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On the extent and origins of the Merton model`s credit spread puzzle

A study of the credit risk pricing of Norwegian corporate bonds

2003-2014

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ABSTRACT

For decades, financial literature has attempted to understand the pricing of credit risk in corporate bonds, and the Merton (1974) model is one of the classic approaches to determine a theoretic size for this credit risk premium. However, empirical studies have shown that the model`s estimates deviate substantially from observed credit spreads, a phenomenon called the “credit spread puzzle”. In our thesis, we implement an augmented Merton model from Feldhütter and Schaefer (2015), and compare the model`s estimates to 13,560 real-life spreads of Norwegian corporate bonds 2003-2014. On an aggregate level, the model only explains 26% of the median spread to the swap rate, a result consistent with previous Norwegian studies. A decomposition of the model mispricing discloses several potential explanations for the credit spread puzzle. Firstly, the model input factors for debt leverage and issuer volatility are key drivers of the puzzle. The model underestimation is particularly strong for safe bonds with low leverage or volatility, and we highlight problems of historic volatility measures and the precautionary motives for holding low leverage as potential explanations for these patterns. Secondly, sector affiliation correlate with the model mispricing, and when we control for other factors, we find that investors in the Norwegian corporate bond market charge an additional premium for companies in the industrial sector compared to others. Thirdly, despite the importance of bond liquidity and the Fama & French (1993) factors for size and growth in previous literature, we find that the presence of these factors seems limited in explaining the credit spread puzzle in our sample. In total, our thesis illustrates the complexity of credit risk pricing. To a large degree, the valuation of Norwegian corporate bonds remains an activity for professional investors, whose analysis of the particular issuer can incorporate a far more detailed level of risk characteristics than what is possible in a simple credit risk model.

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1. INTRODUCTION

1.1 The credit spread puzzle of the Merton model

Companies can finance their operations in a variety of ways, and bonds are one common example. A bond functions like a debt security, where investor lends money to a company for a predefined time-period, against the promise of the company to repay the money borrowed plus an additional amount called interest. The interest rate represents the return of the bond, and according to economic theory, this could be separated into two components (Sæbø, 2015a). The first component is a time premium, compensating the investor for tying up his money over the defined time-period. The size of this time-premium equals the risk-free rate, i.e. the return of an investment in a risk-free asset with similar time-to-maturity. The second component is the credit spread, which is the additional rate the investor charges above the risk-free rate to compensate him for the potential default risk of his investment. As investors must balance their risk-reward relationship properly, determining the size of this credit risk premium is crucially important to the investment decision.

For decades, finance literature has attempted to understand the pricing of credit risk in corporate bonds. In this process, structural credit risk models have emerged as a common framework, applying strict mathematical formulas to describe credit spreads (Leland, 2004). The Merton (1974) approach is among the most classic of these structural models, and applies option-pricing theory. Merton`s idea is that the shareholder`s equity can be viewed as a call option on the firm`s total assets, giving the shareholders the right, but not the obligation to buy out the company`s debt and seize control over the total assets. By pricing this equity call option, Merton (1974) shows how to determine a theoretic size for a bond`s credit spread using only a few input parameters, more specifically, total firm value, face value of debt, asset volatility, risk-free rate, recovery rate and time-to-maturity.

The Merton model`s simplicity and intuitive approach makes it a popular model in the finance literature. However, empirical studies have shown that the model`s estimates deviate substantially from actual observations of credit spreads, a phenomenon called the credit spread puzzle (Sundaresan, 2013). Jones, Mason and Rosenfeld (1984) were among the first to document this empirical shortcoming of the Merton (1974) model, and their results raised questions regarding the validity of the model`s underlying assumptions in real-life. Several structural credit risk models followed the Merton (1974) article, trying to improve the original model through the adaption of more realistic assumptions. Examples are Longstaff and

Schwartz`s (1995) inclusion of stochastic interest rates, Leland and Toft`s (1996) attempt to determine an endogenous default boundary and Collin-Dufresne and Goldstein`s (2001) model with mean-reverting leverage ratios.

Nevertheless, none of these extensions of the Merton (1974) model have been able to fully explain the credit spread puzzle, as these later versions have empirical problems of their own. A study by Eom, Helwege and Huang (2004) compares the precision of the original Merton (1974) model to four modified versions. They find systematic biases in all of the models, where most of them overestimate credit spreads for bonds with high leverage or volatility, whereas they underestimate the spreads when leverage ratios are low. The only exception is the Leland and Toft (1996) model, consistently overestimating the observed credit spreads. Huang and Huang (2003) also point to the low precision of these structural credit risk models, after calibrating five modified versions of the Merton model to fit historic default frequencies. Their findings indicate that the model’s credit spreads only explain a small fraction of the corporate - government bond spread, and that the underestimation is particularly severe for shorter-term maturities.

As the credit spread puzzle has remained unsolved, other explanations have emerged. A group of studies believe that investors pay attention to risk factors other than default risk, and pose this as a natural cause for the credit spread puzzle. One of these is liquidity risk, highlighted in Longstaff, Mithal and Nies (2004). They estimate that default risk accounts for 51% and 71% of AAA-rated and BBB-rated credit spreads respectively, with the large unexplained component showing a strong correlation to factors of bond liquidity. Studies of Perraudin and Taylor (2003) and Driessen (2005) also confirm that liquidity affects bond prices, underlining the importance of including this risk factor in credit spread analyses. Furthermore, tax asymmetries, issuer size and issuer growth-potential might also impact the pricing of bonds, as argued in Elton, Gruber, Agrawal and Mann (2001).

Still, one branch of the literature believes these non-default related explanations must be complemented with a more nuanced view of credit risk. Chen, Collin-Dufresne and Goldstein (2009) and Chen (2010) emphasize the importance of business cycle risk, and points to the fact that default risk correlates with the economic cycles. The reason is that recessions typically include a simultaneous combination of lower firm cash-flows, lower growth expectations and higher discounts on asset liquidations for almost every firm in the entire economy. Together, this will significantly increase the potential loss of a bond investment in these time-periods of slow economic growth. As most structural risk models incorporate only the current level of input parameters, a systematic error may arise if these parameters underestimate the true credit risk of a recession if measured in periods of a booming economy. Chen (2010) illustrates the potential existence of this problem, proving that the inclusion of systematic business cycle risk into a credit risk model would raise the credit risk premiums charged by investors. Furthermore, Chen (2010) argues that risk aversion towards unexpected, “Black-Swan”, events may be important, and that the inclusion of jump-risk will increase the explanatory ability of structural credit risk models. Huang and Huang (2003) partly agree with this argument, demonstrating that the inclusion of a jump-diffusion process raises the estimated model spreads relative to the corporate – government bond spread. That said, Huang and Huang point out that even with jump-risk there is a large unexplained component of credit spreads.

Despite the many potential explanations for the credit spread puzzle, no single structural risk model has yet emerged illustrating a perfect prediction of historic bond prices. However, a recent study by Feldhütter and Schaefer (2015) presents a new implementation of the Merton model that shows extremely promising results of tracking 286,234 observed credit spreads for US industrial bonds 1987-2012. Not only does their model prove a strong ability to match the aggregate level of credit spreads, it also shows a strong correlation of 84-92% with time variations in the BBB-AAA spread. Their results highlight that the Merton model, if implemented correctly, might have the potential to capture a much larger share of credit spreads than previously indicated in the literature.

1.2 Our contribution to the study of the credit spread puzzle

Most of the literature on the credit spread puzzle focuses exclusively on the US bond market. A few studies exist on the Norwegian bond market, among these Sæbø (2015a, 2015b) and Knappskog and Ytterdal (2015). As we wanted to do a study of the credit risk pricing of Norwegian corporate bonds, our thesis is greatly inspired by these Norwegian articles. Sæbø (2015b) examines 10,595 observed credit spreads from traded industrial bonds at the Oslo Stock Exchange 2008-2013. He finds that only 28% of observed credit spreads can be explained by an augmented Merton model from the credit rating agency Moody`s, a result quite similar to previously mentioned international studies of the credit spread puzzle. Sæbø (2015a) also confirms this result, but his further analysis reveals that sector, issuer size and liquidity risk might explain parts of the mispricing between the Merton model and the credit risk pricing of Norwegian investors. However, as this latter study only includes corporate bonds in 2008-2009, it is not certain if these potential risk premiums exist on a longer time-horizon. The master thesis of Knappskog and Ytterdal (2015) follows Sæbø (2015a) closely, agreeing that liquidity risk can be a potentially source of the model mispricing. Yet, their limited sample of only 314 observations of Norwegian high-yield bonds renders questions about the validity of the results in the broader market.

On the background of these previous studies, the goal of our master thesis is twofold. Our first motive is to expand the dataset used by Sæbø (2015a, 2015b) and Knappskog and Ytterdal (2015) to see whether their results hold for a larger sample of Norwegian corporate bonds. Our data sample includes 13,560 observations of credit spreads, and expands the sample relative to these previous studies in two dimensions: 1) time and 2) sector diversity. Our new time-horizon includes observations from 2003 to 2014, thus increasing Sæbø`s (2015b) sample by the period 2003-2007. In addition, we incorporate financial companies in our thesis, as this sector was included in Sæbø (2015a), but not in Sæbø (2015b). Our second motive is to apply the new model implementation from Feldhütter and Schaefer (2015), and see if this method changes any of the previous results in Sæbø (2015a, 2015b).

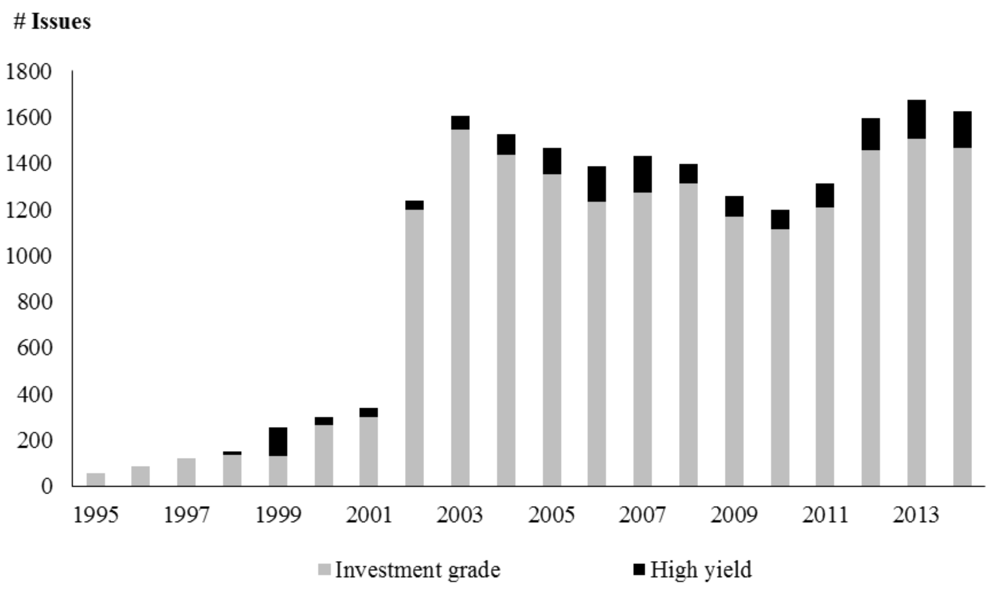
In summary, our thesis seeks to answer the following two questions:

1. Does the credit spread puzzle still exist in the Norwegian corporate bond market when implementing a model similar to Feldhütter and Schaefer (2015)?
2. Given the existence of a mispricing, which factors can explain the deviations between the model's estimates of credit risk and the pricing of Norwegian investors 2003-2014?

Our thesis has a five-part structure. The first part, the methodology, explains the fundamentals of the Merton (1974) model, the augmented approach in Feldhütter and Schaefer (2015), as well as our specific implementation to the Norwegian corporate bond market. The second part presents our data sample of Norwegian corporate bond spreads, before the third part moves into a detailed comparison of the model estimates and the actual spreads. The fourth part discusses our findings relative to previous literature, and addresses some particularly interesting issues. Finally, in the fifth part, we will draw the concluding remarks. Note that our thesis also includes an appendix, where readers can find the exact sources of our data and additional information about our model calibration. We include these to ensure that our results are transparent and replicable.

1.3 Particular challenges of modelling the Norwegian corporate bond market

Before entering into the main analysis, we want to outline some special characteristics of the Norwegian corporate bond market. Contrary to the US, the overall bond market in Norway is small, and bank financing dominates the overall debt market. Bond and certificate financing, excluding the financial and government sector, accounts for NOK 338 billion of the Norwegian gross domestic debt 2015, only a mere 10% share of the NOK 3,381 billion in financing from banks and other credit institutions (Norwegian Central Bank, 2015 p.44). However, the Norwegian bond market is a relatively new marketplace, and has been characterised by strong growth during the last two decades. Graph 1 plots the development in the number of bond and certificate issues listed in the Nordic Trustee`s database, Stamdata, illustrating the massive increase in the market from 2002 onwards. The growth has primarily occurred in the safer investment grade segment (rated AAA-BBB), but there has also been an increase in the riskier high-yield segment (rated BB – CCC). This high-yield segment is significantly smaller than the investment grade segment, but there has been a strong growth in outstanding volume of high-yield bonds in 2005-2007 and 2010-2012. Dahl, Dagslet and Stensrud (2013) argue that generally lower transaction costs and a quick and simple listing procedure of bonds at the Oslo Stock Exchange and the Nordic ABM have been important explanatory factors for the large increase in debt capital into the Norwegian market. Additionally, stricter liquidity and capital regulations for banks following the financial turmoil in 2008 could explain a potential shift from bank financing to bonds.

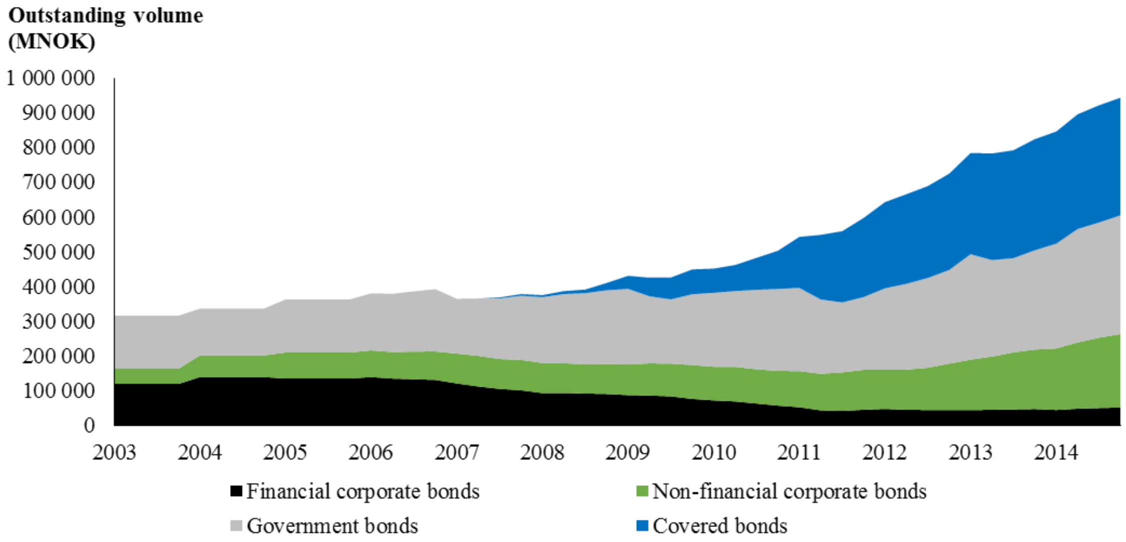


Graph 1: *Number of issues in the Norwegian corporate bond market 1995-2014 registered in the Stamdata database. The graph uses Stamdata`s definitions of investment grade and high yield bond, as public available credit ratings are few. Source: Stamdata*

Haugen (2013) provides a more detailed description of the Norwegian bond market. Out of NOK 1,530 billion in total outstanding volume for Norwegian corporate bonds in 2012, banks and credit institutions account for 61%, public sector 21% and non-financial companies 18%. The historic development has been cyclical, with strong variations in the market composition prior to 2012. In the booming economy of 2006-2007, a large entry of debt capital into high-yield oil and gas related companies increased the share of non-financial bonds from 8% to 32%. However, this share of high-yield bonds contracted in 2008-2010, as the weak economic conditions of the Global Financial Crisis forced many of these bonds' issuers to refinance their debts. At the same time, covered bonds became a new source of bank financing 2009-2010, and the share of financial bonds grew significantly. In 2011-2012, economic conditions began to improve, and non-financial companies were once again the dominant driver of growth. This resulted in a strong increase in the number of bonds issued by firms within sectors such as shipping, corporate real estate, industrials and utilities in 2011-2012.

Several factors make studies of the Norwegian corporate bond market particularly challenging. One reason is the limited availability of public credit ratings. Few of the international credit rating agencies, such as Moody`s and Standard & Poor`s, publish analyses of Norwegian companies. Instead, local investment banks or brokerage houses list "shadow-ratings" for ongoing transactions (Dahl, Dagslet and Stensrud, 2013). In the credit spread puzzle literature, results are typically grouped according to these credit ratings, making it possible to perform direct comparisons of pricing across different risk categories and articles. However, the Norwegian "shadow-ratings" are not available to the wide public, and so we could not use them in our thesis. We will instead use sectors as an alternative risk proxy.

As mentioned, the Norwegian bond market has a relatively short history with few observations before 2002. For this reason, analyses of Norwegian corporate bonds are restricted to a much shorter time-horizon than American studies, typically including bonds issued as early as in the 1980s. Moreover, as credit spreads are not directly observable, we calculate them from traded bond prices. This further restricts the available sample of bonds to those listed on the Oslo Stock Exchange or the Nordic ABM only. In graph 2, we present the outstanding volume at the Oslo Stock Exchange, the larger of the two mentioned public marketplaces for Norwegian bonds. In Q4 2014, the total outstanding volume of government and corporate bonds was NOK 943 billion, but only 28% was regular corporate bonds, i.e. the green and black area in graph 2. As we for comparability reasons only include these regular corporate bonds in our thesis, it is clear that only a smaller share of the Norwegian bond market is available for our analysis. In addition, the large increase of covered bond financing from 2008 has come at the expense of regular financial corporate bonds. Hence, from 2008 onwards an increasingly larger share of our data sample becomes non-financial corporate bonds. Despite the fact that only a small share of the total Norwegian bond market is available to our analysis, our thesis presents one of the largest sample of corporate bonds spreads included in a study of the credit spread puzzle in Norway. Our sample includes 252 different senior unsecured bonds listed on the Oslo Stock Exchange and Nordic ABM, from which 13,560 observations of credit spreads were available.



Graph 2: *Outstanding volume at the Oslo Stock Exchange for different types of bonds 2003-2014. The data are quarterly averages for the period 2006-2014, while for 2003-2005 only annual numbers where available. Source: Oslo Stock Exchange statistics*

2. METHODOLOGY

In section 2, we present a detailed overview of our methodology, which resolves around the modelling of credit risk in structural models. We begin section 2.1 with the basic properties of credit risk and the structural Merton (1974) model, before section 2.2 explains the full details of the augmented Feldhütter and Schaefer (2015) approach. In section 2.3, we outline our own specific model implementation to the Norwegian corporate bond market, and describe how we conduct the further analysis of potential explanatory factors of the credit spread puzzle.

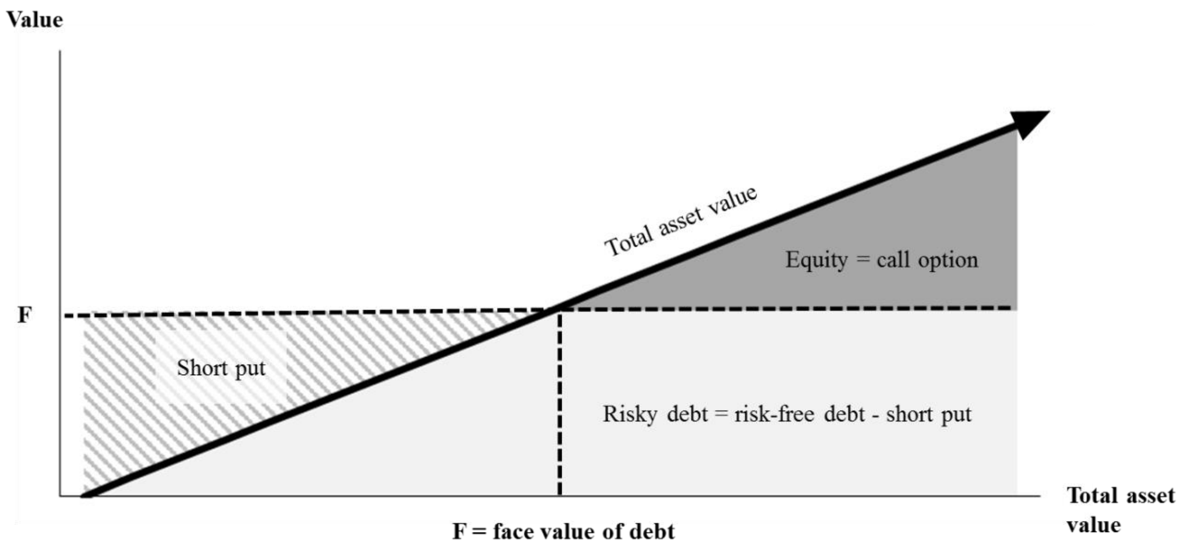
2.1 A theoretic approach to credit risk and the Merton (1974) model

At the core of this thesis is the credit spread. This is the additional interest rate the investor charges above the risk-free rate to compensate him for the risk that the borrower may default on his obligations. According to basic economic theory, we can quantify this default risk as the expected loss (EL) of the bond, which is a function of the probability of default (PD) and the loss given default (LGD) (Johnsen, 2014). Under the assumption that investors are risk averse, we expect them to require a credit spread that at least covers the expected loss of the investment, as illustrated in equation 1.

$$(1)\ Credit\ spread \geq EL = PD\ x\ LGD$$

Nonetheless, the probability of default and loss given default are unknown factors, and real-life investors have to approximate these parameters to determine a theoretic size for the credit spread. For almost a century, credit rating agencies, such as Moody`s and Standard & Poor`s, have provided indicative ratings for the credit risk of different corporate bonds, which serve as important benchmarks for bond pricing internationally. Their ratings build on practical approaches to equation 1, using key firm characteristics to approximate the default probability and loss given default. Examples of these variables include solvency ratios for a firm`s debt leverage, dividend payout and asset recovery in default, amongst more subjective assessments of the firm`s risk profile and growth prospects. As these exact credit risk analyses remain proprietary information of credit rating agencies, the branch of structural credit risk models have become increasingly popular in financial literature. These structural risk models use strict mathematical formulas to determine a theoretic size of the credit spreads, using input factors similar to the credit rating agencies (Leland, 2004). Typically, the models combine data on the firm capital structure and cash flow with theoretic assumptions of the future behaviour of asset values, for example, a random-walk behaviour.

The Merton (1974) model is one of the more classic of these structural models, and use option-pricing theory to determine a bond`s credit risk premium. In graph 3, we illustrate the basic intuition of Merton (1974), where a firm`s total asset value is assumed to follow a Geometric Brownian Motion, i.e. a more advanced random-walk behaviour. The black 45-degree line represents the total asset value of the firm, while the dotted line illustrates the face value of debt. If the value of the firm is greater than the face value of debt, the residual value is the shareholder`s equity. To the contrary, if the firm value falls below the face value of debt, then the shareholders can default on their investment due to limited liability, leaving the entire company in the hands of the debtholders. The important fact that Merton (1974) pointed out was that this analogy implies that the equity value of the firm is equal to a call option on the firm`s assets with an exercise price at the face value of debt. From the put-call parity of Stoll (1969), this implied that the value of the risky debt claim also had a logical equivalent as the sum of a risk-free debt instrument minus the value of a short put option with the same exercise price as the equity call. Consequently, Merton showed that the exact size of the credit spread could be determined from option-pricing theory, knowing just a few input parameters about the firm`s capital structure and the behaviour of asset values. These input parameters included the face value of debt, risk-free rate, recovery rate in default, time-to-maturity of the bond, total asset value of the firm and the volatility of the firm`s asset value. (Sundaresan, 2013)



Graph 3: *The basic concepts of the Merton (1974) model. Merton showed that the credit spread of debt could be determined from the equity value, due to the link between the equity call and the risky debt from put-call parity.*

In part, Merton`s (1974) result relies on a set of eight simplifying assumptions, summarised in table 1. These include assumptions of a perfect capital market, a flat term-structure, the existence of the Modigliani-Miller theorem and a specification of the behaviour of the firm`s asset value. Sundaresan (2013) notes that the assumptions 1-4 of a perfect capital market are easily relaxed, leaving the assumptions 5-8 as the ones critical to the model`s performance. However, the real-life validity of these assumptions is questionable, and several later articles have attempted to incorporate assumptions that are more realistic. Examples include Black and Cox`s (1976) model with bond covenants, Longstaff and Schwartz`s (1995) use of stochastic interest rates, Leland and Toft`s (1996) determination of an endogenous default boundary and Huang and Huang`s (2003) inclusion of a jump-diffusion process for the firm`s asset value.

Table 1:

Assumptions of the Merton (1974) model[1]

Assumption	
1	There is an absence of transaction costs and taxes, as well as no problems with indivisibility of assets.
2	There is sufficient number of participants in the market, thus, allowing the investors to buy and sell as much of an asset as they prefer at the current market price.
3	Borrowing and lending occur at the same rate of interest.
4	Short selling of assets is not restricted.
5	Asset trading occur continuously in time.
6	The Modigliani-Miller theorem that the firm value is independent of the capital structure holds.
7	The term structure is flat and known with certainty, equivalent to the statement that the risk-free rate is constant through time.
8	The dynamic process of the firm value is a Geometric Brownian Motion.

Note 1: We present Sundaresan`s (2013) structure to the eight assumptions

In addition, implementations of the Merton model to empirical observations have revealed yet another problem. Several crucial input parameters are not directly observable, and real-life investors must approximate these parameters from factors they do observe. One example is the absence of an observable risk-free rate, where government bonds serve as the traditional proxy. Another example is the asset volatility, discussed in Bohn and Crosbie (2003). Typically, structural risk models approximate the asset volatility from equity market prices instead, since these are more easily observable. Having said that, such proxy parameters increase the risk of systematic biases in the implementation of the Merton model, since they potentially differ from the actual parameters intended in Merton (1974).

