual spreads by 3% when tested in-sample. Schneider, Sögner and Veza (2009) use a two-factor reduced-form model on CDS-data for U.S. companies and obtain a close fit. However, the authors do not test the model on out-of-sample data. In a recent study by Gündüz and Uhrig-Homburg (2014), the authors compare the empirical performance of a structural and a reduced-form model and find that the latter model outperforms the structural model using in-sample data, but that the two models perform equally well when out-of-sample data is used. However, the reduced-form approach provides better prediction power for CDSs on entities with good rating, which is where structural models in most previous research tend to underperform significantly.

Despite the advantages of reduced-form models, they are of limited assistance when it comes to understanding the underlying drivers of credit spreads, thus this paper will focus on structural models of credit risk. As credit risk is a function of the capital structure and dynamics of the firm, and reduced-form models do not make any effort in trying to explain credit spreads by firms' capital structure theory and are as a consequence of this less rich in their implications.

3 Merton's Structural Model of Credit Risk

Section 3.1 describes the original structural model for credit risk, as presented by Merton in 1974, by going systematically through the different steps. This is followed in Section 3.2 by a description of the extended Merton model, which is the model that is subsequently used throughout this paper.

3.1 Merton's (1974) Original Model

Building on the theoretical framework developed by Black and Scholes (1973), Merton (1974) proposes a model in which a simple capital structure is assumed, where a firm has only raised funds through two different classes of claims, debt with finite maturity and equity. The bond and the equity together make up the value of the firm's assets. The firm's asset value V_t follows a geometric Brownian motion described as:

$$\frac{dV_t}{V_t} = (r - \delta)dt + \sigma_V dW_t \tag{1}$$

where r is the risk free rate, δ is the payout rate, σ_V is the volatility of the assets and dW_t is an increment to a standard Brownian motion. The senior claim is debt in form of a zero-coupon bond with face value F maturing at time T, and the residual claim being equity E. Thus, before the bondholders are paid, the firm is neither allowed to issue any new debt, nor pay any dividends to its shareholders. If the value of the assets is lower than the face value of the bond at maturity ($V_T < F$), the firm defaults leaving the bondholders with the remaining assets, while the equity holders are left empty-handed. Thus, Merton (1974) describes that the value of the firm's equity at time T can be defined as

$$E_T = \max\,[0, V_T - F] \tag{2}$$

which is analogous to the definition of the value of a call option on a non-dividend paying stock (c.f. Black and Scholes (1973), equation 8), where V corresponds to the price of the underlying and F the strike.

The value of the debt can be expressed as

$$D_T = \min[F, V_T] = F - \max[0, V_T - F] \quad (3)$$

implying that the firm is run by the owners of the equity who at the maturity of the bond pay the face value of debt, F, should the asset value be higher than the face value of debt ($V_T > F$). Thus, equity holders pay the face value of the debt, being lower than the value of the firm's assets, to maintain control of the assets. However, should the firm's assets be worth less than the face value of the debt, the limited liability nature of the ownership allows the equity holders to walk away from the payment to the debt holders, who then take over the company and receive a recovery in form of the asset value, V_T, rather than the promised face value, F (Lando, 2004). The payoff functions are illustrated in Figure 3.1. As can be seen, the equity payoff function resembles that of a call option with strike price F, while the debt payoff function is similar to a portfolio[7] consisting of long position in a risk-free asset paying out a value of F at maturity, and a short position in a put option with strike price F and the same maturity as the risk-free asset.

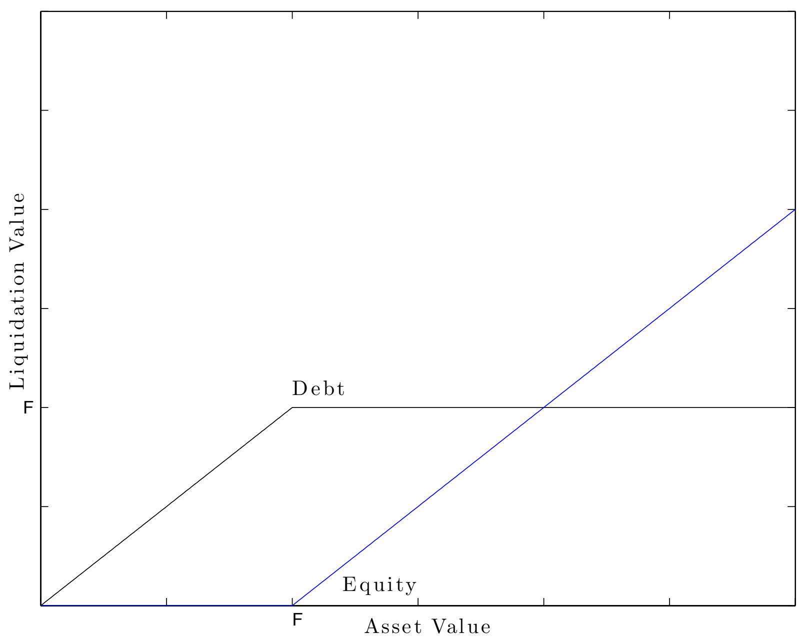

Figure 3.1. The payoffs to debt and equity holders where *F* is the face value of the debt.

[7] From the put-call parity this is equivalent to a portfolio consisting of a long position in the stock and a short position in a call option on the same stock with strike price F (Merton, 1973).

Consequently, Merton (1974) shows that the equity value is equivalent to a call option on the firm's assets, allowing the equity value at time $t = 0$ to be computed as

$$E_0 = V_0 N(d_1) - F e^{-rT} N(d_2) \tag{4}$$

where $N(\cdot)$ denotes the cumulative standard normal distribution, r the risk-free rate and T the time to maturity. Since $D_0 = V_0 - E_0$, using formula (4), we have that

$$D_0 = V_0 \left[N(-d_1) + \frac{F e^{-rT}}{V_0} N(d_2) \right] \tag{5}$$

Furthermore,

$$d_1 = \frac{\ln\left(\frac{V_0}{F}\right) + (r + 0.5\sigma_V{}^2)T}{\sigma_V \sqrt{T}} \tag{6}$$

where σ_V is the volatility of the firms assets. The cumulative standard normal distribution of equation (4), $N(d_1)$, can be interpreted, similar to a call options delta (or the hedge ratio), as the rate of change of the equity value with respect to a change in the value of the assets (Hull, 2009). In addition, we have that

$$d_2 = \mathrm{d}_1 - \sigma_V \sqrt{T} \tag{7}$$

where $N(d_2)$ in turn can be understood as the risk-neutral[8] probability that the firm's assets V_T will exceed the face value of debt F at maturity, i.e. that equity holders will not walk away empty-handed. Hence, $N(-d_2)$ is the probability that the value of the firm's assets is less than the face value of the debt and consequently, that the firm defaults (Hull, Nelken & White, 2004).

In order to perform the calculations from the equations above, the value of the assets and the volatility of this value are needed. These values are not directly observable,

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[8] In a risk-neutral world, investors are not concerned about the level of risk taken on and does therefore not require a return in line with the taken risk. Hence, investors are only compensated with the risk-free rate of return (Hull, 2009).

however, as demonstrated by Jones, Mason and Rosenfeld (1984) Ito's Lemma can be used to obtain

$$\sigma_E E_0 = \frac{\partial E}{\partial V} \sigma_V V_0 \tag{8}$$

where $\frac{\partial E}{\partial V}$ is the partial derivative of the equity with respect to the value of the firm, i.e. the equity's delta, which is equal to $N(d_1)$ as shown previously. By substituting this in the formula above, we get

$$\sigma_E E_0 = N(d_1) \sigma_V V_0 \tag{9}$$

Since the equity volatility (σ_E) and equity value (E_0) can be observed directly from market data, the formulas (6) and (7) can be solved simultaneously or through iterations to obtain the value and volatility of the firm's assets (Hull et al, 2004).

3.2 The Extended Merton Model

As previously stated, Merton (1974) assumes that the bondholders receive 100% of the firm value in case of default. This assumption is not very realistic in reality as various costs of financial distress are likely to emerge in case of a bankruptcy. Several studies relax this assumption by allowing for empirically observed recovery rates to be used. In addition to using recovery rates below 100%, EHH (2004) extends the Merton model by allowing for debt with coupon payments, where the model treats the company's debt as a portfolio of zero-coupon bonds. Furthermore, a firm can default on each coupon payment date and the model can also account for the fact that a company makes periodical dividend payments to its shareholders. Consequently, using the extended Merton model, the price at time $t = 0$ of a corporate bond that pays annual coupons at a rate of c can be calculated as

$$P(0,T) = \sum_{i=1}^{T-1} E^Q\left[e^{-rT_i}\left(1_{\{V_{T_i}\geq F\}}c + \min\left(\psi\, c, V_{T_i}\right) 1_{\{V_{T_i}<F\}}\right)\right] + E^Q\left[e^{-rT}\left(1_{\{V_T\geq F\}} + \min\left(\psi\,(1+c), \frac{V_T}{F}\right) 1_{\{V_T<F\}}\right)\right] \tag{10}$$

where $E^Q[\cdot]$ is the expectation at time zero under the Q measure, $1_{\{.\}}$ is an indicator function and ψ is the recovery rate. With the intuition as explained in formula (7),

$$E^Q[1_{\{V_t\geq F\}}] = N(d_2(F,t)) \tag{11}$$

gives the risk-neutral expectation that the asset value will be above the default barrier at time t, which could either denote a point in time at which the firm needs to pay coupons to its bond holders, or the maturity date of the bond. The second indicator function in formula (12) gives the risk-neutral expectation that the value of the firm's assets will be below the default barrier at time t. In a worst-case scenario, bondholders are at least paid the recovery. The second indicator function is calculated as

$$E^Q[1_{\{V_t<F\}}\min(\psi, V_t)] = \frac{V_0}{D(0,t)} e^{-\delta} N(-d_1(\psi,t)) + \psi[N\left(d_2(\psi,t)\right) - N(d_2(F,t))] \tag{12}$$

where $\psi \in [0,F]$, and $D(0,t)$ is the value of a default-free zero coupon bond at time 0, maturing at time t. Formula (11) increases with an upturn in the asset value, while formula (12) decreases since the rightmost part of the formula approaches zero for an increase in V_0. We also have that

$$d_1(x,t) = \frac{\ln\left(\frac{V_0}{xD(0,t)}\right) + (-\delta + 0.5\sigma_V^2)t}{\sigma_V\sqrt{t}} \tag{13}$$

and

$$d_2(x,t) = d_1(x,t) - \sigma_V\sqrt{t} \tag{14}$$

where δ is the payout ratio.

The direction in which the bond price is pushed from a change in the various variables is summarized in Table 3.1.

Table 3.1. Bond price change given an increase in one variable of the Extended Merton model, keeping all other variables constant.

Variable	Description	Effect on bond price
r	Risk-free rate	Decrease
E	Equity value	Increase
D	Debt value	Decrease
F	Face value of debt	Decrease
V	Asset value	Increase
L	Leverage ratio	Decrease
σ_E	Equity volatility	Decrease
σ_A	Asset volatility	Decrease
ψ	Recovery rate	Increase
δ	Payout ratio	Decrease

4 Methodology

This section discusses what methods we use in order to address the research objectives of our thesis. The first section (4.1) enlightens our motivation for using CDS data as opposed to bond data. Section 4.2 demonstrates how we have estimated the different parameters that we apply to the model. The third section (4.3) explains in detail the application of the model and how our paper differs from previous research. Section 4.4 explains the approach through which the data is split, hence the periods that our data is divided into.

4.1 Credit Spreads

The CDS spread is very close to the credit spread observed in the corporate bond market when the credit spread is measured to the interest rate (Blanco, Brennan & Marsh, 2005; Longstaff, Mithal & Neis, 2003; Hull, Predescu & White, 2004). This is supported by Zhu (2006: 213) amongst other, finding that "although market developments can cause different changes in bond spreads and CDS premia, there exist a long-run relation tying the two pries together, i.e., that they should be equal to each other in equilibrium". Nevertheless, although it should not matter which of the two to base the analysis on, as they are expected to give similar conclusion (should be equal to each other in equilibrium), using bond data involves some applied difficulties, as latterly discussed, which exceed the drawbacks of CDS data.

Furthermore, bondholders are assumed to focus on long-tem investments, and consequently will not alter their portfolios when minor market moves are observed. The CDS market allows market participants to speculate on short movements who can easily enter CDS positions and appreciate profits rapidly by terminating positions through entering opposite contracts. This differs from the bond markets, as investors do not have the possibility to enter and close positions as rapidly as well has having to raise a lot more capital. This implies that the prices of CDSs, compared to bond prices, should reflect the information in the market more accurately. Hence, in contrast to previous studies[9], we

[9] See for example: Avramov, Jostova, and Philopov (2007), Campbell and Taksler (2003), Chen, Lesmond

use CDS data instead of bond data when testing the implementations of Merton's model of default (1974).

As previously stated, there are important differences between CDS and bond markets, and we now turn to look at the reasons CDS data is preferred to be the reference data. The paper by Longstaff, Mithal and Neis (2005: 2219-2220) present seven distinctions to why CDS data is superior to corporate bond data. Before looking at the distinctions, they highlight the importance of CDSs being contracts and not securities, and how these contractual characteristics make them much less subtle to liquidity or convenience yield effects. The first distinction relates to the fact that whereas securities are fixed in supply (i.e. there is a limit to the amount of bonds), the notional amount of CDSs can be arbitrarily large. In other words, the demand and supply pressures that potentially can influence corporate bonds will not affect CDSs. Second, because of the generic and fungible nature of contractual cash flows, CDSs cannot become "special" in the same way that is the case for securities such as treasury bonds or popular stocks (i.e. the most recently issued stocks and bonds are considered the most special, which attracts more short-term hedging and speculation (Geczy, Musto & Reed, 2002). The third element is linked to the dynamism of the CDS market (i.e. CDS contracts can always be created) and how these contracts are far less vulnerable of being "squeezed" than the underlying corporate bonds. The fourth difference links to the similarity between CDSs and insurance contracts, where those taking a long (buy) position in a CDS may aim to do so for a set horizon and, therefore, may not normally arrange to unwind their position earlier. The fifth distinction relates to how an investor who is willing to liquidate a CDS position might instead purely enter a new swap, being less costly, in the opposite direction as an alternative of selling his current position. Hence, as a result of being able to replicate swap cash flows through other contracts, the investors existing liquidity position is less important. The sixth feature emphasizes that it is as easy to short protection as it is to long protection in CDS markets, whereas it might be challenging and costly to sell corporate bonds. The final component, supported by Blanco, Brennan and Marsh (2005), stress how credit derivative markets are seen to be more liquid than

and Wei (2007) and Collin-Dufresne, Goldstein, and Martin (2001).

corporate bond markets, through incorporating new information into the CDS premium more rapidly than into corporate bond prices.

Furthermore, despite the arguments in favor of using CDS data, it is important to highlight the fact that there exist downsides as well. Although previous research emphasize that the CDS market is leading the bond market by being more efficient in price discovery (Blanco, Brennan & Marsh, 2005; Norden & Weber, 2009; Stulz, 2009; Zhu, 2006), this is not necessarily always the case when considering certain market conditions. For instance, this connection is deteriorated for lower graded reference entities and is being reversed during times of crisis (Bai & Collin-Dufresne, 2013). Due to this latter reason, it is said that participants in the market are ought to concentrate on bond yields and not CDS spreads during times of observed high economic uncertainty. This is because during such times, the level of volatility increases drastically, which causes investors holding bonds to modify their portfolios and that causes increased activity within the bond market. Bai and Collin-Dufrense (2013) show that during normal times, the difference between CDS spreads and bond spreads are very small, if anything leaning towards being slightly positive. However, during the financial crisis and a period subsequent to the crisis, they show that bond spreads are lower than CDS spreads. Even though the authors do not find any simple explanation for this, they find some evidence that factors such as liquidity risk, counterparty risk and funding risk may cause this phenomenon. Another factor causing investors to instead devote attention to bond prices relates to the enhanced counterparty risk that is seen intrinsic to CDSs as well as the risk that traders and central counterparties will hinder the informational value of CDSs. Finally, there is a tendency to observe a 'flight-to-safety' to investment-grade bonds during times characterized by financial uncertainty, which is another factor influencing the trading activity in bond markets.

4.2 Parameter Calibration

In order to test the extended Merton model on CDS data, several parameters are needed as outlined in section 3.1 and 3.2. Most of the studies hitherto published on the credit spread puzzle, such HH (2012), use average parameter inputs based on long-term historical data from several companies in order to obtain some average credit spread, usually after pooling the firms with regards to their credit rating. In contrast to these studies, we use the individual and firm specific parameters instead to calculate each firm's credit spread in order to avoid the convexity effect as described by Strebulaev (2007), David (2008) and FS (2013).

As risk-free rate r, the 5-year swap rate in the country in which the firm's stock is mainly listed is used. Previous studies, such as Blanco, Brennan and Marsh (2005), Hull, Predescu and White (2004) find that the CDS market appears to use swap rates in order to price the contracts. Feldhütter and Lando (2008) find that the reason for this is to a large extent that Treasury yields benefit from convenience yield, which leads to rates below the risk-free rate. The swap rates are obtained using Datastream.

The value of equity E is obtained by multiplying each firm's daily share price with the amount of outstanding shares. This data is obtained from Datastream. For the value of debt D, we follow the approach of FS (2013) and use the sum of the latest quarterly reported long-term debt (Long-Term Borrowings in Bloomberg) and short-term debt (Short-Term Borrowings in Bloomberg). Subsequently the leverage ratio L can be found by dividing the debt value with the sum of the debt and equity values; $L = \frac{D}{D+E}$. Since equity values can be obtained on a daily basis, while debt values are only available on a quarterly basis, we follow the method of EHH (2004) and Gündüz and Uhrig-Homburg (2014) in order to sidestep data losses. This entails that for the four months per year where new quarterly data is available, the new values of debt from the balance sheet as well as the current daily equity value are used, while for the subsequent two months, the debt value is kept constant while the current daily equity value is used. Consequently, we can test the data on a monthly basis rather than on a quarterly basis.

Using the same approach as FS (2013), the equity volatility σ_E, which is used to find the asset volatility, is obtained from the last three years' annualized[10] daily standard deviations of the firm's share returns.

[10] The daily equity volatility is multiplied with $\sqrt{252}$, as we have found 252 to be the average number of trading days on the Nordic markets during our sample period.

Merton (1974) does not provide any explanation for how to obtain the asset volatility and therefore one needs an iterative method to obtain this value. However, since assets are the sum of equity and debt, Schaefer and Strebulaev (2008) postulates that the asset volatility can be obtained from

$$\sigma_V = \sqrt{(1-L)^2\sigma_E^2 + L^2\sigma_D^2 + 2L(1-L)\sigma_{ED}} \tag{15}$$

where L is the leverage ratio, calculated as $\frac{debt}{debt+equity}$, σ_E^2 is the variance of equity, σ_D^2 is the variance of debt and σ_{ED} is the correlation between equity and debt returns. If it is assumed that the volatility of debt is zero, the asset volatility can be calculated as

$$\sigma_V = (1-L)\sigma_E \tag{16}$$

Instead of the somewhat tedious process of iterating the asset value and asset volatility, we follow recent studies such as EHH (2004) and FS (2013), and use the current market value of equity plus the book value of debt as asset value, while we estimate the asset volatility by adjusting the equity volatility for the company's leverage. The adjustment factors for the asset volatility are described in Table 5.1 and follows Schaefer and Strebulaev (2008) who use equation (9) and (15) to calculate the asset volatility and find that these are strikingly similar over the various ratings, except for junk rated companies. Based on their results, FS (2013), use equation (16) as the lower bound of the firm's asset volatility, which is then multiplied with a factor depending on the leverage ratio, as summarized in Table 4.1.

Table 4.1. Asset volatility multiplication factor based on leverage ratio.

Leverage Ratio (L)	Volatility Multiplication Factor (γ_L)
L < 0.25	1
0.25 < L ≤ 0.35	1.05
0.35 < L ≤ 0.45	1.1
0.45 < L ≤ 0.55	1.2
0.55 < L ≤ 0.75	1.4
L > 0.75	1.8

This table shows the multiplication factor that the annualized equity volatility is multiplied with in order to obtain an approximation of the asset volatility.
From Feldhütter and Schaefer (2013), based on Schaefer and Strebulaev (2008).