In total, the Merton model, although elegant and simple, has proven difficult to implement to real-life observations of credit spreads.

2.2 The augmented Merton model in Feldhütter and Schaefer (2015)

A recent article by Feldhütter and Schaefer (2015) presents a new augmentation of the Merton (1974) model, with the potential to improve on the aforementioned empirical problems. Their idea is to combine two strands of previous model attempts. First, they incorporate heterogeneity in firm input variables as in Eom, Helwege and Huang (2004) and Ericsson, Reneby and Wang (2007). This allows the model to adapt to firm specific risk characteristics, whilst being able to capture time variations in these variables. Second, they calibrate the model to fit historic default frequencies and recovery rates as in Huang and Huang (2003), Cremers, Driessen and Maenhout (2008) and Chen, Collin-Dufresne and Goldstein (2009). Here, Feldhütter and Schaefer (2015) argue that a long history of default frequencies is particularly important. The reason is that default frequencies correlate with the economic cycle, and large recessions occur infrequently. Thus, observing default frequencies over a shorter time-horizon might underestimate the actual default risk if they ignore large business cycle downturns. In our view, it is this specific implementation that distinct Feldhütter and Schaefer (2015) from the rest of the literature. To keep the complexity of our presentation to a minimum, we will refer to Feldhütter and Schaefer (2015) and Chen, Collin-Dufresne and Goldstein (2009) for the mathematical derivations of the model.

We begin with the fundamental assumptions of the model. Similar to Merton (1974), Feldhütter and Schaefer (2015) assume that a Geometric Brownian Motion governs the development in firm asset values. There are known exogenous parameters, such as the firm`s payout ratio, expected return and asset volatility. If the firm`s asset value (V) falls below a default boundary (D) the firm can default on its obligation at the bond maturity date (T). Feldhütter and Schaefer assume that this default boundary is a fraction (d) of the face value of debt (F), and they later calibrate this default boundary from historic default frequencies. The capital structure of the firm is simple, consisting of equity and a single zero-coupon bond only. In reality, most firms have more complex capital structures, often consisting of multiple bonds or bank loans, typically paying coupons (interest). Feldhütter and Schaefer (2015) account for coupon payments implicitly by including the firm`s total interest expenses in the payout ratio. As a result, the model includes the cash flow to both debt and equity holders, but it treats the firm`s total debt as one unit. Note that the model cannot default on its coupon payments, as default can only occur at the maturity date (T).

The model has two key output parameters: 1) the probability of default and 2) the credit spread. Equation 2 and 3 present their calculation:

$$(2)\ \pi^{p} = N\left[-\left(\frac{1}{\sqrt{\sigma^{2}T}}\right)\left(\log\left(\frac{V_0}{dF}\right)+\left(\mu-\delta-\frac{\sigma^{2}}{2}\right)T\right)\right]$$

$$(3)\ (y-r) = -\left(\frac{1}{T}\right) log\left(1-(1-R)N\left[N^{-1}(\pi^{p})+\theta\sqrt{T}\right]\right)$$

$\sigma = asset\ volatility$	$T = time\ to\ maturity$	$V_0 = firm\ value$
$F = face\ value\ of\ debt$	$d = default\ boundary$	$\theta = asset\ Sharpe\ ratio = \frac{\mu-r}{\sigma}$
$\mu = expected\ return$	$\delta = payout\ ratio$	$y = yield\ on\ the\ bond$
$r = risk\ free\ rate$	$R = recovery\ rate$	$\pi^{p} = probability\ of\ default$

For the sake of simplicity, we will in the following rewrite the Feldhütter and Schaefer (2015) model as a function of its input parameters. Firstly, equation 2 states that the probability of default (PD) can be viewed as a function of the asset volatility(σ), time-to-maturity (T), leverage ratio (L), default boundary (d), expected return (μ) and payout ratio (δ):

$$(2)\ PD = f(\sigma, T, L, d, \mu, \delta)$$

Where the leverage ratio (L) is equal to the face value of debt (F) divided by the firm value (V_0) from equation 2 above.

Secondly, equation 3 states that the credit spread (CS) can be viewed as a function of the probability of default (PD), recovery rate (R), risk-free rate (r), time-to-maturity (T) and the asset Sharpe ratio (θ):

$$(3)\ CS = f(PD, R, r, T, \theta)$$

In total, the model includes nine input parameters. Feldhütter and Schaefer (2015) set the asset Sharpe ratio (θ) equal to Chen, Collin-Dufresne and Goldstein`s (2009) estimate of 0.22. Since the expected return (μ) is a function of the Sharpe ratio and the volatility, this is a free parameter in the model. Therefore, only seven parameters need to be exogenously determined. Table 2 illustrates how Feldhütter and Schaefer (2015) calculate these remaining input parameters.

Table 2:
Overview of the input parameters in Feldhütter and Schaefer (2015)

Parameter		Description
σ	**Asset volatility**	Calculated from equity volatility as follows: $\sigma = (1 - L)\sigma_E$ multiplied with a factor M [1]
σ_E	**Equity volatility**	Estimated as 3-yrs historic volatility of daily stock returns (rolling average). Multiplied with $\sqrt{255}$ to get annualised volatility
T	**Time-to-maturity**	The number of years between the observation date and the maturity date of the bond
L	**Leverage ratio**	L = total book debt divided by firm value. Where firm value = total book debt + market cap
δ	**Payout ratio**	δ = total payout divided by firm value. Where total payout = dividend per shares x number of shares + annual interest expense + annual share repurchase
d	**Default boundary**	Calibrated to fit historical default probabilities from Moody`s (2013). They set d = 1.00
r	**Risk-free rate**	Set equal to the swap rate with the same time-to-maturity as the bond
R	**Recovery rate**	Set equal to Moody`s (2013) estimate of the average historical bond recovery rate. R = 37.8%

Note 1: The multiple that is used on the leverage adjusted equity volatility follows Schaefer and Strebulaev`s (2008) estimates. If L<0.25 then M = 1.00. If 0.25<L<0.35 then M = 1.05. If 0.35<L<0.45 then M = 1.10. If 0.45<L<0.55 then M = 1.20. If 0.55<L<0.75 then M =1.40. If 0.75<L then M=1.80

The seven input parameters serve different purposes in Feldhütter and Schaefer`s (2015) model, and broadly speaking there are three categories. The first category includes the asset volatility, leverage ratio and payout ratio, which are the issuer specific parameters. In the model, each estimated credit spread will incorporate these variables with specific estimates for every single firm at every date of observation. Consequently, the model should allow for heterogeneity in issuer specific risk characteristic, whilst being able to capture time variations in these variables. The second category includes the default boundary and the recovery rate. The purpose of these variables is to calibrate the model to fit historic observations of bond default frequencies and recovery rates. Feldhütter and Schaefer (2015) use a static estimate for the recovery rate of 37.8%. This equals the average recovery rate in 1982-2012 for senior unsecured bonds reported by Moody`s (2013). The default boundary follows as a free parameter in an optimisation procedure explained below, where the idea is to match the model`s estimates of default frequencies with historic default frequencies 1920-2012 reported by Moody`s (2013). The third category includes the risk-free rate and the time-to-maturity.

The time-to-maturity of the bond is the number of years remaining for the bond, calculated as the difference between the observation date and the maturity date specified in the loan contract. The risk-free rate is not directly observable, but approximations exist. Feldhütter and Schaefer (2015) set the risk-free rate equal to the swap rate with the same time-to-maturity as the bond.

As mentioned, asset volatilities are not directly observable. Feldhütter and Schaefer (2015) approximate this parameter from equity volatility (σ_E), using a 3-year rolling volatility measure on daily stock returns. They convert the equity volatility into asset volatility following a two-step procedure. First, they calculate the leverage adjusted equity volatility ($\sigma_L = (1 - L)\sigma_E$). Then, they multiply this value with a constant, M, which value depends on the leverage ratio of the company, as explained in note 1 of table 2. Traditionally, structural models estimate this asset volatility from an iterative procedure with the equity volatility. Bohn and Crosbie (2003) explain this procedure, and at first glance, Feldhütter and Schaefer (2015) deviate from this traditional model approach. However, the constant, M, follows the results of Schaefer and Strebulaev (2008), and is in fact the result of an attempt to generalise the iteration procedure into a more transparent rule. Feldhütter and Schaefer (2015) argue that this method has the advantage of being easier to replicate, which is also the main reason for why they have departed from the traditional equity volatility iteration.

The calculations of the leverage ratio (L) and the payout ratio (μ) are relatively straight forward. Feldhütter and Schaefer (2015) define the leverage ratio (L) as the ratio of the total book value of debt to the total firm value, where firm value is equal to the book value of debt plus the market value of the firm`s equity. The payout ratio (μ) is the total payout to debt and equity divided by the total firm value. Here, the total payout is the annual interest expense plus the annual dividend and annual stock repurchases. It may be important for the reader to note that Feldhütter and Schaefer here combine data with different observation frequencies. A firm`s equity value is observed from daily traded prices, while the book value of debt, dividends, stock repurchases and interest expenses are quarterly observations.

Another important aspect of the Feldhütter and Schaefer (2015) model is the calibration of the model to match historic default frequencies. Due to the aforementioned importance of business cycles, Feldhütter and Schaefer insist on the use of a long-horizon of default frequencies. The empirical foundations for the calibration is therefore Moody`s (2013) reported default frequencies 1920-2012. To perform the calculation, the model needs a free parameter, and previous studies of Huang and Huang (2003) use the asset volatility. However, Feldhütter and Schaefer (2015) argue that the default boundary (d) is much harder to estimate than the asset volatility, and so they imply out the default boundary instead.

The specific procedure in Feldhütter and Schaefer (2015) is to group all $N_{T,a}$ - observations of bond credit spreads according to their time-to-maturity (T) and rating (a). For each observation, they calculated the model implied probability of default (PD^M) from equation 2 above. Then, they calculate the average estimated probability of default ($\overline{PD}^M{}_{T,a}$) for each group with time-to-maturity (T) and rating (a), and compare this to the observed average default probability ($\overline{PD}^O{}_{T,a}$) from Moody`s (2013). At last, they find the default boundary (d) that minimizes the weighted sum of absolute errors between the model estimates and the observed default frequencies, as in equation (4).

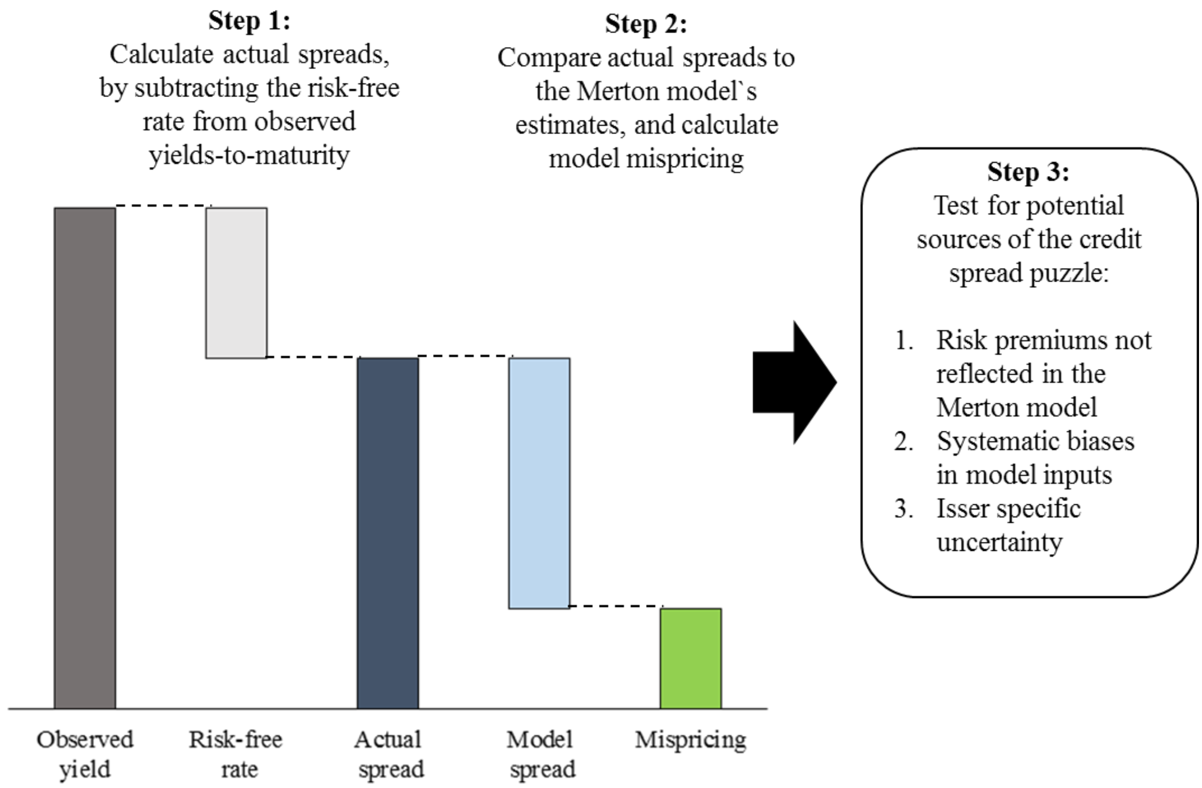
$$(4)\quad \min_{(d)} \sum_{a=AAA}^{BBB} \sum_{T=1}^{20} N_{T,a}(\overline{PD}^M{}_{T,a} - \overline{PD}^O{}_{T,a})$$

Feldhütter and Schaefer (2015) find a value of d = 1.036. This is close to the face value of debt, and so they set d = 1.00 as in the original Merton (1974) model.

In total, the Feldhütter and Schaefer (2015) procedure may appear complex and time-consuming when explained in detail. Nevertheless, the model is easy to implement and scale to numerous credit spread observations in a computer software like Excel. As long as we obtain estimates of the seven input parameters, the credit spread and probability of default follow from equation 2 and 3 above.

2.3 Our three-step approach to analyse the credit spread puzzle

In the introduction, we outlined the purpose of our thesis as a twofold: 1) Test if the credit spread puzzle exists in the Norwegian corporate bond market when using a similar model to Feldhütter and Schaefer (2015) and 2) test for factors that can explain the mispricing between the model estimates and credit spreads observed in the market. Our analysis will follow a three-step procedure inspired by Sæbø (2015a), and graph 4 illustrates its main points.



Graph 4: *Our three-step procedure for testing the credit spread puzzle. Inspired by the approach in Sæbø (2015a), but we use the Feldhütter and Schaefer (2015) model instead of the KMV Moody`s model to estimate theoretic credit spreads.*

In the first step, we calculate the actual credit spreads from the Norwegian corporate bond market. Since credit spreads are not directly observable, we calculate these using other observable factors, i.e. traded bond prices. More specifically, we observe traded bond prices on the Oslo Stock Exchange and the Nordic ABM and calculate the implicit yield-to-maturity from these prices, using information in the loan contracts in Stamdata. From the observed yields we subtract an appropriate risk-free reference rate to get the actual credit spread. In our baseline model we use interbank and swap rates as a proxy for the risk-free rate.

In the second step, we estimate model credit spreads from our implementation of the Feldhütter and Schaefer (2015) model. We follow Feldhütter and Schaefer`s approach closely, but use slightly different estimations for four of the seven key input parameters. This includes the application of a more sensitive volatility measure from Zangari (1996), heterogenic recovery rates as in Sæbø (2015b) and a specific default boundary calculation to financial companies. After calibrating the model from these input parameters, we compare the model estimates to the actual credit spreads. Then, we calculate the model mispricing.

In the third step, we test for potential explanations of the credit spread puzzle. Previous articles on the American and Norwegian bond market has suggested several factors capable of explaining parts of the puzzle, and we identify nine proxy variables that reflect these explanations. With these proxy variables, we then run a series of regression analyses in an attempt to capture the relative impact of each of these explanations on the model mispricing.

To form a systematic framework for our analysis, we group the potential explanations of the credit spread puzzle into three categories. In our first group, we include explanations related to risk premiums not reflected in the Merton model. Here, we identify liquidity risk in Perraudin and Taylor (2003), sector risk aversion in Sæbø (2015a), business cycle premiums in Chen (2010) and the Fama & French (1993) risk premiums for size and growth as in Elton, Gruber, Agrawal and Mann (2001). However, as these factors may not explain the whole puzzle, we also include factors of potential systematic biases related to the model input variables. E.g., Eom, Helwege and Huang (2004) find that the mispricing of the model significantly correlates with the leverage ratio and the volatility measure, while Huang and Huang (2003) point to systematic correlation between the model's precision and the time-to-maturity of the bond. Thus, we also introduce these input parameters in some of our regressions. At last, not all factors are possible for us to control for, and bond pricing includes a large degree of issuer specific uncertainty. This explanation is our third category, and we elaborate on the impact of this type of uncertainty in the discussion part following our results.

The following three sub-sections will move further into our three-step procedure, increasing the level of detail.

2.3.1 Step 1: Estimate bond-yields and subtract the "appropriate" risk-free rate

In this section, we will outline our methodology for calculating the credit spread observations in more detail. As previously explained, credit spreads are not directly observable, and we have to calculate them from factors that we do observe, i.e. the traded bond prices. Financial literature dictates that the value of a bond should equal the present value of the cash flow from the investment (Bjerksund, 2014). So imagine a bond with a specified face value (F), interest/coupon rate (c) and time-to-maturity (T). For a yield-to-maturity (y) observed on an investment with comparable risk and time-to-maturity, the present value of the bond`s cash flow is calculated from equation 5. In finance terminology, this is the "dirty" price of the bond.

$$(5)\ P_{Dirty} = PV_{Bond} = \sum_{t=1}^{T} \frac{cF}{(1+y)^t} + \frac{F}{(1+y)^T}$$

However, the "dirty" price is not the price that we observe in the market. The price listed on bond exchanges is the "clean" price, which is the dirty price less accrued interest, as in equation 6. (Bjerksund, 2014)

$$(6)\ P_{Clean} = P_{Dirty} - accrued\ interest$$

In our thesis, we run this process in reverse. We observe the "clean" price of a bond at a date (t), and try to determine the implicit return on the investment. This is the yield-to-maturity (y) in equation 5, and we imply out this parameter.

Note, that in the introduction we focused on the interest rate (c) of the bond, and called this the actual return of the investor. However, this is somewhat misleading. In reality, the return of the bond is the yield-to-maturity (y), which is slightly different from the interest rate (or coupon rate) specified in the bond contract. For example, if the bond is tradable on a bond exchange, price changes will move the yield of the bond even though the interest rate stays the same. The only time the yield is equal to the interest rate is when the bond is trading at its original amount (par). In our calculations, we always use the yield and not the interest rate, which we calculate from the observed bond prices as explained above.

We implement this procedure in practice by using the yield-formula in Excel. The formula has six input factors; 1) settlement date, 2) maturity date, 3) coupon rate, 4) clean price, 5) redemption type and 6) frequency of coupon payments. Input factors 2, 3, 5 and 6 are observable in the loan contract of a bond, in our case in Stamdata`s database. The clean prices of the bonds are observable on the bond exchange, and we include only prices from dates where we identify an actual trade volume. The settlement date is by convention 3-days after the trade date. (Datastream, 2016). On top of that, we control our calculations of yields against Datastream`s estimates for the yield-to-maturity where available.

An additional comment about the yield calculations is necessary. For fixed interest rate bonds, the calculation above is straight forward since we know all input factors. Having said that, our floating rate bonds have coupons rates tied to the NIBOR-rate plus an additional fixed spread, and when the NIBOR-rates move in the future so does the coupon rate of the bond. This affects our yield calculation, as we cannot know the future coupon rates for floating rate bonds. In our thesis, we use a simple approximation to solve this problem. We calculate the floating coupon rate as the NIBOR-rate observed on the trade date plus the additional coupon spread specified in the loan contract, and then we assume this coupon rate is constant for the remaining maturity of the bond. Thus, we incorporate today's level of the NIBOR, but not necessarily the correct expectations about future rates. A more advanced method will be to incorporate the market expectations reflected in the NIBOR yield-curve into the floating rate coupon payments. Nevertheless, this method would have greatly increased the complexity of the yield calculations. For simplicity, we therefore use the constant NIBOR-rate assumption for our 13,560 credit spread calculations.

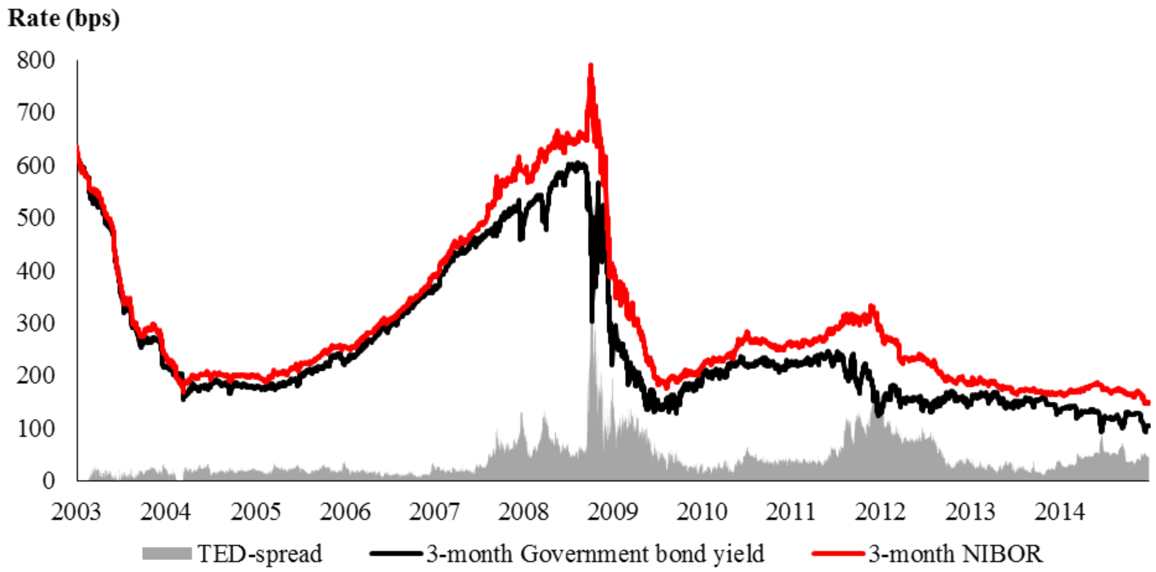
After estimating the bond`s yield-to-maturity, we move on to the calculation of the credit spread (CS). From economic literature, the credit spread is the additional rate the investor charges above the risk-free rate to compensate any potential default risk of the bond. It is equal to the difference between the yield (y) and the risk-free rate (r_f), and equation 7 illustrates this relationship:

$$(7)\ CS = y - r_f$$

The theoretically correct risk-free rate is the return on a risk-free asset with similar time-to-maturity as the bond (Sæbø, 2015a). Unfortunately, pure risk-free assets do not exist, and we have to rely on approximations. From previous studies of the credit spread puzzle we identify three potential candidates for a risk-free rate proxy: 1) Government bond yields, 2) Interbank and swap rates and 3) AAA rated corporate bond interest rates.

Traditionally, yields on government securities have been the natural proxy for a risk-free reference rate for corporate bonds. A large part of the credit spread puzzle literature use this proxy, but there are several arguments in favour of interbank/swap rates instead. Rakkestad (2004) studies the development in long-term reference rates in Norway 1997-2003. He argues that the limited market for Norwegian government bonds makes government yields very sensitive to short-term shifts in demand and supply. These shocks can potentially move the government yields quite far away from the underlying risk-free rates, making them poor proxies for risk-free rates. Rakkestad therefore suggests swap rates as a better alternative for long-term risk-free rates, as these yields are more stable.

Despite the benefits of swap rates as long-term reference rates, they are not available for maturities shorter than 1 year. Here, interbank rates are the only alternative to government bonds, and these rates are far less stable. The reason is that interbank rates reflect credit and liquidity conditions in the interbank market, and in financial turmoil, perceived credit risk of the banking sector may increase way above the risk-free rates. In Norway, this happened in the weeks following the collapse of Lehman Brothers, 15 September 2008. Graph 5 illustrates the development in short-term reference rates 2003-2014, and clearly, there is a large spike in the 3-month NIBOR at the end of 2008.



Graph 5: *Development in short-term reference rates in the Norwegian bond market. The TED-spread is the difference between the two alternative rates. Source: Norges Bank and Macrobond.*

To further complicate the picture, graph 5 shows that shocks in government yields and interbank rates typically occur simultaneously. In 2008-2009 and 2011-2012, we see that increases in the NIBOR-rate coincide with decreases in the government yield, and reflect a "flight-to-safety" in the bond market. The consequence is that neither the government yields nor the interbank/swap rates are fully appropriate as risk-free proxies during financial turmoil, as both include liquidity premiums in these periods. Feldhütter and Schaefer (2015) suggest AAA-rated bonds as an alternative, and argue that these rates are less sensitive to liquidity conditions. However, public credit ratings are rare in the Norwegian bond market, and it was not possible for us to calculate this alternative. In the end, we decided on the swap/interbank rates as our base-case reference rate, due to the arguments of Rakkestad (2004) that swap rates are more stable for longer maturities. Sæbø (2015a) also argues that swap/interbank rates are the market practice for bond pricing in Norway, adding further support for this alternative.

In summary, we see interbank/swap rates as the preferred alternative for risk-free reference rates in the Norwegian bond market. Our implementation begins with a calculation of the yield curve of the swap/interbank rates for each observation date. For fixed rate bonds, we use risk-free rates with the same time-to-maturity as the bond. However, for floating rate notes, we use risk-free rates equal to the reference rate in the loan contract. E.g. for a bond with coupon rate linked to 3-month NIBOR, we use the 3-month NIBOR as the risk-free rate.

2.3.2 Step 2: Implement the Feldhütter and Schaefer (2015) model and compare model estimates to actual observations of credit spreads

In the second step, we estimate model credit spreads from our implementation of the Feldhütter and Schaefer (2015) model. We use the same specification of equation 2 and 3 from Feldhütter and Schaefer, but apply different estimations for five out of eight input parameters. Table 3 presents our choice of input parameters. The calculations of the risk-free rate, time-to-maturity and asset volatility from equity volatility are exactly equal to Feldhütter and Schaefer (2015). However, the calculations of the equity volatility, leverage ratio, payout ratio, recovery rate and default boundary are different, and in the follow sections, we elaborate on these changes.

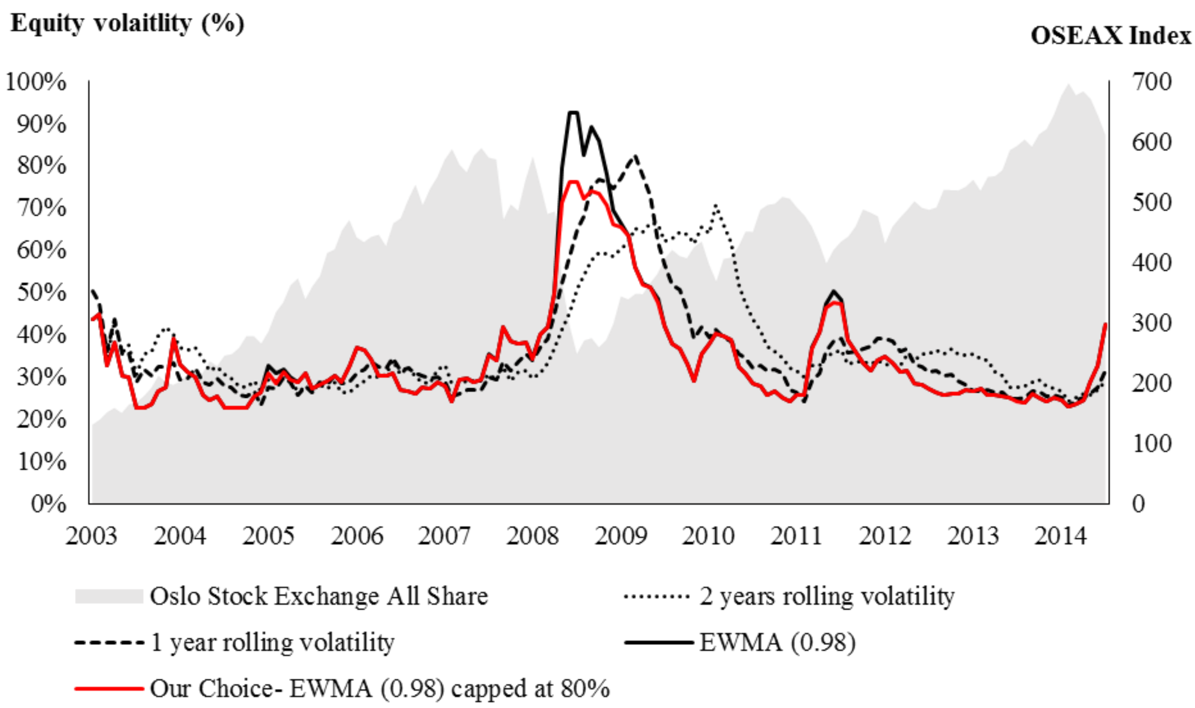
Table 3:
Our choice of input parameters in the augmented Merton model

Parameter		Our implementation	Difference from Feldhütter and Shaefer (2015)
σ	**Asset volatility**	Calculated from equity volatility as follows: $\sigma = (1 - L)\sigma_E$ multiplied with a factor M [1]	Same as Feldhütter and Schaefer
σ_E	**Equity volatility**	We use an exponentially weighted moving average volatility on daily stock returns. High volatilities capped at 80%	We use a more sensitive volatility measure, due to the timing-problems with regular historic volatility discussed below
T	**Time-to-maturity**	The number of years between the observation date and the maturity date of the bond	Same as Feldhütter and Schaefer
L	**Leverage ratio**	L = total book debt divided by firm value. Where firm value = total book debt + market cap	Same as Feldhütter and Schaefer. However, we have less frequent observations, and implement a linear average to smooth the leverage ratio.
δ	**Payout ratio**	δ = total payout divided by firm value. Where total payout = dividend per shares x number of shares + annual interest expense	We could not include total share repurchases, as it was not available in Datastream.
d	**Default boundary**	For non-financial firms we set d = 1.00 as in Feldhütter and Schaefer (2015). For financial firms we calibrate the model against Moody`s (2011) default frequencies, and find d = 0.953766	Feldhütter and Schaefer (2015) only inlcude industrial firms, and find d = 1.00. We follow their result for non-financial companies, but financial firms have very different characteristics. Here, we recalibrate the model.
r	**Risk-free rate**	Set equal to the swap rate with the same time-to-maturity as the bond	Same as Feldhütter and Schaefer
R	**Recovery rate**	We use recovery rates with sector hetereogenity: Financial = 49.2% Industrial, Oil, Shipping = 48.0% Other = 39.7% Utilitites = 70.0%	Feldhütter and Schaefer has only one sector of firms and use a static R=37.8%. We follow Sæbø (2015b), and set different recovery rates according to Altman and Kuehne (2012).

Note 1: The multiple that is used on the leverage adjusted equity volatility follows Schaefer and Strebulaev`s (2008) estimates. If L<0.25 then M = 1.00. If 0.25<L<0.35 then M = 1.05. If 0.35<L<0.45 then M = 1.10. If 0.45<L<0.55 then M = 1.20. If 0.55<L<0.75 then M =1.40. If 0.75<L then M=1.80

The first change from Feldhütter and Schaefer (2015) is to modify the procedure for measuring equity volatility. We believe the appropriate volatility measure in a forward-looking credit risk model should satisfy two criteria: 1) relevance and 2) stability. First, the volatility measure must be relevant, and incorporate the newest information available. If a shock hits equity market prices, the volatility measure should reflect changes in investor`s perception of credit risk immediately. Consequently, if the volatility measure takes a long-time to reflect current market information it will misprice the credit risk relative to real-life investors. Secondly, the volatility measure must be stable. We expect investors to look for long-run trends in credit risk, and so the volatility measure must not over-exaggerate the effect of new information relative to long-term trends. In theory, the ideal equity volatility measure is the implied-volatility of a traded option on the firm`s stock with a time to expiration similar to the bond's time-to-maturity. This implied volatility will incorporate the market expectations for future volatility of the stock, and hence be both forward-looking and stable. That said, traded option prices currently exist for only a small sample of stocks at the Oslo Stock Exchange. We therefore have to approximate the forward-looking equity volatility from historic measures.

Graph 6 presents the monthly development in four alternative volatility measures implemented on our data sample. The red line is our choice of volatility measure, an exponentially weighted moving average (EWMA) volatility inspired by Zangari (1996), and we compare this to the dotted lines, i.e. standard historic rolling volatilities with a 1- and 2-year horizon of daily stock return. In periods of normal market activity, 2003-2008 and 2012-2014, the volatility measures behave similarly, ranging from 20-40%. However, during the financial crisis of 2008-2011 there are large differences. On the one hand, the 2-year rolling volatility reacts slowly to the falling equity prices following the collapse of Lehman Brother 15 September 2008, and reaches 60% first in June 2009. It takes more than two years for this volatility measure to return to normal levels in January 2011. By this time, the real-life equity market has been in normal activity for over a year, as seen by the OSEAX index. On the other hand, the 1-year rolling volatility and the EWMA (0.98) are more sensitive to changing conditions, and reflects movements in the OSEAX more closely. Clearly, a longer-horizon volatility measure is in conflict with our relevance criteria, and has strong problems reflecting extreme market behaviour.



Graph 6: *Development in different volatility measures. We calculate the monthly average of different volatility measures, and plot them on the left axis. The right axis plots the monthly development in the Oslo Stock Exchange All Share Index. The red line illustrates our choice, i.e. an exponentially weighted moving average (EWMA) volatility with* λ *= 0.98 and a cap on 80%. Source for OSEAX: Macrobond*

In their article, Feldhütter and Schaefer (2015) use a 3-year historic rolling volatility, and due to the aforementioned problems with the application of such a long time-horizon, we believe a change in the volatility measure is appropriate. Yet, a more sensitive volatility measure comes with a trade-off to stability. The higher the weight the volatility measure places on new information, the more we are in the risk of extreme values. Graph 6 illustrate this trend, as the EWMA (0.98)-volatility measure and the 1-year rolling volatility are more prone to extreme volatility levels than the 2-year rolling volatility. Our solution to this trade-off problem is to add a cap on the EWMA (0.98), restricting it from having values above 80.0 %. In our view, this measure is the most relevant, whilst having the same stability as the rolling volatilities.

Based on these arguments we introduce the EWMA-volatility measure from Zangari (1996) into the augmented Merton model. Part of the problem of traditional rolling volatilities is that they place equal weight on all observations. E.g., a 2-year rolling volatility will view observations 2-years ago as equally important as observations today. The consequence is that extreme observations, such as the financial turmoil in late 2008, will stay in the volatility measure for 2 years, first disappearing on the first day of the third year. Contrarily, Zangari`s (1996) exponentially weighted moving average (EWMA) will place a lower and lower weight on historical observations, viewing the most recent observations as the most relevant.

The calculation of the EWMA volatility is straightforward. Assume we observe daily returns of a stock (r_t) and volatility (σ_t) at time (t). By choosing an appropriate weight ($\lambda < 1$) the EWMA-variance at time (t+1) can be calculated from equation 8: (Zangari, 1996 p. 81)

$$(8)\ \sigma_{t+1}^2 = \lambda\sigma_t^2 + (1-\lambda){r_t}^2$$

Where the volatility is simply the square root of the variance from equation (9):

$$(9)\ \sigma_{t+1}^{EWMA} = \sqrt{\sigma_{t+1}^2}$$

A key parameter is the weight (λ), and in our thesis we set this equal to 0.98. This implies that we weigh historic variance (σ_t^2) with 98% and the square of the most current return observation (${r_t}^2$) with 2%. Hence, we let historic observations slowly fade out from our volatility measure, whilst placing a higher weight on the current observations. Note that if we had set (λ) equal to 1.00, the EWMA-volatility would have been equal to the traditional rolling volatility. However, there is no true value of (λ), and determining its proper value is a guessing game. For example, Zangari (1996) estimates the EWMA-volatility on US dollar currency and finds that the most appropriate (λ) is 0.94. We chose our volatility measure by the following procedure, illustrated in table A2 and A3 in appendix A2. First, we estimated the augmented Merton model using different volatility measures; the 2-year rolling volatility, the 1-year rolling volatility, EWMA with $\lambda = 0.96$ and EWMA with $\lambda = 0.98$. Then we calculated the correlation between the model estimates and the actual credit spreads in the market, and chose the volatility measure with the highest correlation. This was the EWMA with $\lambda = 0.98$. Secondly, we calculated the Merton model with volatility caps on 80.0%, 70.0%, 60.0% and 55.0% respectively. For monthly aggregate data, there was increased correlation by adding a cap on volatility, and the optimal choice appeared to be a cap level of 60%. To the contrary, for all data, the correlation was highest for a cap on 80%. We ultimately chose the cap on 80%, viewing the all data comparison as the most relevant.

The second change from the Feldhütter and Schaefer (2015) model relates to the leverage ratio and the payout ratio. We calculate these in the same way as Feldhütter and Schaefer (2015), but due to the availability of firm data there are some minor differences. Firstly, when calculating leverage ratio, Feldhütter and Schaefer use quarterly observations for the value of total book debt. In Datastream, these variables were only available in annual observation for our Norwegian sample, and so we have less frequent observations for each firm. Since firms in real-life can alter their debt level at any time during the year, observing the debt level only at the beginning of the year may give rise to systematic biases in the leverage ratio. For instance, if a firm choose to increases its debt level in February, then the “real” leverage ratio will be underestimated all the time until next annual report if we rely on the debt level reported in the annual report from January. To deal with this problem we use a linear approximation between the numbers reported in the annual report at 1) the start of the year and 2) the end of the year. Graph 7 illustrates this approximation for one company, DNO. The idea is to smooth the leverage curve, so that we get closer to a curve with quarterly observations, as in Feldhütter and Schaefer (2015).

Graph 7: *The effect of using a linear average of book debt. The company example is DNO, and the black line illustrates the debt level using the total book debt reported in last year’s annual report. The red line is our linear average of the observations in the annual report, and allows us to smooth the debt level, ex-post.*

Secondly, our payout ratio is slightly different from Feldhütter and Schaefer (2015). Their payout ratio is calculated using the sum of 1) annual interest expense, 2) annual dividend payments and 3) annual share repurchase, as an approximation for the total payout to debt and equity holders. In our thesis, we were not able to include annual share repurchase, as it was not available directly in Datastream. It would have been possible to collect this data for each single firm, but for time concerns, we were not able to do this when calculating over 13,560 credit spreads.

The third change from Feldhütter and Schaefer (2015) is to alter the default boundary estimation for financial firms. In their analysis, Feldhütter and Schaefer only use industrial firm bonds, and set a default boundary of 1.00 in their model as previously noted. Since Feldhütter and Schaefer (2015) have a far larger data sample from which they calibrate the default boundary, we see no reason to alter this estimate for the non-financial companies in our sample. However, for financial firms the default boundary should not necessarily be equal to 1.00. Nagel and Purnanandam (2015) study the implementation of structural credit risk models to the special characteristics of bank`s assets. They find that the usual assumption of log-normally distributed returns of asset values is not appropriate for banks, as their assets are risky-debt claims equal to a short-put option on the borrowers underlying assets. Hence, bank`s equity payoff is a mezzanine claim, rather than a call option, and this affects the calculation of equity volatility and distance-to-default for these financial companies.

Therefore, in our thesis, we recalibrate the default boundary for financial firms, matching the model`s estimates of default frequencies for financial companies to the historically observed default frequencies from Moody`s (2011). We use the procedure in equation 4 from Feldhütter and Schaefer (2015), and minimize the absolute error between model-implied probability of default and historic default rates for the financial sector in table 4. We find d = 0.953667, which implies a slightly lower default boundary for financial companies than non-financial companies.

Table 4:

Average cumulative default rates for the financial sector 1970-2010[1]

Year	1	2	3	4	5	6	7	8	9	10
Default rate (%)	0.709	1.474	2.224	2.911	3.537	4.151	4.736	5.323	5.946	6.616

Source: Moody`s (2011)

Note 1: We use Moody`s estimates for the sector FIRE: Financial, Insurance and Real Estate.

The last difference from Feldhütter and Schaefer (2015) is the recovery rates. Here, Feldhütter and Schaefer (2015) use a static estimate of 37.8% equal to the average recovery rate for senior unsecured bonds from Moody`s (2013). However, our data sample includes a broader range of sectors than Feldhütter and Schaefer, and so we have chosen to use a heterogenic recovery rate, depending on sector estimates of recovery rates 1971-2011 from figure 27 in Altman and Kuehne (2012). This procedure is the same as in Sæbø (2015b), with whom we compare our results. We set the recovery rate to 49.2% and 70.0% for financial companies and utilities respectively. For industrial companies we set R = 48.0%, i.e. the average of energy and miscellaneous industrial companies. For our miscellaneous sector, we use the average of conglomerates, transport, media, retail, health care and leisure of 39.7%, which we believe reflect the same type of companies that we include in this sector. In our view, the importance of a heterogenic recovery rate is to differ between companies with large fixed assets and strong collateral, such as banks, utilities and industrial companies, versus companies with less collateral abilities, such as the typical miscellaneous firm.

2.3.3 Step 3: Determine potential causes of the mispricing between the model estimates and the observed credit spreads

In the third step, we test for factors that might explain the credit spread puzzle in the Norwegian corporate bond market. As mentioned, we group the potential candidates in three categories; 1) risk premiums not reflected in the Merton model, 2) systematic biases in input factors and 3) issuer specific uncertainty. To determine the relative impact of each of these explanations we develop a framework of regression analyses, combining univariate regression models with multivariate analyses.

We begin with an overview of the regressions. First, we calculate the model mispricing for all $i \sim (1, n)$ observations as the difference between the model estimate and the actual observed credit spreads. Then, we regress this mispricing against (K) different control-factors,(X_k), where we use the ordinary least squared (OLS) estimator to determine the coefficients (β_k) and the intercept (β_0). As heteroscedasticity typically arise in time-series analysis, we report heteroscedasticity robust standard errors. Moreover, the error-term (u_i) and the regression models rely on the assumptions of a standard linear regression of *linearity in parameters, no perfect collinearity between the regressors, zero conditional mean* and *no serial correlation for the error term* (Woolridge, 2015). Equation 10 gives the mathematical presentation. The reader should note that a negative value of the mispricing, our dependent variable, indicates that the Merton model underestimates actual credit spreads, whereas a positive value reflects an overestimation of actual observations.

$$(10)\ Mispricing_i = \beta_0 + \sum_{k=1}^{K} \beta_k X_{i,k} + u_i$$

Table 5 presents the input factors incorporated in the regression analyses. The first group includes risk premiums not reflected in the Merton model. Here, we identify liquidity risk, sector risk aversion, the Fama & French (1993) factors of size and growth and business cycle risk as potential candidates from previous literature on the credit spread puzzle. The other group includes the input factors of the augmented Merton model, since we wish to control for potential biases in their specification. As it is not possible for us to include variables that incorporate issuer specific uncertainty in the regressions, we discuss this potential explanation more in part 5 of our thesis. In the third column of table 5, we list the proxy variables for each of the factors. These variables are the ones included as independent variables in our regressions, and in the following, we will elaborate on the exact choices of these parameters.

Table 5:
Overview of potential explanations for the credit spread puzzle, and the proxy variables we include in the regression analysis

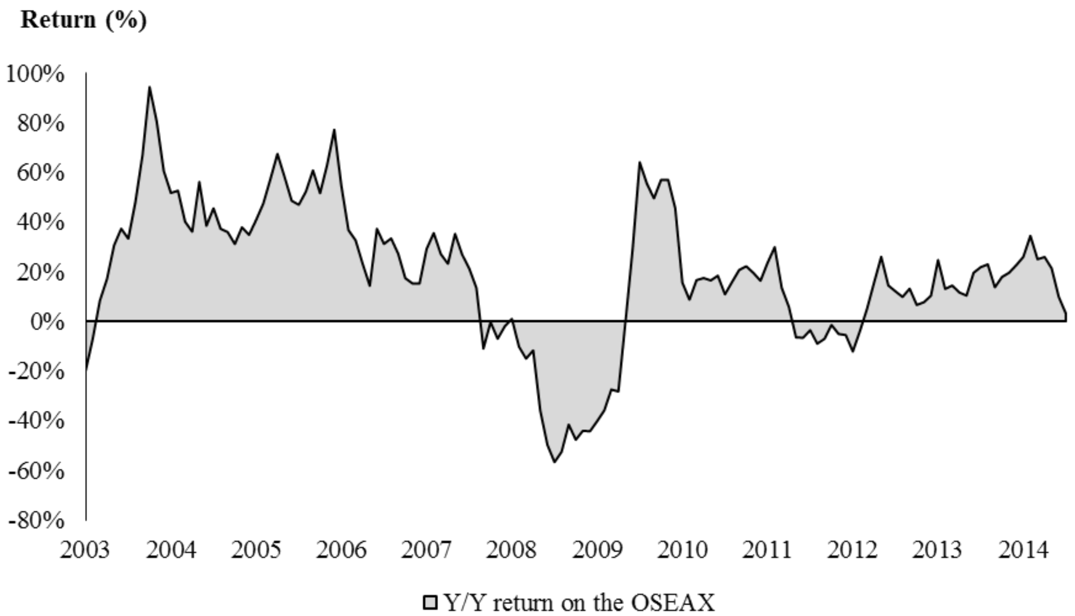
Explanatory factor	Description	Proxy variable	Predicted coefficient from theory
Potential risk premiums not reflected in model:			
Liquidity risk 1: Bond specific	Perraudin and Taylor (2003) and Longstaff, Mithal and Nies (2004) find evidence for liquidity premiums among different types of bonds. Bond size is a proxy for issuer specific liquidity.	Bond size in NOK	Positive
Liquidity risk 2: Overall market	The same articles find that general market liquidity also have an impact. Sæbø (2015a) argues that a possible proxy here is the Norwegian TED-spread, i.e. the 3 month NIBOR - 3 month government yield.	TED-spread (bps)	Negative
Sector risk aversion	Sæbø (2015a) argues for sector risk aversion, and find that sector dummies can explain parts of the mispricing of the Merton model.	Sector dummy variables	Different for each sector
Small company aversion	Elton, Gruber, Agrawal and Mann (2001) find that the Fama & French (1993) factors of size and growth might explain credit spreads. We include the natural logarithm of the market cap for size, as in Sæbø (2015a).	Log market capitalisation	Positive
Growth company aversion	The other Fama & French factor (1993) is growth. Here we include the market-to-book ratio of the equity value.	Market-to-book ratio	Negative
Business cycle risk	Chen (2010) illustrates that default risk is highly procyclical. We include the return on the OSEAX to test the cyclicality of model mispricing.	Y/Y return on OSEAX	Negative
Potential biases in input factor specifications:			
Issuer specific volatility	Eom, Helwege and Huang (2004) find that the model systematically underestimates safe bonds with low leverage and low volatility, whilst overestimating bonds with the opposite characteristics. We include these input factors.	Equity volatility	Positive
Debt leverage	Same as above.	Leverage ratio	Positive
Payout to debt & equity	Although not found in literature, the mispricing might also relate to the payout ratio.	Payout ratio	Positive
Time-to-maturity	Huang and Huang (2003) indicate that the underestimation of spreads is particularly strong for short time-to-maturity bonds. A potential argument for jump-risk.	Time-to-maturity	Positive

Liquidity risk concerns investors` fear of investments in illiquid assets, where the lack of potential buyers might trap them in the assets or force them to sell at large discounts to the underlying value. It is a popular explanation for the credit spread puzzle, and several studies find this factor to be a potential explanatory factor of corporate bond spreads. Among these are Longstaff, Mithal and Nies (2004), decomposing spreads into default and non-default components. They find that default accounts for 51% and 71% of AAA-rated and BBB-rated bonds, with the unexplained component strongly related to proxy measures of bond liquidity. These include bond-specific liquidity measures as the bid-ask spread of the bond and the principal amount outstanding, as well as market wide liquidity measures, such as flows into mutual funds and the total amount of new corporate debt issued. Moreover, Perraudin and Taylor (2003) find that sorting bonds into high- and low-liquidity groups might explain as much as 30bps of high-quality dollar denominated Eurobond spreads, and Sæbø (2015a) finds that the bid-ask spread of Norwegian government bonds correlate with the mispricing of the Merton model. As we want our analysis to be consistent with these previous studies, we include the bond size (principal amount outstanding) in NOK and the TED-spread as our proxy variables for liquidity risk. The bond size reflects issuer specific liquidity, while the TED-spread will reflect general market liquidity conditions. Sæbø (2015a, p.7) mentions the latter as a potential proxy for market liquidity, and we measure the TED-spread as the difference between the 3-month NIBOR and the 3-month government bond yield. The idea is that a widening TED-spread will indicate a "flight to safety" from the interbank market to government bonds, possibly consistent with worsening liquidity conditions in the bond market in general.

Other studies have argued for the potential existence of risk premiums related to sector, issuer size and the market-to-book ratio. The idea is that investors will be particularly risk averse to specific types of companies, for instance, due to different sector cyclicality or asymmetric information for companies with small size or high growth prospects. One of these studies is Sæbø (2015a), who include the aforementioned factors in his analysis of Norwegian corporate bond spreads. He finds that sector and issuer size have a strong correlation to the mispricing of the augmented Merton model. Another is Elton, Gruber, Agrawal and Mann (2001). They decompose the spread between American corporate and government bonds, discovering that default can only explain a smaller part. However, the Fama & French (1993) factors of size and growth explain as much 84% of the component not explained by default or taxes in the corporate – government bond spread. In our regressions, we therefore include these factors.

We use sector dummies and log market capitalization as in Sæbø (2015a) to capture potential sector and size risk premiums. For the Fama & French (1993) factor of growth, we use the market-to-book ratio for the equity value of the firm, where a high ratio indicates that the market price reflects a strong growth prospect.

Chen (2010) emphasizes the importance of business cycle risk, and his results highlight the potential existence of a countercyclical risk premium on top of the Merton model`s estimates. The reason is that economic recessions typically include a simultaneous combination of lower firm cash-flows, lower growth expectations and higher discounts on asset liquidations for almost every firm in the entire economy. Together, this will significantly increase the potential loss of a bond investment at these time-periods, since both the default probability and the loss given default will increase in these circumstances. As most structural risk models incorporate only the current level of input parameters, a potential error may arise if these parameters underestimate the true credit risk of a recession if measured in periods of a booming economy. To check if the model mispricing follows Chen`s (2010) arguments that structural model typical underestimate the business cycle risk, we include a cyclicality variable into our regression analysis. More specifically, we use the year-over-year (Y/Y) return of the Oslo Stock Exchange All Share Index (OSEAX) presented in graph 8. All companies in our sample have listed stocks on the Oslo Stock Exchange, and so we believe this variable will capture the business cycle sentiment in our data sample.



Graph 8: *The year-over-year return on the Oslo Stock Exchange All Share Index (OSEAX), measured at a monthly basis. We include this variable as our proxy variable for business cycle risk in the regression analysis. Source: Macrobond*

As previously highlighted, another explanation of the credit spread puzzle is systematic errors in the specification of the input parameters. In their study of five versions of the Merton model, Eom, Helwege and Huang (2004) discover a systematic tendency for the models to underestimate credit spreads for safe bonds with low debt leverage or volatility, meanwhile overestimate spreads for bonds with the opposite characteristics. This could indicate that the Merton model`s implementation of these parameters mispresent the true credit risk perceived by real-life investors. Furthermore, Huang and Huang (2003) calibrate five augmented Merton models to historic default frequencies. They find that the underestimation of spreads is particularly strong for shorter time-to-maturity bonds, and argue that a possible explanation is that the model disregards the possibility of jump-risk in the short-term, i.e. the fear of a sudden and extremely negative idiosyncratic shock to the company. To control for these factors we include the input parameters for debt leverage, equity volatility and time-to-maturity in our regression. In addition, we include the payout ratio of the firm, since it is also possible that the mispricing relates to this factor.