As previously mentioned, the original Merton (1974) model, assumes that bondholders receive the entire asset value in case of a default, which is not very realistic since defaults tend to be associated with various costs of financial distress. Therefore, this assumption is relaxed in the extended Merton model. Following FS (2013), empirically observed recovery rates are used. However, instead of an average global recovery rate that is applied by the mentioned authors, we use the average recovery rate for European companies since the global recovery rate sample set is to a large extent comprised of defaults by American companies (Moody's, 2014). We use the average recovery rate for European senior unsecured bonds[11], which over the period 1987-2012 is 32.40% (Moody's, 2013). This is lower than the rates used by FS (2013) who use 49.20%, and HH (2012) as well as EHH (2004) who use 51.31%. Bai and Wu (2013) use a recovery rate of 40%, which they describe as the standard simplifying assumption in the CDS literature. However, European recovery rates tend to be lower than global recovery rates for unsecured bonds (Moody's 2013), which we believe justifies our choice of recovery rate.

The payout ratio δ is calculated as the annual interest payments to bond holders, plus dividend payments to shareholders and net share buybacks. This ratio is calculated as the

[11] A senior unsecured bond is commonly used as the reference obligation, i.e. the bond that defines the seniority of debt on which a credit event can be observed and that is used as a deliverable in case of a credit event, for credit default swaps (Douglas, Goodman & Fabozzi, 2006).

total outflow to bond and equity holders, divided by the firm value (the sum of market value of equity plus the book value of debt).

The parameter inputs and its estimations are all summarized in Table 4.2.

Table 4.2. Calibration of model parameters.

Parameter	Description	Estimated as	Data Source
r	Risk-free rate	5 year swap rate in the country in which the company is listed	Datastream
E	Equity value	Stock price times number of shares outstanding	Datastream
D	Debt value	Sum of long-term and short-term borrowings	Bloomberg
F	Face value of debt	Set equal to debt value D	Bloomberg
V	Asset value	Sum of equity and debt ($E + D$)	Bloomberg, Datastream
L	Leverage ratio	Debt divided by asset value	Bloomberg, Datastream
σ_E	Equity volatility	Average daily standard deviation for last three years' stock returns, multiplied by $\sqrt{252}$	Datastream
σ_A	Asset volatility	Historical equity volatility, adjusted for leverage	Datastream
ψ	Recovery rate	Historical average recovery rates on European senior unsecured debt	Moody's
δ	Payout ratio	Sum of interest payments, dividend payments and net share buybacks divided by firm value	Bloomberg

This table presents the parameters used in the extended Merton model and the sources from which the data is obtained.

4.3 Application of Model

By using the extended Merton model, as presented by EHH (2004) and described in sections 3.1 and 3.2, we can incorporate a recovery rate different from 100%. In contrast to their model, we assume that the company's debt is in the form of zero-coupon bonds as we compare the results with CDS data and not corporate bond data. This is an assumption also made by FS (2013), in spite of the fact that the authors use bond data throughout their study. The market price of the company's debt, using equation (10), is therefore

$$P(0,T) = E^Q \left[e^{-rT} \left(1_{\{V_T \geq F\}} + \min\left(\psi\,, \frac{V_T}{F}\right) 1_{\{V_T < F\}} \right) \right]$$

where

$$E^Q[1_{\{V_T \geq F\}}] = N(d_2(F,T))$$

and

$$E^Q[1_{\{V_T<F\}} \min\,(\psi, V_T)] \\ = \frac{V_0}{D(0,t)} e^{-\delta} N(-d_1(\psi,T)) + \psi[N\big(d_2(\psi,T)\big) \\ - N(d_2(F,T))]$$

In the formulas above, $d_1(x,T)$ and $d_2(x,T)$ are given by equation (13) and (14).

The formula for asset volatility can be described as

$$\sigma_V = (1-L)\sigma_E \gamma_L$$

where γ_L denotes the volatility multiplication factor, as found in Table 1.

As previously mentioned, the recovery rate is obtained from historical average recovery rates for European companies, $\psi = 34.20\%$.

Thereafter, the credit spread can be calculated as

$$s = -\frac{1}{T}\ln\big(\,P(0,T)\big) - \,r$$

where r is the risk-free rate and T is the time to maturity.

Credit spreads are subsequently calculated for each individual company on a monthly basis, using the extended model as described above, and thereafter compared with the corresponding market-observed CDS. Similar to HH (2012), we divide the model spread with the observed spread to see how well the model performs and to what extent the observed CDS spread can be explained by default risk. As previously mentioned, in contrast to HH (2012), this is done with individual companies' monthly model spreads in order to avoid convexity effects. In addition, similar to Gündüz and Uhrig-Homburg (2014), we compute the mean error, which is the mean difference between the model spread and the observed bond spread, and the mean percentage error, which is the mean error, divided by the mean observed bond spread, the mean absolute error, which is the mean absolute difference between the model spread and the observed bond spread, and the mean absolute percentage error, which is the absolute mean error, divided by the mean observed bond spread.

To get a better overview while still being able to break down the details of the results, the companies are divided into categories with regards to their respective rating, as assigned by Standard & Poor's. The firms are assigned the average rating they had during the testing period.

4.4 Data Subdivision

With regards to the claims in previous research that the level of information contained in CDS data and bond data differs depending on the various states of the economy, the data is divided into three sub-periods, one before the crisis, one during the crisis and one after the crisis. In order to determine the time and length of these different periods, i.e. what is assumed to be the Pre-Crisis, the Crisis and the Post-Crisis period, data obtained from International Monetary Fund (IMF), Bank for International Settlements (BIS), National Bureau of Economic Research (NBER), Nordic Investment Bank (NIB), the World Bank Group (WBG) is used. Although these sources all have different explanations to what is determined as the exact origin of the global financial crisis, they all document that the crisis ended in the second quarter of 2009. For that reason we have decided to set the Post-Crisis period from the second quarter of 2009 (1st of July 2009) until the end of the sample at 14th of February 2014. The start of the Pre-Crisis period is the start of the sample period, 14th of February 2006. Although the rescue of Bear Stearns during March 2008 was a preclude to the risk management meltdown, it is the demise of Lehman Brothers on 15th of September 2008 that is considered the peak of the crisis by causing a global loss of confidence, as many financial institutions failed or had to be rescued. Despite this, the above entities have different views on what they determine to be the start of the global financial crisis – e.g. what they refer to be the period when the economic activity started declining.

The majority of previous research focuses on finding the point at which the financial crisis actually began in the U.S. According to BIS, it was the summer of 2007 that onset the financial stress with "unusually low real interest rates, easy credit conditions, low volatility in financial markets and widespread increases in asset prices that had generated large-scale but hidden characteristics" (BIS 79th Annual Report; 2009: 16). Whereas the IMF, NBER, NIB and WBG agree that the global financial crisis started in December in 2007 (Frankel, 2009; Claessens & Kose, 2009; NIB 2009). NBER created a committee whom after a year of working announced that the crisis started in December 2007.

However, as this study looks into the Nordics, the start of the crisis diverges compared to that of the U.S. By looking at Figure 4.1 and 4.2, which demonstrates annual GDP growth, it can be seen that the Nordic countries (Denmark, Finland, Sweden and Norway) were all affected by the downturn in August 2007 as previously mentioned.

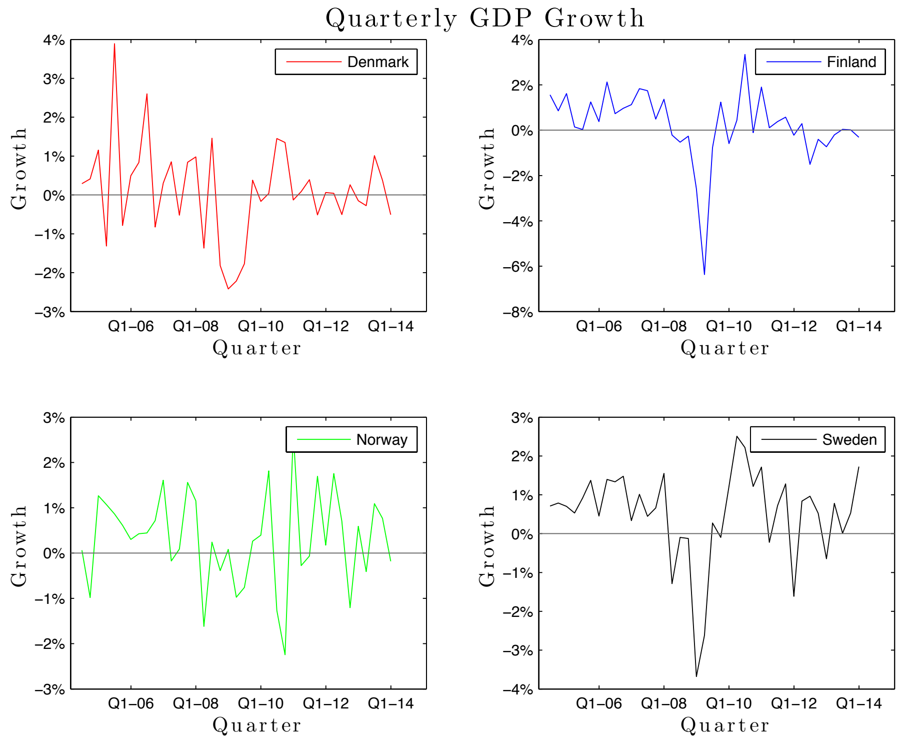

Figure 4.1. GDP Growth in the Nordics between Q1 2004 and Q1 2014. Source: OECD Statistics.

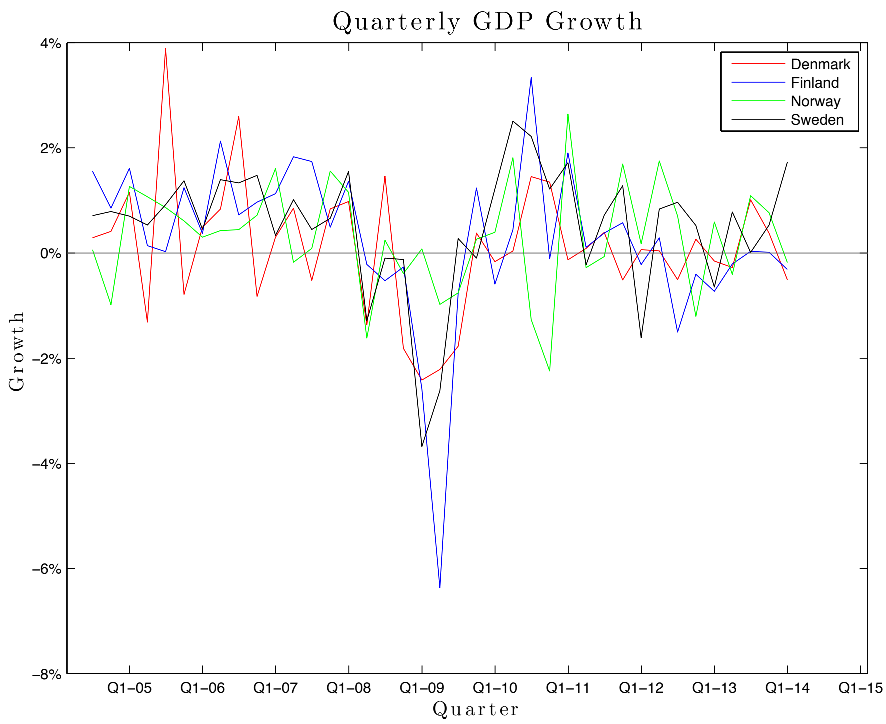

Figure 4.2. GDP Growth in the Nordics between Q1 2004 and Q1 2014. Source: OECD Statistics.

However, growth recovered after this in all Nordic countries, as seen in Figures 4.1-4.2, and it was not until early 2008 that the all countries actually experienced negative growth numbers. Based on this, the start of Crisis period is set to be the 1st of January 2008 and as previously mentioned, the end of the Crisis period is set equal to 30th of June 2009. The Post-Crisis period starts 1st of July 2009 and ends 14th of February 2014. The first figures demonstrate each of the individual countries quarterly GDP growth, whereas the second figure combines the data of the four countries into one, in order to display the differences amongst them. As can be seen, they are all affected during 2007, however it can clearly be seen that there is a notable fall during the first quarter of 2008 and a drastic increased GDP growth during the second quarter of 2009. The subdivision of the sample period is summarized in Table 4.1.

Table 4.3. Subdivision of sample period.

Period	Start of period	End of period
Period I - "Pre-Crisis"	2006-02-14	2007-12-31
Period II - "Crisis"	2008-01-01	2009-06-30
Period III - "Post-Crisis"	2009-07-01	2014-02-14

5 Data Collection

Whereas Section 2.2.1 looks more deeply into the nature of CDS and how it function, this section illuminates why we decide to use CDS data in contrast to bond data. It also explains certain parameters that we apply as well as outlining descriptive data that are central to our thesis.

5.1 Bond Data and CDS Data

The following section start by briefly explaining the use of bond data in previous research and why this have altered in later examinations. The second part clarify the use of CDS data, which is the data we base our paper on, by emphasizing different advantages as well as downsides that can be found in comparison to use bond data. A final paragraph enhances the main reasons for why we use CDS data as opposed to bond data.

5.1.1 Bond Data

Previous research on standard structural model's role of predicting spreads or explaining spreads and default rates simultaneously have typically been analyzed using corporate bond data (Jones & Rosenfeld, 1984; Delianedis & Geske, 2001; Eom, Helwege and Huang, 2004). This is partly due to the data availability of bonds being much more superior than for CDSs[12], but also because it is the most straightforward and intuitive alternative with a naïve approach. In comparison to previous research, later examinations have demonstrated that bond data "fail to price corporate bonds adequately due to omitted risks" (Ericsson, Reneby & Wang, 2006: 2). Despite the lack of available CDS data, the CDS market has grown tremendously during the past years and it has provided researchers with an alternative way of studying credit risk. It is considered a more accurate way of studying credit risk because dealers in the CDS market tend to exploit their informational advantage (e.g. private information) about the credit risk of a reference entity. They would as a consequence naturally trade in the CDS market because of the lower or almost no short selling cost and higher liquidity, and accordingly this new

[12] However, the majority of CDS data are on U.S. companies.

information should get reflected in the CDS market before the bond market. In addition, it is commonly thought that bond data is influenced more by non-default components, in particular an illiquidity premium, in contrast with CDS data (Ericsson, Reneby & Wang, 2007; Longstaff, Mithal & Neis, 2004). However, these non-default features will be further discussed in the following sections.

Nevertheless, in spite of our focus on CDS data, bond data for the sampled firms is used as a robustness check (see Section 8.1). This data is collected from Bloomberg and comprises 104 bonds, as summarized in Appendix A.1. In line with previous research, we have omitted bonds with a maturity of less than one year as well as those with so-called special features, such as callable, putable and perpetual bonds (Eom et al, 2004; Feldhütter & Schaefer, 2013). We have selected the bonds that have an issuing date and a maturity date as close as possible to the starting period and ending period of our CDS sample. The bonds in our sample are denominated in either the currency of the country in which the company is based or the currency of the CDS contracts.

5.1.2 CDS Data

The CDS data that our paper is based on is collected from Bloomberg. On the Nordic market there are CDS contracts available on 40 companies. From this sample non-publicly traded firms as well as subsidiary companies for which required data is not available are removed. In addition, in line with prior research, financial institutions are removed from the sample. This leaves us with a sample of 25 companies, of which 1 is Danish, 7 Finnish, 4 Norwegian and 13 Swedish. For these companies the five-year CDS, being the most liquid CDS contract and the most commonly used in the literature (Bai & Collin-Dufresne, 2013), are collected with monthly frequency. The sample period, as emphasized in Section 4.4 starts at 2006-02-14, which is chosen since at this point in time there are CDS spreads available for all firms in the sample, and ends eight years later, 2014-02-14. For the days during which there are no CDS quotes available, the prior day's quote is used.

5.2 Risk-Free Rate & Firm-Specific Data

The remaining data required for the study, which follows previous literature on the topic in general, and FS (2013) in particular, comprises market value of equity, equity volatility, total debt and interest expense as well as dividend payments. In addition, recovery rates and credit ratings are necessary. For the risk-free rate, five-year swap rates are obtained from Datastream. For the firm-specific data that is required by the model, Bloomberg and Datastream are used. Market value of equity and equity volatility are obtained from Datastream. Quarterly financial statement data, such as total debt, dividend payments and interest expenses, as well as credit ratings are collected from Bloomberg. Average recovery rates are collected from Moody's annual summaries.

5.3 Descriptive Data

This section looks into parts of the descriptive data by first describing company data based on the 25 individual non-financial corporate entities through looking at the CDS spreads, leverage ratio and equity volatility. The next part focuses on the assigned ratings by looking into the same parameters, which are more in line with the standards found in the literature.

5.3.1 Individual Based Company Data

The following three tables demonstrate the average CDS spread, leverage ratio and equity volatility, of the 25 non-financial Nordic companies that our paper focuses on. Each of the tables looks at data from the different subdivisions that were discussed in the previous section. Hence, each table shows data extracted from the entire, Pre-Crisis, Crisis and Post-Crisis period, in order to highlight the variations amongst them and discuss the most interesting findings. Our sample initially consisted of 26 companies, however, one firm (TDC A/S) has intentionally been omitted from this sample. The reason is due to the fact that this firm is significantly different from the others in the sample in that it has made two abnormal dividend payouts during the sample period, which structural models are not made to capture. When initially included in our sample, it was a clear outlier that affected and drove the whole results and we therefore decided to exclude it.

Table 5.1 presents an overview of the sample companies country of origin, its assigned industry (according to Bloomberg) as well as average rating and the CDS spreads. By looking at the average CDS spreads according to the different subdivisions it can clearly be seen that the spreads during the Pre-Crisis period are notably lower both compared to the Crisis and Post-Crisis periods. Although the difference depends on the type of company, what country the firm is from, the industry as well as rating, there is a clear distinction. As naturally expected, and as outlined in Section 2.1.2, during the Crisis period the CDS spreads across all asset classes and rating categories amplified to extraordinary levels (Stulz, 2009; ISDA, 2010). Looking at the figures in Table 5.1, the total CDS spreads of all firms during the Crisis period increased about four times when compared to the spreads from the Pre-Crisis period. However, when the financial crisis came to an end, the CDS spreads accompanied, as seen in the figures from the Post-Crisis period.

There are some interesting findings when looking at the following table (Table 5.1). First, it is important to highlight that although the spreads we see during the Post-Crisis period (230.99 bps) have not returned to the Pre-Crisis levels (65.96 bps), they are considerably lower than during the Crisis (318.44 bps)[13], at least for the majority of the companies. Second, when looking at the different firms, there are in particular five companies (Metsa, Norske Skog, SAS, Stora Enso and UPM Kymmene) demonstrating a drastic increase in CDS spreads from the Pre-Crisis to Crisis period – with an average of 203.348 bps during the Pre-Crisis to 997.99 bps during the Crisis. A common feature amongst the firms, apart from SAS, is that they are all from the materials industry. Third, looking at the period from the Crisis to Post-Crisis, the CDS spreads of almost all firms decreased. However, there are a handful firms showing a further increase in CDS spreads (Nokia, Norsk Hydro, Norske Skog and SAS). In contrast, it is remarkable to observe the fall in Metsa's CDS spreads during this period; from 2330.1 bps during the Crisis period to 636.17 bps during the Post-Crisis period. Furthermore, when comparing the Pre-Crisis to

[13] These figures are found in Table 5.4.

Post-Crisis period, most firms have higher CDS spreads after the Crisis. However the firms with the highest increase in CDS spreads from the Pre-Crisis to Crisis period persist to have the highest CDS spreads, both in absolute and relative terms, in the Post-Crisis period.

Table 5.1. Companies in the sample, its ratings and average CDS spreads.

Company Name	Country	Industry (Bloomberg)	Latest Rating (S&P)	Avg. CDS Spread Entire Period (std dev)	Avg. CDS Spread Period I "Pre – Crisis" (std dev)	Avg. CDS Spread Period II "Crisis" (std dev)	Avg. CDS Spread Period III "Post – Crisis" (std dev)
ASSA ABLOY AB	SWE	Industrials	A-	63.29 (35.03)	26.34 (9.19)	114.15 (44.15)	62.12 (9.28)
ATLAS COPCO AB	SWE	Industrials	A-	61.95 (31.83)	25.32 (5.42)	108.78 (35.55)	61.94 (9.34)
CARLSBERG A/S	DEN	Customer Staples	BBB	121.64 (85.00)	47.21 (10.27)	249.18 (118.13)	111.21 (22.43)
ELECTROLUX AB	SWE	Consumer Discretionary	BBB+	77.42 (35.86)	40.19 (8.03)	133.63 (35.56)	74.64 (14.36)
ELISA OYJ	FIN	Communications	BBB	115.90 (94.22)	56.65 (18.86)	257.14 (141.27)	94.84 (27.13)
ERICSSON AB	SWE	Technology	BBB+	114.15 (73.70)	42.33 (18.68)	222.00 (85.87)	108.98 (32.74)
FORTUM OYJ	FIN	Utilities	A-	55.36 (25.64)	20.95 (10.36)	72.37 (25.72)	64.03 (15.30)
INVESTOR AB	SWE	Financials	AA-	77.49 (59.48)	16.54 (7.73)	160.21 (84.68)	75.93 (11.85)
METSA OYJ	FIN	Materials	B+	901.67 (101.71)	430.21 (25.08)	2330.10 (155.18)	636.17 (42.22)
METSO OYJ	FIN	Industrials	BBB	149.43 (934.24)	53.59 (111.94)	269.77 (1344.20)	150.11 (357.01)
NOKIA OYJ	FIN	Technology	B+	209.71 (267.31)	14.36 (6.04)	74.88 (29.53)	333.27 (294.93)
NORSK HYDRO ASA	NOR	Energy	BBB	82.95 (66.04)	15.62 (5.57)	68.84 (44.03)	115.14 (63.13)
NORSKE SKOG ASA	NOR	Materials	CCC+	1185.00 (829.73)	169.61 (101.06)	1087.30 (186.39)	1633.50 (740.13)
SAS AB	SWE	Consumer Discretionary	B-	702.77 (362.93)	295.79 (87.54)	780.73 (244.62)	844.86 (341.37)
SCA AB	SWE	Customer Staples	A-	83.52 (50.50)	32.53 (10.14)	157.63 (63.04)	80.64 (16.98)
SCANIA AB	SWE	Industrials	A-	94.41 (78.66)	30.59 (8.09)	192.87 (131.07)	88.97 (23.64)
SECURITAS AB	SWE	Consumer Discretionary	BBB	82.48 (33.88)	34.39 (7.32)	98.59 (21.80)	97.04 (23.81)
SKF AB	SWE	Industrials	BBB+	76.47 (55.80)	27.80 (3.93)	155.70 (85.43)	70.99 (9.87)
STATOIL ASA	NOR	Energy	AA	51.20 (29.63)	11.95 (5.88)	68.72 (33.28)	61.69 (17.89)
STORA ENSO AB	FIN	Materials	BB	287.05 (150.63)	64.50 (32.93)	436.67 (110.20)	330.37 (73.95)
SWEDISH MATCH AB	SWE	Customer Staples	BBB	69.75 (24.95)	34.56 (5.36)	98.88 (20.16)	74.84 (11.30)
TELENOR ASA	NOR	Communications	A-	67.63 (39.17)	30.61 (10.19)	120.09 (51.22)	65.97 (18.69)
TELIASONERA AB	SWE	Communications	A-	57.40 (20.38)	35.90 (7.77)	83.41 (18.99)	57.86 (13.21)
UPM KYMMENE OYJ	FIN	Materials	BB	255.22 (126.51)	56.63 (25.58)	355.15 (67.94)	304.66 (63.21)
VOLVO AB	SWE	Industrials	BBB	158.30 (117.09)	34.74 (10.48)	264.20 (187.57)	175.01 (51.68)

Table 5.2 demonstrates the different leverage ratios of the various corporations over the three periods. From the Pre-Crisis (0.25) to Crisis (0.37)[14] period, the majority of firms had increased leverage ratios. However, four firms (Metsa, Metso, Norske Skog and Volvo) had significantly higher ratios – with an average of 0.401 during the Pre-Crisis to 0.644 during the Crisis. Interestingly, there is one firm (Norsk Hydro), which during the same periods demonstrating a particular fall in leverage ratio – from 0.063 to 0.037. Furthermore, when comparing the Crisis and Post-Crisis periods, we see three firms (Carlsberg, Metsa and SKF) with a significant decrease in leverage ratio compared to the other firms – with an average of 0.629 during the Crisis to 0.438 during the Post-Crisis. In addition, Ericsson is the only firm with a near identical leverage ratio during the two periods - 0.115 during the Crisis period and 0.114 during the Post-Crisis period). When identifying the differences between the Pre-Crisis (0.25) and Post-Crisis (0.33)[15] period, there is a notable variation amongst firms. In contrast, Nokia and Norske Skog are the firms with the highest level of increase in leverage ratios – Nokia from 0.006 to 0.247 and Norske Skog from 0.531 to 0.894. It can be assumed that the increase in leverage is mainly due to a decrease in face value, and not just issuing activities.

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[14] These figures are found in Table 5.4.

[15] These figures are found in Table 5.4.

Table 5.2. Sample companies' leverage ratios.

Company Name	Average Leverage Ratio Entire Period (std dev)	Average Leverage Ratio Period I "Pre-Crisis" (std dev)	Average Leverage Ratio Period II "Crisis" (std dev)	Average Leverage Ratio Period III "Post-Crisis" (std dev)
ASSA ABLOY AB	0.230 (0.068)	0.231 (0.018)	0.328 (0.042)	0.198 (0.058)
ATLAS COPCO AB	0.129 (0.060)	0.086 (0.049)	0.220 (0.050)	0.119 (0.031)
CARLSBERG A/S	0.381 (0.083)	0.378 (0.059)	0.505 (0.090)	0.342 (0.041)
ELECTROLUX AB	0.227 (0.064)	0.170 (0.032)	0.324 (0.055)	0.220 (0.035)
ELISA OYJ	0.228 (0.060)	0.142 (0.027)	0.291 (0.043)	0.245 (0.026)
ERICSSON AB	0.099 (0.032)	0.051 (0.019)	0.115 (0.017)	0.114 (0.016)
FORTUM OYJ	0.297 (0.080)	0.194 (0.016)	0.290 (0.080)	0.343 (0.049)
INVESTOR AB	0.214 (0.065)	0.143 (0.023)	0.181 (0.029)	0.255 (0.052)
METSA OYJ	0.664 (0.121)	0.645 (0.027)	0.848 (0.062)	0.613 (0.102)
METSO OYJ	0.234 (0.110)	0.137 (0.020)	0.369 (0.155)	0.233 (0.061)
NOKIA OYJ	0.155 (0.132)	0.006 (0.002)	0.070 (0.051)	0.247 (0.095)
NORSK HYDRO ASA	0.081 (0.053)	0.063 (0.045)	0.037 (0.025)	0.104 (0.052)
NORSKE SKOG ASA	0.794 (0.160)	0.531 (0.070)	0.837 (0.050)	0.894 (0.037)
SAS AB	0.633 (0.111)	0.518 (0.084)	0.634 (0.079)	0.682 (0.094)
SCA AB	0.348 (0.081)	0.327 (0.018)	0.462 (0.071)	0.320 (0.068)
SCANIA AB	0.294 (0.088)	0.223 (0.071)	0.390 (0.104)	0.293 (0.054)
SECURITAS AB	0.349 (0.058)	0.291 (0.042)	0.364 (0.018)	0.370 (0.056)
SKF AB	0.402 (0.086)	0.409 (0.033)	0.532 (0.070)	0.358 (0.058)
STATOIL ASA	0.171 (0.058)	0.106 (0.028)	0.128 (0.047)	0.213 (0.024)
STORA ENSO AB	0.518 (0.086)	0.409 (0.039)	0.534 (0.082)	0.559 (0.057)
SWEDISH MATCH AB	0.189 (0.034)	0.176 (0.010)	0.242 (0.021)	0.178 (0.020)
TELENOR ASA	0.240 (0.070)	0.232 (0.037)	0.330 (0.104)	0.214 (0.038)
TELIASONERA AB	0.228 (0.071)	0.124 (0.023)	0.236 (0.051)	0.270 (0.038)
UPM KYMMENE OYJ	0.430 (0.081)	0.334 (0.029)	0.496 (0.086)	0.449 (0.055)
VOLVO AB	0.412 (0.103)	0.293 (0.035)	0.521 (0.115)	0.428 (0.062)

Table 5.3 shows the equity volatilities for the various corporations during the different periods. When looking at the changes between the Pre-Crisis (26.08%) and Crisis (36.90%)[16] period, all firms within the sample show increased equity volatilities. However, the equity volatility of certain firms (Metsa, Norsk Hydro, Norske Skog, SAS and Scania) increased considerably more than others – with an average of 0.294 during the Pre-Crisis to 0.474 during the Crisis. Elisa had in contrast a minimal increase during the two periods – with an average of 0.288 to 0.306. Moreover, when relating the Crisis to Post-Crisis period, we see an almost 50/50 division of firms having increased/decreased equity volatilities. Furthermore, there are four firms (Metsa, Nokia, Norske Skog and SAS) showing a statistically significant increase in equity volatility compared to the other firms with an average of 47.0% during the Crisis to 61.9% during the Post-Crisis period. Additionally, when matching the Pre-Crisis (26.08%) to Post-Crisis (39.93%)[17] period the equity volatility of all firms increased, apart from Elisa having a decreasing equity volatility going from 28.8% during the Pre-Crisis to 27.5% during the Post-Crisis. In contrast, there are three firms (Metsa, Norske Skog and SAS), which have much higher equity volatilities than all of the other firms – with an average of 31.5% during the Pre-Crisis period and an average of 66.8% during the Post-Crisis period.

[16] These figures are found in Table 5.4.

[17] These figures are found in Table 5.4.

Table 5.3. Sample companies' equity volatility.

Company Name	Average Equity Volatility Entire Period (std dev)	Average Equity Volatility Period I "Pre-Crisis" (std dev)	Average Equity Volatility Period II "Crisis" (std dev)	Average Equity Volatility Period III "Post-Crisis" (std dev)
ASSA ABLOY AB	32.4% (6.2%)	27.1% (2.1%)	35.1% (4.8%)	33.8% (6.5%)
ATLAS COPCO AB	37.7% (7.8%)	29.1% (1.6%)	40.9% (5.8%)	40.4% (7.2%)
CARLSBERG A/S	33.4% (10.6%)	21.1% (1.1%)	33.7% (9.4%)	38.6% (8.8%)
ELECTROLUX AB	38.1% (7.5%)	28.8% (3.3%)	41.3% (5.3%)	41.0% (6.1%)
ELISA OYJ	28.4% (6.1%)	28.8% (3.2%)	30.6% (4.1%)	27.5% (7.3%)
ERICSSON AB	35.9% (6.2%)	32.4% (4-.7%)	38.4% (5.3%)	36.6% (6.5%)
FORTUM OYJ	29.2% (5.5%)	24.7% (0.7%)	30.5% (5.3%)	30.7% (5.8%)
INVESTOR AB	26.9% (5.3%)	22.3% (0.8%)	30.2% (4.2%)	27.8% (5.5%)
METSA OYJ	49.9% (14.4%)	31.2% (1.1%)	45.3% (9.1%)	59.4% (9.4%)
METSO OYJ	41.1% (8.9%)	28.8% (0.9%)	41.3% (6.9%)	46.4% (5.5%)
NOKIA OYJ	39.7% (8.8%)	28.1% (3.3%)	34.6% (5.3%)	46.2% (3.5%)
NORSK HYDRO ASA	40.4% (11.2%)	28.4% (2.6%)	43.8% (8.8%)	44.4% (10.6%)
NORSKE SKOG ASA	58.9% (19.8%)	27.6% (2.4%)	54.8% (9.8%)	73.7% (2.2%)
SAS AB	53.7% (14.2%)	34.0% (1.8%)	49.9% (11.2%)	63.4% (6.8%)
SCA AB	26.3% (6.4%)	18.0% (0.7%)	27.3% (5.2%)	29.5% (4.7%)
SCANIA AB	35.4% (9.2%)	22.9% (3.0%)	38.5% (6.2%)	39.8% (6.4%)
SECURITAS AB	28.7% (3.0%)	27.4% (2.3%)	31.0% (2.7%)	28.6% (3.0%)
SKF AB	34.6% (6.4%)	26.4% (1.6%)	36.6% (4.8%)	37.5% (5.1%)
STATOIL ASA	31.4% (7.2%)	27.6% (1.4%)	35.8% (4.9%)	31.6% (8.3%)
STORA ENSO AB	35.9% (9.8%)	22.5% (1.5%)	33.9% (7.9%)	42.3% (5.4%)
SWEDISH MATCH AB	23.9% (4.3%)	19.7% (0.5%)	26.4% (3.5%)	24.8% (4.3%)
TELENOR ASA	32.7% (8.8%)	27.0% (1.1%)	35.8% (6.5%)	34.2% (10.2%)
TELIASONERA AB	25.6% (4.5%)	23.5% (1.0%)	28.5% (3.2%)	25.6% (5.2%)
UPM KYMMENE OYJ	33.4% (8.6%)	21.3% (1.6%)	31.0% (6.1%)	39.3% (3.8%)
VOLVO AB	36.5% (9.1%)	24.5% (1.4%)	36.7% (6.9%)	41.5% (6.6%)

5.3.2 Ratings-Based Data

When looking at the following table (Table 5.4), we see that the majority of our sample firms (a total of 25) have either A (7 firms) or BBB (11 firms) rating, whereas a few hold ratings of AA (2 firms), BB (2 firms) and B (3 firms) during the entire period. Throughout the entire period, we see that the number of firms with ratings AA, BBB and B increase consistently from the Pre-Crisis (1, 10 and 1 firms) to Crisis (2, 11 and 2 firms) until Post-Crisis (2, 12 and 3 firms) period. On the other hand, the number of firms with a rating of A and BB decrease steadily from the Pre-Crisis (10 and 3 firms) to Crisis (8 and 2 firms) until Post-Crisis (7 and 2 firms) period. This is what we can naturally expect, as firms in financial distressed positions tend to be downgraded, which can be seen during, but especially after the Crisis period. Despite the periodic changes, considering the firms within our sample, the majority maintains a rather stable rating.

Furthermore, when examining how the average CDS spreads change with regards to the firms' rating, there is a clear difference between the three periods. Although the ratings remain roughly the same for most firms throughout the entire sample period, we see more dramatic changes in CDS spreads between the Pre-Crisis (65.96 bps) to Crisis (318.44 bps) period than between the Crisis (318.44 bps) and Post-Crisis (230.99 bps) period. When comparing the Pre-Crisis to Crisis period, the BB and B-rated firms show the most significant increases in average CDS spreads. BB-rated firms have a mean of 176.63 bps during the Pre-Crisis period and 761.98 bps during the Crisis, whereas B-rated firms have a mean of 430.21 bps during the Pre-Crisis period and 1555.40 bps during the Crisis, despite that the same number of firms remain for category BB and there is an increase in firms rated B. From the Crisis to Post-Crisis period, the average CDS spreads of all rated-firms is reduced from 318.44 bps to 230.99 bps, however the BB and B-rated firms maintain the highest level of average CDS spreads – BB-rated (317.51 bps) and B-rated (1038.20 bps). Finally, all firms in the sample persist to have higher average CDS spreads during the Post-Crisis compared to the Pre-Crisis, however the BB and B-rated-firms persist to have the highest figures.

Despite that the average leverage ratio of all rated companies increase from the Pre-Crisis (0.25) to Crisis (0.37) period, the amount by which they increase varies quite notably depending on the assigned rating. This is consistent with U.S. data and according to

Korajczyk and Levy (2003), leverage varies counter-cyclically with macroeconomic conditions as well as highlighting that there is a move toward debt financing during economic downturns. This differentiation can be explained, by the fact that a company is either down or upgraded. In other words, a firm that is assigned an A-rating during the Pre-Crisis period whilst during the Crisis period the same company is downgraded and assigned a BBB-rating. As a result of this change in rating, a company can be added or removed from a subgroup in the sample and the leverage ratio will naturally be affected by this change. Whereas, there are three BB-rated firms during the Pre-Crisis period, with an average leverage ratio of 0.48, the number of firms in this sub-sample during the Crisis is reduced to two, which may partly cause the ratio to increase to 0.69. However, it is likely that decreased share prices during the Crisis are the main reason for the increase in leverage across all rating categories, affecting figures in the Crisis period. Furthermore, when comparing the Crisis to the Post-Crisis, the ratio decrease amongst all firms, apart from the AA-rated firms showing an increase from 0.15 in during the Crisis period to a ratio of 0.23 during the Post-Crisis period. In addition, AA is also the only rating category with an unchanged sample group of two firms. Finally, when contrasting the Pre-Crisis and Post-Crisis period, the average leverage ratios persist to be higher after the Crisis, when the entire sample's average is 0.33 compared to 0.25 before the crisis.

When comparing the change in average equity volatility from the Pre-Crisis (26.08%) to Crisis (36.90%) period, it is evident that all credit rating categories increase. This is in line with the literature, emphasizing that we observe high equity volatilities during the subprime crisis, because volatilities move counter-cyclically (Campbell, Lettau, Malkiel & XI, 2001; Ang & Bekaert, 2004; Feldhütter and Schaefer, 2013). Despite both up and downgrades in firm rating, there is a notable increase in this parameter amongst all companies, although some more than others – B-rated firms show a volatility of 31.28% during the Pre-Crisis and 47.56% during the Crisis. Furthermore, when looking at the Crisis in distinction to the Post-Crisis period, the AA-rated and A-rated firms are the only ones with an average fall in equity volatility from 33.01% and 35.17% during the Crisis period to 29.73% and 34.58% respectively during the Post-Crisis period. However, the A-rating subsample were also the only ratings with a decrease in the number of firms, which could have an impact on the average. Considering changes from the Pre-Crisis and Post-Crisis period, all rating categories show increased average equity volatilities, hence none have returned to Pre-Crisis levels. For B-rated firms, equity volatility skyrockets to 65.52% going into the Post-Crisis, compared to 31.28% during the Pre-Crisis and 47.56% during the Crisis.

Looking at the asset volatilities over the various periods, it can be observed that these tend to follow the same trend as equity volatilities, although it is evident that it increases slightly more than the equity volatility figures. Asset volatilities increase across all rating categories going from the Pre-Crisis (20.71%) into the Crisis (24.99%) period, where the most significant increases are seen amongst firms rated AA and BBB – from 19.42% to 28.27% for AA-firms and 20.67% to 26.46% for BBB-firms. Thus, the increased equity volatility is not only caused by the companies increased leverage. Going into the Post-Crisis period, asset volatilities keep increasing, except for the AA-rated firms having a decreased volatility from 28.27% to 23.58%. It is of particular notice that the asset volatility of the lower rating categories, namely BB and B, which increase very steeply – from 17.53% and 18.49% during the Crisis to 25.05% and 25.17% in the Post-Crisis period. In addition, when looking at Table 5.4, it is evident that these two ratings are most closely aligned throughout all periods. Furthermore, when comparing the Post-Crisis figures with those of the Pre-Crisis period, to see how the asset volatilities have altered, it is clear that the volatilities across all rating categories maintain a significantly higher level during the Post-Crisis period. This is evident when looking at the mean for the Pre-Crisis (20.71%) with the Post-Crisis (27.60%) period.

When examining the payout ratios, we see that all ratios increase significantly amongst the different rating categories. However, it is the highest (AA) and lowest (BB and B) categories demonstrating the highest upturns, as can be seen in Panel B and C of Table 5.4. The raise in payout ratio during the Crisis period could be related to the erosion of equity prices while dividend payments remained on the same levels. Comparing the next periods it is evident that the payout ratios decrease rather notably amongst all rating categories, especially for BBB-rated firms going from 6.08% to 3.97%. When contrasting the Pre-Crisis to Post-Crisis period, it is rating categories; AA, BB and B, namely the highest and lowest, having higher payout ratios in the Post-Crisis than during the Pre-Crisis period. In contrast, rating categories A and BBB, have lower ratios during the Post-Crisis compared to the Pre-Crisis, as seen in Panel C and D of Table 5.4.

Table 5.4. Observed spreads, leverage ratios, equity volatilities, calibrated asset volatilities and observed payout ratios for the sample.