There are multiple potential explanations of the credit spread puzzle, and to determine the attribution of each factors we structure the regression analysis in two parts. In the first part, we run a univariate regression analysis with only one explanatory factor at each time, together with a constant. From these simple regression models, we can compare the relative impact of each explanation from previous literature independently, giving us an objective measure of their relative importance in the Norwegian corporate bond market. Nevertheless, the factors may correlate with one another, and in the second part, we combine the factors in a multivariate regression analysis. Here, we use a step-wise procedure to determine which factors actually contribute to the credit spread puzzle, and in the end, we build a base-line regression model consisting of these factors.

3. DATA AND DESCRIPTIVE STATISTICS

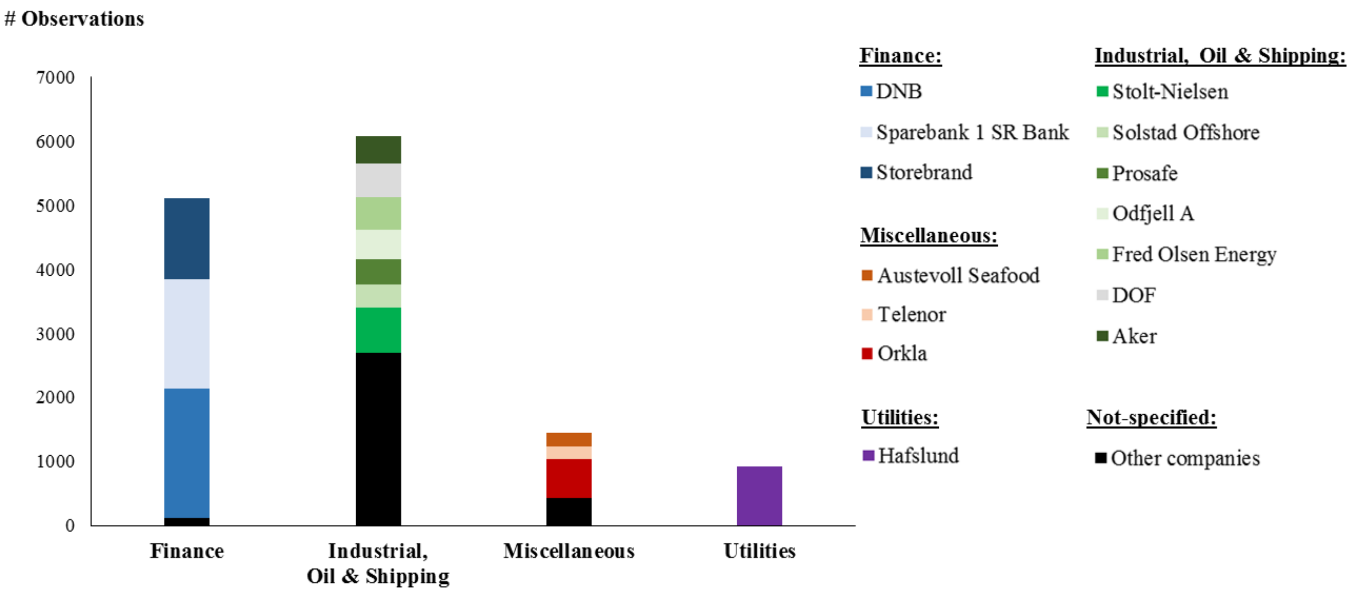
Section 3 presents our data sample and descriptive statistics. In part 3.1, we describe how we determined the sample of Norwegian corporate bonds, before part 3.2 moves on to the descriptive statistics for observed credit spreads. In part 3.3, we present the development in the firm specific input variables in the augmented Merton model, which are the volatility measures, the leverage ratio and the payout ratio. Furthermore, appendix A1 contains an overview of the sources of all data presented in this thesis.

3.1 Determining the sample of Norwegian corporate bonds

In the introduction part 1.3, we outlined some particular difficulties of the Norwegian corporate bond market. One of these difficulties is the short time-horizon of available data. In our thesis, we set our sample-period for the Norwegian bond market from 2003 to 2014 based on the available data. Due to the small number of issues in the Norwegian corporate bond market before 2002 and the fact that data series on short-term government bonds were not available before 2003, we decided to exclude observations before 2003. Moreover, accounting numbers for the annual reports 2015 were not yet available at the time of calculation. For this reason, we also excluded observations in 2015. In total, our data sample includes Norwegian corporate bonds from the period 2003-2014.

During this total period, Stamdata`s registers contain a total of 17,472 number of bonds. From these available bonds, we narrowed down the dataset based on the following four criteria. First, traded bond prices formed the basis of our credit spread calculation, and so we could only include bonds listed on the Oslo Stock Exchange and Nordic ABM 2003-2014. Second, equity volatility is an important input parameter of the Merton model, and hence we could only include bonds where the issuer had listed stocks. Our sample includes observations of bonds where the issuer`s stocks was listed on the Oslo Stock Exchange at least two years before the observation date. Third, the bonds had to be comparable in terms of structure type, seniority and collateral. Therefore, we exclude bonds that have any of the following characteristics; convertible, perpetual, linked notes, zero-coupon, irregular redemption type, callable, putable, caps or floors, collars, guarantee, security, or any other type of seniority either than senior unsecured. At last, we chose only to include bonds denominated in NOK to avoid any currency effects and to exclude bonds with less than two months remaining time-to-maturity.

In summary, our dataset consist of 252 different bonds, where all are “plain-vanilla” senior unsecured coupon bonds, i.e. bonds that have regular coupon payments, no collateral claim and a fixed time-to-maturity. The large reduction from the total number registered in Stamdata was primarily a cause of removing public sector bonds, bonds without listed equity and bonds not traded on the Oslo Stock Exchange or the Nordic ABM. From these 252 bonds, we determined our dataset of credit spread observations from traded bond prices in Datastream. We only included prices at dates where we could identify an actual trade volume, to avoid using shadow-prices. The reason is that there are no actual investors backing these shadow-prices, and so they may not reflect the actual risk perception of the market at that time. From these observations, we calculated credit spreads in accordance with the methodology, part 2.3.1. In total, we ended up with 13,560 observations of credit spreads from the Norwegian corporate bond market 2003-2014. Graph 9 presents the distribution of credit spreads on different sectors and issuers.



Graph 9: *The distribution of observed credit spreads for sectors and companies. We have outlined the companies with the most observations in each sector, and the black parts are other companies not specified directly. The number of different issuers are 5, 29, 12, and 1 for the sectors finance, industrials, miscellaneous, and utilities respectively.*

In our thesis, we have grouped the bonds into four broad sector categories, defined according to sector labels in Stamdata`s database. The first group is financial companies, in our case banks and insurance companies. The sector consists mostly of three large issuers, which are DNB, Sparebank 1 SR Bank and Storebrand. To the contrary, the industrial sector includes a broad range of 29 different industrial, shipping and oil-related companies, and is the dominant in our sample. Graph 9 illustrates that there are some large issuers in this sector as well, but in general, the issuer base is well-diversified. The last categories, miscellaneous and utilities firms, include significantly less observations than the former. Still, the utilities category includes one large important issuer, Hafslund, although this is the only utility firm in the sample. The miscellaneous category includes a wide range of companies in the sectors telekom, IT, seafood, media, health care and consumer goods and services.

The reason we have grouped the issuers into four different sectors is to highlight the performance of the Merton model on different types of companies. Our sector-choice is not necessarily the perfect definition, but we believe they will highlight some of the most important differences between companies. In part 3.3, we illustrate that the typical company in these four sectors have very different characteristics in terms of the leverage ratio and asset volatility. In addition, we believe these sectors to exhibit different characteristics in terms of collateral possibilities, justifying our use of heterogenic recovery rates. For example, the sector industrial, shipping and oil & gas includes a large number of capital-intensive companies with large fixed asset, against which the borrower can claim collateral. On the other hand, the miscellaneous sector include IT, telekom and consumer goods companies, typically with a large share of immaterial assets which borrowers cannot claim collateral against. We find support for these arguments in the empirical estimates of recovery rates for different sectors in Altman and Kuehne (2012) figure 27.

3.2 Descriptive statistics for observed credit spreads

As explained, in part 2.3.1, credit spreads are not directly observable in the market, and we calculate them from factors that we do observe, i.e. traded bond prices. Hence, our actual observations of credit spreads follow the procedure explained in part 2.3.1, where we subtract the swap/interbank rate from observed yields-to-maturity.

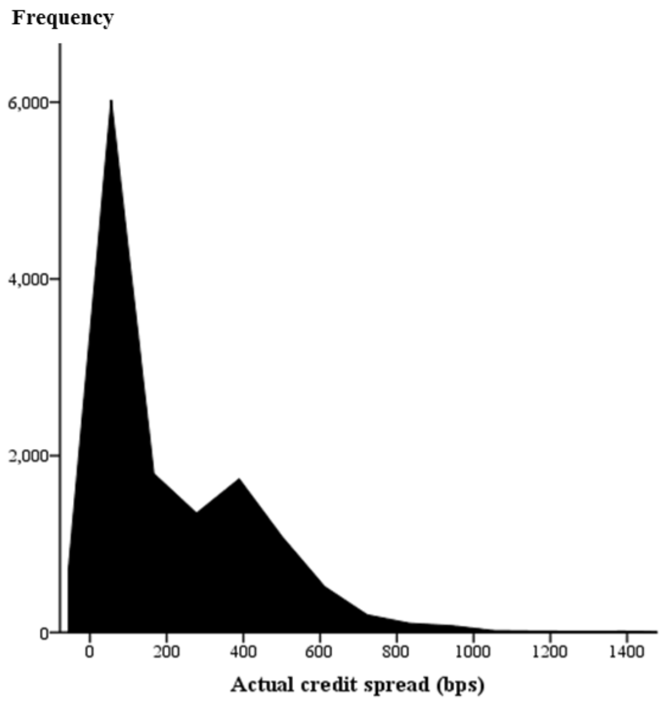
Table 5 presents the summary statistics for our 13,560 observations of real-life credit risk pricing in the Norwegian bond market 2003-2014. The median credit spread is 118bps with the interquartile range from 38-357bps, and so the central tendency of our distribution is quite narrow around the median. Hence, most observations in our sample are relatively safe investments, and include several large companies such as DNB, Storebrand, Orkla and Telenor. On the other hand, the range of credit spreads is very wide, and our sample includes extreme polar points of credit risk perceived by investors. At the absolute low we have a risk-free pricing at -35bps, contrasting the extremely high risk premium of 5605bps for Norske Skog the autumn of 2011.

Table 6:
Summary statistics for observed credit spreads (in basis points - bps)

	#Observations	**Mean**	**Median**	Minimum	25th percentile	75th percentile	Maximum
Actual credit spread[1]	13,560	**214**	**118**	-35	38	357	5605

Note 1: actual credit spreads calculated as yield-to-maturity minus the swap/interbank rate with equal time-to-maturity

Graph 10 takes a closer look at the distribution, where we have capped the outliers at 1500bps. The strong skewness towards lower credit spreads is an important characteristic of the bond market. Most bonds are low risk investments, priced at credit premiums below 250bps by the investors. The large peak to the left represents the majority share of these credit spreads, where most of them are noted as “investment grade” bonds in Stamdata`s database. The other smaller peak to the right indicate the majority of the “high-yield” bonds in our sample, priced at spreads from 250bps to 1000bps. Many of these relate to the industrial, shipping and oil & gas sector, and are particularly common in the Norwegian bond market. Only a few numbers of observations have credit premiums larger than 1000bps. Yet, these extreme observations have a strong impact on the mean statistic, making it a biased estimator of the central tendency in this skewed distribution. For this reason, we will in the following focus on the medians as our measures of central tendencies and the interquartile ranges (25^{th} to 75^{th} percentile) as our measures of deviations from these central tendencies.



Graph 10: *Distribution of actual credit spreads for our entire sample, limited to spreads below 1500bps.*

Our sample of credit spreads correlates with the sector and time-to-maturity of the bond, as illustrated in table 7. For sectors, there are large differences between the industrial companies and the others. The median industrial, shipping and oil company is priced at 366bps, equivalent to risky high-yield bond pricing. The interquartile range from 240-481bps is significantly higher than the other sectors, pointing out the large concentration of risky companies in the industrial sector. Contrarily, the perceived risk for financial and utilities companies are much lower. The median spreads are 41bps and 44bps, with low interquartile ranges from 12-81bps and 17-77bps respectively. The miscellaneous companies (IT, telekom etc.) have slightly higher median spreads at 99bps, but the interquartile range from 42-254bps indicates that most bonds are in the investment grade region. Note that all sectors have a negative minimum spread, and so there is no tendency that sector is a limitation for solid companies to issue low yielding bonds in strong market conditions.

Table 7:

Distribution of observed credit spreads for different sectors and remaining time-to-maturity

	Actual credit spreads (basis points)						
	#Observations	**Mean**	**Median**	Minimum	25th percentile	75th percentile	Maximum
Sectors:[1]							
Finance	5113	**54**	**41**	-35	12	81	473
Industrial, Oil & Shipping	6080	**387**	**366**	-35	240	481	5605
Miscellaneous	1449	**154**	**99**	-35	42	254	608
Utilities	918	**53**	**44**	-26	17	77	346
Time-to-maturity:							
Below 6 months	720	**172**	**24**	-35	7	181	5605
6-12 months	1109	**109**	**25**	-33	9	159	2737
1-3 years	5540	**185**	**79**	-35	30	289	4420
3-6 years	5252	**253**	**183**	-33	71	402	3093
Above 6 years	939	**323**	**375**	11	114	463	730

Note 1: Our sector definitions are based on the following groups in Stamdata`s database.
Finance: bank and insurance.
Industrials, Oil & Shipping: industrial, pulp and paper, shipping, oil & gas.
Miscellaneous: consumer goods and services, media, IT, telekom, transportation and health care.
Utilities: utilities

Looking at remaining time-to-maturity, we see that there is a clear tendency towards lower spreads for shorter time-to-maturity. Hence, the average Norwegian investors seemed to demand a higher credit risk premium for holding a longer-term bond in 2003-2014. This could be a consequence of investors` perception of higher default risk for longer horizons, but it could also be a compensation for increased interest-rate risk since long-term bonds have higher duration.

Time is also a factor that affects bond spreads, and in table 8, we have split credit spreads into three defined time-periods. We have used the bankruptcy of Lehman Brothers 15 September 2008 as a proxy for the start of the Global Financial Crisis, a period of especially high volatility and perceived risk in the global financial markets (Sæbø, 2015a). In the period prior to Lehman Brothers' default, credit spreads were especially low for all sectors. At this time, our sample is almost exclusively investment grade firms and so it is not surprising that credit spreads are low. During 2008-2009, financial turmoil spread to the Norwegian bond market, causing credit spreads to increase significantly for all sectors. Even the safe banks and insurance companies were affected as spreads jumped from a median level of 8bps to 62bps. In the latter period 2011-2014, the financial turmoil calmed down, yet credit spreads did not seem to fall back to previous levels. Credit premiums in the financial sector remained high, as did the spreads for industrial and miscellaneous companies. The latter fact is mostly a cause of the large increase of high-yield issuers into the industrial and miscellaneous sector of our sample 2011-2014. Since the industrial sector 2011-2014 also dominates our total sample, it is not surprising that we see the strong rise in total sample spreads when we move into the last period.

Table 8:

Development in observed credit spreads for different time-periods

	2003 - Lehman[1]			**Lehman - 2010[1]**			**2011-2014**		
Sectors:	#Spreads	Median	Inter-quartile	#Spreads	Median	Inter-quartile	#Spreads	Median	Inter-quartile
Finance	1373	8	(-1-17)	810	62	(11-108)	2930	61	(32-95)
Industrials, Oil & Shipping	772	76	(44-149)	301	401	(280-895)	5007	386	(293-495)
Miscellaneous	359	28	(2-54)	279	104	(66-209)	811	179	(83-337)
Utilities	542	26	(8-56)	94	100	(65-151)	282	66	(38-96)
Total sample	**3046**	**19**	**(4-57)**	**1484**	**92**	**(37-195)**	**9030**	**246**	**(74-412)**

The table illustrates the development in the median observed credit spread. Interquartile ranges in paranthesis indicate the uncertainty from the 25th to 75th percentile observation.

Note 1: the bankcruptcy of Lehman Brothers, 15 September 2008, marks the beginning of the financial crisis 2008

3.3 Development in firm specific input parameters

In this section, we look at the development in the leverage ratio, the volatility measure and the payout ratio of the Feldhütter and Schaefer (2015) model. These firm parameters allow the model`s credit spread estimates to adapt to each firm`s specific risk characteristics, as well as being able to capture time variations in these risk parameters. Understanding the development in these parameters is essential for explaining the development in model estimates across time and sectors. We calculate these input variables according to the methodology explained in section 2.3.2, and update them for each single observation.

The leverage ratio is the first important risk characteristic, and captures the total level of debt in each company. Isolated, an increase in debt level should be offset by an increase in the credit risk premium. Table 9 presents the summary statistics for the leverage ratios, where we report the median observation and interquartile range for each sector and time period. The left column highlights that there are large differences in the debt level of our defined sectors. The typical financial company is highly levered, with a median ratio of 83% and a lower 25th percentile of 70%. These high debt levels distinct financial firms from the non-financial firms, as the median debt levels for the sectors industrial, miscellaneous and utilities are 56%, 28% and 67% respectively. From the interquartile ranges of non-financial firms, we see that the debt levels vary significantly within each sector, but the general order is that utilities and industrial companies are medium to highly levered, while the other miscellaneous companies have low debt levels. These observations fit well with economic theory. Generally, utility companies have a strong and stable cash flow, and capital-intensive shipping and oil-related companies will have strong collateral positions. These firm characteristics are generally attractive for bond investors, allowing the firm to achieve high debt levels. To the contrary, a typical company in the IT, telecom or seafood sector will have a far lower level of fixed assets against which the investor can make collateral claims. Furthermore, a relatively more unstable cash flow and/or high operational investment requirements will favour a low-debt capital structure to support flexibility in operations.

The different columns in table 9 show the development in aggregate debt levels for our three periods. In the period before the Lehman Brothers` bankruptcy, leverage ratios were generally low due to favourable financial conditions and mostly strong investment grade issuers in our sample. However, after the Lehman Brothers’ bankruptcy, the leverage ratios increased on a general basis. The conditions of the financial firms were particularly tight, as falling equity prices raised the leverage ratios to a median level of 89%. In addition, only 25% of observations from financial firms had a lower leverage ratio than 88% in this period. The leverage ratio in miscellaneous firms also increased, as well as for several industrial firms, where the 75th percentile increases to 81% from 56% in the former period. In 2011-2014, the general trend was a return to more normal levels of debt, particularly for financial and miscellaneous firms. On the other hand, the median debt level for industrial firms increased significantly, as a large number of high-yield and highly-levered firms entered the bond market in this period. The development in leverage for the utilities firm, Hafslund, was to a low degree affected by the financial turmoil following the Lehman Brothers' bankruptcy 15 September 2008. The general trend for Hafslund was relatively high and stable leverage ratios around 60-70% for all time-periods.

Table 9:

Summary statistics for firm leverage ratios [1]

	Time period							
	Total period 2003-2014		**2003 - Lehman**		**Lehman - 2010**		**2011-2014**	
	Median	Inter-quartile	Median	Inter-quartile	Median	Inter-quartile	Median	Inter-quartile
Finance	83%	(70-89)	80%	(61-88)	89%	(88-93)	82%	(72-87)
Industrial, Oil & Shipping	56%	(33-73)	45%	(15-56)	45%	(27-81)	59%	(41-75)
Miscellaneous	28%	(17-43)	21%	(16-30)	36%	(30-39)	27%	(17-46)
Utilities	67%	(57-70)	66%	(46-74)	62%	(61-63)	67%	(66-68)
Total sample	**66%**	**(46-83)**	**60%**	**(43-79)**	**86%**	**(40-90)**	**67%**	**(48-82)**

Interquartile range in paranthesis indicates the uncertainty from the 25th to 75th percentile observation.
Note 1: Leverage ratio measured as total book debt divided by firm value.

The second important input parameter is the asset volatility. All else equal, a higher volatility of asset values increases the risk of repayment of the debt, and should increase the risk premium charged by credit investors. Since we calculate asset volatility from the more observable equity volatility, we will present the latter first. Table 10 illustrates the development in our EWMA-volatility measure calculated from traded prices of a firm`s stocks. In the left column, we see that the general level of equity volatility is quite similar for our four sectors. The median levels are slightly different, but since the interquartile ranges overlap there are no reasons to believe that strong sector differences exist. Moreover, all sectors show a similar pattern in the different periods. In 2003 – Lehman equity volatilities were generally low and stable around 20-40%. After the bankruptcy of Lehman Brothers equity volatilities increased sharply, as the financial turmoil sent equity prices on a several months decline. The financial and the industrial sectors had the sharpest increases in equity volatility, but several stocks in the miscellaneous sector were also affected. Nevertheless, in the later period 2011-2014, the financial turmoil calmed down, and equity volatilities returned to pre-crisis levels of around 20-35%.

Table 10:

Summary statistics for firm equity volatility[1]

	Time period							
	Total period 2003-2014		**2003 - Lehman**		**Lehman - 2010**		**2011-2014**	
	Median	Inter-quartile	Median	Inter-quartile	Median	Inter-quartile	Median	Inter-quartile
Finance	25%	(21-33)	24%	(20-30)	52%	(35-76)	24%	(20-29)
Industrial, Oil & Shipping	28%	(23-37)	30%	(26-37)	49%	(40-65)	27%	(23-35)
Miscellaneous	27%	(22-34)	27%	(23-31)	33%	(26-50)	26%	(21-35)
Utilities	30%	(23-37)	33%	(29-39)	39%	(25-48)	22%	(19-24)
Total sample	**27%**	**(22-35)**	**28%**	**(23-34)**	**45%**	**(33-66)**	**26%**	**(21-33)**

Interquartile range in paranthesis indicates the uncertainty from the 25th to 75th percentile observation.
Note 1: Equity volatility measured by the exponentially weighted moving average function, with a cap on values above 80%. (As explained in the methodology)

The real input parameter in the Merton model is not the volatility of the shareholder equity, but the volatility of the total firm value (asset volatility). In table 11, we present the development in asset volatility for our sectors. Remember that we calculate the asset volatility by adjusting equity volatility for differences in firm leverage as commented earlier. Consequently, the asset volatilities are very different for our four sectors, despite the similarities in equity volatilities seen in table 10. The financial companies have low asset volatilities, not surprising given their large amount of debt relative to equity. The median asset volatility has an interquartile range from 6% to 12%, indicating that the total firm value for banks and insurance companies are quite stable over our total sample. The effect of the financial crisis 2008 on financial companies` asset volatility was also limited. The reason is that the increased equity volatility was met by higher leverage ratios, and in total these two effects cancelled each other out. Having said that, we must emphasise that table 11 focuses only on the central tendency in asset volatility, and deviations outside the interquartile range exist.

Table 11:

Summary statistics for asset volatility[1]

	Total period 2003-2014		2003 - Lehman		Lehman - 2010		2011-2014	
	Median	Inter-quartile	Median	Inter-quartile	Median	Inter-quartile	Median	Inter-quartile
Finance	7%	(6-12)	7%	(5-15)	8%	(6-10)	7%	(6-10)
Industrial, Oil & Shipping	15%	(12-21)	18%	(16-32)	28%	(15-37)	14%	(11-19)
Miscellaneous	20%	(16-25)	20%	(16-25)	23%	(19-35)	19%	(15-24)
Utilities	13%	(10-21)	19%	(12-22)	21%	(13-25)	10%	(9-11)
Total sample	**13%**	**(7-19)**	**16%**	**(8-21)**	**12%**	**(8-24)**	**13%**	**(7-18)**

Interquartile range in paranthesis indicates the uncertainty from the 25th to 75th percentile observation.
Note 1: Asset volatility measured as leverage adjusted equity volatility mulitplied by factors explained in the methodology.

For non-financial companies the asset volatilities are generally higher. Differences between sectors are largely attributable to differences in leverage ratios, as seen in table 9. The low debt levels in miscellaneous companies contribute to relatively high asset volatility with a median of 20%, while industrials and utilities have a median of 15% and 13% respectively. Note that the asset volatility increases significantly for the industrial firms in the Lehman – 2010 period. This is a consequence of a strong increase in equity volatility that was not cancelled out by increased leverage, as for the financial firms.

The last firm parameter is the payout ratio to debt and equity holders, presented in table 12. The median issuer in our total sample pays out 3.5% of the firm value in dividends and interest expenses. There are some differences between the sectors, but in general the central tendency in all sectors lie within the total interquartile range of 2.2% to 4.7%. In our view, there is no reason to believe differences in total payout ratio relates strongly to sectors, since payments to debt and equity holders will balance according to the capital structure. On the one hand, companies with large debt levels will have large interest payments pressuring their cash flow requirements, but their relatively low share of equity will result in lower total dividends. On the other hand, companies with low debt and interest levels have more cash left over for shareholders, and naturally, they will return some as dividends. The total result is that payout ratio does not seem to be very different for a typical firm in each sector. That said, there exist significant differences in payout ratios depending on the specific issuer, which will affect credit spreads. Hence, we note that payout ratio does not seem to relate strongly to the specific sector, but it could matter for individual spread estimates.

Table 12:

Summary statistics for firm payout ratio[1]

	Time period							
	Total period 2003-2014		**2003 - Lehman**		**Lehman - 2010**		**2011-2014**	
	Median	Inter-quartile	Median	Inter-quartile	Median	Inter-quartile	Median	Inter-quartile
Finance	2.4%	(1.7-3.5)	3.4%	(2.4-4.2)	1.7%	(1.7-2.6)	2.3%	(1.6-3.1)
Industrial, Oil & Shipping	4.4.%	(3.0-5.5)	2.8%	(1.2-4.4)	3.0%	(2.3-4.8)	4.7%	(3.3-5.6)
Miscellaneous	3.4%	(2.0-4.3)	2.5%	(1.3-2.9)	3.7%	(3.3-4.1)	3.8%	(1.9-4.9)
Utilities	4.2%	(3.6-4.6)	3.8%	(2.8-4.7)	4.1%	(3.9-4.5)	4.3%	(4.2-4.4)
Total sample	**3.5%**	**(2.2-4.7)**	**3.1%**	**(2.3-4.2)**	**2.6%**	**(1.7-3.9)**	**3.7%**	**(2.3-5.0)**

Interquartile range in paranthesis indicates the uncertainty from the 25th to 75th percentile observation.
Note 1: Payout ratio measured as annual interest expense plus dividends, divided by firm value

In summary, there are patterns in the input parameters that will affect the model`s credit spread estimates. The leverage ratio relates strongly to sectors, with the highest debt levels to be found in financial companies. Among the non-financial firms, company characteristics allow firms in utilities, shipping or oil & gas to lever up to higher debt levels than their non-financial counterparts. The equity volatility seems to be stable across sectors, but the effect of the financial turmoil after the collapse of Lehman Brothers 15 September 2008 is clearly visible. For industrial firms this translates into much higher asset volatility, which ultimately is the real input factor in the Merton model. However, for financial companies the increase in equity volatility is to some extent cancelled out by increases in leverage, and the total effect on asset volatility seems limited. At last, payout ratios seem to have no clear patterns across sectors or time periods, yet, this does not imply that payout ratio will not play an important role in determining credit spread for some individual companies.