Rating	Observed CDS Spread	Observed Leverage Ratio	Observed Equity Volatility	Calibrated Asset Volatility	Observed Payout Ratio	N
PANEL A: Entire Period *(2006-02-14 – 2014-02-14)*						
AA	64.34 (10.88; 101.13)	0.19 (0.1; 0.28)	29.21% (21.54%; 40.51%)	24.14% (17.03%; 32.68%)	3.67% (2.32%; 5.57%)	2
A	68.07 (24.83; 104.98)	0.26 (0.12; 0.4)	32.60% (23.18%; 44.43%)	25.24% (17.16%; 34.99%)	4.08% (02.21%; 6.67%)	7
BBB	115.02 (31.52; 212)	0.25 (0.09; 0.42)	34.80% (22.98%; 48.19%)	27.54% (17.24%; 38.63%)	4.80% (2.00%; 8.49%)	11
BB	271.14 (44.05; 433.36)	0.47 (0.35; 0.61)	34.73% (21.32%; 46.77%)	21.59% (14.7%; 29.19%)	4.88% (3.83%; 6.16%)	2
B	929.82 (272.85; 1963.8)	0.70 (0.5; 0.91)	54.42% (31.04%; 74.41%)	21.95% (11.99%; 37.4%)	4.61% (1.47%; 6.97%)	3
ENTIRE SAMPLE	208.09 (30; 458.98)	0.32 (0.11; 0.61)	36.08% (22.84%; 50.33%)	25.48% (15.98%; 36.64%)	4.49% (2.19%; 7.27%)	25
PANEL B: Pre Crisis *(2006-02-14 – 2007-12-31)*						
AA	16.54 (9.86; 26.72)	0.14 (0.12; 0.17)	22.26% (21.52%; 23.55%)	19.42% (18.21%; 20.7%)	2.30% (2.02%; 2.61%)	1
A	24.36 (9.97; 38.72)	0.17 (0.01; 0.35)	26.21% (22.95%; 29.69%)	22.42% (17.57%; 28.78%)	4.88% 02.66%; 7.7%)	10
BBB	42.87 (26.5; 61.38)	0.22 (0.1; 0.36)	25.27% (19.01%; 31.81%)	20.67% (13.61%; 27.39%)	5.56% (2.07%; 11.44%)	10
BB	176.63 (42.11; 373.48)	0.48 (0.39; 0.61)	27.93% (21.38%; 35.05%)	17.24% (14.32%; 21.36%)	4.02% (0%; 6.02%)	3
B	430.21 (314.17; 584.19)	0.64 (0.61; 0.68)	31.28% (29.51%; 32.4%)	15.81% (14.02%; 17.75%)	4.19% (3.61%; 4.58%)	1
ENTIRE SAMPLE	65.96 (13.44; 127.75)	0.25 (0.06; 0.47)	26.08% (20.18%; 31.97%)	20.71% (14.54%; 27.5%)	4.92% (2.2%; 8.84%)	25
PANEL C: Crisis *(2008-01-01 – 2009-06-30)*						
AA	114.47 (34.72; 241.86)	0.15 (0.09; 0.2)	33.01% (26.2%; 41.4%)	28.27% (22.52%; 34.45%)	4.41% (2.98%; 6.09%)	2
A	133.30 (57.44; 304.12)	0.32 (0.12; 0.58)	35.17% (26.61%; 45.04%)	25.63% (20.11%; 33.83%)	5.14% (2.95%; 8.06%)	8
BBB	184.63 (73.53; 394.46)	0.32 (0.09; 0.53)	35.58% (24.23%; 47.06%)	26.46% (16.74%; 36.46%)	6.08% (2.56%; 10.40%)	11
BB	761.98 (333.87; 1249.9)	0.69 (0.47; 0.89)	44.33% (25.89%; 64.71%)	17.53% (12.34%; 23.48%)	5.81% (4.24%; 7.00%)	2
B	1555.40 (560.01; 3595.8)	0.74 (0.6; 0.9)	47.56% (36.16%; 63.45%)	18.49% (08.68%; 32.06%)	5.46% (3.64%; 7.75%)	2
ENTIRE SAMPLE	318.44 (62.9; 705.85)	0.37 (0.11; 0.67)	36.90% (25.6%; 48.38%)	24.99% (16.03%; 34.51%)	5.57% (02.99%; 08.53%)	25
PANEL D: Post Crisis *(2009-07-01 – 2014-02-14)*						
AA	68.81 (50.12; 89.87)	0.23 (0.19; 0.31)	29.73% (21.38%; 40.56%)	23.58% (16.76%; 32.75%)	3.31% (2.46%; 4.28%)	2
A	67.41 (50.29; 89.06)	0.26 (0.12; 0.38)	34.58% (23.41%; 45.77%)	27.00% (16.43%; 36.39%)	3.71% (1.89%; 6.39%)	7
BBB	128.70 (66.16; 205.02)	0.25 (0.12; 0.41)	38.06% (25.71%; 50.2%)	29.83% (18.7%; 39.97%)	3.97% (1.01%; 6.97%)	11
BB	317.51 (231.69; 399.73)	0.50 (0.39; 0.61)	40.80% (34.44%; 47.5%)	25.05% (20.14%; 29.93%)	4.58% (3.41%; 5.64%)	2
B	1038.20 (415.01; 2040.8)	0.73 (0.56; 0.91)	65.52% (51.28%; 74.96%)	25.17% (11.71%; 40.08%)	4.59% (0%; 6.99%)	3
ENTIRE SAMPLE	230.99 (57.11; 573.28)	0.33 (0.13; 0.61)	39.93% (24.56%; 55.89%)	27.60% (16.99%; 38.68%)	3.97% (1.90%; 6.62%)	25

This table presents the market observed CDS spreads, the leverage ratios, equity volatilities, asset volatilities and payout ratios, as described in section 4, based on company rating. In the parenthesis, the lower and upper 10th percentiles are stated. The number of firms in each rating is found in the rightmost column.

6 Empirical Results

In section 6.1 we present the model's performance compared with observed CDS spread for each rating subcategory.

6.1 Spreads From the Extended Merton Model

In Table 6.1, the model's predicted spreads are summarized together with observed CDS spreads and prediction errors. The table is divided into four panels, each one representing one testing period. Panel A contains data for the entire sample, Panel B covers the Pre-Crisis period, Panel C the Crisis period and in Panel D, the Post-Crisis data is presented. The data is divided into rating categories, as shown in the first column. The second column contains the model's predicted spreads, the third column shows the observed CDS spreads and in the fourth column, the model spread is divided by the observed spread, which measures how much of the observed spread that can be explained by the model. The fifth column presents the mean error (ME), which is the average of the difference between the model spread and the observed spread, while the sixth column shows the mean percentage error (MPE), calculated as the ME divided by the observed spread. The seventh column represents the Mean Absolute Error (MAE) being the absolute value of the difference between the model and the observed CDS spread. The final column displays the Mean Absolute Percentage Error (MAPE), which is the percentage value of the division of MAE by the observed CDS spread. The differences between the model spread and the observed spread are, except for A rated firms in the Pre-Crisis period and AA rated firms in the Post-Crisis period, all significant at the 1% level using two-sided t-tests.

Table 6.1. Predicted spreads by the extended Merton model and market observed CDS spreads.

Rating	Model Spread (std dev)	Observed Spread (std dev)	% Explained by Model (std dev)	ME (std dev)	MPE (std dev)	MAE (std dev)	MAPE (std dev)	N
PANEL A: Entire Period *(2006-02-14 – 2014-02-14)*								
AA	12.35	64.34	15.92%	-52.00	-84.08%	52.00	84.08%	2
	(15.45)	(42.27)	(20.16%)	(36.89)	(20.16%)	(36.89)	(20.16%)	
A	52.40	68.07	63.12%	-15.68	-36.88%	31.65	57.27%	7
	(56.49)	(38.42)	(52.94%)	(32.2)	(52.94%)	(16.53)	(29.37%)	
BBB	75.78	115.02	57.97%	-39.25	-42.03%	45.92	48.71%	11
	(62.68)	(61.95)	(39.89%)	(40.43)	(39.89%)	(32.56)	(31.28%)	
BB	245.25	271.14	76.41%	-25.89	-23.59%	81.75	41.28%	2
	(175.92)	(137.47)	(48.12%)	(109.77)	(48.12%)	(77.29)	(34.01%)	
B	585.98	929.82	64.63%	-343.84	-35.38%	364.36	38.85%	3
	(292.11)	(509.9)	(25.94%)	(354.86)	(25.94%)	(333.53)	(20.29%)	
ENTIRE SAMPLE	138.94	208.09	62.41%	-69.15	-37.60%	72.16	39.38%	25
	(83.44)	(108.88)	(28.26%)	(57.99)	(28.26%)	(54.16)	(25.69%)	
PANEL B: Pre Crisis *(2006-02-14 – 2007-12-31)*								
AA	0.01	16.54	0.04%	-16.53	-99.96%	16.53	99.96%	1
	(0.01)	(7.73)	(00.04%)	(7.72)	(00.04%)	(7.72)	(00.04%)	
A	2.63	24.36	10.49%	-21.73	-89.52%	21.73	89.52%	10
	(1.54)	(5.7)	(04.19%)	(4.78)	(04.19%)	(4.78)	(04.19%)	
BBB	5.91	42.87	12.74%	-36.96	-87.26%	36.96	87.26%	10
	(5.86)	(10.67)	(09.26%)	(8.13)	(09.26%)	(8.13)	(09.26%)	
BB	67.77	176.63	37.09%	-108.86	-62.91%	108.86	62.91%	3
	(35.28)	(55.67)	(08.52%)	(30.38)	(08.52%)	(30.38)	(08.52%)	
B	182.69	430.21	44.35%	-247.53	-55.66%	247.53	55.66%	1
	(21.51)	(111.94)	(08.38%)	(101.06)	(08.38%)	(101.06)	(08.38%)	
ENTIRE SAMPLE	18.86	65.96	28.11%	-47.10	-71.89%	47.10	71.89%	25
	(7.48)	(16.57)	(04.5%)	(10.59)	(04.5%)	(10.59)	(04.5%)	
PANEL C: Crisis *(2008-01-01 – 2009-06-30)*								
AA	15.71	114.47	10.58%	-98.76	-89.43%	98.76	89.43%	2
	(18.12)	(57.01)	(12.68%)	(46.69)	(12.68%)	(46.69)	(12.68%)	
A	110.97	133.30	72.27%	-22.32	-27.73%	37.81	38.51%	8
	(84.8)	(65.66)	(38.53%)	(37)	(38.53%)	(19.57)	(27.%)	
BBB	126.10	184.63	59.21%	-58.53	-40.79%	59.52	41.35%	11
	(98.05)	(63.62)	(35.65%)	(45.73)	(35.65%)	(44.36)	(34.96%)	
BB	410.96	761.98	53.03%	-351.02	-46.97%	351.02	46.97%	2
	(140.15)	(139.74)	(11.69%)	(83.75)	(11.69%)	(83.75)	(11.69%)	
B	617.97	1555.40	42.62%	-937.44	-57.39%	937.44	57.39%	2
	(221.13)	(748.43)	(08.55%)	(546.1)	(08.55%)	(546.1)	(08.55%)	
ENTIRE SAMPLE	174.56	318.44	50.92%	-143.87	-49.09%	143.87	49.09%	25
	(99.33)	(118.11)	(14.57%)	(35.58)	(14.57%)	(35.58)	(14.57%)	
PANEL D: Post Crisis *(2009-07-01 – 2014-02-14)*								
AA	16.26	68.81	23.49%	-52.55	-76.51%	52.55	76.51%	2
	(15.3)	(14.28)	(22.49%)	(19.11)	(22.49%)	(19.11)	(22.49%)	
A	54.84	67.41	79.72%	-12.57	-20.28%	32.49	49.93%	7
	(37.47)	(11.8)	(53.%)	(34.36)	(53.%)	(16.31)	(26.24%)	
BBB	89.86	128.70	75.35%	-38.85	-24.65%	50.19	36.10%	11
	(33.67)	(33.8)	(35.65%)	(49.39)	(35.65%)	(37.58)	(23.72%)	
BB	355.56	317.51	111.83%	38.04	11.83%	58.50	18.76%	2
	(92.01)	(67.32)	(20.14%)	(59.75)	(20.14%)	(39.49)	(13.77%)	
B	768.03	1038.20	80.06%	-270.13	-19.94%	305.68	25.96%	3
	(122.78)	(329.77)	(23.84%)	(302.06)	(23.84%)	(265.33)	(16.93%)	
ENTIRE SAMPLE	176.80	230.99	80.19%	-54.19	-19.82%	59.40	22.91%	25
	(34.3)	(57.46)	(21.53%)	(56.34)	(21.53%)	(50.71)	(18.13%)	

The table shows the mean and standard deviations of the extended Merton model's predicted credit spreads, the market observed CDS spreads, the percentages of the model spread to the observed spread, the differences between the model spread and the observed spread (ME), the differences between the model spread and the observed spread, divided by the observed spread (MPE), the absolute differences between the model spread and the observed spread (MAE) and the absolute differences between the model spread and the observed spread, divided by the observed spread (MAPE). The data is divided into three sub-periods and classified based on the firms' credit ratings.

Mean Error (ME) is the mean of the difference between the model's and the observed CDS spread. Mean Percentage Error (MPE) is the mean percentage of the difference between the model's spread and the observed CDS spread, divided by the observed CDS spread. Mean Absolute Error (MAE) is the mean of the absolute difference between the model's and the observed CDS spread. Mean Absolute Percentage Error (MAPE) is the mean percentage of the absolute difference between the model's spread and the observed spread, divided by the observed spread.

Our results clearly indicate that for AA-rated companies, the predicted spreads by the extended Merton model are persistently, during all periods, lower than real spreads, which is evident in Table 6.1. Throughout the entire period, the model explains 15.92% of the observed spreads for firms rated AA, which is the category where the model spreads is the least accurate in predicting the market-observed spreads. For the Pre-Crisis period the model only manages to capture 0.04% of the observed CDS spread, with an average predicted spread of 0.01 bps, being extensively lower than the average observed spread of 16.54 bps. Also throughout the first period of the Crisis, the model spreads are substantially lower than market-observed spreads; whereas from the end of the Crisis period until the mid Post-Crisis, the model spreads manage to predict the CDS spreads to a larger extent, which is apparent from Figure 6.1. During the last part of the Post-Crisis, the model severely underpredicts the market-observed CDS spreads, as can also be seen in Figure 6.1. For this last period, the model on average predicts 23.49% of the CDS spread, with a mean error of -52.55 bps, an error that is highly statistically significant at the 1% level. For the other periods, the results for AA rated companies are significant at the 1% level.

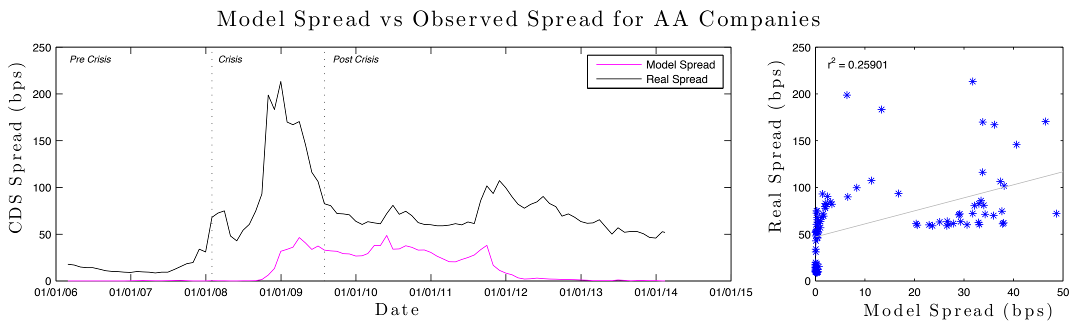

Figure 6.1. Model spread and observed CDS spread for AA-rated companies.

When looking at A-rated companies for the entire period, we see that the model's spread match the market-observed fairly well, where the model's spreads are 63.12% of the observed spreads as seen in Panel A in Table 6.1. During the Pre-Crisis and the first half of the Crisis period, the model spreads notably underpredict the market-observed spreads, as can be seen in Figure 6.2. Whereas during the mid Crisis period, the model spreads are virtually comparable and converge towards the observed CDS spreads, corresponding to 72.27% of observed spreads during the whole Crisis period, being the rating with the best estimation. The mean error for this period is -22.32 bps, which is the most statistically significant of all ratings during this period. However, from the mid Crisis and until the mid Post-Crisis period, the model mainly overpredicts observed spreads, whereas during the later months of the Post-Crisis period, the predicted spreads are below real spreads, as can be seen in Figure 6.2. Overall, during the Post-Crisis period, the models spreads are 79.72% of the observed spreads, with a mean error of -12.57 bps, as can be seen in Panel D in Table 6.1. Of all ratings, the model shows the highest *R*-squared value for A-rated firms at 0.6995.

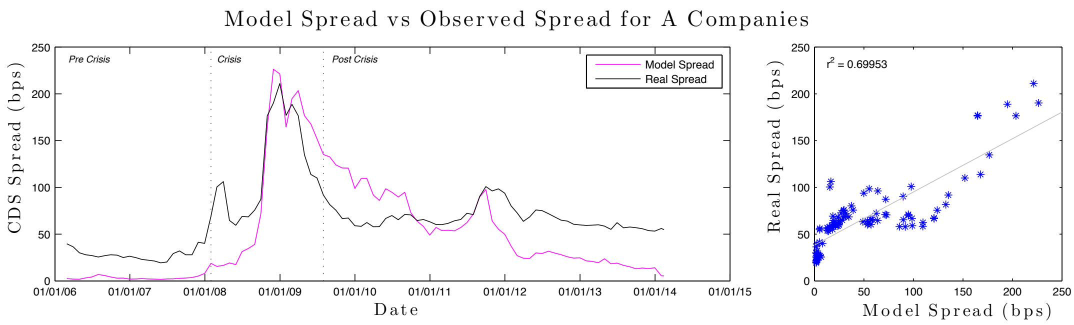

Figure 6.2. Model spread and observed CDS spread for A-rated companies.

For companies assigned a BBB-rating, we see a similar trend as with the other ratings where model spreads underpredict market-observed spreads from the Pre-Crisis until the mid Crisis period. The model's predictions are 57.97% of the observed spreads during the entire period, with a mean error of -39.25 bps, a substantial underprediction that is significant at the 1% level, as can be seen in Panel A of Table 6.1. Conversely, during the end of the Crisis and until the mid Post-Crisis period, we see that the models spreads are on average above the market-observed spreads. Whereas during the latter part of the Post-Crisis period the model spread underpredict real spreads even more than during the Pre-Crisis. Overall the underpredictions are most substantial during the last half of the Post-Crisis period. In contrast, during the first half of the Post-Crisis period, the model's spreads tend to move towards the actual spreads and they match rather well, as is evident when looking at Figure 6.3. All in all, the model on average predicts 75.35% of the CDS spreads, with a mean error of -38.85 bps.

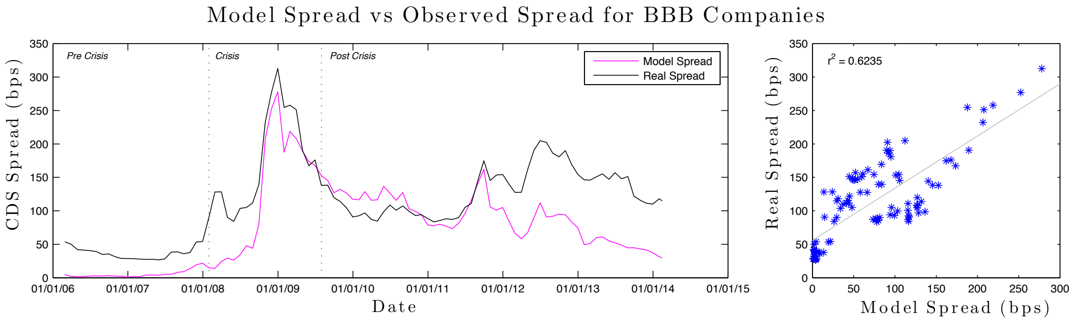

Figure 6.3. Model spread and observed CDS spread for BBB-rated companies.

When looking at BB-rated companies from the Pre-Crisis until the last-half of the Crisis period, it is evident that model-spreads severely underpredict observed spreads, as seen in Figure 6.4. During the Pre-Crisis period, BB-rated firms show the worst prediction in relative terms, equivalent to 37.09% of observed spreads with a negative error of 108.86 bps. In contrast, from the end of the Crisis and throughout the Post-Crisis, we see in Figure 6.4, how the model spreads closely converge and persistently follow the real spreads. Of all rating categories, the model spreads of BB-rated firms match the actual spreads fairly well, apart form the severe underprediction during the Pre-Crisis period. This can be seen in Panel D of Table 6.1, where the model's predicted spreads for BB rated companies during the Post-Crisis are 111.83% of the observed spreads with a positive mean error of 38.04 bps. Nevertheless, similar to the other rating categories, spreads turn south during the latter months of the sample period, as can be seen in Figure 6.4.