4. RESULTS

In section 4, we present the results of our analysis. The ultimate goal of this section is to determine factors that explain the credit spread puzzle, and previously we have defined three potential causes; 1) risk premiums not reflected in the Merton model, 2) systematic biases in input factors and 3) issuer specific uncertainty. In part 4.3, we develop a framework of regression analyses to determine the relative impact of each of these explanations. However, before that point, we must compare the Merton model`s estimates to real-life credit risk pricing. In part 4.1 and 4.2, we therefore dig deeper into the ability of the model to predict actual observations.

4.1 The ability of the augmented Merton model to predict actual credit risk premiums

We begin with a comparison of the model estimates to real-life observations on an aggregate level. For now, we will assume that each estimate from the augmented Merton model has no direct counterpart among actual spreads, and only see if the central tendency of the model and the actual spreads looks similar. Table 13 presents the results of this analysis, where we split the median credit spreads by different sectors and time-periods. Note that we focus on the median observation, due to arguments presented earlier that the mean statistic is extremely sensitive to large outliers in our sample.

Table 13:

Comparing the aggregate credit spread estimate of the Merton model to real-life credit pricing

		Median credit spreads (basis points)			
	Spread type:	**Total period 2003 - 2014**	**2003 - Lehman[1]**	**Lehman - 2010[1]**	**2011-2014**
Finance	Observed	41	8	62	61
	Merton model	22	6	125	26
Industrial, Oil & Shipping	Observed	366	76	401	386
	Merton model	71	9	110	93
Miscellaneous	Observed	99	28	104	179
	Merton model	1	0	18	0
Utilities	Observed	44	26	100	66
	Merton model	45	64	73	15
Total sample	**Observed**	**118**	**19**	**92**	**246**
	Merton model	**29**	**8**	**102**	**36**

In this table, we group observed and model credit spreads independently, then we report the median for each group.
Note 1: the bankcruptcy of Lehman Brothers, 15 September 2008, marks the beginning of the financial crisis 2008

Starting with the total sample estimates in the left column, we clearly see the presence of the credit spread puzzle in our Norwegian bond sample. The median estimated credit spread from our augmented Merton model is 29bps, significantly lower than the real-life median of 118bps. Thus, on an aggregate level, the Merton model strongly understates the general level of credit risk in the Norwegian bond market relative to the perception of real-life bond investors. The same result is visible in three out of four sectors, and for financial, industrial and miscellaneous companies the model`s estimates are markedly lower than the observed levels. The only exception is the utility company, Hafslund, where the Merton model hits the correct median level for the total period 2003-2014. That said, correctly predicting the median level for 2003-2014 does not necessarily imply that the Merton model does a good job of tracking Hafslund`s credit spreads. When we split the estimates into three sub-periods in table 13, we reveal that the model in fact overestimates spreads prior to the default of Lehman Brothers 2008, meanwhile underestimates the spreads in the two later periods.

On the up side, the relative rank of model spreads among sectors corresponds quite well with the observed ranking. The Merton model correctly estimates that the aggregate level of credit risk is highest among the industrial companies, with a median estimate of 71bps. This is higher than 22bps for financials, 1bps for miscellaneous and 45bps for utilities. However, a 71bps credit spread implies that the median industrial, oil and shipping company is priced as a low risk investment grade bond, standing in strong contrast to the risk perception of real-life Norwegian investors, who price the median bond at a risky high-yield 366bps. Perhaps even more worrisome is the Merton model`s estimate of the median miscellaneous company at an almost risk-free rate of 1bps. This is much lower than the actual observation of 99bps. Hence, the low accuracy of the model`s estimates seems mostly to come from the fact that the model is unable to generate high enough spreads, and not necessarily, that it is unable to predict relative levels. This tendency fits well with the results of previous literature, as studies of Huang and Huang (2003), Eom, Helwege and Huang (2004), Chen, Collin-Dufresne and Goldstein (2009) and Sæbø (2015a, 2015b) all find that the aggregate level of Merton model estimates (or variants thereof) understates the observed credit risk premiums in the market.

Columns 2, 3 and 4 show the ability of the Merton model to capture the aggregate level of credit spreads in different time-periods. The model correctly estimates that credit risk was lowest in the 2003 – Lehman period, with a total sample median of 8bps for the Merton model versus 19bps for the actual observations. After the bankruptcy of Lehman Brothers 2008, the model again correctly estimates that credit spreads should increase to a median of 102bps, which is close to the actual pricing in the market at 92bps. Nevertheless, in the later period 2011-2014 actual credit spreads continued to rise to 246bps for our total sample, due to the large entry of high-yield industrial issuers. The Merton model fails to capture this trend, and estimates that the total sample median should fall to 36bps.

In conclusion, table 13 shows clear evidence of a credit spread puzzle in the Norwegian bond market 2003-2014. The general trend is that the model strongly underestimates the aggregate level of credit risk, but under some circumstances, the model actually overstates real-life pricing. E.g., for the financial sector in the Lehman-2010 period, the model estimate of 125bps is twice as high as the median real-life spread at 62bps. The results may seem puzzling, as the miscalculation of the model appears arbitrary at this point. We must therefore increase the level of detail to get a better understanding of what drives the model`s behaviour.

In the following, we restructure our data sample, and try to uncover the uncertainty around the median level. We pair each model estimate with the actual spread counterpart, and calculate the explained percentage. For example, a 100% explained percentage would indicate that the model perfectly captures the actual credit spread levels, while a percentage below 100% will indicate an underestimation and so forth. Table 14 presents the median explained percentage, split by sectors and different time-periods. The parentheses report the interquartile range from the 25th to 75th percentile, and indicate the level of uncertainty around the median.

Table 14:

The Merton model`s explained share of actual credit spreads for different sectors and time-periods

	Explained share of observed credit spreads (%)							
	Total period 2003-2014		**2003 - Lehman**		**Lehman - 2010**		**2011-2014**	
Sectors:	Median	Inter-quartile	Median	Inter-quartile	Median	Inter-quartile	Median	Inter-quartile
Finance	42%	(3-123)	5%	(0-157)	145%	(51-382)	41%	(12-84)
Industrial, Oil & Shipping	21%	(1-72)	9%	(0-74)	23%	(2-85)	23%	(2-72)
Miscellaneous	1%	(0-12)	0%	(0-8)	16%	(1-100)	0%	(0-7)
Utilities	62%	(4-231)	168%	(12-371)	67%	(25-106)	22%	(2-56)
Total sample	**25%**	**(1-88)**	**10%**	**(0-129)**	**85%**	**(8-189)**	**25%**	**(2-71)**

In this table, we pair each model estimate with its observed credit spread counterpart. The explained share is the model estimate divided by the observed spread. We report the median explained share and interquartile range from the 25th to 75th percentile observation.

Similar to table 13, the results in table 14 highlight the tendency of the Merton model to underestimate Norwegian corporate bond spreads. The median model spread only explains

25% of the observed credit spread, quite similar to the results of previous Norwegian studies from Sæbø (2015a, 2015b). Having said that, the uncertainty around this estimate is large, and the interquartile range from 1% to 88% implies that there are large differences in the model`s ability to predict depending on the particular bond observations. Clearly, most observations understate credit risk, as three-quarters of model estimates explain less than 88% of actual spreads. Among these observations, one third explains less than 1%, as seen by the 25th percentile. The reason for this is that the augmented Merton model prices several bonds close to a risk-free 0bps credit spread. However, as real-life investors rarely do this, the explained share from the model approaches 0%. On the positive side, the 75th percentile indicates that a quarter of the observations explain more than 88%. We must note that some of these strongly overstate the actual credit risk.

The wide interquartile ranges for columns 2, 3, and 4 signal that the low precision of the model is consistent for all time-periods. Moreover, the very low 25th percentile for all time-periods implies that the Merton model has no explanatory power for about a quarter of our observations no matter the time-period. Nevertheless, the median level reveals some possible trends in the data. For instance, in the Lehman – 2010 period, the median explained share from the Merton model is 85%, which is significantly higher than in the two other periods. This points out a clear tendency for the model to explain a larger share of actual spreads in the period corresponding with business cycle downturn and financial turmoil. We see this as potential evidence of a procyclical risk premium in the Norwegian bond market, consistent with the arguments of Chen (2010). Note also that the upper 75th percentile increases to 189% during the financial crisis 2008-2010, and so a particularly large share of observations overestimate the credit risk perception of Norwegian bond investors during this period.

If we take a closer look at the development for each sector, possible systematic biases emerge. First, for utilities companies in 2003-2008 and financial companies in 2008-2010 the Merton model systematically overestimate real-life observations. The median explained share for financial firms during the financial crisis 2008-2010 is 145%, clearly indicating a strong exaggeration of credit risk. Second, model estimates for the miscellaneous sector are extremely low with an interquartile range from 0-12% for the total period 2003-2014. When we split this sector on different time-periods, we see that the model is almost insensitive to changes in economic conditions for miscellaneous companies. In the financial crisis 2008-2010, the median explained share for the miscellaneous sector only increases to 16%, up from 0% in the other periods. Thus, there seem to be systematic biases in both directions depending on the particular sector. On the one hand, for some companies the Merton model reacts too strongly to the increased volatility and leverage during the financial turmoil after Lehman Brother`s collapse. On the other hand, for other companies the model has little or no explanatory ability, almost regardless of the changes in the underlying risk parameters.

In addition to these sector trends, the model shows systematic biases when grouped according to remaining time-to-maturity, as in table 15. For short-term loans, i.e. less than 6 months to maturity, the Merton model has no predicting ability for credit spreads whatsoever. The median explained share is 0%, and the interquartile range indicates almost no variation around the median. For maturities 6-12 months, the same trend is mostly evident, with the exception of the Lehman – 2010 period. However, for bonds longer than 1 year there are clear differences. The median explained share is 22% for maturities 1-3 years, 47% for 3-6 years and 26% for above 6 years respectively. The reason for these results is that the model implied default risk approaches zero as time-to-maturity gets shorter, but increases for longer maturities. Clearly, the Merton model and real-life investors disagree on the perceived credit risk of these short-term instruments, since the model prices them as risk-free assets, while real-life investor add a small risk premium. This result is quite interesting, and similar to the findings of Huang and Huang (2003) that the underestimation is particularly strong for shorter-term maturities.

Table 15:

The Merton model`s explained share of actual credit spreads for different remaining time-to-maturity

	Explained share of observed credit spreads (%)							
	Total period 2003-2014		**2003 - Lehman**		**Lehman - 2010**		**2011-2014**	
Time-to-maturity:	Median	Inter-quartile	Median	Inter-quartile	Median	Inter-quartile	Median	Inter-quartile
Below 6 months	0%	(0-0)	0%	(0-0)	0%	(0-10)	0%	(0-0)
6-12 months	0%	(0-15)	0%	(0-2)	45%	(0-357)	0%	(0-5)
1-3 years	22%	(1-99)	10%	(0-99)	122%	(22-312)	21%	(2-79)
3-6 years	47%	(8-98)	61%	(0-273)	84%	(28-141)	43%	(10-80)
Above 6 years	26%	(7-62)	6%	(1-63)	61%	(23-107)	27%	(10-58)

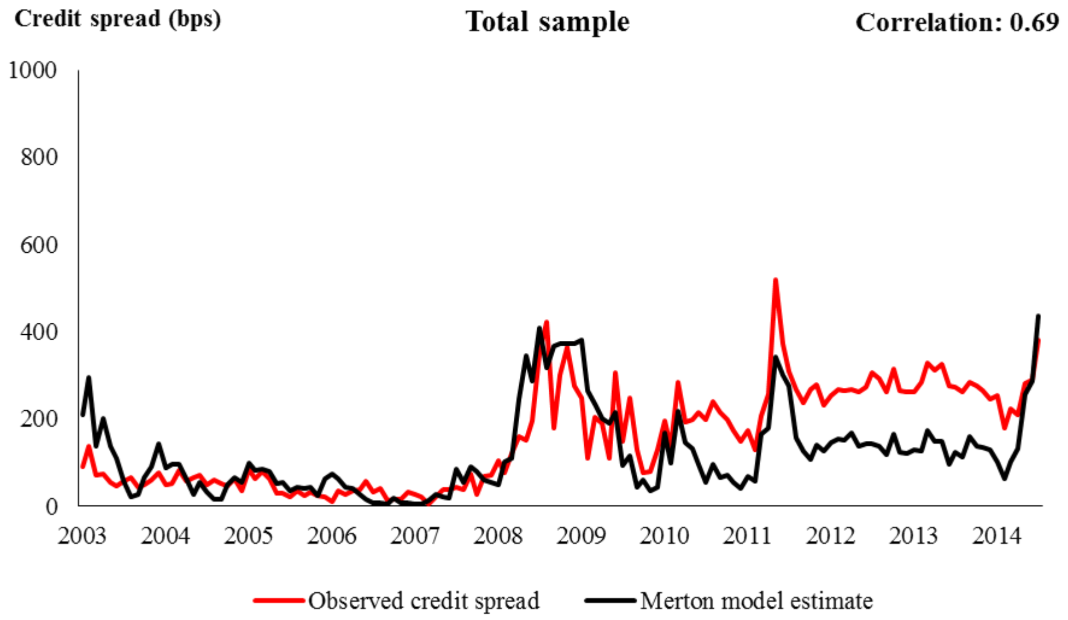
As in table 14, we pair each model estimate with its observed credit spread counterpart, and report the median explained share and interquartile range. However, we group the observations according to remaining-to-maturity.

In conclusion, part 4.1 has uncovered the strong presence of the credit spread puzzle in the Norwegian corporate bond market. Not only are there large uncertainties regarding the model`s ability to predict depending on the particular observation, but the general trend is a strong underestimation. A key summary statistic is that 75% of observations explain less than 88% of actual spreads. The results are not surprising, and the median level of 26% is close to previous studies of the Norwegian market in Sæbø (2015a, 2015b). Moreover, there seem to be systematic biases that possibly coincide with American studies of the credit spread puzzle, such as ignorance of business cyclical risk in Chen (2010) and particular problems of shorter-maturity bonds as in Huang and Huang (2003). Apparently, the implementation of the Feldhütter and Schaefer (2015) model has not changed these underlying trends in the data. However, to draw any direct conclusion on the causes of the credit spread puzzle, we must proceed with further analyses.

4.2 Time series development in model estimates and actual credit spreads

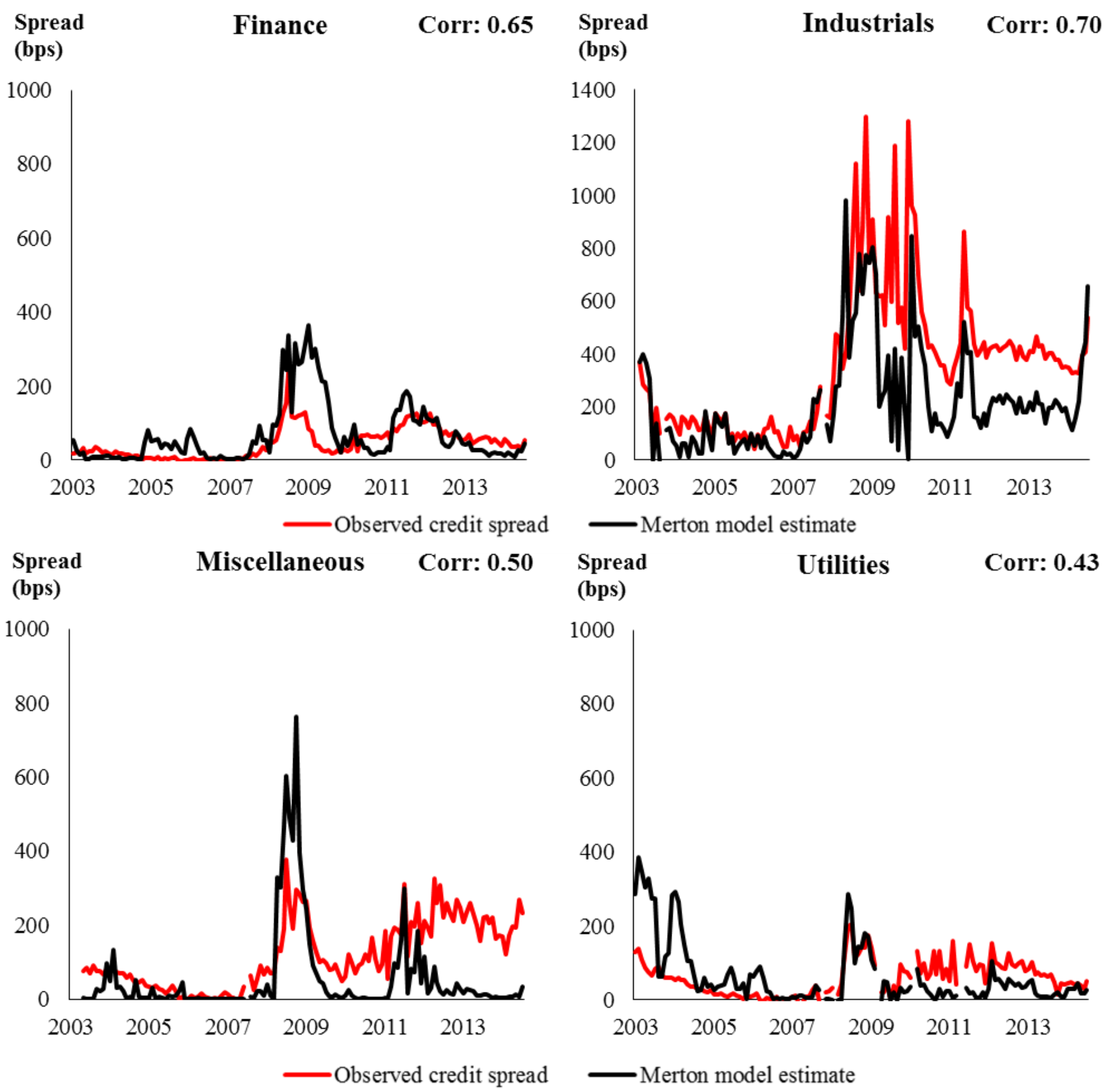
In this section, we look at another important attribute of the Merton model, which is the ability to capture time series variation in observed credit spreads. If we can prove that the model adequately captures time series development, then, in theory, we should be able to create a better model of the Norwegian corporate bond market by simply adding potential risk premiums on top of the model`s estimates. In the following, we therefore restructure our data set once more. We group all observations according to month of observations, and calculate the average spread within that month, a similar procedure to Feldhütter and Schaefer (2015).

Graph 11 presents the development in observed credit spreads versus the model estimates for our total sample from 2003-2014. The correlation between the model`s predictions and real-life observations is 69%, and indicates that the augmented Merton model has a quite good ability to capture time variations for the sample average. This is a promising sign that the model is not that far from reality as one could believe from part 4.1. In 2003-2008, the average observed credit spreads are low, and during this time-period, the Merton model`s estimates are not deviating much from this in absolute basis points. The only exception is 2003, where the model clearly overstates the average credit risk in the sample. During the financial turmoil in 2008-2009, real-life risk premiums increased to 300-400bps on average, but as we can see from graph 11, the model`s estimates captures this trend quite adequately for the total sample. Furthermore, the model spreads fall quickly in 2009, and mirror the perception of decreased credit risk in the Norwegian market. However, from 2010 and onwards, the model and the actual observations deviate quite substantially, as the model estimates stay approximately 100bps below the observed credit spreads. In our view, this trend is particularly interesting, given that a large share of our data sample are observations from this period. It seems that the strong underestimation of credit spreads is a particular phenomenon of the post-financial crisis era, and this raises questions about the existence of the credit spread puzzle before 2008. Sæbø (2015b) only include observations in 2008-2013, and so our thesis is among the first to gather data on this earlier period.



Graph 11: *The time-series development for the total sample of observed credit spreads and Merton model estimates. We follow Feldhütter and Schaefer (2015) and group credit spreads according to the month of observation. Then we calculate the average credit spread within each month.*

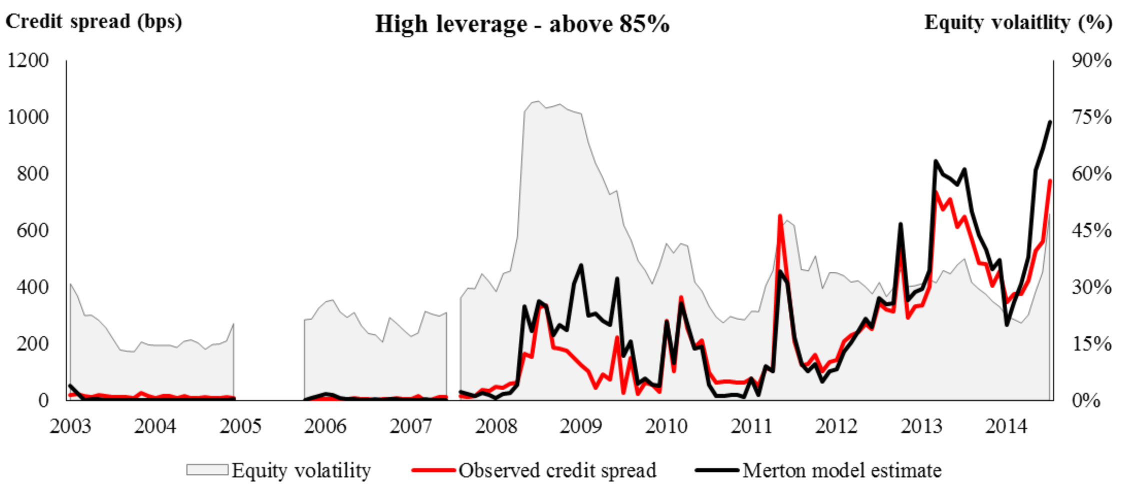
A deeper analysis reveals that the strong correlation between the model estimates and real-life observations differs substantially between sectors, as presented in graph 12. The model fit is strongest for industrial companies with a correlation of 70%, and here the model and actual spreads move closely in the early period 2003-2009. From 2010 and onwards, we again see that actual spreads decouple from the model estimates, and that the distance proves relatively constant over the later period to 2014. Nevertheless, for the other sectors, clear biases emerge. Firstly, despite the high correlation of 65% for the financial sector, graph 12 shows that there are systematic errors in the model. In 2005-2007 and 2009-2010, the model`s credit risk premiums are much larger than those used by Norwegian investors. The overestimations seem to correlate with high equity volatility, and there is a tendency for the Merton model to exaggerate the credit risk for financial bonds when equity prices move substantially. Secondly, model estimates of the miscellaneous companies are close to 0bps for large parts of the sample period, but during the financial crisis 2008, the model spreads increases sharply to 600-700bps. These estimates deviate strongly from the actual credit spreads of investors, who price miscellaneous firms higher than the model in 2003-2007 and 2010-2014, meanwhile lower than the model during the financial turmoil 2008-2009. At last, the development in the utilities sector is cluttered, with a correlation of only 43%. Clearly, something wrong happens with the model`s prediction of Hafslund`s credit spreads during the 2003-2005 period.

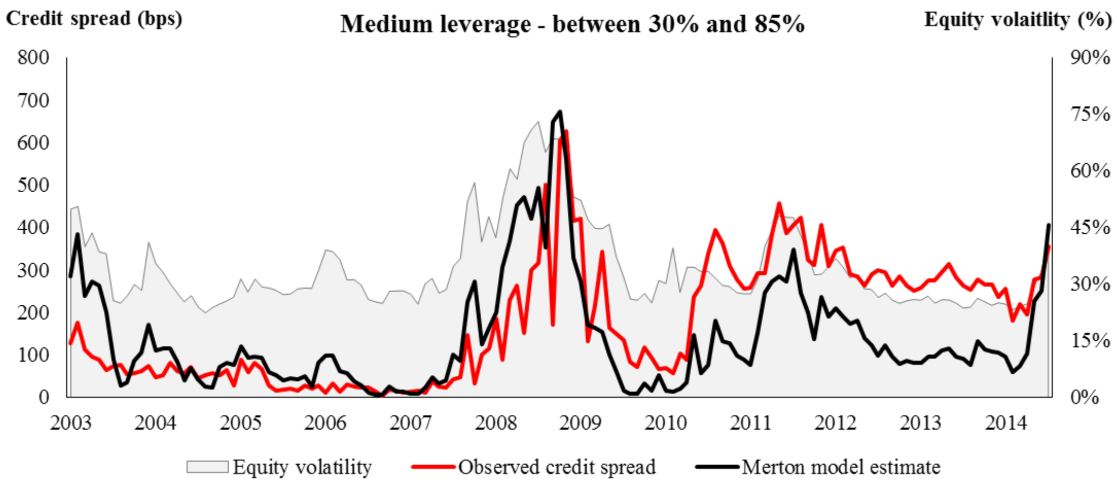


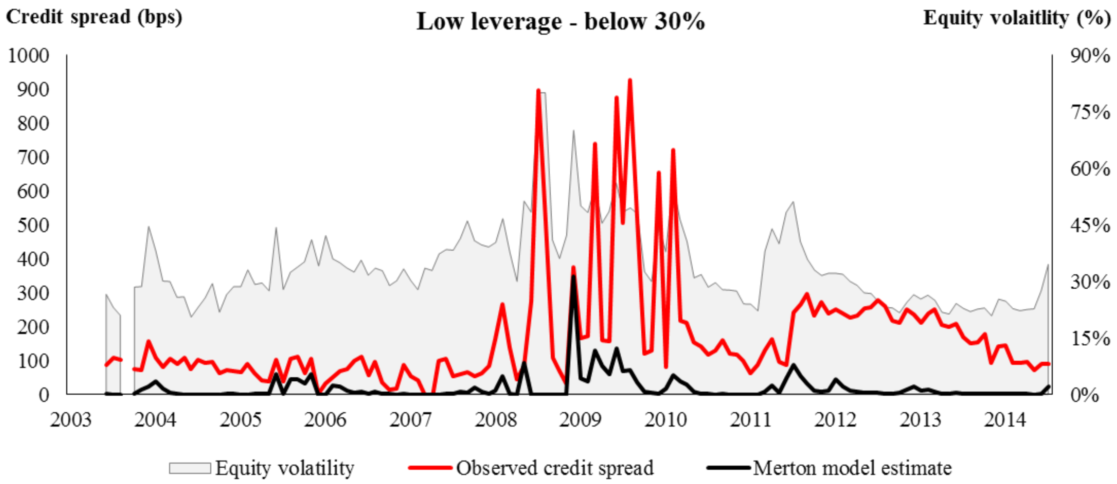
Graph 12: *The time-series development in observed spreads and model estimates for different sectors. We report the monthly average and correlation. Note that this is the relative development within each sector, and hence the y-axes have different scales for different sectors.*

Not only are there large differences between the sectors, but the model fit also greatly depends on the actual company we observe. In appendix A3, we illustrate the model estimates versus actual credit spreads for a selection of 12 companies. In some cases, the model works surprisingly well, for instance, attaining a correlation of 87%, 86% and 80% for DOF, Odfjell and Norske Skog respectively. However, in other cases the model proves useless, as with Kongsberg Gruppen, where the correlation is merely 2%. When comparing these results to the input parameters of the model, we discovered that there seemed to be a relationship between the levels of the leverage ratio and volatility measure and how well the model correlated with actual spreads. For instance, for observations with abnormally low leverage ratios or equity volatility, the model seemed to severely understate credit risk.

We decided to investigate this hypothesis further, and in graph 13, we have split the observations into three groups of leverage ratios; those above 85% leverage, those between 30% and 85% leverage and those below 30% leverage. In the background, we plot the average level of equity volatility for the particular group. As expected, graph 13 indicates that there are systematic differences in the Merton model`s ability to explain credit spreads depending on the debt leverage of the company. For high-levered companies, the correlation between the model and actual observations are impressively 95%, and contrasts the correlation of 59% and 41% for the medium- and low-levered companies. The problems of the Merton model are especially clear for the companies with leverage ratios below 30%, where the model is mostly unable to explain credit spreads. Here, it estimates credit risk premiums in the area of 0-50bps, while the real-life credit risk pricing is much higher. Hence, the augmented Merton model shows systematic bias towards underestimating credit spreads when the leverage ratio is low. Moreover, when the equity volatility increases to about 75-80% during the financial turmoil 2008-2009, the Merton model overestimates spreads for the highly levered companies. This illustrates another potential bias of the model, where it systematically overestimates credit spreads when high leverage ratios and high volatilities occur simultaneously. In total, these systematic biases correspond well with the results of Eom, Helwege and Huang (2004), who find that most versions of the Merton model underestimate spreads for safe bonds with low leverage or volatility, meanwhile overestimate spreads for bonds with the opposite characteristics.







Graph 13: *Time-series development for credit spreads from firms with different debt levels. We group observations into three groups according to the estimated leverage ratio, i.e. below 30%, above 85% and between 30% and 85%. Then we calculate the monthly average. The right axis illustrate the monthly average for the equity volatility.*

4.3 Determining potential causes of the credit spread puzzle in the Norwegian bond market

In sections 4.1 and 4.2, we compared the Merton model`s estimates to the actual level of credit spreads, but we did not systematically attribute the mispricing to different explanatory factors. In this part, we implement the regression analysis outlined in the methodology part 2.3.3. The goal of the analysis is to determine the relative importance of each factor to the credit spread puzzle in the Norwegian corporate bond market. We will judge each explanation according to three criteria: 1) the statistical significance of its coefficient, 2) the contribution to explained variance in the adjusted R^2 measure and 3) the consistency of the coefficient to economic theory. The dependent variable is the model mispricing, defined as the difference between the model estimate and the observed credit spread. Hence, a negative mispricing indicates an underestimation by the augmented Merton model, while a positive mispricing indicates an overestimation.

To determine the relative impact of each factor on the credit spread puzzle we begin with a univariate regression analysis, modelling the mispricing as a function of each explanatory factor independently. Table 16 presents the results of this analysis, and here we can see that sector stands out as the single most important explanation. Allowing the intercept to depend on sectors results in a model adjusted R^2 of 25.7%, and all coefficients are significantly different from zero. The model underestimation is clearly stronger among the industrial and miscellaneous sector relative to financial companies and utilities, as seen by the dummy coefficients. The debt leverage ratio and issuer specific equity volatility follow as the second most important factors, explaining 10.8% and 7.8% of the mispricing respectively. Both coefficients are significant and positive, and imply that the mispricing relates to these input factors similar to findings of Eom, Helwege and Huang (2004). Clearly, the model tends to underestimate credit spreads for safer bonds with low leverage or volatility, whilst overestimating those with opposite characteristics, as seen in part 4.2. The Fama & French (1993) factors for size and growth are also statistically significant. The negative coefficient on the market-to-book ratio indicate a stronger underestimation for growth companies with high ratios, while the positive coefficient on size shows that the underestimation is strongest for smaller companies. Both are consistent with economic intuition, as we expect investors to charge a risk premium for small companies or those with strong growth prospects. That said, the adjusted R^2 of the Fama & French (1993) factors are low, and these factors seem unable to explain the credit spread puzzle on their own.

Contrary to findings of Perraudin and Taylor (2003) and Longstaff, Mithal and Nies (2004) liquidity risk has a low impact on the model mispricing in our sample. Even though the coefficients on both the bond size variable and the TED-spread are statistically significantly in table 16, we cannot conclude that they capture any real-economic effects. The reason is that both coefficients are inconsistent with economic theory, in addition to very low adjusted R^2 measures. Moreover, neither firm payout ratio nor business cycle risk are able to predict the model mispricing. The p-value of both variables are high, and the explained variances are low with 0.0% adjusted R^2. For time-to-maturity the R^2 squared of 2.1% indicates a systematic tendency. However, as the coefficient in table 16 is negative, the interpretation contradicts with the results of Huang and Huang (2003) that the mispricing is particularly strong for shorter maturities. We therefore believe that this variable might be capturing other unexplained effects, when modelled independently.

Table 16:

Results of the univariate regresssion analysis for the nine explanatory factors [1]

Factor	Coefficient	P-value	Adjusted-R^2	According to theory?[2]
Risk premiums:				
Liquidity 1: Bond size	-11.39	0.001	0.1%	No
Liquidity 2: TED-spread	0.36	< 0.001	0.3%	No
Sector dummies[3]:			25.7%	Yes
1) Finance	14.48	< 0.001		
2) Industrial	-168.46	< 0.001		
3) Miscellanous	-108.65	< 0.001		
4) Utilities	25.54	< 0.001		
Size premium: Log market cap	14.62	< 0.001	0.8%	Yes
Growth premium: Market-to-book	-45.02	< 0.001	3.3%	Yes
Business cycle risk: Return OSEAX	-0.62	0.961	0.0%	Yes
Systematic input factor biases:				
Debt leverage ratio	294.71	< 0.001	10.8%	Yes
Issuer specific equity volatility	443.57	< 0.001	7.4%	Yes
Payout ratio to debt and equity	103.51	0.441	0.0%	Yes
Time-to-maturity	-16.98	< 0.001	2.1%	No

The univariate analysis follows a simple regression model with the listed factors as the only independent variable, plus a constant. We report the coefficient for the explantory factor, the p-value for the t-test of the coefficient and the r-squared of the univariate regression.
Note 1: The model mispricing is the dependent variable. Defined as model spread - actual spread. Note 2: The right column indicate if the sign of the coefficient follow economic intuition/previous literature. Note 3: The univariate regression with sector dummies include no constant, and only the four dummy variables.

It seems surprising that neither time-to-maturity nor business cycle risk are able to explain the model mispricing, as the results in part 4.1 looked promising for both factors. However, there is a natural explanation. Firstly, the strong underestimation we saw in table 15 relates to the explained percentage for time-to-maturity, i.e. mispricing in relative terms. In the univariate regression we measure mispricing in absolute basis points, and here the opposite is true. The longer the maturity of the bond, the stronger the underestimation in basis points. Secondly, in table 14, the median explained share of the model seemed to be countercyclical, consistent with a potential business cycle premium as argued in Chen (2010). Interestingly, the negative coefficient for OSEAX return in table 16 is consistent with that, but the coefficients is not statistically significant and the R^2 is 0.0%. We therefore have no reason to believe that the trend reflects any actual cyclical risk premiums, and it must instead have captured other effects.

Several of the explanatory variables are possibly interrelated, and we continue the analysis with multivariate models combining different factors. Table 17 presents the results of part 1 of the multivariate regression analysis, where we focus primarily on factors reflecting potential risk premiums. Model 1 combines sector premiums with the Fama & French (1993) factors for size and growth. Similar to the results of the univariate analysis, we see that sector and growth are both statistically significant and consistent with economic theory. Even though the sector coefficients have changed from table 16, the internal rank stays stable. The general trend is that industrials have the lowest mispricing, followed by miscellaneous companies. Financial companies and utilities have the highest mispricing, and due to the large standard errors, the difference between them is statistically negligible.

The coefficient for the market-to-book ratio still points to a potential risk premium for growth companies in model 1. However, the size coefficient turns negative and contradicts economic intuition, and it seems that issuer size has no additional power once we control for sector and growth. The adjusted R^2 of 27.3% is slightly lower than the sum of the independent R^2 measures from the univariate analysis, highlighting that these four explanations of the credit spread puzzle overlap, although to a low degree. Note that the precision of the model is very low with an average standard error of regression of 199.8 bps. There is clearly a large unexplained portion of the credit spread puzzle in model 1.

In model 2, we include liquidity risk as a potential explanatory factor. Despite being statistically significant, neither the coefficient for bond size nor the coefficient for TED-spread follow economic theory, and we must conclude that they capture no real-economic effects. Furthermore, the adjusted R^2 of model 2 is only 0.3% higher than model 1, underlining the low effect of both liquidity measures. Thus, it seems liquidity risk is unable to explain the credit spread puzzle after controlling for sector and the Fama & French (1993) factors. In fact, the only two factors staying consistent with economic intuition are sector and growth, as in model 1. In spite of the dramatic changes to sector coefficients, the internal rank stays true to model 1. In addition, the joint χ^2 test for sector dummies imply that the coefficients are significantly different, reflecting, as previously, that sector may be an important driver of model mispricing. Model 2 is also interesting relative to Sæbø`s (2015a) Norwegian corporate bonds analysis, since we include many of the same factors as him. In his article, Sæbø finds that sector, size and liquidity are the main drivers of model mispricing, yet our results bear signs that neither issuer size nor liquidity are actually important. To the contrary, a high market-to-book ratio for growth companies seems to be a far more important factor.

Table 17:

Results of part 1 of the multivariate regression analysis[1]. Models 1-2 includes risk premium explanations only. Models 3-5 illustrate the relative impact of cyclicality or issuer specific shocks when controlling for risk premiums.

Factors included as independent variable	Model (1): Sector + Fama & French	Model (2) Sector, Fama & French + Liquidity	Model (3): Risk premiums + business cycle risk	Model (4): Risk premiums + issuer specific volatility	Model (5): Risk premiums + volatility and cyclicality
Sector 1: Finance	**173.86*** (30.38)**	**535.59*** (65.90)**	**531.06*** (70.56)**	**420.57*** (59.16)**	**221.08*** (59.72)**
Sector 2: Industrials	-11.35 (29.91)	**357.56*** (66.65)**	**352.48*** (71.07)**	**237.77*** (59.94)**	41.11 (60.31)
Sector 3: Miscellanous	**74.91** (30.93)**	**433.95*** (64.96)**	**429.60*** (69.43)**	**315.25*** (58.08)**	**122.25** (8.67)**
Sector 4: Utilities	**180.31*** (28.03)**	**549.11*** (65.29)**	**542.87*** (70.16)**	**431.43*** (58.58)**	**217.57*** (59.42)**
Size: Log market cap	-7.38*** (1.81)	-0.88 (1.98)	-0.98 (2.00)	2.22 (1.88)	**3.77** (1.87)**
Growth: Market-to-book	**-30.22*** (3.26)**	**-32.31*** (3.23)**	**-33.21*** (3.26)**	**-25.61*** (2.55)**	**-31.59*** (2.52)**
Liquidity 1: Bond size		-23.50*** (3.60)	-22.72*** (3.69)	-27.25*** (3.55)	-21.57*** (3.54)
Liquidity 2: TED-spread		0.18*** (0.07)			
Cyclicality: Return OSEAX			-1.97 (12.42)		168.61*** (13.57)
Issuer specific volatility				**454.22*** (29.77)**	**574.08*** (33.71)**
χ^2 - test for sector (p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
# observations	13,560	13,560	13,560	13,560	13,560
Adjusted R^2	27.3%	27.6%	27.6%	34.3%	36.0%
Avg. standard error (bps)	199.8	199.3	199.4	189.9	187.3

*The multivariate analysis follows a multiple regression model with the listed factors as independent variable. We do not include a constant, since we include all sector dummies. For each factor we report the coefficient value and standard error in paranthesis. We use heteroscedasticity robust standard errors. The asterixes denote the following levels of statistic significance; *** 1% level, **5% level, *10% level.* ***Coefficients that are both stastically significant on a 5% level, and follow economic intuition are outlined in bold font.*** *The $\chi 2$ - test for sector test the joint hypothesis of equal dummy variables.*

Note 1: The model mispricing is the dependent variable. Defined as model spread - actual spread.

In models 3-5 in table 17, we compare the relative impact of business cycle risk and issuer specific volatility after controlling for other risk premiums. As the TED-spread is highly correlated with the cyclicality of the OSEAX return, we test the models without this factor. In short, model 3 confirms the results of the univariate analysis that business cycle risk is not an important explanatory factor for model mispricing. The coefficient for OSEAX return is not significant at a 5% level, and neither the adjusted R^2 nor the average standard error of regression indicate a model improvement of including this factor. For that reason, Chen`s (2010) argument that investor`s charge an additional premium in booming economies to protect for upcoming recessions seems not to be the case in the Norwegian corporate bond market. Instead, model 4 reveals that we should focus our attention on issuer specific volatility, as the inclusion of this factor improves the model fit on the adjusted R^2 and the average standard error of regression. The coefficient is positive and clearly significant, highlighting the systematic tendency for the model mispricing to correlate with the volatility level as described by Eom, Helwege and Huang (2004). So even after adjusting for other risk premiums, the Merton model seems to underestimate the credit risk of bonds with low volatility relative to real-life investors. On the one hand, the result suggests that the model has systematic biases in its specification of the volatility measure. On the other hand, as issuer specific volatility is more important than cyclicality, it could be the case that Norwegian investors are more afraid of idiosyncratic shocks to the specific issuer rather than systematic shocks to the overall economy. This latter explanation could be consistent with Huang and Huang (2003) and Chen (2010), who argue that idiosyncratic jump-risk can explain parts of the credit spread puzzle.

The combination of both cyclicality and issuer specific volatility in model 5 does not change any of the aforementioned conclusions. The coefficient for the return on OSEAX turns positive, the opposite of what we expect from Chen`s (2010) model with countercyclical risk premiums. Thus, this variable must capture some other effect not necessarily related to business cycle risk premiums in the model 5 specification. Moreover, models 3-5 in table 17 have interesting implications for the other explanatory factors, and sector and growth prove to be robust factors over all models. The sector coefficients changes for each model, but as mentioned, the interesting aspect is that the relative rank is consistent and that the joint χ^2 test indicates that the dummies are significantly different. Issuer specific liquidity, approximated by bond size, is significant across all models, but with the wrong sign on the coefficient. Like the cyclicality proxy, this variable cannot reflect an underlying risk premium, and must be capturing other non-specified effects. Interestingly, size turns positive and statistically significant in model 5. Consequently, there may be small signs of a risk premium on smaller companies once we control for other factors, although the impact seems almost negligible due to the unstable coefficient for this parameter.

In table 18, we present the results of the second part of the multivariate analysis, where we allow the mispricing to correlate with the input parameters of the augmented Merton model in addition to the risk premiums. Model 6 presents a specification with the input parameters for debt leverage ratio, firm payout ratio and time-to-maturity as the only explanations for model mispricing. Both the coefficient for debt leverage and the coefficient for firm payout are positive and significant, and imply that high ratios correlate with model overestimation, while low ratios correlate with underestimation. Time-to-maturity, on the other hand, has a negative coefficient, whose interpretation still conflicts the findings of previous literature. As the debt leverage ratio has the highest explained variance in the univariate analysis in table 16, we expect this parameter to be the main contributor to the adjusted R^2 of 12.3% in model 6. However, it is interesting to see that payout ratio turns statistically significant once we control for the debt leverage and maturity, especially since this variable was insignificant in the univariate analysis. The result indicate that although payout is not the primary driver of model mispricing, it can be an important factor to explain why the model misprices the credit risk for specific companies with excessive high or low payout to debt and equity holders.

Models 7-8 test the relative impact of issuer specific volatility and cyclicality risk once we control for systematic biases in the other input parameters. Similar to models 3-5 in table 17, there are no evidence of business cycle risk premiums, and we find that issuer specific volatility is a far more important factor. The inclusion of issuer specific volatility in model 7 raises the adjusted R^2 to 17.6%, and the coefficient is significantly positive likewise to models 4 and 5. The model specifications once again indicate that our augmented Merton model misprices Norwegian corporate bonds just as predicted in Eom, Helwege and Huang (2004), where the model underestimates the risk of safe bonds with low leverage or volatility. Clearly, a potential cause of the credit spread puzzle can be that these input parameters mispresent the actual credit risk perceived by investors in the Norwegian corporate bond market. All models 6-8 have a negative coefficient for the time-to-maturity factor, and we now feel that it is safe to claim that the findings of Huang and Huang (2003) are not transferable to our data sample.

Table 18:

Results of part 2 of the multivariate regression analysis[1]. Model 6 presents the effect of input factors only. Model 7-8 illustrate the relative impact of cyclicality or issuer specific shock when controlling for input factors. Models 9 combines the risk premiums with potential biases in model inputs. Model 10 removes insignificant factors, and Model 11 sets a baseline model.

Factors included as independent variable	**Model (6):[2] Input factors only**	**Model (7)[2] Input factors + issuer specific volatility**	**Model (8):[2] Input factors + cyclicality**	**Model (9): All risk premiums + input factors**	**Model (10): Removing bond size, cyclicality, maturity and sectors**	**Model (11): Base model**
Constant	-248.62*** (9.79)	-352.52*** (10.81)	-264.32*** (10.53)		-987.20*** (27.03)	
Debt leverage ratio	**293.47*** (8.35)**	**271.16*** (8.77)**	**300.01*** (8.29)**	**256.74*** (12.20)**	**329.80*** (8.93)**	**199.80*** (12.75)**
Firm payout ratio	**739.41*** (135.05)**	**581.19*** (128.33)**	**828.41*** (134.84)**	**2475.55*** (127.39)**	**1419.61*** (127.16)**	**2193.52*** (132.24)**
Time-to-maturity	-12.78*** (1.00)	-10.90*** (0.9)	-13.00*** (0.98)	-4.66*** (0.80)		
Issuer specific volatility		**376.34*** (29.70)**		**595.88*** (33.59)**	**495.26*** (32.38)**	**524.67*** (32.16)**
Cyclicality: Return OSEAX			54.31*** (12.08)	173.82*** (13.50)		
Sector 1: Finance				41.82 (58.94)		**-420.34*** (31.22)**
Sector 2: Industrials				-94.38 (59.27)		**-592.50*** (29.38)**
Sector 3: Miscellanous				26.99 (56.79)		**-460.39*** (28.88)**
Sector 4: Utilities				65.21 (58.67)		**-410.89*** (28.53)**
Size: Log market cap				**25.11*** (1.74)**	**32.72*** (1.6)**	**5.89*** (1.69)**
Growth: Market-to-book				**-5.83** (2.30)**	1.84 (2.37)	
Liquidity 1: Bond size				-44.06*** (3.02)		
Liquidity 2: TED-spread				**-0.48*** (0.07)**	**-0.95*** (0.08)**	**-0.99*** (0.08)**
χ^2 - test for sector (p-value)				< 0.001		< 0.001
# observations	13,560	13,560	13,560	13,560	13,560	13,560
Adjusted R^2	12.3%	17.6%	12.6%	41.2%	21.3%	38.4%
Avg. standard error (bps)	206.2	199.9	205.9	179.6	195.3	183.9

*The multivariate analysis follows a multiple regression model with the listed factors as independent variable. We do not include a constant when we include all sector dummies. For each factor we report the coefficient value and standard error in paranthesis. We use heteroscedasticity robust standard errors. The asterixes denote the following levels of statistic significance; *** 1% level, **5% level, *10% level.* ***Coefficients that are both stastically significant on a 5% level, and follow economic intuition are outlined in bold font.*** *The $\chi 2$ -test for sector test the joint hypothesis of equal dummy variables*

Note 1: The model mispricing is the dependent variable. Defined as model spread - actual spread.

Note 2: Models 6-8 include a constant since sector dummies are excluded.

In model 9, we combine all risk premiums with the input parameters, and the adjusted R^2 increases to 41.2%. Similar to models 6-8, the coefficients on debt leverage, issuer specific volatility and firm payout are statistically significant and positive. Obviously, the results of Eom, Helwege and Huang (2004) seem robust to the inclusion of other risk premiums. Neither of the sector dummies are statistically significant, but the joint χ^2 test and the rank stay consistent with previous findings. This is an interesting result, as a possible interpretation is that the sector dummies to a large degree reflect the differences in debt leverage among sectors (seen in table 9 in the descriptive statistics), with the consequence that when we control for leverage the sector dummies approach zero. In addition, model 9 points out an additional effect of size and growth after controlling for the model input factors. Model specification 9 is also the first to reveal a potential liquidity premium, as seen by the negative coefficient for the TED-spread. The interpretation could be that increasing TED-spreads following a "flight to safety" from the interbank market to government bonds transfer into a stronger underestimation of the model due to additional liquidity premiums.

In model specifications 10 and 11, we build a baseline model for the credit spread puzzle. Due to the results of the previous models, we feel confident that the variables for maturity, bond size and cyclicality capture no real-economic explanation, and we therefore exclude these factors from the base model. However, the effect of sector seems uncertain because of the aforementioned linkage to the leverage ratio, and so we want to test the consequence of excluding sector as an explanatory factor. Model 10 implements this hypothesis, where we have substituted the sector dummies with a unified constant term. The difference to model 9 is dramatic, as the adjusted R^2 drops to 21.3% and the average standard error of regression widens to 195.3bps. In our view, the result highlights the importance of allowing for different sector intercepts in explaining the model mispricing, even after controlling for differences in debt leverage across sectors. Therefore, sector seems an important factor in explaining the credit spread puzzle. On top of that, the exclusion of other factors in model 10 renders the growth coefficient statistically insignificant, and a further analysis reveals that this factor is negatively correlated with the debt leverage ratio. This raises questions about the existence of the growth premium, as it potentially is just a smaller part of the biases related the debt leverage ratio.

In the end, we end up with a baseline specification to the credit spread puzzle according to model 11. On the one hand, there is a clear positive correlation between the model mispricing and the input parameters for debt leverage, issuer specific volatility and the firm payout ratio, consistent with Eom, Helwege and Huang (2004) and our results in part 4.2. On the other hand, sector is a non-negligible risk factor, and we find a robust ranking of sectors across all models. Norwegian investors price industrial companies on a consistently higher premium to the Merton model than in other sectors, even after controlling for other factors. In addition, the baseline model suggests that the factors of macroeconomic liquidity (TED-spread) and issuer size may be other contributing explanations to the puzzle. As these factors prove less stable across different model specifications, it is uncertain to what extent these two premiums actually holds for all Norwegian corporate bonds in the sample. The adjusted R^2 of 38.4% indicates that the baseline specification explains a substantial amount of the model mispricing. We therefore feel confident that the total combination of the aforementioned factors could be important explanations of the credit spread puzzle in our Norwegian bond sample. However, a substantial amount of variance in the data remains unexplained, and the credit spread puzzle is to a large degree attributable to issuer specific uncertainty. The wide standard error of regression of 183.9bps highlights that behind the systematic trends, credit risk pricing of Norwegian corporate bonds remains mostly a case-by-case procedure. Hence, Norwegian investors must place additional weight on other issuer-specific factors not included in our analysis.

In the following, we do some additional robustness tests of our results. In table 19, we present five model specifications, where we use the baseline model 11 on different subgroups of our data sample. Model 12 illustrates the effect of excluding outliers from the data sample. Here, we define outliers as observations outside the 1^{st} and 99^{th} percentile mispricing, and to a large degree model 12 is true to the results of model 11. The coefficients on the model input factors for leverage, volatility and payout stay positive and statically significant, and the same is true for the TED-spread proxy for macroeconomic liquidity risk. As previous, the sector coefficients move in absolute value, but the relative rank and the joint χ^2 test are in line with previous conclusions.

In model 12, the coefficient for issuer size changes to negative, and highlights our suspicion that size premiums not necessarily hold for the wider data sample. In fact, it seems that the outliers that we exclude from the sample in model 12 were the key drivers of the previously significant size premium. The adjusted R^2 of the trimmed model 12 increases to 56.2%, and the large jump from model 11 suggests that the systematic trends in the mispricing are stronger than first assumed, and that the issuer specific uncertainty to a large extent relates to outlier observations.

Table 19:

Results of part 3 of the multivariate regression analysis [1]. Model 12 illustrate the baseline model where we trim the dataset for potential outliers. Model 13-16 present the basline model 11 on the different sectors [2].