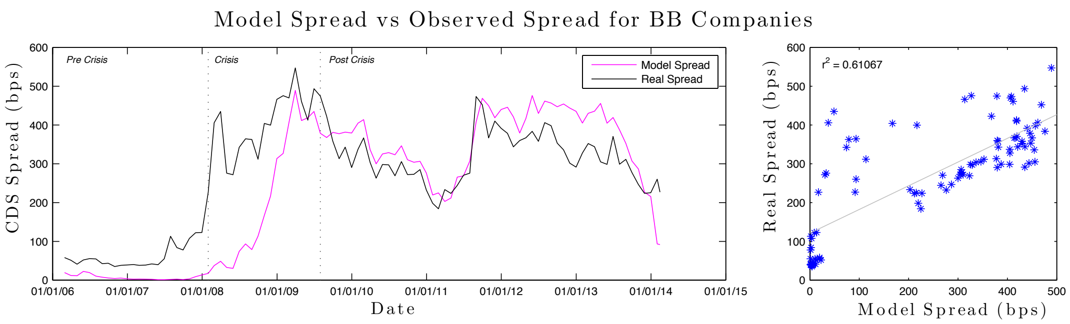

Figure 6.4. Model spread and observed CDS spread for BB-rated companies.

For the lowest rating category in the sample, comprising firms assigned a rating of B; the model's predicted spreads for the entire period are 64.63% of actual CDS spreads, a prediction error of -343.84 bps seen in Panel A. This indicates that this is the rating with the highest level of underprediction in absolute terms. Hence, model spreads continue to underpredict real spreads throughout the entire period, apart form a minor overprediction as seen in Figure 6.5. The Pre-Crisis spreads as predicted by the model are lower than actual spreads, amounting to 44.35% of the actual spreads, an average error of -247.53 bps. For the Crisis period, the model's spreads are significantly lower than the observed spreads, explaining only 42.62% with an average error of -937.44 bps, which is the period during which it demonstrates the highest underprediction, seen in Panel C. During the Post-Crisis period, the B-spreads are volatile, but model spreads mainly underpredict real spreads, on average 80.06% with an error of -270.13 bps. The previously observed pattern, where model spreads decrease during the later phase of the Post-Crisis period is also valid for B-rated firms, as seen in Figure 6.5.

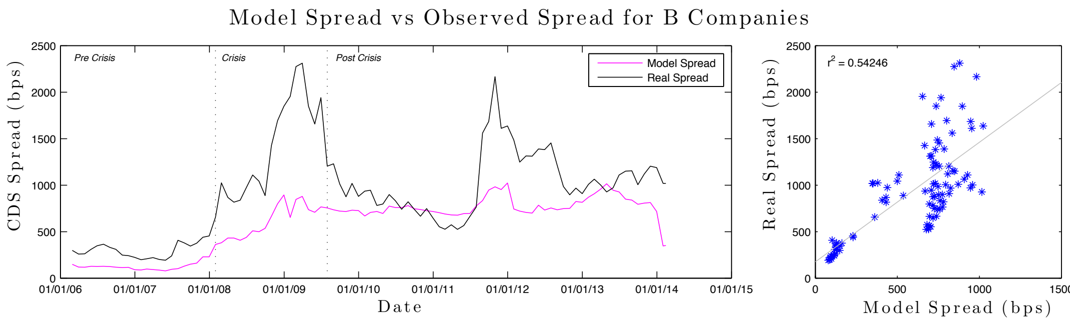

Figure 6.5. Model spread and observed CDS spread for B-rated companies.

Looking at the entire sample, we see that the model's predicted spreads understate observed spreads during all time periods - 62.41% of observed spreads for the entire sample period, 28.11% for the Pre-Crisis period, 50.92% for the Crisis period and 80.19% for the Post-Crisis period. The same pattern as previously observed is visible when looking at the entire sample, namely that spreads are mostly underpredicted from the Pre-Crisis until the latter part of the Crisis period. Whereas during the first half of the Post-Crisis and until the mid Post-Crisis period, the model-implied spreads are closely aligned with the actual spreads, whereas from the last half of the Post-Crisis period, the model spreads again underpredict market-observed spreads, as seen in Figure 6.6.

Nevertheless, the R-squared value is rather high, 0.7234, indicating that the model does a relatively good job at explaining the movements of the market-observed CDS spreads.

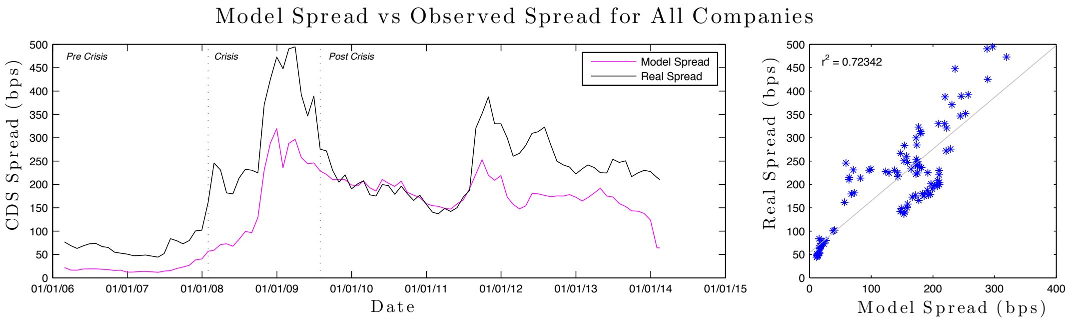

Figure 6.6. Model spread and observed CDS spread for the entire sample of companies.

7 Discussion

In this section, we scrutinize our findings in order to find the underlying drivers. The results are also compared with existing literature on the subject, both qualitatively and quantitatively.

7.1 Fundamental Drivers Of Credit Spreads

As previously noted, there is a clear connection between market-observed CDS spreads and leverage ratios as well as equity volatilities for the Nordic companies during our sample period, which is consistent with the theory as well as previous studies. Looking at the outputs from the extended Merton model, as presented in Table 6.1, it is evident that models predicted spreads also increase in leverage ratio and equity volatility, as presented in Table 5.4, which is in line with the theory. The aim of this section is to identify to what extent the level of model spreads are driven by leverage ratios, equity volatilities, asset volatilities and payout ratios and also to see whether this differs as the economic conditions change going through the three time periods. Furthermore, we try to find patterns that can offer some explanation to the accuracy of the model's predictions.

For the Pre-Crisis period, looking at Panel B of Table 5.4, it can be observed that leverage ratios and equity volatilities tend to increase as the credit rating decreases. It should be noted that asset volatility, which is calibrated as outlined in section 4.2 and 4.3, decreases in credit rating. This is likely caused by the fact that firms assigned a lower rating tend to have a larger portion of its assets financed by debt, which is assumed to be a lot less volatile than equity, as previously explained in section 4.2. The payout ratio is, quite surprisingly, the lowest for companies with the highest credit rating of AA (2.30%), while BBB-firms pay out the most (5.56%). Unsurprisingly, the model spreads increase in leverage ratio and equity volatility. Looking at the accuracy of the model in Panel B of Table 6.1, we can see that the relative errors decrease in rating, which indicates that predictions are best for the lower credit ratings, and consequently the larger the leverage ratio and equity volatility. This could indicate that the market does not find the low leverage ratios and equity volatilities as safe as the structural model does, or that some other factor, not captured by the model, has the largest effect when these two variable are the smallest. EHH (2004) who find similar results argue that this could be because of poor measurement of leverage, or that the model does not assign these leverage levels appropriate risk.

Going into the Crisis period, increased leverage ratios, equity volatilities, asset volatilities as well as payout ratios can be observed across all the different rating categories when looking at Panel C of Table 5.4. The turbulence in the stock markets during the financial crisis is a possible explanation for the larger volatilities and the fact that asset volatilities become larger, in spite of increased leverage, indicates that the increased equity volatility is not only caused by the increased leverage but also by enhanced risk levels in general for the firms in the sample. As for the increased leverage ratios and equity volatilities, it could be the case that these may be caused by deteriorating equity values during this time period of financial turmoil. This in turn drives the level of model-implied spreads to become even higher, which continue to increase as credit rating decrease, as is anticipated. However, when looking at the accuracy of the model's predictions in Panel C of Table 6.1, the errors are no longer the smallest for firms with the lowest credit ratings or the largest leverage ratios. Instead, the model's predicted A-spreads are the most accurate with the lowest MPE of -27.73% and MAPE of 38.51%, while AA-spreads followed by B-spreads are the least precise.

For the Post-Crisis period, the leverage ratios[18] as well as payout ratios decrease, as demonstrated in Panel D of Table 5.4, which is likely caused by expanding equity values whilst the market recovers after the financial crisis. In spite of this, the overall level of equity volatilities and asset volatilities increase even though the Nordic economies recover around the summer of 2009, as outlined in section 4.4. This may be a result of the Eurozone crisis that emerged in Europe in the aftermath of the financial crisis. Even though the crisis can be originated to countries relatively far from the Nordics and did not affect the fundamentals of Nordic firms noticeably, it is likely to have created tensions in the international financial markets, which could partly explain the increased volatilities that are observed in the Post-Crisis period. The lower volatilities and payout ratios are counterbalanced by increased asset volatilities, causing the overall levels of model spreads not to change remarkably from the Crisis to the Post-Crisis period. As for the accuracy of the model's predictions, AA-spreads are once again the least accurately

[18] Except for AA-rated firms, for which leverage ratios increase.

predicted, while least errors are found for BB-spreads, albeit being overpredicted, both when looking at the MPE of 11.83% and the MAPE of 18.76%.

As can be seen, the accuracy of the model's prediction differs over the three time periods, where the Pre-Crisis is the least accurate. FS (2013), who use a subperiod relatively similar[19] to our Pre-Crisis period, argue that this could be caused by high leveraged buyout activity during these years. Companies with high ratings and low leverage would in case of a debt financed buyout see its leverage jump substantially, to which the market assigns some probability and consequently pushes the credit spread north. This is however not captured by the Merton model, which therefore would explain the large prediction errors for low-leveraged firms. We believe that while this may provide an explanation to some fraction of the discrepancies between the model spread and the market spread, it still does not explain the entire difference as the prediction errors remain large for low-levered firms both during the Crisis and the Pre-Crisis periods, which are considered to be times when the LBO activity is reduced, according to FS (2013). Going into the Crisis period, it is evident that prediction errors are lower, but still substantial. FS (2013) who use a time period not too different from our Crisis period[20] claim that their underprediction of spreads for high rated companies during this time period can be attributed to a strong liquidity component for high rated bonds through this period of time. However, as we use CDS data, which as previously outlined, should not be affected to the same extent as bonds by illiquidity, we believe there are other factors that should explain the discrepancies in spreads. Furthermore, we observe underpredictions across all rating categories. Going into the Post-Crisis period, we see that the accuracy of the model's predictions improves further when looking at the relative prediction errors MPE and MAPE, but most spreads are still underpredicted. FS (2013), who use a period similar to our Post-Crisis period[21], argue that underpredictions during this period could be related to the risk-free rate being underestimated during periods of market imbalances, which also affects swap rates. While this may offer an explanation to some of the underpredictions, we believe that the truth is more complex than that, as the

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[19] They use a period from 2005Q1 to 2007Q2, while our Pre-Crisis period stretches from 2006-02-14 to 2007-12-31.

[20] While their period goes from 2007Q3 to 2009Q4, our Crisis period starts at 2008-01-01 and ends 2009-06-30.

[21] They use a subperiod stretching from 2010Q1 to 2012Q2, while our Post-Crisis goes from 2009-07-01 to 2014-02-14.

prediction errors vary greatly depending on rating quality and as mentioned, BB-firms are overpredicted during this period.

7.2 Comparison With Existing Literature

The following section looks into how our model-implied and market-observed spreads differ from what is discovered in the existing literature. We discuss those papers to which our thesis is particularly related - EHH (2004), HH (2012) and FS (2013). Nonetheless, it is important to highlight the fact and bear in mind that in addition to studying the U.S. market, previous studies base their analysis using bond data, whereas we base our paper using CDS data.

Before looking into the subsequent section, we want to highlight the main results in order for this part to be more intuitive as well as to review what has been highlighted in preceding sections. In general, we find that our results are qualitatively in line with the existing literature (Collin-Dufresne & Goldstein, 2001; EHH, 2004; Chen, 2010; Bhamra, Kuehn & Strebulaev, 2010a; Bhamra, Kuehn & Strebulaev, 2010b; HH, 2012; FS, 2013). However, when considering the quantitative aspect, there is a tendency to see that, in the majority of all cases, our model-implied spreads show a closer match with market-observed spreads compared to existing literature, despite that the time horizon is different (EHH, 2004; HH, 2012) and even when accounting for the convexity bias (FS, 2013). This may be caused by the lower recovery rate that we use, or that our results are based on CDS data, while the mentioned authors use bond data. Another explanation is that the credit spread puzzle is not as strong in the Nordics as in the U.S. Overall, our results are in line with the majority of existing literature, but in contrast to FS's (2013) findings, as we do find that the credit spread puzzle persist, in the Nordics.

First, when looking at the different rating categories throughout the various subdivided periods in Table 6.1, we see that the model-implied spreads generated for all rating categories understate market-observed spreads, apart from for BB-rated firms, for which model spreads are above actual spreads during the Post-Crisis period. Despite this occurrence of overprediction, the cases of underprediction are far more numerous and extreme. Further, it seems to be a somewhat stronger tendency amongst the lower rating categories to show higher levels of underprediction in absolute terms, which is in line with previous research (Collin-Dufresne & Goldstein, 2001; EHH, 2004; HH, 2012). These researchers emphasize that higher spreads are linked to bonds considered very risky and having low ratings (i.e. junk bonds), whereas very low spreads tend to be linked with bonds that the models considered safe and that are of high-quality, which is again similar to our findings. The fact that credit spreads are more sizable amongst the lower rating categories (i.e. BB and B-ratings) and during volatile times is supported by Chen (2010: 2175) saying "defaults are more concentrated in bad times, which generates sizable credit spreads despite the small default probability". Disregarding the BB-rated firms, the model-implied spreads of all other rating categories are persistently understated compared to market-observed spreads. Hence, the results are qualitatively in line with the existing credit spread puzzle as has previously been observed in the U.S. market (HH, 2012).

Furthermore, when EHH (2004: 535) test and examine the five corporate bond pricing models' (Merton, 1974; Geske, 1977; Longstaff & Schwartz, 1995; Leland & Toft, 1996; Collin-Dufresne & Goldstein, 2001) abilities to predict corporate bond spreads, they find that "all five models tend to generate extremely low spreads on the bonds that the models consider safe (usually low leverage and low asset volatility) and to generate very high spreads on the bonds considered to be very risky". These findings are all in line with our results, apart from the fact that our model-implied spreads, which are predominantly lower in absolute terms than what previous research finds. In addition, EHH (2004) state that the majority of empirical studies on resolving the credit spread puzzle do not find support for the models and several studies conclude that the models severely underpredict the market-observed spreads (Deliandeis & Geske 1998; Collin-Dufresne, Goldstein & Martin, 2001; HH 2012). In addition, they emphasize that "the bonds with the low predicted spreads have an average rating of about an A- or an A" (EHH, 2004: 526), which is in line with our results showing lower predicted spreads for the highest rating categories, namely AA and A, as can be seen in Table 6.1.

Having highlighted the fact that the majority of our rating categories are qualitatively in line with the existing literature, the following section will quantitatively compare our results with the literature, to see whether, and how, our figures differ from other studies.

As the foregoing sections describe, when looking at the different subdivided periods, there is a clear distinction between the three periods with regards to the differences in model-implied spreads compared to the market-observed spreads, as can be seen in the ME (fifth) column of Table 6.1.

First, when comparing our results to the findings of HH (2012), we contrast the figures from our entire period with their 'base case' results for all rating categories, except for Aaa (with a maturity equal to 4 years) as our sample does not contain any firms having this rating. Rather than comparing the mean errors, we compare the HH's "% of Spread due to Default" with our "% Explained by Model" as their sample period goes from 1973 to 1998, while our sample ranges from 2006 to 2014 and consequently, the absolute levels of credit spreads may diverge significantly because of business cycle differences. This is evident when looking at HH's (2012) base case results, as their model-implied spreads are smaller than ours, ranging from 6 to 445.7 bps, compared to ours that go from 12.35 to 585.98 bps. In contrast the market-observed spreads are larger in HH's sample, except for B-rated companies. Looking at the accuracy of the model-implied spreads, we can conclude that for firms rated AA-BBB, i.e. investment grade, our model spreads show better predictions of market-observed spreads than HH, explaining between 15.92% and 63.12% of actual spreads, compared to HH's that range from 2.1% to 10.3%. This may partly be explained by the lower recovery rate of 32.40% that we use compared to HH who use a rate of 51.31%. However, for firms assigned a credit rating of B, HH's model predictions are more accurate. These findings are stable, even when looking at the developed models that HH test[22]. As mentioned, our market-observed spreads are all, except for B-spreads, tighter than in HH's sample, which may be a result of the various time periods for which the data has been collected. In addition, as HH's sample period stretches over 25 years, compared to ours of 8 years, it could capture larger economic swings, which may be reflected in the data.

Furthermore, the fact that our model spreads are more accurate than HH's (2012), who use bond data, may be caused by the CDS-bond basis as previously described. Looking at the firm-specific variables, we note that the companies in our sample generally

[22] Except for Leland-Toft with endogenous default and strategic default models, for which HH do not present any results for bonds with a maturity of 4 years.

demonstrates lower leverage ratio levels, where the differences are mainly observable for investment grade firms, stretching from 0.19 to 0.26, compared to HH's that reaches from 0.21 to 0.43. For asset volatility, differences can be observed across all rating categories. In our sample, asset volatilities stretches from 21.59% to 27.54%, while HH's asset volatilities are within the range of 28.9% to 39.6%. Since our sample period differs from HH's we cannot fully conclude that U.S companies are more volatile than Nordic firms. However, it is notable that in spite of lower leverage ratios and asset volatilities, our results show more accurate predictions than HH. Some of this difference may be attributed to the lower recovery rate, however the accuracy of the models predictions are only slightly improved, but still far worse than ours for investment grade firms, when HH adjust the recovery rate to 45% in the sensitivity test in Table 9 of their study. Thus, the results suggest that there might be better accuracy in our model, which could be a result of a less distinct credit spread puzzle in the Nordics, or caused by the fact that our results are not affected by the convexity bias, as described in preceding sections, in contrast to HH who use average firm variables and may therefore get its results distorted as a result of this.

As previously outlined, EHH (2004) test the performance of five structural models, including the extended Merton model. The authors do not divide their data with regards to rating categories and therefore we compare the results from our entire sample to their results. The bond data in their sample is for the period 1986-1997 and as presented in Table 1 Panel A of their paper. From the table it can be seen that EHH's mean observed spread is 93.53 bps, which is smaller than our entire sample's of 208.09 bps. Thus, EHH's mean credit spread is tighter than in our sample, in spite of the fact that the authors use bond data. However, as we do not know what firms are included in their sample, we cannot draw any direct conclusions from this. Our sample may contain more risky companies with larger credit spreads, which would push our average spread north. It may also be caused by lower overall levels of credit spreads during their sample period compared to ours, which would then explain why there appears to be a positive and large CDS-bond basis. Alas, the authors do not present the predicted yield spreads numerically, instead looking at the prediction errors one can however assess the accuracy of the model spreads. This shows that our predicted spreads are far more accurate, with a MPE of -37.60% and a MAPE of 39.38%, compared to their Merton model performance, which shows a MPE of -50.42% and a MAPE of 78.02%. This shows that EHH's model-spreads are further below actual spreads than ours. Furthermore, it can be observed that our predicted spreads are more accurate compared to the other structural models that EHH examine[23]. Moreover, comparing the mean firm variables, it can be noted that both leverage ratios and asset volatilities in EHH's sample are similar to ours. EHH use a leverage ratio of 0.30, slightly lower than ours of 0.32, they also find an asset volatility of 23.6%, which is slightly lower than ours of 25.48%. From this, it can be inferred that their sample consists of firms with a slightly lower risk than our sample, which may explain a small part of the lower credit spreads in their study.

Looking at the results of FS (2013), we compare their absolute numbers with the entire period of our sample (Panel A in Table 6.1) as their study covers transactions over the period 20002Q3-2012Q2, which is rather similar. When examining the various rating categories, we observe a notable difference between our figures and those of FS, both with regards to model-implied and market-observed spreads. First, when investigating the model-implied spreads we see that the figures of our high-level ratings, namely AA and A, are higher (12.35 bps and 52.40 bps) compared to FS having 1 bps (AA) and 13 bps (A). For the remaining rating categories, our model spreads are persistently adequately lower than theirs, especially for rating BB (245.25 bps against 1117 bps) as can be seen in Panel A in Table 6.1 in our paper and Table 7 in FS's (2013: 48) paper. It should be noted however that FS's predicted spreads for the lowest rating categories (BB and B), are significantly above market spreads, having positive mean errors of 513 bps and 393 bps, which can be seen in Table 7 of their paper. This can be compared with the corresponding figures from our sample of -25.89 bps and -343.84 bps, thus our model predictions are more accurate albeit being underpredicted. Going further to contrast our market-observed spreads with those of FS (2013), we see a similar trend as we did with HH (2012), namely that the majority of our real spreads are lower than theirs. Whereas all our real spreads are lower than HH's (2012), across every rating category, this is not the case when comparing our figures with FS (2013). Nevertheless, when taking an overall look at all rating categories, we observe that our results have smaller mean errors, in addition to being more accurate in relative terms. Even if our errors are all negative,

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[23] The LS-model in EHH's study does in fact demonstrate a lower MPE of -6.63%, however with a MAPE of 96.83% the low MPE is likely caused by large over- and underpredictions that cancel out each other.

model-implied spreads are overall more accurate in predicting market-observed spreads than FS's (2013).

Furthermore, FS (2013) highlight that their sample includes periods with both low spreads (2005-06) and periods with very high spreads (2008-09) and emphasize that if one ignores the variations in spreads over time, this can lead to incorrect conclusions. When looking at the graphs depicting model-implied and actual spreads presented in their paper (FS, 2013: 51 & 53) it demonstrates that the model-implied spreads are tracking the real spreads fairly well, apart from underpredictions during the period 2005-06, when actual spreads are low, and 2008-09, when actual spreads are high. The same trend is apparent in our results, namely that the model's worst predictions are during times when actual spreads are either the lowest, as during the Pre-Crisis period, or the highest, as during the Crisis period. In addition, when examining Figures 6.1 to 6.6 in our paper, it is evident that from 2012 and onwards (the financial years of 2013 and 2014), the model-implied spreads cannot quite match the level of actual spreads to the same extent as in previous years. This might be due to the Eurozone crisis, which pushes credit spreads upwards as a result of people's fear of contagion effects within the European market, which the model does not pick up, as firm variables for our Nordic sample stay reasonably stable during this period.

Furthermore, for the lowest and riskiest rating category, which in our sample is B and in FS (2013) is C, market-observed spreads are significantly wider compared to the model spreads. Interestingly, FS's model spreads for non-investment grade bonds are extensively overpredicted, except for C-spreads being significantly underpredicted at 1483 bps compared to the observed 6009 bps. The same pattern is visible for our riskiest firms, as previously described, however not to the same extent. A potential reason for such large underpredictions for the lowest rated firms can be, as Davydenko and Strebulaev (2007: 2646) explain not only attributable "to different probabilities of default, but also to the lower liquidity of speculative grade bonds". This is supported by HH (2012: 158) who point out "several studies have documented empirically that liquidity has a significant impact of corporate yield spreads or spread changes". The reason why the underpredictions in most of the periods are not as stark as in FS's study may be that we use data for CDS, which are affected by increased default probabilities, but not affected by low liquidity to the same extent as bonds, as outlined in previous sections. In addition, since FS's lowest rating is C, which is riskier than our lowest of B, this effect may be magnified.

Looking further into the firm-specific data, it can be observed that the leverage ratios in our sample are not as large as those FS (2013) present in Table 1 and Table 2 of their study. The largest difference is found among firms rated BBB and BB, which in our data show leverage ratios of 0.25 and 0.47 respectively, being significantly smaller than the 0.53 and 0.66 that FS find. Furthermore, differences can also be found when looking at equity volatility, which in our sample stretches from 29.21% to 54.42%, compared to the mentioned study that spans from 25% to 73%. Again, the largest differences are found for firms rated BBB and BB, for which our sample's averages are 34.80% and 34.73% compared to FS's sample averages of 66% and 93%. Hence, it can be inferred that firms within these rating categories in the U.S. market are more risky than the Nordic equivalents, which also would explain why market-observed spreads for these credit ratings are larger in FS's study compared to ours. This can also be attributed to larger volatilities in turbulent times in the U.S. stock market, which was the center of the financial crisis. In addition, FS's sample has higher asset volatilities, even if the differences are not as large as for equity volatilities, which is caused by FS's larger leverage ratios that push asset volatilities down.

Overall, when looking at our paper in relation to recent literature examining the credit spread puzzle (EHH, 2004; HH, 2012; FS, 2013), it is evident that the results of the different studies vary significantly. While EHH and HH find that its model spreads are persistently below actual spreads, FS show that its model actually overpredict spreads for some ratings. However, when looking at FS's results using bonds with a maturity of 4 years, we can see that the overpredictions are only the case for firms rated BB and B. For the other rating categories, we see results that are similar to ours, namely that the model spreads are the least accurate for the highest rating categories, and for the worst. For investment grade firms, our model predictions show, albeit being below actual spreads, better predictions than EHH, HH and FS, both in absolute terms and in relative terms for most rating categories. This may be caused by the lower recovery rate that we use, or that our results are based on CDS data, while the mentioned authors use bond data. As previously outlined, bond spreads tend to be pushed upwards as a result of both increased default risk and decreased liquidity during times of financial turbulence. While CDS spreads are affected by the increased default risk, it is unaffected by liquidity drying up as a result of its contractual nature. This may provide an explanation for our more accurate spreads, and we look further into it in subsequent sections where the robustness of the results are tested.

Furthermore, when comparing the various studies, it is important to emphasize that HH (2012) cover transactions from 1973-1998, and EHH (2004) look at data during the time period 1986-1997, being clearly different from our sample period (February 2006-February 2014). Despite that all time periods are affected and influenced by financial turbulence, it is challenging to make a direct comparison between these figures due to the significant dissimilarities. In contrast, although the sample period of FS (2013) from 20002Q3 to 2012Q2, is more appropriate, it is worthy of note that our sample is the only one that incorporates figures during the Eurozone crisis, which by nature affect European countries, including those domiciled in the Nordics, more significantly than U.S. corporations. Hence, ignoring differences in spreads over time can easily lead to incorrect conclusions and it is therefore natural to expect a different result as there exists no direct comparison material and the sample period is not exactly comparable. Regardless of having a different sample period, we apply the same approach as FS (2013), apart from using CDS data and not bond data, and our results are more aligned. Adding up, in contrast to their results, we find that the credit spread puzzle exist, in the Nordics.

We observe quite surprising findings with regards to FS's (2013) equity volatility. The equity volatility for BB-firms in their sample (93%) is unexpectedly three times larger than ours (35%), which is in line with previous literature. This large volatility could partly explain why their model's spreads are so much higher than their market-observed BB-spreads. In addition, one could expect the U.S. market to be more hectic during the financial crisis, which originated in the U.S., compared to the Nordics and, hence, the U.S. stocks are naturally more volatile and demonstrated larger decreases during this period. As this also leads to larger leverage ratios, the model spreads are affected twice, both by larger levels of leverage and volatility, which in turn leads to their model spreads being higher.

7.3 Further Notes on the Credit Spread Puzzle

From examining our results and comparing them to previous studies, we are able to draw conclusions regarding the accuracy of our model's spreads and the fact that the credit spread puzzle, while being existent, do not seem to be as sizeable in the Nordics as in the U.S. However, we are not able to draw any clear conclusions for why the puzzle can be observable in the Nordics. We have noted that the model in general predicts spreads the most accurately during times characterized by some degree of economic instability[24], for firms rated A, BBB and BB. Thus, it seems that during times of financial stability, investors' fear large negative downside risks, and one possible explanation is that this will lead to spreads more sizable than what the structural models that are based on fundamental data are able to predict.

Firms with the largest errors in our sample tend to be those with the highest and the lowest credit ratings, as well as the lowest and highest leverage ratios. This is also the case in FS's (2013) study. Translating this to the option-pricing framework that the extended Merton model is based on, these firms can be said are the *deepest in-the-money* as well as the *deepest out-of-the-money*. For options with this moneyness, it is known that an implied volatility smile is observable, i.e. that volatilities are larger for options whose strike price is significantly below or above the current price of the underlying asset. This is not consistent with Black and Scholes's (1973) option pricing model, which assumes that volatility is constant. Thus, a similar pattern may be consistent with the observed differences for firms with low and high leverage, which coheres with our beliefs that the volatility calibration as outlined in Section 4.2 may not be optimal[25]. This is also in line with the suggestions of EHH (2004), i.e. that the credit spread puzzle for investment grade firms may be caused either due to the fact that leverage is measured poorly or that structural models do not assign the low leverage levels an appropriate amount of risk. Parallels can also be drawn to the claims of HH (2012), who argue that there is a need for a new type of structural models that can accurately predict credit spreads for investment grade firms without having to use parameters that are calibrated to values that diverge

[24] The financial crisis during the Crisis period and the Eurozone crisis during the Post-Crisis period.

[25] In fact, implying out the asset volatilities and plotting these against the leverage ratios generates a pattern that resembles a smile. This can be seen in Appendix A.3.

significantly from what can be empirically observed. The authors suggest that one possibility is to look into a model that allows for the asset value process to have stochastic volatility. It is also important to focus on the consideration by HH in that credit risk models should not only explain the credit spread puzzle, but also generate realistic credit spreads on both investment grade and high-yield bonds. We believe this finding is truly interesting and its validity across a larger sample of companies as well as its explanations should be subject to further research. In addition, a more sophisticated structural model trying to capture this effect, may imaginably lead to more accurate spreads.

As can be observed in our data, market-observed CDS spreads as well as company-specific variables differ notably, not only across the credit ratings, but also between the three time periods, which have been derived with regards to the financial crisis. Since the model spreads' accuracy differ significantly, both between and within the periods, it may be inferred that it might not be enough to describe the state of the economy as either good or bad in order to get a deeper understanding of the underlying causes of the credit spread puzzle. Rather, it may be necessary to add more nuances, such as the nine business cycle states, during which not only credit spreads differ, but also company-specific parameters including volatilities and recovery rates, as described by Chen (2010).

There have been suggested solutions to the credit spread puzzle in previous studies (Bhamra, Kuehn & Strebulaev; 2010a; Bhamra, Kuehn & Strebulaev; 2010b; Chen, 2010), which have been outlined in Section 2.2. Our results are in line with this literature, in that we have a strong tendency of counter-cyclicality of credit spreads (i.e. credit spreads are much larger in recessions, see Panel C in Table 6.1.). According to Bhamra, Kuehn and Strebulaev (2010a: 23), this is equivalent to saying that distance to default is lower in bad states, *ceteris paribus*. It should also be noted that despite finding similar results as in the literature, part of the explanations to resolving the puzzle might not be equally relevant in the Nordics as in the U.S. (for instance, one possibility is that business cycles are more important and affecting credit spreads to a larger extent in the Nordics than in the U.S.). In addition, due to the low default frequencies and the high recovery rates historically observed in the Nordics, it seems fair to assume that expected recovery rates would be higher there than in the rest of Europe. This is based on the reasoning that during the aftermath of the financial crisis and going into the Eurozone crisis, certain countries might push the mean recovery rate downwards (i.e. Greece, Ireland, Spain, Portugal etc.), which is supported by Moody's (2012, 2013), and as a consequence of this, the average recovery rate in Europe is smaller than the actual Nordic average. Thus, rather than being weaker compared to the U.S., as our findings indicate, the credit spread puzzle might actually be larger in the Nordics than what our results show. However, due to the lack of empirically observed company defaults in the Nordics and therefore the scarce amount of studies on this matter, these are mere speculations and grants further investigation.

Despite having found differences in our results compared to previous studies, it remains unanswered which of the factors that are the main reasons for the differences. Whether it is because of our different sample period, the fact that CDS spreads rather than bond spreads are used, the recovery rate applied or if it is just that the Nordic is different from the U.S., are questions we believe to be truly interesting and crucial to consider in order to get closer to a solution to the credit spread puzzle. We therefore believe that this should be scrutinized further in future research.

8 Robustness Tests

In order to test the robustness of the model's performance, we carry out further examinations using bond data, as well as altering the recovery rate.

8.1 Robustness Test 1: Bond Data

Most existing literature investigating the credit spread puzzle uses bond data rather than CDS data. Moreover, the empirical findings on the CDS-bond basis by Bai and Collin-Dufresne (2013), shows that discrepancies may emerge between CDS spreads and bond spreads in times of financial turbulence as earlier portrayed. Consequently we wish to assess the robustness of our findings by testing the model's performance on bond data. The bond data is obtained from Bloomberg where bonds from the companies in the sample, traded during as many days as possible of our testing period, are used. The spreads for each bond are obtained by subtracting the yield of a government bond issued, by the country in which the company is listed, with a maturity as close as possible to the corporate bond's maturity, from the corporate bond's yield. A summary of the bonds used for this can be found in Appendix A.1. We restrict the bond sample by removing bonds with a maturity of less than one year. In line with existing literature, we also remove bonds with so-called special features, accordingly bonds that are callable, convertible, putable, perpetual or denominated in another currency than the domestic or Euro are omitted from the sample. This leaves us with a sample of 104 bonds from 23 companies[26], which are all summarized in Appendix A.1. For each bond in the sample, a corresponding model spread is calculated using the extended Merton model as previously described. In order for the robustness check to reflect our previous investigations as closely as possible, the model and bond spreads are averaged for each company, so that the companies in the sample are as equally weighted as possible.

[26] No bond data matching our criteria are available for Norsk Hydro ASA and Swedish Match AB, thus these firms are left out the sample.

Table 8.1. Robustness test using corporate bond data: Predicted spreads by the extended Merton model and market observed bond spreads.

Rating	Model Bond Spread (std dev)	Observed Bond Spread (std dev)	% Explained by Model (std dev)	ME (std dev)	MPE (std dev)	MAE (std dev)	MAPE (std dev)	N
PANEL A: Entire Period *(2006-02-14 – 2014-02-14)*								
AA	10.95 (12.54)	112.28 (61.60)	8.56% (8.88%)	-101.34 (56.85)	-91.45% (8.88%)	101.34 (56.85)	91.45% (8.88%)	2
A	38.61 (47.75)	112.67 (81.68)	25.83% (16.38%)	-74.06 (39.29)	-74.17% (16.38%)	74.06 (39.29)	74.17% (16.38%)	7
BBB	57.17 (60.59)	155.84 (92.32)	34.79% (22.75%)	-98.67 (53.88)	-65.22% (22.75%)	98.67 (53.88)	65.22% (22.75%)	9
BB	225.08 (154.14)	172.14 (114.46)	139.96% (88.00%)	52.93 (141.80)	39.96% (88.00%)	125.58 (83.52)	85.13% (44.97%)	2
B	713.50 (462.12)	986.26 (684.29)	76.29% (46.15%)	-272.76 (615.05)	-23.71% (46.15%)	424.18 (521.20)	44.30% (26.75%)	3
ENTIRE SAMPLE	133.18 (82.78)	232.76 (137.97)	56.63% (34.16%)	-99.57 (103.75)	-43.37% (34.16%)	102.37 (100.96)	45.15% (31.75%)	23
PANEL B: Pre Crisis *(2006-02-14 – 2007-12-31)*								
AA	0.17 (0.14)	166.56 (22.18)	0.10% (0.09%)	-166.39 (22.15)	-99.90% (0.09%)	166.39 (22.15)	99.90% (0.09%)	2
A	3.78 (2.09)	67.50 (17.94)	5.80% (2.67%)	-63.72 (17.18)	-94.20% (2.67%)	63.72 (17.18)	94.20% (2.67%)	9
BBB	3.96 (5.73)	79.78 (32.27)	5.22% (6.25%)	-75.82 (30.97)	-94.78% (6.25%)	75.82 (30.97)	94.78% (6.25%)	9
BB	63.05 (45.69)	173.18 (62.59)	32.29% (22.3%)	-110.13 (42.25)	-67.72% (22.3%)	110.13 (42.25)	67.72% (22.3%)	3
B	140.90 (20.02)	461.35 (113.09)	31.46% (4.57%)	-320.46 (96.04)	-68.54% (4.57%)	320.46 (96.04)	68.54% (4.57%)	2
ENTIRE SAMPLE	15.82 (8.87)	106.61 (26.98)	13.88% (5.02%)	-90.79 (19.02)	-86.13% (5.02%)	90.79 (19.02)	86.13% (5.02%)	23
PANEL C: Crisis *(2008-01-01 – 2009-06-30)*								
AA	5.71 (5.87)	169.23 (81.08)	2.50% (2.14%)	-163.53 (75.66)	-97.50% (2.14%)	163.53 (75.66)	97.50% (2.14%)	2
A	104.39 (81.66)	250.65 (109.41)	35.06% (18.80%)	-146.25 (37.94)	-64.94% (18.8%)	146.25 (37.94)	64.94% (18.80%)	8
BBB	116.75 (96.25)	277.05 (111.76)	35.33% (21.62%)	-160.30 (38.09)	-64.67% (21.62%)	160.30 (38.09)	64.67% (21.62%)	9
BB	244.02 (79.87)	757.81 (266.23)	33.18% (7.07%)	-513.78 (218.43)	-66.82% (7.07%)	513.78 (218.43)	66.82% (7.07%)	2
B	745.53 (429.33)	2334.40 (1469.20)	34.44% (8.59%)	-1588.90 (1084.90)	-65.56% (8.59%)	1588.90 (1084.90)	65.56% (8.59%)	2
ENTIRE SAMPLE	151.66 (92.75)	426.96 (183.47)	32.60% (8.39%)	-275.31 (94.48)	-67.40% (8.39%)	275.31 (94.48)	67.40% (8.39%)	23
PANEL D: Post Crisis *(2009-07-01 – 2014-02-14)*								
AA	17.09 (12.92)	109.30 (53.04)	13.97% (8.03%)	-92.21 (45.87)	-86.03% (8.03%)	92.21 (45.87)	86.03% (08.03%)	2
A	34.46 (27.17)	94.79 (50.69)	30.17% (13.52%)	-60.33 (25.02)	-69.83% (13.52%)	60.33 (25.02)	69.83% (13.52%)	7
BBB	58.21 (25.48)	124.93 (49.04)	47.88% (12.62%)	-66.72 (33.59)	-52.12% (12.62%)	66.72 (33.59)	52.12% (12.62%)	9
BB	281.86 (125.43)	158.50 (84.84)	187.42% (53.7%)	123.36 (85.56)	87.42% (53.7%)	128.43 (77.60)	90.04% (49.10%)	2
B	1020.70 (291.02)	1034.90 (325.58)	106.73% (36.8%)	-14.21 (366.49)	6.73% (36.80%)	276.49 (238.09)	28.93% (23.41%)	3
ENTIRE SAMPLE	175.45 (39.72)	222.14 (58.44)	81.92% (20.02%)	-46.69 (53.85)	-18.08% (20.02%)	51.55 (49.13)	21.16% (16.66%)	23

The table shows the mean and standard deviations of the extended Merton model's predicted credit spreads, the market observed bond spreads, the percentages of the model spread to the observed spread, the difference between the model spread and the observed spread (ME), the differences between the model spread and the observed spread, divided by the observed spread (MPE), the absolute differences between the model spread and the observed spread (MAE) and the absolute differences between the model spread and the observed spread, divided by the observed spread (MAPE). The data is divided into three sub-periods and classified based on the firms' credit ratings.

Mean Error (ME) is the mean of the difference between the model's and the observed bond spread. Mean Percentage Error (MPE) is the mean percentage of the difference between the model's spread and the observed bond spread, divided by the observed bond spread. Mean Absolute Error (MAE) is the mean of the absolute difference between the model's and the observed bond spread. Mean Absolute Percentage Error (MAPE) is the mean percentage of the absolute difference between the model's spread and the observed spread, divided by the observed spread.

Looking at the results from the robustness test using bond data, as presented in Table 8.1, it is evident that these are consistent with our previous findings. However, what can be seen is that both the model spreads and the observed credit spreads are not fully aligned with the findings from the CDS data. This is mainly due to three factors. First of all, while the model-implied and market-observed CDS spreads have a fixed maturity of five years, the maturity of the model-implied and market-observed bond spreads vary significantly, from two to twenty years, as can be seen in Appendix A.1. Second, as previously mentioned, two firms from the original sample, Norsk Hydro ASA and Swedish Match AB, have been left out as they are missing available bond data for the sample period that fit our criteria. Third, while each company is given equal weight throughout the entire sample period when testing the CDS data, this is not possible for the bond test due to the sparse availability of data. Some firms, for which there is a considerable availability of data, are included throughout the entire sample period, while the bond data for other companies are more limited and the firm is merely included during segments of the testing period. While this is somewhat of a limitation, we do not believe it affects the usefulness of the test for the sake of testing the robustness of the results.