Factors included as independent variable	**Model 12: Trimmed dataset[3]**	**Model 13: Finance**	**Model 14: Industrials**	**Model 15: Miscellanous**	**Model 16: Utilities**
Constant		-124.77*** (13.35)	-692.50*** (94.16)	-1577.12*** (59.27)	6096.33*** (700.55)
Debt leverage ratio	**124.99*** (7.35)**	**34.01*** (8.03)**	**297.00*** (23.70)**	**92.36*** (28.05)**	-1263.46*** (155.32)
Firm payout ratio	**1304.76*** (68.47)**	**1166.38*** (127.28)**	**2222.79*** (199.43)**	**1299.04*** (178.63)**	**1736.64*** (452.35)**
Issuer specific volatility	**523.21*** (11.10)**	**502.81*** (9.29)**	**627.71*** (74.12)**	**231.94*** (42.48)**	**571.86*** (23.44)**
Sector 1: Finance	**-201.86*** (17.66)**				
Sector 2: Industrials	**-378.95*** (16.44)**				
Sector 3: Miscellanous	**-270.35*** (17.68)**				
Sector 4: Utilities	**-200.75*** (16.55)**				
Size: Log market cap	-2.34*** (0.89)	-2.64*** (0.79)	8.00 (5.28)	**76.75*** (3.43)**	-349.98*** (38.40)
Liquidity 2: TED-spread	**-0.92*** (0.04)**	**-0.64*** (0.07)**	**-1.48*** (0.17)**	0.38* (0.21)	**-0.73*** (0.09)**
χ^2 - test for sector (p-value)	< 0.001				
# observations	13,288	5,113	6,080	1,449	918
Adjusted R^2	56.2%	41.6%	16.6%	39.5%	68.9%
Avg. standard error (bps)	120.2	84.5	249.0	114.1	50.2

*The multivariate analysis follows a multiple regression model with the listed factors as independent variable. We do not include a constant when we include all sector dummies. For each factor we report the coefficient value and standard error in paranthesis. We use heteroscedasticity robust standard errors. The asterixes denote the following levels of statistic significance; *** 1% level, **5% level, *10% level.* ***Coefficients that are both stastically significant on a 5% level, and follow economic intuition are outlined in bold font.*** *The $\chi2$ - test for sector test the joint hypothesis of equal dummy variables.*
Note 1: The model mispricing is the dependent variable. Defined as model spread - actual spread.
Note 2: Models 13-16 include a constant since sector dummies are excluded when we regress each sector independently.
Note 3: The trimmed dataset removes observations with mispricing outside the 1st and 99th percentile.

Models 13-16 test the baseline specification on the different sectors, with several interesting results. Firstly, with the exception of the utilities sector all input factor coefficients are consistent with the findings of Eom, Helwege and Huang (2004). Yet, the absolute magnitude of each factor is very different, and we see that the coefficients for the industrial sector for debt leverage, volatility and firm payout are all greater than in the other sectors. Generally higher spreads among industrial companies could be the cause. On the other hand, the larger coefficients show that the model mispricing is more sensitive to large input parameter changes among the industrial companies, and, in our view, this corresponds well with the interpretation of the industrial sector as highly cyclical. More specifically, if we assume Norwegian investors expect the industrial sector to move a lot in strong business cycles, it is natural that they will charge an additional credit risk premium for these bonds as the debt leverage and volatility may understate the true credit risk if the business segment is moving in an upward cycle. This argument might also explain why the industrial sector`s dummy is consistently lower than the other sectors for all model specifications, since Norwegian investors might charge an additional risk premiums for holding these bonds.

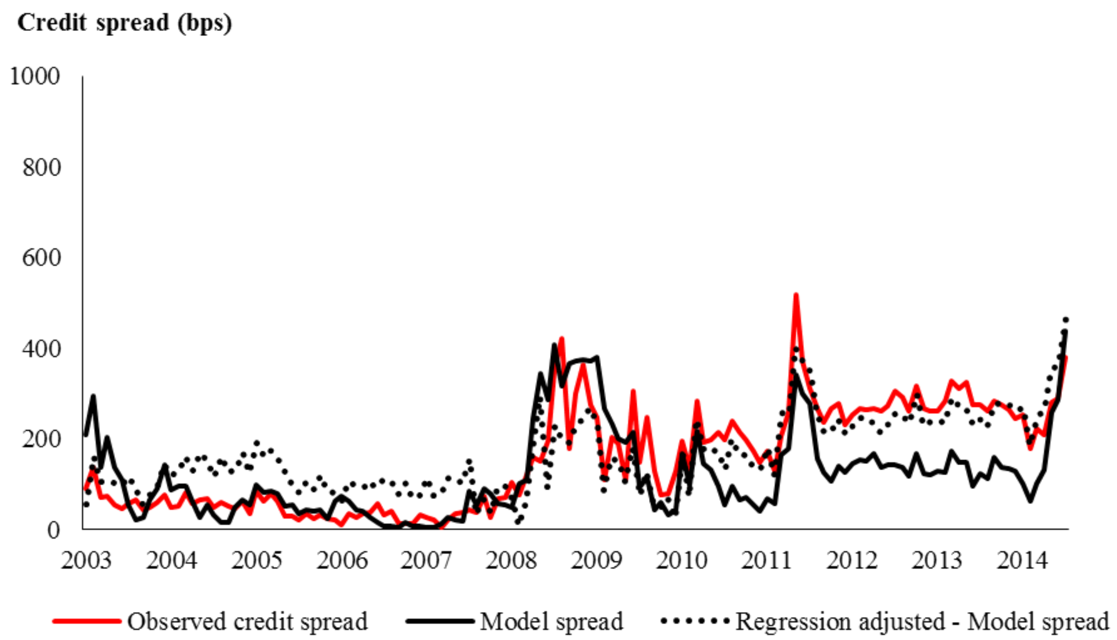
Secondly, the subgrouping to different sectors reveals that both the liquidity and size premium not necessarily hold for all sectors. For example, the size premium is significant and in line with economic intuition in the miscellaneous sector only. This may not be surprising as there are large size differences within the miscellaneous sector, while the differences are much smaller in the other sectors. One interpretation is that the size premium is mostly important for excessively small companies, and since the financial, industrial and utilities sectors mostly include large public-traded companies there are no real practical consequences to size difference among these companies. To the contrary, macroeconomic liquidity risk from the TED-spread seems important for these sectors with large issuers, and only the miscellaneous sector have a statistically insignificant TED-spread coefficient.

At last, we note that the adjusted R^2 deviates substantially between the sectors, and the measure is clearly lowest among the industrial companies. Hence, we must conclude that the issuer specific uncertainty is strongest in this sector, not surprising, given that the industrials constitute of a much wider range of different companies than the other sectors.

5. DISCUSSION

5.1 There is a clear credit spread puzzle in the Norwegian corporate bond market

The results of our analysis point to a large credit spread puzzle in the Norwegian corporate bond market. The general trend is a strong underestimation, where three-quarters of model estimates explain less than 88% of actual spreads. However, the results are not necessarily surprising, and the median level of 26% is close to previous studies of the Norwegian bond market in Sæbø (2015a, 2015b). It seems apparent that the Feldhütter and Schaefer (2015) model cannot alter this general trend in the data. Nevertheless, the model is quite good at capturing time-series variations, and we believe that the Merton model can attain a much better fit to the Norwegian bond market if we are able to adjust for the in general too low level of model estimates. In part 4.3, we proved that the model mispricing correlates with systematic biases in input factors or risk premiums not reflected in the model. In graph 12, we compare a regression-adjusted model to the original specification to illustrate how adjusting for these factors might potentially improve the model fit.



Graph 14: *Comparing the model fit for the regression-adjusted model spread to the original model. All series present monthly averages.*

These simple regression-adjustments have a dramatic effect on the augmented Merton model`s ability to explain actual credit spreads. The median observation of the regression-adjusted model explains 93% of the median observed credit spreads, and the time-series correlation between the average spread levels is 84%. Thus, on an aggregate level, the regression-adjustments show a significant improvement to the model fit. Having said that, the large issuer specific uncertainties are still present in the regression-adjusted model, and for practical purposes, the precision of the augmented Merton model is very low. We therefore believe it is important to address the issues of the model in future specifications. In the following, we elaborate on the possible explanations of the credit spread puzzle in more detail.

5.2 Explanation 1: Risk premiums not reflected in the Merton model

The most common explanation to the credit spread puzzle is that the Merton model disregards important risk factors for bond investors, such as bond liquidity, issuer size, sector dependence or systematic business cycle risk. In our regression analysis in part 4.3, we showed that the mispricing of the model correlates with several of these factors, and it is important to understand how the factors potentially affect the pricing of credit risk in Norwegian corporate bonds.

5.2.1 Sector premiums: Cyclicality or risk aversion?

The univariate regression analysis in part 4.3 revealed that sector was the single most important explanation of the credit spread puzzle in our Norwegian bond sample. Allowing the regression model to have different intercepts for each sector explained 25.7% of the mispricing alone. This finding is not new for the Norwegian bond market, and Sæbø (2015a) finds that sector accounts for about 46% of the mispricing in his study of Norwegian corporate bonds 2008-2009. Based on these results, it seems clear that Norwegian bond investors place a much larger weight on the sector of the issuer than the Merton model. However, as sector definitions per se cannot be regarded as an economically viable risk premium, there must be other underlying factors that make some sectors appear particularly risky in the eyes of Norwegian bond investors.

One possibility is different sector cyclicality. In the multivariate analysis in part 4.3, the industrial companies had consistently the lowest sector dummy coefficient, even after controlling for leverage ratio and issuer-specific volatility. In our view, this could indicate that Norwegian investors demand an additional risk premium for holding industrial sector bonds, relative to bonds issued by firms from other sectors. As many of the industrial companies are in oil & gas production, oil services or shipping, it seems possible that this risk premium reflects investors' risk aversion towards the cyclical nature of these business segments. More specifically, if investors know that the profitability of these companies moves in strong cycles, they naturally expect that the leverage ratio and equity volatility tend to underestimate the underlying credit risk when the company is in an upward cycle. Therefore, in time-periods of strong economic profits, investors might demand an additional risk premium to compensate them for the risk that the cycle may end. The regression analysis in table 19 in part 4.3 shows that the mispricing of bonds in the industrial sector is more sensitive to an excessively high or low leverage ratio or volatility. This observation supports the view that investors believe that the leverage ratio or volatility measures may be especially misleading for these companies depending on the sector cycle.

On the other hand, a sector risk premium could reflect more psychological reasons, and not necessarily cyclicality. Sæbø (2015b) argues that the mispricing between his augmented Merton model and actual spreads can be interpreted as investor`s risk aversion towards particular bond types. For example, some bond investors may exhibit extra aversion towards high-yield bonds, potentially due to larger asymmetric information for these issuers. Since the industrial sector in our sample is almost exclusively high-yield bonds according to Stamdata`s registers, the sector risk premium could instead be a signal of risk aversion towards high-yield bonds in general, and not industrial sector bonds per se.

There is also a strong link between the debt leverage ratio and the sector specifications in our sample, as seen in table 9 in the descriptive statistics. The leverage of financial companies and utilities are consistently higher than for miscellaneous companies and industrials. Thus, the important role of sectors is potentially correlated with the systematic biases of the leverage ratio. Particularly for miscellaneous companies, who mostly have low debt leverage, there could be an overlap between the explanation of sector premiums and the potential errors in debt leverage. However, as the leverage ratio is generally quite high among industrial companies, debt leverage alone cannot explain the risk premium for this sector. It is therefore likely that the sector premiums relative to the Merton model are driven by factors unknown to us at this point. As our sector definitions are quite broad, it is also possible that the effect of sector would be even larger, if we allowed for more nuanced sector definitions.

5.2.2 The Fama and French (1993) factors for size and growth exist in the Norwegian market, but only to a limited extent

Elton, Gruber, Agrawal and Mann (2001) is one of the first studies to decompose corporate bond spreads. They find that direct default risk only explains a smaller amount of observed credit spreads in the American bond market, and they list taxes and other risk factors as potential candidates. Among these are the systematic risk factors related to size and growth, as discovered by Fama and French (1993) for stocks. Elton, Gruber, Agrawal and Mann

(2001) argue that as much as 85% of the spread not explained by default and taxes relates to these systematic risk factors. The idea is that investors exhibit particular risk aversion towards small companies or those with large growth prospects, and that this translates into an additional risk premium on the corporate bond credit spreads.

The previous Norwegian study by Sæbø (2015a) finds that a significant part of the credit spread puzzle in Norway is consistent with a size premium for bonds issued by smaller companies. From an average credit spread of 315bps, Sæbø estimates that size accounts for roughly 20bps. He argues that this premium reflects aversion towards smaller companies, potentially due to lower liquidity for smaller companies` bonds. In our thesis, we cannot find the same importance for issuer size. The univariate analysis predicts that size accounts for merely 0.8% of the mispricing, and when combining size with other explanations, the coefficient for size is unstable. We therefore raise question about the viability of this premium, at least as a general premium for all bonds in the Norwegian sample. One potential reason for this is that the size premium only exists for large size differences, where bond investors have reason to believe that the lack of size presents a risk of asymmetric information or low liquidity. Since most issuers in our sample are large public companies, it could be that the size differences between these companies are not sufficiently large to attain an additional risk premium. This could also explain why the size coefficient is only significant for the miscellaneous sector in table 19, as this is the only sector that contains several companies with relatively small market capitalization.

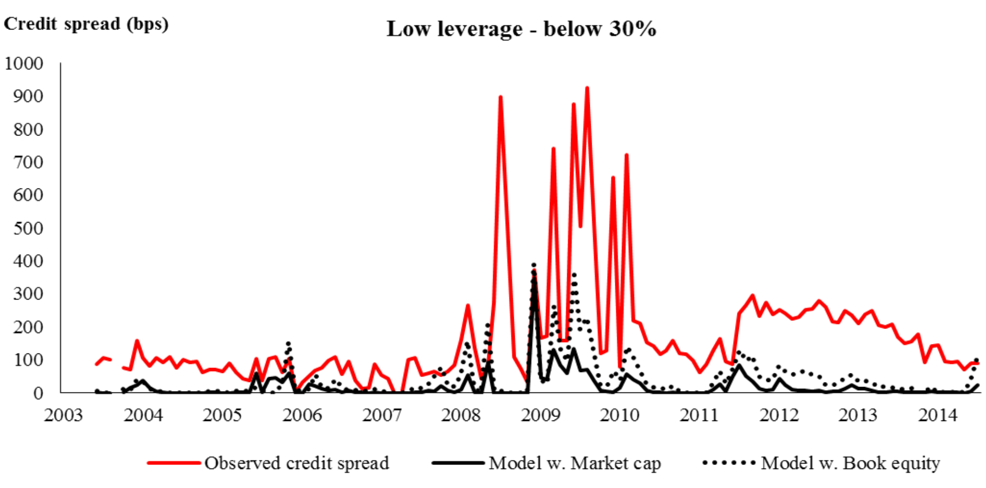
In contrast with Sæbø (2015a), our regression analysis reveals the potential existence of a risk premium for growth companies. In the univariate analysis, the market-to-book ratio explains 3.3% on its own, and in most model specifications in the multivariate analysis, the coefficient stays significant and negative. As a high market-to-book ratio typically reflects that the equity market discounts strong growth prospects, we see this as a potential risk aversion towards these types of companies. In table 20, we present the market-to-book ratio for companies with different debt levels in our sample. There is clear correlation between low-levered companies and a high market-to-book ratio, and so we believe that a part of the leverage problem relates to these companies. The intuition is uncontroversial, and companies that need to grow through capital investments, necessarily puts a tight strain on their cash-flow. This means less money available to service debt payments, thus, making the risk of the debtholders higher. In addition, the market values of these companies tend to be much higher than underlying cash-flow at the current time. This "inflated" market value further lowers the market-based leverage ratio in the Merton model, and makes the bond seem less risky.

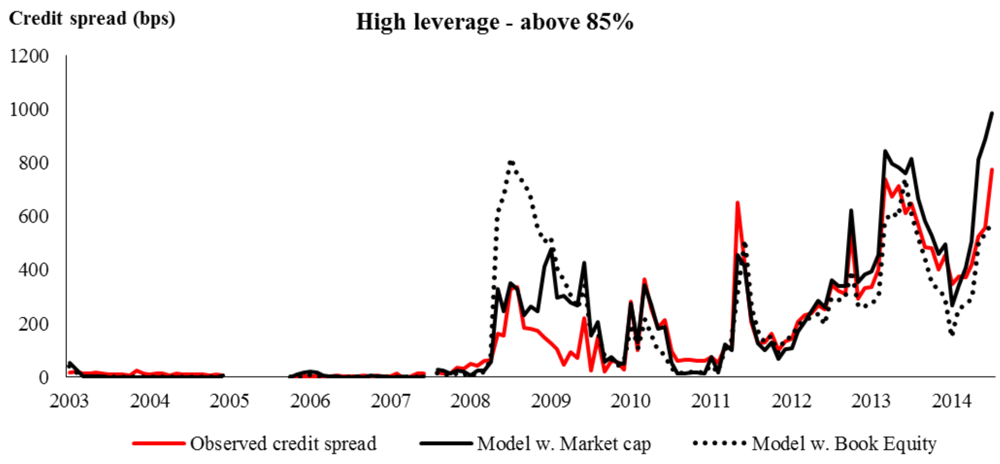
Table 20:
Average market-to-book ratio for companies with different debt levels

Groups	**Total sample**	High leverage above 0.85	Medium leverage between 0.30 and 0.85	Low leverage below 0.30
Market-to-book ratio	**1.31**	0.92	1.17	2.38

Note 1: Market-to-book ratio calculated as market capitalisation divided by book value of equity.
Note 2: We group the dataset according to the leverage ratio of total book debt to total firm value, where firm value is calculated as total book debt plus market capitalisation.

If we follow this intuition, we would expect the model to improve if we calculate the leverage ratio using book values of equity instead of market capitalization. Graph 15 explores this hypothesis, and from the exhibit of low-levered firms, we see that the estimated credit spreads from the Merton model increases when we use book equity. Nevertheless, a large share of the actual credit spread among these companies remains unexplained. This suggests that a high market-to-book ratio for growth companies partly explains the leverage problem of the model, but that it is not the full explanation. Moreover, a book equity leverage ratio has several unwanted side effects for highly levered companies, as seen in the lower panel. The model strongly overestimates the actual spreads during the financial crisis 2008, and the reason is that the book equity of several companies became close to negative in this period. Furthermore, book equity is an accounting number and measured infrequently. The book equity leverage ratio may therefore become biased, if investor`s perception about credit risk has changed from the latest accounting report.





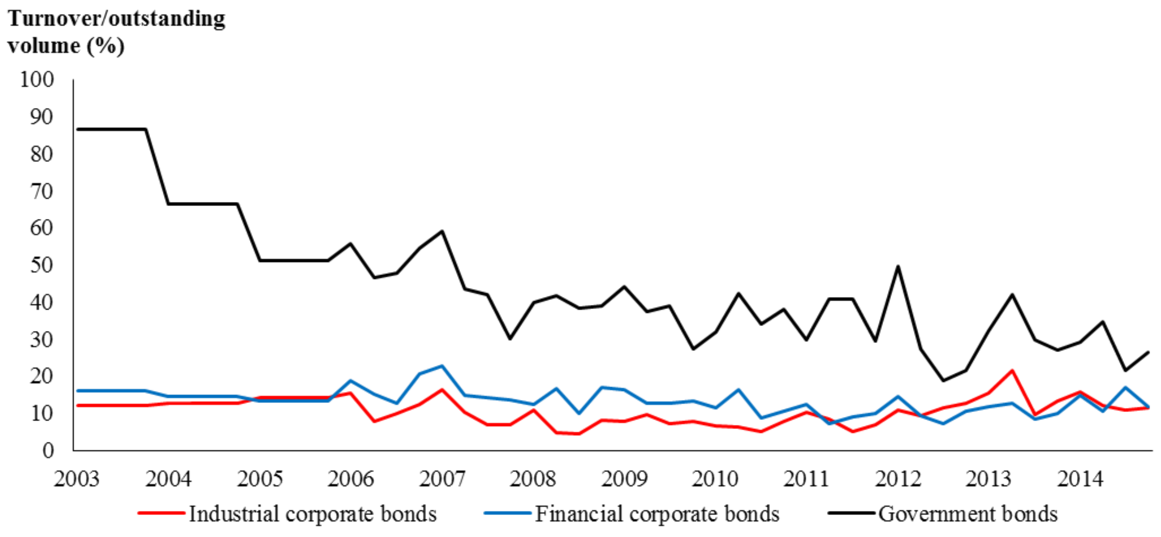
Graph 15: *Illustrating the effect of using book equity instead of market cap in the specification of the leverage ratio in the Merton model. The upper panel illustrates the effect for low-levered companies, while the lower panel illustrate the effect for high-levered companies.*

In conclusion, neither growth nor size premiums can explain the total credit spread puzzle in the Norwegian market. The factors may be important for particular companies where the issuer`s size or strong growth prospect may pose additional risks for the investor. However, for most bonds in our sample other factors seem more important.

5.2.3 Liquidity risk is not bond specific among Norwegian corporate bonds

In American studies of the credit spread puzzle, liquidity risk is a common explanation for the large difference between the Merton model`s estimates and the observed spreads. One example is Longstaff, Mithal and Nies (2004), decomposing spreads into default and non-default components. They find that default accounts for 51% and 71% of AAA-rated and BBB-rated bonds, with the unexplained component strongly related to proxy measures of bond liquidity. These include bond-specific liquidity measures as the bid-ask spread of the bond and the principal amount outstanding, as well as market wide liquidity measures, such as flows into mutual funds and the total amount of new corporate debt issued. In addition, Perraudin and Taylor (2003) finds that sorting bonds into high- and low-liquidity groups might explain as much as 30 bps of high-quality dollar denominated Eurobond spreads, and Sæbø (2015a) finds that the bid-ask spread of Norwegian government bonds correlates with the mispricing of the Merton model.

In our thesis, we implement two measures of liquidity risk, bond size for issuer specific liquidity and the TED-spread for market-wide liquidity. The regression analyses in part 4.3, reveal that there are no tendency for issuer specific liquidity to explain the credit spread puzzle in the Norwegian bond market. This seems surprising given that both Longstaff, Mithal and Nies (2004) and Perraudin and Taylor (2003) find this factor to be highly significant in the American bond market. That said, there are important differences between the American and Norwegian bond market, and in fact, Norwegian bonds are in general much less liquid than their American counterparts. E.g., Rakkestad (2004) points out that the market for government bonds in Norway is small and illiquid, and public data show that the market for Norwegian corporate bond is no different. Graph 16 compares the traded volume (turnover) for government bonds to the traded volume for corporate bonds on the Oslo Stock Exchange 2003-2014. As the size of bonds issued in each category differs substantially, we adjust the turnover for the outstanding amount in each category. This gives us a brief overview of the relative liquidity in government bonds and corporate bonds. Clearly, graph 16 shows that there is more trading activity in the government bond category than the corporate bonds, and since the government bonds were known to be illiquid, the corporates must be illiquid too. Furthermore, there seems to be no practical difference between the two groups of corporate bonds, when we compare to government bonds. We therefore believe that liquidity differences among Norwegian corporate bonds are very small in practical terms, and this may be the reason why issuer specific liquidity risk is not important in our sample. Instead, there should be a liquidity premium for all corporate bonds in general, as these are less liquid than the government bonds.



Graph 16: *Development in liquidity in government bonds and different sectors of corporate bonds at the Oslo stock exchange. We estimate the liquidity measure as the turnover in MNOK divided by the outstanding volume. The financial corporate bonds exclude covered bonds. We use the monthly data for Oslo Stock Exchange, and aggregate the data to quarterly observations. Source: Oslo Stock Exchange statistics.*

On the other hand, the regression analysis signals that macroeconomic liquidity risk may be important. The TED-spread becomes statistically significant once we controlled for other factors, and the negative coefficient indicated that “a flight to safety” from the interbank market to government bonds could be linked to a risk premium on corporate bonds. This seems a viable explanation since a reduction in general market liquidity also could affect the corporate bond market. That said, the effect of the TED-spread seemed limited in the regression analysis, and so the effect may be small. One explanation is that the TED-spread effect only happens during the financial crisis 2008, and in this period, very few observations exist in our sample.

5.2.4 No evidence for business cycle risk emerges. Still, issuer-specific cyclicality could play an important role in the credit spread puzzle

One attempt to explain the credit spread puzzle is Chen`s (2010) model of business cycle risk and the dynamics of the firm capital structure. The idea of the model is to endogenize the firm`s capital structure decision over the business cycles of the economy, where each firm faces a trade-off between the tax benefits of debt and the deadweight losses associated with a default. Chen (2010) argues that default losses are highly countercyclical, and that recessions increase both the probability of default and the loss given default (the deadweight loss). The reason is that recessions typically include a simultaneous state of lower firm cash-flows, lower growth expectations and higher costs of asset liquidation in default. Chen (2010) further illustrates empirical evidence from the rating agency Moody`s, and historically, default frequencies and credit spreads have increased in recessions, while recovery rates have fallen. These data seems to support Chen`s arguments, and when Chen introduces the countercyclical variations of default losses into his model, the prediction of credit spreads and leverage ratios get closer to the patterns observed in real-life. The important driver of this is that business cycle risk can explain why some firms have very low leverage, one of the key drivers of the credit spread puzzle according to Eom, Helwege and Huang (2004) and our results. The cause is that “(…) *firms are reluctant to take on leverage not because the deadweight losses of default are high on average, but because the losses are particularly high in those states in which defaults are more likely and losses are more painful.”* (Chen, 2010, p. 2174). .

In our case, there is a problem with this interpretation of the credit spread puzzle, as we see no link between the business cycles risk of our firms and the mispricing of the Merton model. The regression analysis in part 4.3 found no statistical evidence of a countercyclical relationship between the return on the OSEAX and the model mispricing, in both the univariate and multivariate analysis. One possibility, is that business cycle risk premiums do not exist in our sample because the Feldhütter and Schaefer (2015) model already incorporates this risk. In the calibration of the model to fit historic default frequencies, Feldhütter and Schaefer (2015) argue that the use of a long history of data is critically important. The reason is that default rates are correlated in recessions, just as Chen (2010) points out. Therefore, it may be the case that the calibration of the model to the long horizon of Moody`s default rates from 1920–2012 may already have incorporated business cycle risk into the model.