As can be observed from Table 8.1, the model's predicted credit spreads are below the market-observed spreads, apart from the firms with a BB-rating during the Post-Crisis period. For the full sample of companies over the entire sample period, the average predicted bond spread is 133.18 bps, while the average market bond spread is 232.76 bps or on average 56.63% of observed spreads corresponding to a negative mean error of 99.57 bps. This is larger than the negative mean error of 69.15 bps for the CDS data, which may be caused by the sample discrepancy, as previously outlined. Another possibility is that this is caused by the larger non-default component in bond spreads. In accordance with our previous findings, the most understated estimates from the model in absolute terms are found during the Crisis period, where the mean error is -275.31 bps, compared to -143.87 bps for the CDS data. This could relate to the findings by Bai and Collin-Dufresne (2013), i.e. that a negative CDS-bond basis is present and exacerbated during times of financial turbulence.

Looking at the relative accuracy of the model, we can see that the bond results are consistent with the CDS results as well, as the Pre-Crisis period demonstrates the largest relative error, predicting 13.88% of actual spreads for bond data, and 28.11% for the CDS data. Furthermore, we observe similar to previous studies and to the results using CDS data that the model has more difficulties with predicting the credit spreads for the higher ratings. The underestimates for the highest rated companies are even more evident in the bond results compared to our CDS results, where the differences in absolute errors also are the largest during the Crisis period.

As with the results using CDS data, the only scenario where model spreads overpredict market-observed spreads are during the Post-Crisis with companies assigned a BB-rating. It is noteworthy that the model's predicted B-spreads are more accurate for bond data compared to the CDS data, with a mean error of -14.21 bps compared to -270.13 bps, which is a deviation from the overall pattern. In general, the levels of underprediction are much more numerous and extreme in the bond results compared to our CDS results.

Compared to previous studies, we can see that our model predictions are still more accurate than those of HH (2012) for most ratings. Compared to EHH (2004), it can be noted that the mean percentage error and mean absolute percentage error are lower in our study, thus our model spreads show to be more accurate predictions of market spreads than those of the mentioned authors. Compared to FS (2013), our model manages better to predict spreads for all ratings in relative terms and in absolute terms for all ratings except AA-rated companies.

This further confirms that our findings are in line with previous studies on the credit spread puzzle, namely that is persists in the Nordics, however not to the same degree as in the U.S. The robustness test shows that it is not caused by discrepancies between CDS spreads and bond spreads.

8.2 Robustness Test 2: Altered Recovery Rate

By increasing the recovery rate, spreads should according to the theory, decrease as previously described. As the recovery rate used in our study differs somewhat from that in previous literature, we test to what extent this affects our findings by changing the recovery rate from 32.40% as previously used, to 51.31%, which is the rate that is used in the studies by EHH (2004) and HH (2012) and slightly larger than the recovery rate of 49.20% FS (2013) use. It is also larger than the 40% that is used by Bai and Wu (2013), a rate of recovery the authors claim to be standard in literature on CDS. Except for altering the recovery rate in the model, which implies that $\psi = 51.31\%$, the methodology is identical to the main examination as outlined in Section 4.2-4.3. The result of this robustness test is summarized in Table 8.2.

Table 8.2. Robustness test using a recovery rate of 51.31%: Predicted spreads by the extended Merton model and market-observed CDS spreads.

Rating	Model Spread (std dev)	Observed Spread (std dev)	% Explained by Model (std dev)	ME (std dev)	MPE (std dev)	MAE (std dev)	MAPE (std dev)	N
PANEL A: Entire Period *(2006-02-14 – 2014-02-14)*								
AA	7.81	64.34	10.03%	-56.54	-89.97%	56.54	89.97%	2
	(9.78)	(42.27)	(12.74%)	(38.22)	(12.74%)	(38.22)	(12.74%)	
A	33.55	68.07	40.52%	-34.52	-59.48%	35.61	61.17%	7
	(35.82)	(38.42)	(33.97%)	(21.64)	(33.97%)	(19.78)	(30.78%)	
BBB	48.82	115.02	37.33%	-66.20	-62.67%	66.20	62.67%	11
	(39.46)	(61.95)	(25.75%)	(38.92)	(25.75%)	(38.92)	(25.75%)	
BB	159.76	271.14	49.78%	-111.38	-50.23%	111.54	50.28%	2
	(115.83)	(137.47)	(32.03%)	(89.01)	(32.03%)	(88.8)	(31.95%)	
B	352.19	929.82	38.78%	-577.63	-61.22%	577.63	61.22%	3
	(178.11)	(509.9)	(15.79%)	(399.66)	(15.79%)	(399.66)	(15.79%)	
ENTIRE SAMPLE	86.55	208.09	38.74%	-121.54	-61.26%	121.54	61.26%	25
	(52.42)	(108.88)	(18.03%)	(70.46)	(18.03%)	(70.46)	(18.03%)	
PANEL B: Pre Crisis *(2006-02-14 – 2007-12-31)*								
AA	0.00	16.54	0.02%	-16.54	-99.98%	16.54	99.98%	1
	(0.01)	(7.73)	(00.03%)	(7.72)	(00.03%)	(7.72)	(00.03%)	
A	1.59	24.36	6.35%	-22.77	-93.65%	22.77	93.65%	10
	(0.92)	(5.7)	(02.51%)	(5.12)	(02.51%)	(5.12)	(02.51%)	
BBB	3.54	42.87	7.64%	-39.33	-92.36%	39.33	92.36%	10
	(3.43)	(10.67)	(05.4%)	(8.78)	(05.4%)	(8.78)	(05.4%)	
BB	39.69	176.63	21.85%	-136.94	-78.15%	136.94	78.15%	3
	(19.46)	(55.67)	(04.85%)	(40.02)	(04.85%)	(40.02)	(04.85%)	
B	109.86	430.21	26.72%	-320.35	-73.28%	320.35	73.28%	1
	(13.47)	(111.94)	(05.35%)	(106.17)	(05.35%)	(106.17)	(05.35%)	
ENTIRE SAMPLE	11.21	65.96	16.76%	-54.75	-83.24%	54.75	83.24%	25
	(4.2)	(16.57)	(02.47%)	(13)	(02.47%)	(13)	(02.47%)	
PANEL C: Crisis *(2008-01-01 – 2009-06-30)*								
AA	9.89	114.47	6.65%	-104.58	-93.36%	104.58	93.36%	2
	(11.45)	(57.01)	(08.%)	(49.98)	(08.%)	(49.98)	(08.%)	
A	69.51	133.30	44.77%	-63.78	-55.23%	63.78	55.23%	8
	(54.5)	(65.66)	(25.24%)	(28.1)	(25.24%)	(28.1)	(25.24%)	
BBB	77.44	184.63	36.27%	-107.19	-63.73%	107.19	63.73%	11
	(60.85)	(63.62)	(22.5%)	(24.62)	(22.5%)	(24.62)	(22.5%)	
BB	236.85	761.98	30.37%	-525.13	-69.63%	525.13	69.63%	2
	(91.4)	(139.74)	(08.05%)	(84.14)	(08.05%)	(84.14)	(08.05%)	
B	361.49	1555.40	24.67%	-1193.90	-75.33%	1193.90	75.33%	2
	(135.68)	(748.43)	(04.36%)	(619.84)	(04.36%)	(619.84)	(04.36%)	
ENTIRE SAMPLE	104.97	318.44	30.26%	-213.46	-69.74%	213.46	69.74%	25
	(62.66)	(118.11)	(09.6%)	(60.01)	(09.6%)	(60.01)	(09.6%)	
PANEL D: Post Crisis *(2009-07-01 – 2014-02-14)*								
AA	10.30	68.81	14.85%	-58.51	-85.15%	58.51	85.15%	2
	(9.68)	(14.28)	(14.19%)	(15.77)	(14.19%)	(15.77)	(14.19%)	
A	35.72	67.41	51.92%	-31.70	-48.08%	33.58	51.02%	7
	(23.85)	(11.8)	(33.64%)	(21.7)	(33.64%)	(18.6)	(28.9%)	
BBB	59.15	128.70	49.39%	-69.56	-50.61%	69.56	50.61%	11
	(21.32)	(33.8)	(22.48%)	(40.45)	(22.48%)	(40.45)	(22.48%)	
BB	233.71	317.51	73.50%	-83.80	-26.50%	84.10	26.59%	2
	(61.92)	(67.32)	(13.83%)	(47.19)	(13.83%)	(46.66)	(13.64%)	
B	466.80	1038.20	48.56%	-571.37	-51.44%	571.37	51.44%	3
	(73.11)	(329.77)	(13.96%)	(305.76)	(13.96%)	(305.76)	(13.96%)	
ENTIRE SAMPLE	111.56	230.99	50.49%	-119.43	-49.51%	119.43	49.51%	25
	(21.3)	(57.46)	(13.05%)	(53.38)	(13.05%)	(53.38)	(13.05%)	

The table shows the mean and standard deviations of the extended Merton model's predicted credit spreads, the market observed CDS spreads, the percentages of the model spread to the observed spread, the differences between the model spread and the observed spread (ME), the differences between the model spread and the observed spread, divided by the observed spread (MPE), the absolute differences between the model spread and the observed spread (MAE) and the absolute differences between the model spread and the observed spread, divided by the observed spread (MAPE). The data is divided into three sub-periods and classified based on the firms' credit ratings.

Mean Error (ME) is the mean of the difference between the model's and the observed CDS spread. Mean Percentage Error (MPE) is the mean percentage of the difference between the model's spread and the observed CDS spread, divided by the observed CDS spread. Mean Absolute Error (MAE) is the mean of the absolute difference between the model's and the observed CDS spread. Mean Absolute Percentage Error (MAPE) is the mean percentage of the absolute difference between the model's spread and the observed spread, divided by the observed spread.

The anticipated decrease in credit spreads when the recovery rate is altered from 32.40% to 51.31% is confirmed when looking at Table 8.2. The results demonstrate that the average spread for the entire period is 86.55 bps when using a higher recovery rate, compared to 138.94 bps, which is obtained when a rate of 32.40% is used. This should be compared to the average actual market spread of 208.09 bps. The model spreads correspond to 38.74% of the observed spreads on average, which indicates that the model's predicted spreads are underestimated compared to the actual spreads. During the Pre-Crisis period, the model's predicted spreads are too tight, corresponding merely to 16.76% of observed spreads. During the Crisis period the predicted spreads are also lower than observed spreads compared, where it can be noted that the model across all rating categories are insufficient in capturing the magnitude of credit spreads, especially for companies assigned a rating of A, where model spreads merely amount to 6.65% of observed spreads. Although, the model still underpredicts actual spreads during the Post-Crisis period, this is the period for which the model provides the best estimates, on average at 50.49% of market-observed spreads. However, when looking at Table 8.2, it is clear that rating category AA is the persistent outlier throughout the different periods, being significantly underpredicted.

Looking at Figure 8.1, we can again see that the model using a recovery rate of 51.31% predicts the spreads to a lesser extent than what it does when using a recovery rate of 32.40%. When contrasting the different recovery rates, we see that when times turn turbulent, the spreads for both recovery rates are not quick enough to manage to react to the initial bump in spreads that can be observed in the market during the early months of the Crisis period. Subsequently, the model spread using a recovery rate of 32.40% does converge towards the real spread during the first half of the Post-Crisis period, which is not the case when setting the recovery rate equal to 51.31%. For the second half of this period, both predictions are far off the actual spread. Looking at the scatterplots in Figure 8.1, the change in recovery rate interestingly enough has no apparent effect on the R-squared value, which still remains relatively high at 0.644.

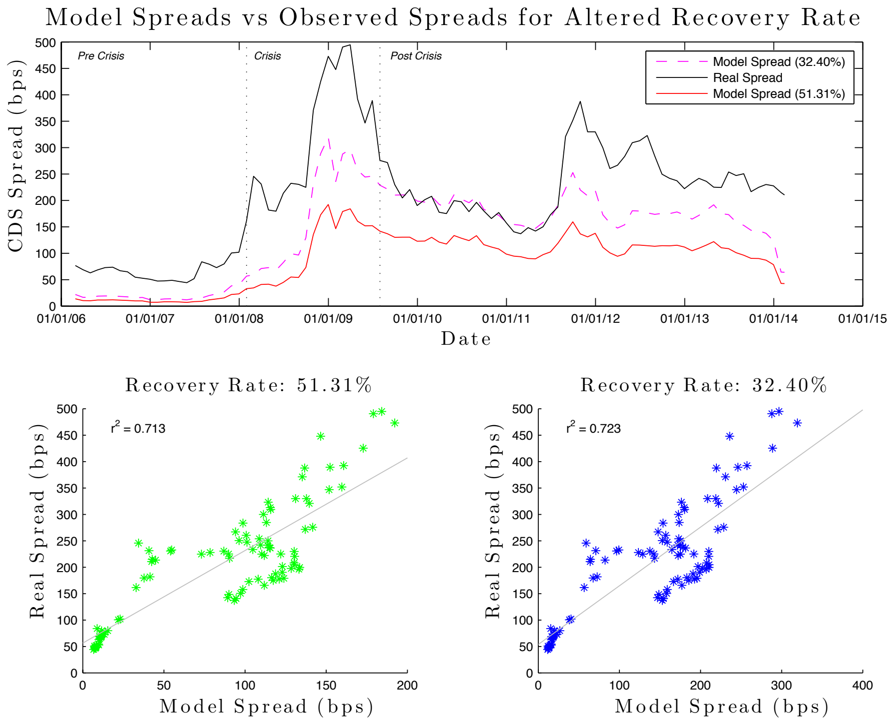

Figure 8.1. Model spreads and observed CDS spreads using a recovery rate of 51.31%.

This test further strengthens our previous findings in that there persists a credit spread puzzle in the Nordics. As expected, the magnitude of the underprediction of credit spreads is notably higher when altering the recovery rate from 32.40% to 51.31%, as can be seen in Figure 8.1. However, the model's predicted spreads are still more accurate than what both HH and EHH find, when comparing the predictability of the model and the absolute as well as relative errors in spreads. When the results from using the higher recovery rate is paralleled with the results of FS, we can see that in terms of relative differences, spreads for all ratings are more accurate than FS's, and in absolute differences, A-, BBB- and BB-spreads are more accurate. Thus, this robustness test shows that applying lower recovery rates compared to previous studies does not cause the differences between our findings and that of existing literature. Instead, we can conclude that the credit spread puzzle is not as eminent in the Nordics as in the U.S.

Considering that the recovery rate of 51.31% is larger than the average global recovery rate as reported by Moody's (2014) for senior unsecured bonds of 37.20%, and that European recovery rates tend to be lower than the global equivalent (Moody's, 2012), we believe this further indicates that our results are robust.

We further test the robustness of our results using an equally weighted average recovery rate for the two observed Nordic corporate defaults during our sample period by Moody's, which are the Norwegian firms Norske Skogindustrier ASA in 2012 (Moody', with a recovery rate for its senior unsecured bonds of 80.3% (Moody's, 2013) and Trico Shipping AS in 2010 with a recovery rate of 83.5% (Moody's, 2012). The average of 81.9% for the two Nordic defaults is far above the European average of 32.40% as reported by Moody's (2013). Using a recovery rate of 81.9% we find that the accuracy of model spreads decline even further. For the entire period, the model's predicted spreads are only 7.04% of market-observed spreads, a significant underprediction with a mean error of -188.99 bps. Hence, using the extremely small sample of observed recovery rates in the Nordics within the last 5 years, we find the credit spread puzzle to be even larger than as previously described and as found in previous literature. Yet, it should be highlighted that the two empirical recovery rate observations is a far too small sample to be able to make any significant inferences from this. As previously outlined, the number of historically observed default events in the Nordics are very sparse, therefore no conclusions can be drawn regarding what recovery rate investors expect should a Nordic company default. However, we believe that the average of 81.9% is far too large, given the globally observed rates. Rather, the interval between 32.40% and 51.31% seems to be a fairer approximation of the recovery rate in the Nordics. In addition, the assumption that the recovery rate is constant may not be that realistic either. As mentioned, Chen (2010) shows that the recovery rate differs throughout his nine states of the economy, something future studies should investigate, not only for companies in the Nordics, but for firms world-wide.

A summary of the results for the entire period with the altered recovery rates is found in Appendix A.2.

9 Suggestions for Future Research

Throughout the thesis, we have encountered several matters that we highlight to be subject for future research. These include a more direct comparison of the credit spread puzzle between the Nordics and the U.S., as we rely on previous literature for non-Nordic numbers. A study like this could also aim to find drivers causing the discrepancies. In addition, we would like to emphasize that we are unaware whether there exists a credit spread puzzle in the U.S. using our approach (using CDS data instead of bond data) with the extended Merton model, as we are not acquainted with any paper having tested this before. The purpose of this study would be to scrutinize to what extent the results are actually driven by credit spreads or if the less eminent puzzle is caused by the CDS-bond basis.

As noted, recovery rates affect the predicted spreads extensively and the assumption of a constant recovery rate may not be very realistic. Thus it would be interesting to see not only how actual recovery rates, but also how expected recovery rates vary throughout the business cycles, which as mentioned, should be distinguished by several states and not only into a good state and a bad state. Also, to what extent recovery rates differ between various countries or regions would be interesting and helpful in order to get a deeper understanding of the underlying causes behind credit spread puzzle. It seems fair to assume that if understanding and incorporating such features within a structural modeling framework, it would be more accurate at predicting credit spreads.

Furthermore, it would also be interesting for future research to look into the industry specific variables, in order to see whether certain industries or sectors should be assigned different recovery rates to get a more suitable and appropriate fit with the market-observed spread. This is because, despite having a small sample in our study, firms being within the same industry show linear leverage ratios and equity volatilities. In addition, it is vital to contemplate the statement by Strebulaev (2007: 1748) that "at any point in time, any two firms are likely to exhibit different reactions to the same shock even if these firms are identical from the date zero perspective".

Finally, we as well as most previous studies, have found that firms with the lowest leverage ratios are those for which the discrepancies between structural models' spreads and market-observed spreads are the most evident. As commented on briefly, we observe some similarities between the credit spread puzzle and the volatility smile within option pricing, namely that we find the credit spreads for firms with very low leverage and very high leverage to be the most underpredicted. This could perhaps be caused by poorly estimated asset volatility, which can be seen and is further commented on in Appendix A.4. It would certainly be noteworthy to see if connections between these two puzzles are mere speculations or if they somehow are related. A study investigating common drivers of these two puzzles would undeniably be interesting and may provide guidance to comprehend the systematic underpredictions of structural models.

10 Conclusion

The main question that this thesis has sought to address is whether there persists a credit spread puzzle in the Nordics. The puzzle, dating back to the findings of Jones, Mason and Rosenfeld (1984) as well as in a working paper from 2003 by Huang and Huang (2012), refers to the inability of structural models to predict credit spreads, even when calibrated to historical default probabilities. Several structural models, most often based on the seminal developments by Merton (1974) have been developed to resolve this issue but none seems to accurately manage to predict credit spreads. The research question is particularly interesting, as no other paper has examined this in the context of the Nordics. Rather, most studies have been conducted based U.S. market data because of its wide access. We therefore believe this paper contributes to the literature of empirical studies on the credit spread puzzle. Although no direct comparison can be made with existing literature, due to the use of a different time horizon and focus on a different market, we find robust results that confirm the existence of a credit spread puzzle in the Nordics.

In contrast to previous examinations, this thesis has covered data from the most recent financial periods as well as using CDSs as reference data, instead of bond data. We have found the credit spreads generated by our structural models to be inferior to the market-observed credit spreads and we can therefore conclude that there seems to persist a credit spread puzzle in the Nordics. However, albeit being underpredicted, our model-implied credit spreads show more accurate predictions of observed market spreads compared to previous literature. The largest absolute differences are found during the period of the financial crisis while the largest relative differences occur during the period prior to the financial crisis, whereas the model spreads match actual spreads particularly well during the period subsequent to the financial crisis.

Despite that our model underestimates actual spreads, it is apparent that our prediction errors (the difference between predicted and actual spreads) are smaller when contrasted with the recent literature; see Section 7.2 for further details. These results are robust, even when performing the tests using bond data and altering the recovery rate to match that of the previous studies. A possible explanation for why the prediction errors from our model spreads are less severe than existing literature might be related to the fact that we use a different time period or that we cover the Nordic market, and not the U.S., being the standard in this field of research. Although this paper presents several explanations for this observation, due to the scope of this thesis, we have determined such matters to be subject for further research.

Nevertheless, the results and findings of our paper can assist to further develop a better understanding of the relationship between the differences amongst the U.S. and the Nordics as well as the importance of accounting for differences between the CDS and bond market. An important implication of the results is that using CDS data when testing whether the credit spread puzzle persists in the Nordics prove to generate more accurate predicted spreads compared to the use of bond data, as can be seen in section 8.1. In addition, it is important to bear in mind that during times of financial difficulty and economic uncertainty, structural models struggle to forecast and make projections for such events that tend to influence and impact individual corporations. Also, although the sample size in our study is rather small, the fact that the Nordic market is significantly different from the U.S. is another factor that needs to be taken into account.

From our analysis we conclude that the credit spread puzzle exists in the Nordics, but not to the same extent as in the U.S. In addition, we find that using CDSs as reference data to be a better proxy than bond data, at least for this sample. Although, as previously highlighted, having encountered several matters and discussed potential resolutions, these are subject for future research.

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Appendix A.1: Corporate Bonds Used for Robustness Test

Table A.1. List of corporate bonds used for robustness test.

COMPANY NAME	TICKER	COUPON	ISSUE DATE	MATURITY DATE	CUSIP NO
ASSA ABLOY AB	ASSABS	6.52	6/22/2009	6/22/2016	EH8579151
ATLAS COPCO AB	ATCOA	4.6	5/25/2007	5/25/2012	EG4571881
ATLAS COPCO AB	ATCOA	4.75	6/5/2007	6/5/2014	EG4761474
CARLSBERG A/S	CARLB	6	5/28/2009	5/28/2014	EH8375824
CARLSBERG A/S	CARLB	3.375	10/13/2010	10/13/2017	EI4291965
ELECTROLUX AB	ELTLX	3.65	3/1/2005	3/1/2010	ED8396167
ELECTROLUX AB	ELTLX	4.5	1/29/2007	11/1/2012	EG1355114
ELISA OYJ	ELIAV	4.375	9/22/2004	9/22/2011	ED6211806
ELISA OYJ	ELIAV	4.75	3/1/2007	3/3/2014	EG2041135
ERICSSON AB	LMETEL	5.1	6/29/2007	6/29/2012	EG5859251
ERICSSON AB	LMETEL	5	6/22/2009	6/24/2013	EH8684795
ERICSSON AB	LMETEL	5.375	6/27/2007	6/27/2017	EG5854179
FORTUM OYJ	FUMVFH	3.75	4/6/2006	4/6/2011	EF3441575
FORTUM OYJ	FUMVFH	5	11/19/2003	11/19/2013	ED2129747
FORTUM OYJ	FUMVFH	4.625	3/20/2009	3/20/2014	EH7603325
FORTUM OYJ	FUMVFH	5.25	5/22/2009	5/22/2014	EH8301861
FORTUM OYJ	FUMVFH	3.125	9/14/2010	9/14/2015	EI3974397
INVESTOR AB	INVSA	6.125	3/5/2002	3/5/2012	EC5254197
INVESTOR AB	INVSA	4	3/14/2006	3/14/2016	EF3078807
INVESTOR AB	INVSA	3.25	9/17/2010	9/17/2018	EI4033870
INVESTOR AB	INVSA	5.25	9/4/2009	9/4/2019	EH9583574
INVESTOR AB	INVSA	4.875	11/18/2009	11/18/2021	EI0448528
INVESTOR AB	INVSA	4.5	5/12/2011	5/12/2023	EI6671222
METSA BOARD OYJ	METSA	8.75	3/29/2006	4/1/2013	EF3407337
METSO OYJ	METSO	5.125	11/19/2004	11/21/2011	ED6951104
METSO OYJ	METSO	7.25	6/10/2009	6/10/2014	EH8497776
METSO OYJ	METSO	4.625	5/13/2011	5/13/2018	EI6685115
NOKIA OYJ	NOKIA	5.5	2/4/2009	2/4/2014	EH7057639
NOKIA OYJ	NOKIA	6.75	2/4/2009	2/4/2019	EH7057670
NORSKE SKOG ASA	NSINO	11.75	6/10/2011	6/15/2016	EI7036847
NORSKE SKOG ASA	NSINO	11.75	6/10/2011	6/15/2016	EI7036888
NORSKE SKOG ASA	NSINO	7	6/26/2007	6/26/2017	EG5827688
SCANDINAVIAN AIRLINES	SAS	6	6/20/2001	6/20/2008	EC4016811
SCANDINAVIAN AIRLINES	SAS	9.65	3/23/2011	6/16/2014	EI6119719
SCANIA CV AB	SCANIA	3.625	2/22/2006	2/22/2011	EF2893560
SCANIA CV AB	SCANIA	5.25	2/24/2009	2/24/2012	EH7280280
SCANIA CV AB	SCANIA	3.2	10/6/2011	10/6/2014	EI8276210
SCANIA CV AB	SCANIA	4.5	5/12/2011	5/12/2015	EI6662098
SKF AB	SKFBSS	3	6/27/2005	6/28/2010	ED9923068
SKF AB	SKFBSS	4.25	12/13/2006	12/13/2013	EF9908213
SKF AB	SKFBSS	2.95	4/27/2010	4/27/2015	EI2311906
SKF AB	SKFBSS	3.875	5/25/2011	5/25/2018	EI6856146
STATOIL ASA	STLNO	6.25	10/27/1999	1/15/2010	EC1895670
STORA ENSO OYJ	STERV	3.25	6/22/2005	6/22/2010	ED9751154
STORA ENSO OYJ	STERV	5.125	6/23/2004	6/23/2014	ED5148983
STORA ENSO OYJ	STERV	5.75	9/1/2010	9/1/2015	EI3856578
SVENSKA CELLULOSA AB SCA	SCABSS	4	11/4/2010	2/4/2016	EI4531873
SVENSKA CELLULOSA AB SCA	SCABSS	3.625	5/26/2011	8/26/2016	EI6837534
SWEDISH MATCH AB	SWEMAT	4.6	2/14/2007	2/14/2012	EG1850825

SWEDISH MATCH AB	SWEMAT	4.61	2/15/2007	2/15/2012	EG1943281
SWEDISH MATCH AB	SWEMAT	4.6	2/21/2007	2/21/2012	EG2022317
SWEDISH MATCH AB	SWEMAT	4.625	6/28/2006	6/28/2013	EF5017324
SWEDISH MATCH AB	SWEMAT	6.35	5/6/2008	3/19/2014	EH3362801
SWEDISH MATCH AB	SWEMAT	5.95	5/22/2009	1/27/2015	EH8319574
SWEDISH MATCH AB	SWEMAT	4.34	7/12/2010	7/12/2015	EI3154719
SWEDISH MATCH AB	SWEMAT	4.76	2/28/2011	2/29/2016	EI6027961
SWEDISH MATCH AB	SWEMAT	4	12/22/2011	12/22/2016	EI9131836
SWEDISH MATCH AB	SWEMAT	3.875	11/24/2010	11/24/2017	EI4735672
SWEDISH MATCH AB	SWEMAT	4.25	9/19/2011	9/19/2018	EI8112530
TELENOR ASA	TELNO	4.5	9/28/2006	3/28/2014	EF7181524
TELENOR ASA	TELNO	4.875	5/29/2007	5/29/2017	EG4568168
TELENOR ASA	TELNO	4.125	3/26/2010	3/26/2020	EI1971395
TELIASONERA AB	TLSNSS	3.9	6/21/2006	6/21/2010	EF4902310
TELIASONERA AB	TLSNSS	5.5	9/10/1999	9/10/2010	EC1737245
TELIASONERA AB	TLSNSS	5	11/16/2007	11/16/2011	EH0166312
TELIASONERA AB	TLSNSS	3.625	5/9/2005	5/9/2012	ED9244226
TELIASONERA AB	TLSNSS	5	1/25/2008	1/25/2013	EH1710555
TELIASONERA AB	TLSNSS	4.45	9/1/2006	9/3/2013	EF6697579
TELIASONERA AB	TLSNSS	6	12/3/2008	1/15/2014	EH6308785
TELIASONERA AB	TLSNSS	5.125	3/13/2009	3/13/2014	EH7430208
TELIASONERA AB	TLSNSS	4.5	3/21/2007	3/21/2014	EG2492361
TELIASONERA AB	TLSNSS	4.5	12/17/2004	12/17/2014	ED7334557
TELIASONERA AB	TLSNSS	4.25	2/9/2005	2/9/2015	ED7970491
TELIASONERA AB	TLSNSS	4.125	5/9/2005	5/11/2015	ED9244267
TELIASONERA AB	TLSNSS	3.3	1/20/2012	7/20/2016	EI9635190
TELIASONERA AB	TLSNSS	4.75	3/7/2007	3/7/2017	EG2210979
TELIASONERA AB	TLSNSS	4.25	2/18/2011	2/18/2020	EI5726514
TELIASONERA AB	TLSNSS	5.7	10/8/2009	10/8/2021	EH9904812
TELIASONERA AB	TLSNSS	4.785	10/16/2009	10/16/2021	EI0085049
TELIASONERA AB	TLSNSS	4.75	11/16/2009	11/16/2021	EI0380358
TELIASONERA AB	TLSNSS	4	9/22/2011	3/22/2022	EI8165108
TELIASONERA AB	TLSNSS	3.625	2/14/2012	2/14/2024	EJ0161509
TELIASONERA AB	TLSNSS	4.6	4/1/2010	4/1/2025	EI1949169
TELIASONERA AB	TLSNSS	3.875	10/1/2010	10/1/2025	EI4162364
TELIASONERA AB	TLSNSS	4	1/18/2012	1/18/2027	EI9521606
TELIASONERA AB	TLSNSS	5.135	4/1/2011	4/1/2031	EI7260942
TELIASONERA AB	TLSNSS	5.03	7/1/2011	7/1/2031	EI7260900
UPM-KYMMENE OYJ	UPMKYM	6.125	1/23/2002	1/23/2012	EC5083695
VOLVO TREASURY AB	VLVY	5.2	11/21/2003	11/21/2008	ED2281100
VOLVO TREASURY AB	VLVY	5.375	11/21/2002	1/26/2010	EC7515918
VOLVO TREASURY AB	VLVY	4	5/19/2006	5/19/2011	EF4140234
VOLVO TREASURY AB	VLVY	8.5	3/20/2009	3/20/2012	EH7580580
VOLVO TREASURY AB	VLVY	7	6/18/2009	6/18/2012	EH8676353
VOLVO TREASURY AB	VLVY	7.875	5/19/2009	10/1/2012	EH8272104
VOLVO TREASURY AB	VLVY	4.15	3/11/2011	3/11/2013	EI5988841
VOLVO TREASURY AB	VLVY	4.25	3/31/2011	4/2/2013	EI6229419
VOLVO TREASURY AB	VLVY	9.875	2/27/2009	2/27/2014	EH7329392
VOLVO TREASURY AB	VLVY	4.5	4/4/2007	4/4/2014	EG3155348
VOLVO TREASURY AB	VLVY	5	12/8/2011	12/8/2016	EI8954659
VOLVO TREASURY AB	VLVY	5	5/31/2007	5/31/2017	EG4763512

Appendix A.2: Results From Robustness Tests With Altered Recovery Rates

Table A.2. Robustness test: Predicted spreads by the extended Merton model and market observed CDS spreads with altered recovery rates.

Rating	Model Spread (std dev)	Observed Spread (std dev)	% Explained by Model (std dev)	ME (std dev)	MPE (std dev)	MAE (std dev)	MAPE (std dev)	N
PANEL A: Recovery rate: 32.40%								
AA	12.35	64.34	15.92%	-52.00	-84.08%	52.00	84.08%	2
	(15.45)	(42.27)	(20.16%)	(36.89)	(20.16%)	(36.89)	(20.16%)	
A	52.40	68.07	63.12%	-15.68	-36.88%	31.65	57.27%	7
	(56.49)	(38.42)	(52.94%)	(32.2)	(52.94%)	(16.53)	(29.37%)	
BBB	75.78	115.02	57.97%	-39.25	-42.03%	45.92	48.71%	11
	(62.68)	(61.95)	(39.89%)	(40.43)	(39.89%)	(32.56)	(31.28%)	
BB	245.25	271.14	76.41%	-25.89	-23.59%	81.75	41.28%	2
	(175.92)	(137.47)	(48.12%)	(109.77)	(48.12%)	(77.29)	(34.01%)	
B	585.98	929.82	64.63%	-343.84	-35.38%	364.36	38.85%	3
	(292.11)	(509.9)	(25.94%)	(354.86)	(25.94%)	(333.53)	(20.29%)	
ENTIRE SAMPLE	138.94	208.09	62.41%	-69.15	-37.60%	72.16	39.38%	25
	(83.44)	(108.88)	(28.26%)	(57.99)	(28.26%)	(54.16)	(25.69%)	
PANEL B: Recovery rate: 51.31%								
AA	7.81	64.34	10.03%	-56.54	-89.97%	56.54	89.97%	2
	(9.78)	(42.27)	(12.74%)	(38.22)	(12.74%)	(38.22)	(12.74%)	
A	33.55	68.07	40.52%	-34.52	-59.48%	35.61	61.17%	7
	(35.82)	(38.42)	(33.97%)	(21.64)	(33.97%)	(19.78)	(30.78%)	
BBB	48.82	115.02	37.33%	-66.20	-62.67%	66.20	62.67%	11
	(39.46)	(61.95)	(25.75%)	(38.92)	(25.75%)	(38.92)	(25.75%)	
BB	159.76	271.14	49.78%	-111.38	-50.23%	111.54	50.28%	2
	(115.83)	(137.47)	(32.03%)	(89.01)	(32.03%)	(88.8)	(31.95%)	
B	352.19	929.82	38.78%	-577.63	-61.22%	577.63	61.22%	3
	(178.11)	(509.9)	(15.79%)	(399.66)	(15.79%)	(399.66)	(15.79%)	
ENTIRE SAMPLE	86.55	208.09	38.74%	-121.54	-61.26%	121.54	61.26%	25
	(52.42)	(108.88)	(18.03%)	(70.46)	(18.03%)	(70.46)	(18.03%)	
PANEL C: Recovery Rate: 81.90%								
AA	0.97	64.34	1.18%	-63.37	-98.82%	63.37	98.82%	2
	(1.35)	(42.27)	(01.74%)	(41.63)	(01.74%)	(41.63)	(01.74%)	
A	5.92	68.07	7.18%	-62.15	-92.82%	62.15	92.82%	7
	(6.6)	(38.42)	(07.04%)	(33.89)	(07.04%)	(33.89)	(07.04%)	
BBB	10.07	115.02	7.36%	-104.96	-92.64%	104.96	92.64%	11
	(8.49)	(61.95)	(06.25%)	(55.88)	(06.25%)	(55.88)	(06.25%)	
BB	40.12	271.14	12.29%	-231.02	-87.71%	231.02	87.71%	2
	(35.39)	(137.47)	(10.49%)	(119.57)	(10.49%)	(119.57)	(10.49%)	
B	55.87	929.82	5.32%	-873.94	-94.68%	873.94	94.68%	3
	(50.47)	(509.9)	(05.01%)	(483.95)	(05.01%)	(483.95)	(05.01%)	
ENTIRE SAMPLE	16.08	208.09	6.58%	-192.01	-93.42%	192.01	93.42%	25
	(13.26)	(108.88)	(05.47%)	(100.23)	(05.47%)	(100.23)	(05.47%)	

The table shows the mean and standard deviations of the extended Merton model's predicted credit spreads, the market observed CDS spread, the percentage of the model spread to the observed spread, the difference between the model spread and the observed spread (ME), the difference between the model spread and the observed spread, divided by the observed spread (MPE), the absolute difference between the model spread and the observed spread (MAE) and the absolute difference between the model spread and the observed spread, divided by the observed spread (MAPE). The data is divided into three sub-periods and classified based on the firms' credit ratings.

Mean Error (ME) is the mean of the difference between the model's and the observed CDS spread. Mean Percentage Error (MPE) is the mean percentage of the difference between the model's spread and the observed CDS spread, divided by the observed CDS spread. Mean Absolute Error (MAE) is the mean of the absolute difference between the model's and the observed CDS spread. Mean Absolute Percentage Error (MAPE) is the mean percentage of the absolute difference between the model's spread and the observed spread, divided by the observed spread.

Appendix A.3: Implied Asset Volatilities and Leverage Ratios

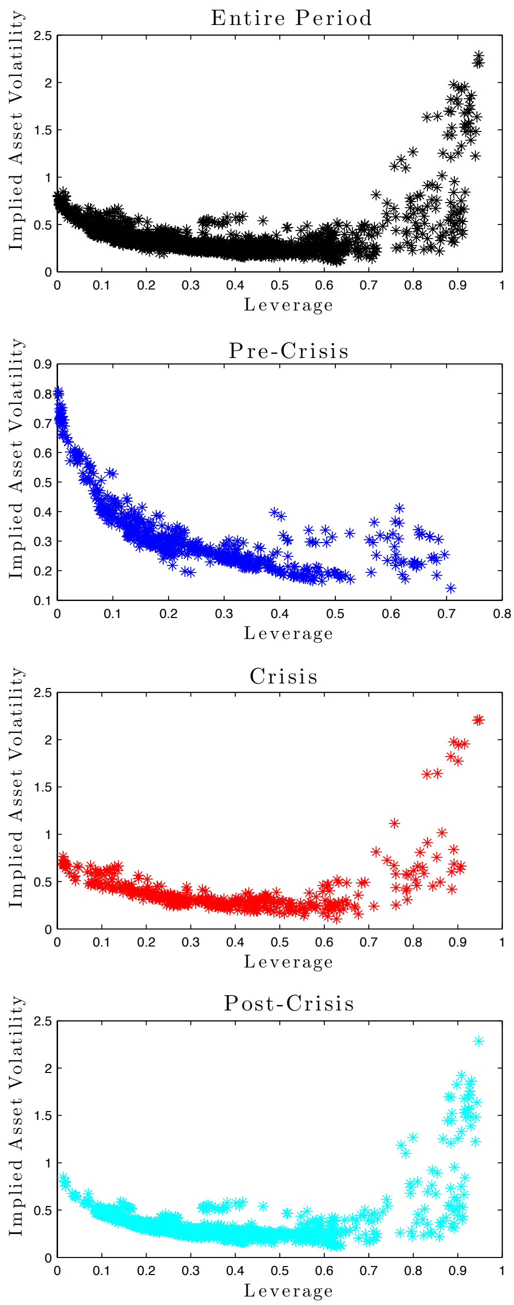

Figure A.3. Implied asset volatilities and leverage ratios for the entire sample period and the subperiod as described in footnote 25. The asset volatilities have been approximated by matching the model's spread with the observed CDS spread for each firm at each of the 97 observation dates, instead of being calibrated as described in section 4.2.

Appendix A.4: Matlab Code

```
% MERTON MODEL, EOM ET AL's (2004) DEVELOPMENTS
% -------------  I  N  P  U  T  S  --------------
%
% E         Equity Value
% F         Default Barrier or Face value of debt
% r         Risk-free interest rate
% sigA      Asset Volatility
% T         Time to maturity
% D         Debt
% delta     Payout ratio
% x         input in d1 & d2 formula
%
% ----------------------------------------------
% ------------v.karlsson@gmail.com---------------


function [ cdsspread ] = MertonEon( E, F, r, sigA, T, D, delta, x )

% Calculates the asset value

V=D+E;


% The value of a zero-coupon bond

D0T = exp(-r.*T);


d1xT = ( log(V./(x.*D0T)) + (-delta + sigA.^2/2).*T )./( sigA.*sqrt(T) );
d2xT = d1xT - sigA.*sqrt(T);

d1FT = ( log(V./(F.*D0T)) + (-delta + sigA.^2/2).*T )./( sigA.*sqrt(T) );
d2FT = d1FT - sigA.*sqrt(T);

% Indicator function for V_T > F

indf1 = normcdf(d2FT,0,1);


% Indicator function for V_T < F

indf2 = V./(F.*D0T).*exp(-delta.*T).*normcdf(-d1xT,0,1) + ...
    x.*(normcdf(d2xT,0,1) - normcdf(d2FT,0,1) );


% Calculates the bond price

BONDPRICE_0 = exp(-r.*T).*indf1 + indf2;


% Calculates the credit spread

cdsspread = -1./T.*log( BONDPRICE_0 ) - r;

end
```