In addition, our regression analysis suggests that issuer specific volatility is far more important than general business cycle risk in explaining the mispricing of the Merton model. We believe a possible interpretation of this is that Norwegian investors seem to exhibit larger risk aversion to idiosyncratic shocks to that particular issuer than general systematic risk of the economy. Chen (2010) also finds room for jump risk and Brownian risk as a factor in the credit spread puzzle. When he isolates the effect of such shocks on credit spreads and capital structure, he finds that a model with jump-risk can generate higher spreads than a normal static one, although lower than a model with both jump risk and cyclical default losses. Huang and Huang (2003) partly agree with this argument, demonstrating that the inclusion of a jump-diffusion process into the Merton model raises the estimated model spreads relative to the corporate – government bond spread. However, while Chen (2010) argues that such jumps are largely attributable to large macroeconomic shocks to the discount factor of bonds, our results imply that Norwegian investors are more afraid of issuer specific shocks.

As mentioned, such risk aversion to issuer specific shocks seems closely linked to the sector risk premiums identified in our analysis. Different cyclicality among sectors is a potential explanation of the extra premium we observe on our industrial sector companies. The reason is that investors might expect that the input parameters for the debt leverage ratio or the equity volatility might underestimate the true underlying credit risk if the company is in a strong profit cycle. On the one hand, this argument is linked to Chen`s (2010) explanation, who argues that firm`s with procyclical cash flows should have lower leverage than those with less cyclical cash flows. Sundaresan (2013) also notes the interest rates can spike substantially, even short-term rates, and so there are several arguments for why investors care about sudden “Black-Swan” risk factors.

In total, business cycle risk or cyclicality is a viable explanation of the credit spread puzzle. However, our analysis suggests that in the Norwegian bond market, issuer specific cyclicality is more important than general systematic risk to the economy.

5.3 Explanation 2: Systematic biases in input parameters

This far, we have elaborated on risk premiums that are important to investors, but that may be neglected in the Merton model. We now proceed with another explanation, systematic biases in input factors. Most likely, these two explanations are interlinked, but we believe there are several problems with the input parameters of the Merton model that needs to be addressed further. Particularly this concerns the debt leverage ratio and the equity volatility measure, as we have uncovered the same systematic errors in the Merton model as described in Eom, Helwege and Huang (2004). In addition, we will explain some particular issues when choosing the risk-free reference rate, and the modelling of financial companies.

Before we commence the discussion, we will comment on two other factors, the payout ratio and the time-to-maturity. In part 4.3., we discovered that the mispricing of the model partly relates to systematic patterns in the firm payout ratio. We will not discuss this factor in much detail at this point, but keep to the conclusions of part 4.3. It seems that payout ratio is not the most important factor, as seen by the low R^2 in the univariate analysis. However, biases in firm payout ratio could be important to explain the mispricing for some companies, where the payout ratio is either excessively high or low.

Another factor is time-to-maturity. Previous studies of Huang and Huang (2003) finds that the underestimation of the Merton model (or variants thereof) is particularly strong for shorter-term maturities. Nevertheless, in our sample no clear pattern emerged on this factor. If we look at the relative mispricing in percentages, then short-term maturities clearly underestimates, as the Merton model`s estimates approaches zero as time-to-maturity gets shorter. That said, if we look at absolute mispricing in basis points instead, the opposite pattern is true; the underestimation is strongest for longer-term bonds after controlling for other factors. In conclusion, we cannot find any strong pattern for time-to-maturity.

5.3.1 Low debt leverage is at the core of the credit spread puzzle

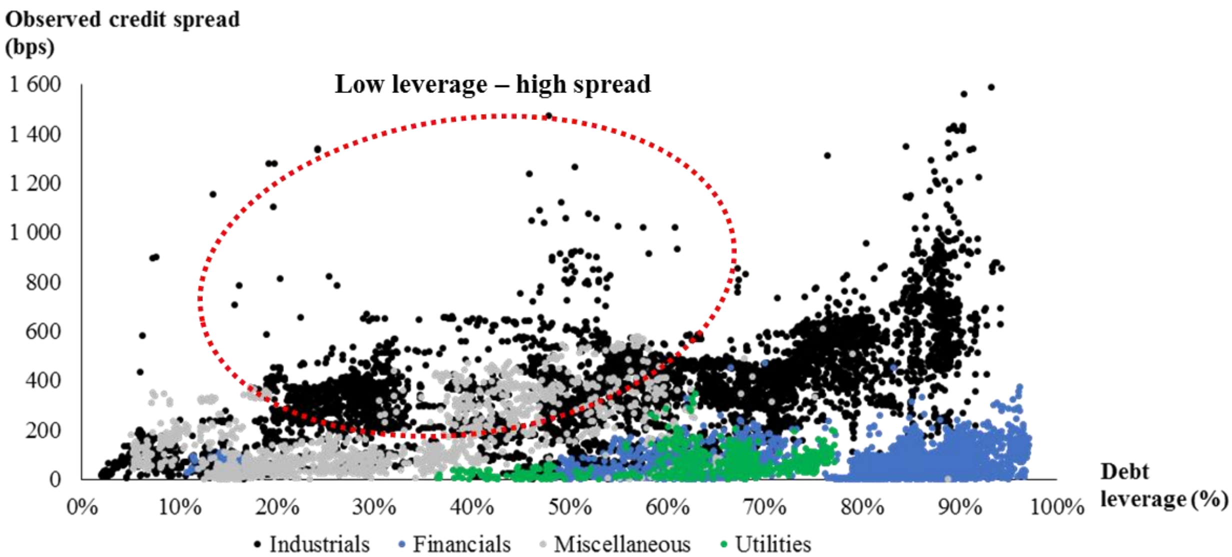
An absolute key trend in our data is that the Merton model underestimates credit spreads for bonds with low leverage ratios. This finding fits well to previous literature, and in many ways the credit spread puzzle seems related to a leverage puzzle. Sundaresan (2013) explains this puzzle of leverage as the strong difference between leverage ratios observed among real-life companies and the implied leverage ratio from structural credit spreads needed to attain sufficiently high credit spreads. Thus, the Merton model`s leverage measure with market based asset values seems to misrepresent the credit risk of corporate bonds.

Collin-Dufresne and Goldstein (2001) propose that the original Merton model suffers from an unrealistic assumption about static capital structures. In reality, firms alter their capital structure dynamically and according to changing economic conditions. The Merton model assumes leverage stays constant over the lending periods, and contradicts real-life behaviour. For this reason, Collin-Dufresne and Goldstein suggest that the model must allow for a dynamic capital structure, and they further implement a model with mean-reverting leverage ratios. This model is able to generate higher credit spreads for low-levered companies, and could seem to be a good solution. However, the Collin-Dufresne and Goldstein (2001) model are among the ones tested in Eom, Helwege and Huang (2004), where they find an underestimation of spreads. Therefore, mean-reverting leverage ratios cannot be the whole explanation.

Another possibility is that our specification of the leverage ratio forgets to consider the credit risk effect of loan commitments and cash holdings. In real-life, many companies hold large amount of cash and credit lines in addition to regular debt (Sundaresan, 2013). As these are alternative sources for the company to fund their operations and investments, they are a vital part of a company's total debt burden. It is however not clear if the inclusion of these measures into the leverage ratio will improve the underestimation of low-levered companies. On the one hand, loan commitments represent additional off-balance sheet liabilities, and in isolation loan-commitments increase the credit risk. On the other hand, large excess cash balances are equivalent to a negative debt burden for the company, and in total, the effect on the leverage ratio depends on which effect is the greatest.

On top of that, these alternative sources of financing serve as additional protective layers for the companies, and structural risk model should take this into consideration. Asvasnut, Broadie and Sundaresan (2011) argue that one reason why companies hold loan-commitments and excess cash is that debt markets may be unavailable to them in periods of financial turmoil. In addition, a study by Acharya, Davydenko and Strebulaev (2011) find an empirical positive correlation between excess cash balances and credit spreads. These findings suggest that firms have precautionary motives for holding loan-commitments or large amounts of cash, and in fact, companies with large cash holdings and loan commitments may be the riskiest ones.

In part, this intuition of precautionary motives can be translated to the companies` leverage ratio. In graph 17, we plot the relationship between the observed credit spread in the Norwegian corporate bond market, and the asset debt leverage ratio that we incorporate in the Merton model. On an overall perspective, the relationship is positive, where investors compensate the higher debt level with a higher credit spread. However, there are large deviations around this trend, and the positive relationship between debt leverage and the credit spread are mostly true within each sector group. If instead we compare the relationship across sector groups, we see that a large share of low-levered industrial and miscellaneous companies are priced at a higher credit spread than highly-levered utilities and financial companies, as illustrated in the red ring. This trend highlights the possible linkage between the leverage ratio and the possible sector premiums in the credit spread puzzle.



Graph 17: *The relationship between the observed credit spread in the Norwegian corporate bond market, and the debt leverage ratio. The debt leverage ratio is the total book debt to the firm value, where firm value is the market capitalisation plus total book debt. The red ring outlines a group of observations that have a low leverage and high observed spread.*

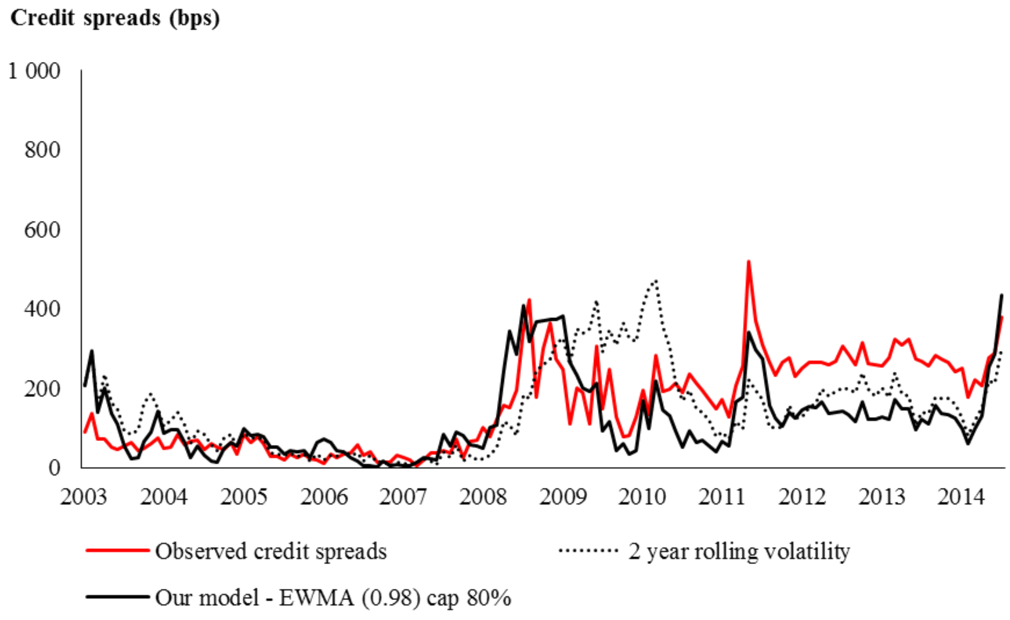
One explanation for this pattern is precautionary motives of the management when designing the firm`s capital structure. For example, companies with highly volatile cash-flows cannot sustain a high debt leverage due to the risk of going cash-negative. However, for shorter periods of time the cash-flow may be solid, and then the leverage ratio appears safe. For this reason, industrial and miscellaneous companies may actually have low leverage ratios because they in fact are the riskiest companies, and it seems that credit risk pricing of Norwegian investors reflects this idea. Since the Merton model mostly sees the relationship between the debt leverage ratio and the credit risk as strictly positive, this may be a large cause of the credit spread puzzle, as the model forgets the precautionary motive for holding low leverage for particular companies.

Still, a key part of the leverage puzzle remains: Can we find other measures of a firm`s debt level that better reflect the credit risk of the company? Eom, Helwege and Huang (2004) elaborate on this subject, and argue that such a measure of debt levels must be one that raises the leverage for safe bonds, whilst lowering the leverage for particularly risky bonds. We have already tested the effect of book equity in the leverage ratio, and this slightly improved the underestimation problem, but also led to a larger overestimation for riskier bonds. In general, we are therefore sceptic to asset based leverage ratios, as they seem to misinterpret several important aspects of a company`s credit risk. The key reason for this is that asset value leverage can become partly delinked from the underlying cash-flow. Since cash-flow is what ultimately pays the coupons and amortisation on the bonds, a better measure should instead assess the risk of the company`s cash flow. Here, coverage metrics such as operating cash flow to interest or the debt-to-EBITDA metric (Earnings Before Interest, Tax, Depreciation and Amortization) are possible alternatives. In his countercyclical model of credit risk, Chen (2010) implements the debt-to-EBITDA measure for firm leverage, and argues that this is a much better measure for cyclical risk. The reason is that the optimal default boundary for firms in the debt-to-EBITDA measure is countercyclical, but if measured in asset values as in the Merton model it becomes procyclical. Chen argues that default boundaries should be countercyclical, as firms will want to wait longer in recessions to default due to the larger deadweight loss, and instead they will issue equity or restructure their debt. Asset debt measures, on the other hand, forget this tendency of company behaviour.

Another problem with asset leverage ratios is that stock markets can possibly misprice the risk of default, and “inflate” the market cap of the company. Since debt-holders are more concerned about the current underlying cash flow to pay the debt, it may be unwise of the Merton model to rely so heavily on equity market prices in the leverage ratio. On top of that, then the Feldhütter and Schaefer (2015) model does not allow the companies to default prior to maturity. In reality, the firm may default on the coupon payments, and this option is disregarded in our model. According to Feldhütter and Schaefer (2015), it is possible to allow for coupon payments in the model, as in Eom, Helwege and Huang (2004), but this adds a completely new layer of complexity to the calculations. Therefore, for simplicity reasons they have left this out. They do note, however, that this would have led to slightly higher credit spread estimates by the Merton model, as the firm could default on coupon payments before the maturity date. This can be another contributing explanation of the underestimation puzzle of the estimated credit spreads.

5.3.2 The problems of historic volatility measures

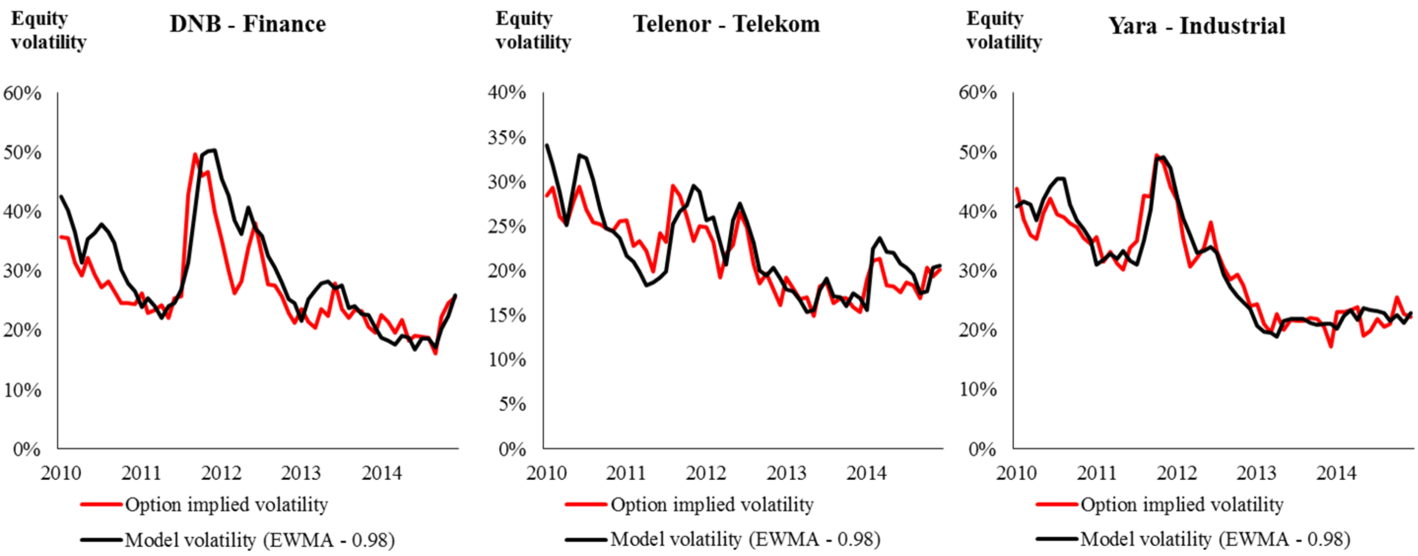
The systematic biases of the augmented Merton model may also be a cause of systematic errors in the volatility measure. One possible error in the Feldhütter and Schaefer (2015) model may be the calculation from equity volatility to asset volatility. Firstly, this calculation assumes that the assessment of default risk between equity markets and debt markets are transferable. However, as argued above this may not be the case. It may therefore be problematic for the model to rely so heavily on the equity volatility to assess the default risk of the company. Secondly, Feldhütter and Schaefer (2015) use a transparent calculation of the asset volatility, by adding a constant multiple on the leverage-adjusted equity volatility. This multiple comes from the estimates of Schaefer and Strebulaev (2008), and so our model relies on the assumption that these estimates are transferable to the Norwegian bond market and all of our sectors. Possible biases may emerge if this assumption is not true.



Graph 18: *The development in observed spreads relative to model estimates using different volatility measures. We calculate credit spreads as monthly averages for our total data sample.*

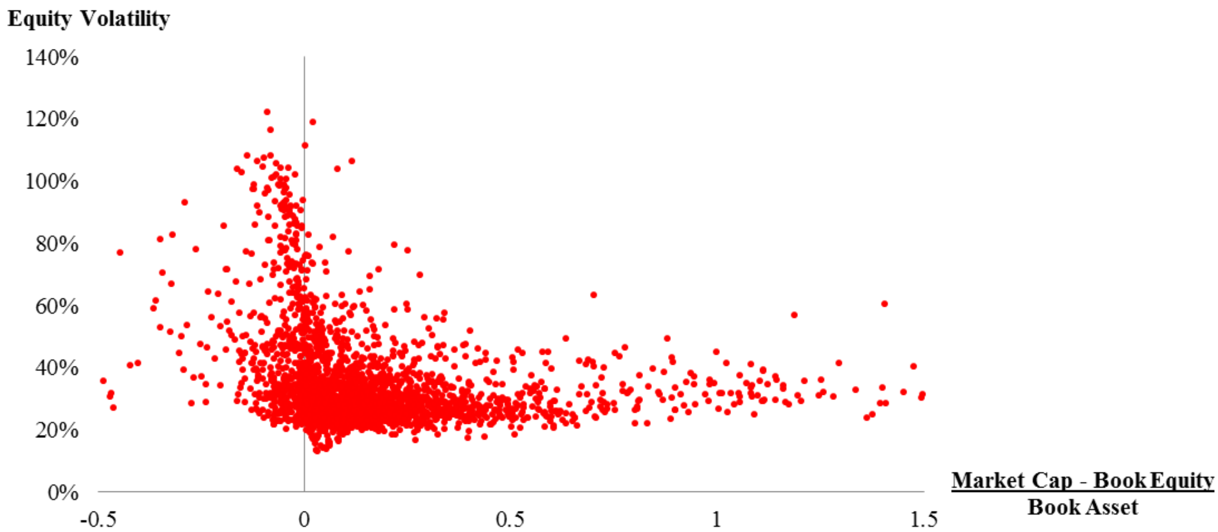
As discussed in the methodology, there are several problems with the use of historical volatility measures. One of these is that such measures place to large weight on outdated observations. In our thesis, we therefore changed the 3-year historic volatility of Feldhütter and Schaefer (2015) with an exponentially weighted moving average volatility (EWMA).

Graph 18 presents the effect of this change on the estimated credit spreads by the augmented Merton model, where the dotted line illustrates a similar long horizon rolling volatility measure as Feldhütter and Schaefer (2015) but with two years instead of three. Clearly, the more sensitive EWMA measure performs a lot better, particularly in the 2008-2010 period. The reason for this is that the observations from financial crisis of 2008 stays in the 2-year rolling volatility measure for exactly 2-years, and neglect the fact that by this time real-life investors' risk perceptions have calmed down from the crisis. The EWMA measure places a steadily decreasing weight on these extreme observations, and therefore the credit spreads come down more quickly. It is only during the crisis years that there seems to be a large benefit of using the more sensitive volatility measure. For periods of normal market activity, the two measures perform relatively similar.



Graph 19: *Comparison of the our model volatility measure to the option implied volatility for three call options listed on the Oslo Stock Exchange 2010-2014.*

Despite the apparent benefits of the EWMA volatility measure, we cannot be certain that this measure adequately reflects the risk perception of Norwegian bond investors. In our view, the optimal volatility measure is the implied volatility of a traded option on the firms' stocks with a time to expiration similar to the bond's time-to-maturity, as this measure is both forward-looking and reflects the risk perception of the market participants. In graph 19, we compare our EWMA measure to the implied volatility for three options traded on the Oslo Stock Exchange 2010-2014. The two measures resemble each other quite closely, and it seems that our EWMA measure is not that far away from the real-life volatility used by Norwegian investors in the stock market. That said, traded options on Norwegian stocks are quite rare, and we could not find data for all companies and for longer time-periods. For that reason, it is hard to assess the performance of the EWMA measure for our total data sample. We hope that such traded options will be available for future studies of the Norwegian corporate bond market, and the use of option-implied volatility may potentially improve the ability of the Merton model to predict corporate credit spreads.



Graph 20: *Illustrating the L-shaped relationship between equity volatility and the valuation of firms' underlying assets. All data observations outside the range of -0.5-1.5 for our x-axis variable are removed in order to zoom in on the general pattern in the plot. When the market's valuation of firm assets is high, the volatility seems to be rather insensitive to changes in the value of the firms' underlying assets, whereas small changes in asset values seem to have large effects on the volatility once underlying assets are priced low. The left axis plots our EWMA measure for the equity volatility.*

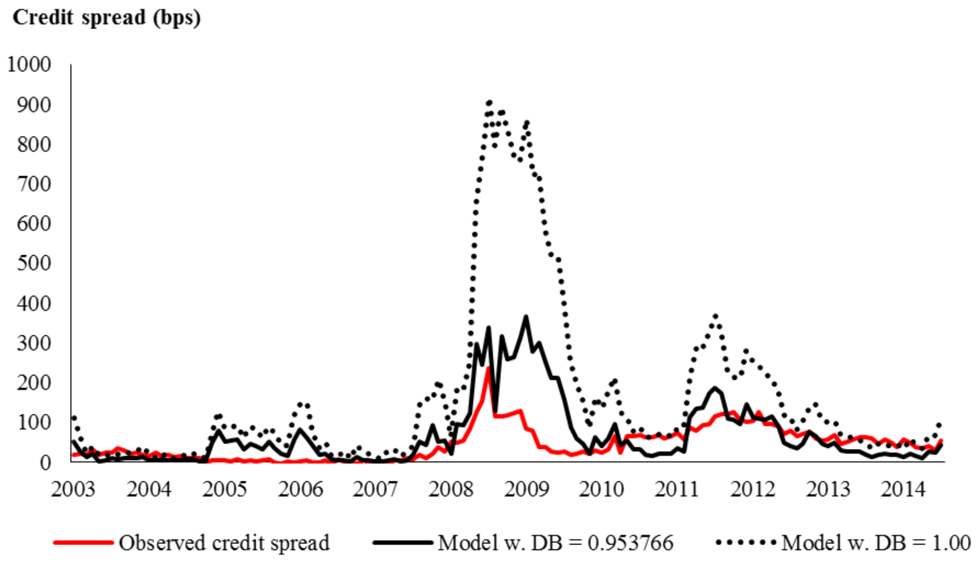
An important characteristic of volatility measures is that they differ substantially depending on the state of the company`s performance. Typically, share prices move steadily in periods of strong performance, and decrease quickly and dramatic to bad news. In graph 20, we illustrate this asymmetry by plotting equity volatilities against a proxy-value for the market's valuation of firms' underlying assets, defined as the difference between the market valuation of equity and the book value of equity, divided by the book value of the firm's assets. This proxy captures periods where the stock market valuation of a company is especially high relative to the underlying accounting values, and from graph 20, we observe an L-shaped relationship between these variables. This shape shows that when market valuation falls down towards the book values, equity volatility typically spikes and reflects negative news-flows in the market. This has interesting consequences for the use of volatility measures in the Merton model, as the non-linear relation contradicts the assumption of a constant volatility level as in the Merton (1974) model. Therefore, one could possibly improve the model if the asset volatility was allowed to change throughout bonds' time-to-maturity. Du, Elkhami, Ericsson and Ming (2013) emphasize this problem, and incorporate stochastic asset volatility in the Merton model. Doing so, they find that the Merton model matches historical spreads quite adequately. Moreover, Eisfeldt (2015) argues that firms are likely to face decreasing returns to scale or scope, which implies that firm values in general tend to be concave in underlying asset values.

The possible existence of time-varying asset volatility could be important to fully understand the credit spread puzzle. In part 4.3, we saw that the model underestimation was linked to a low value of equity volatility. This indicates that the pricing of credit risk by Norwegian investors imply higher volatility levels than what we see in historical volatility measures. We believe that this reflects that investor`s take into account the probability that negative shocks to the firm value might cause the asset volatility to incline sharply. As this asset volatility spike typically occurs simultaneously as the leverage ratio increases, the effect on credit spreads is potentially strong.

5.3.3 Financial companies are particularly difficult to model correctly

Precise estimation of the credit spreads for financial companies have proved to be one especially challenging task. This difficulty seems largely related to the high leverage ratios we typically observe for these types of firms, which make the probability of a default very sensitive to changes in the level of volatility. Consequently, we observe overestimation of credit spreads in periods of financial crisis 2008-2010, when volatility levels rise substantially. However, during normal market conditions, the equity volatility for financial companies is typically in the range of around 20%, which is insufficient to generate market near spreads.

At the same time, the precision of our estimation for the credit spread of the financial companies would have been significantly worse if we had not calibrated the default boundary for this sector to fit historical default probabilities. In graph 21, we see that the reduction of the default boundary of financial firms improves the model fit drastically. If we had used the default boundary of 1.00 as in Feldhütter and Schaefer (2015), the Merton model would have dramatically overestimated credit spreads, but when we recalibrated the model to better-fit historic default frequencies for financial companies we found a slightly lower default boundary of 0.953766. This result highlights the important differences of financial companies, especially regarding the default boundary calculation.

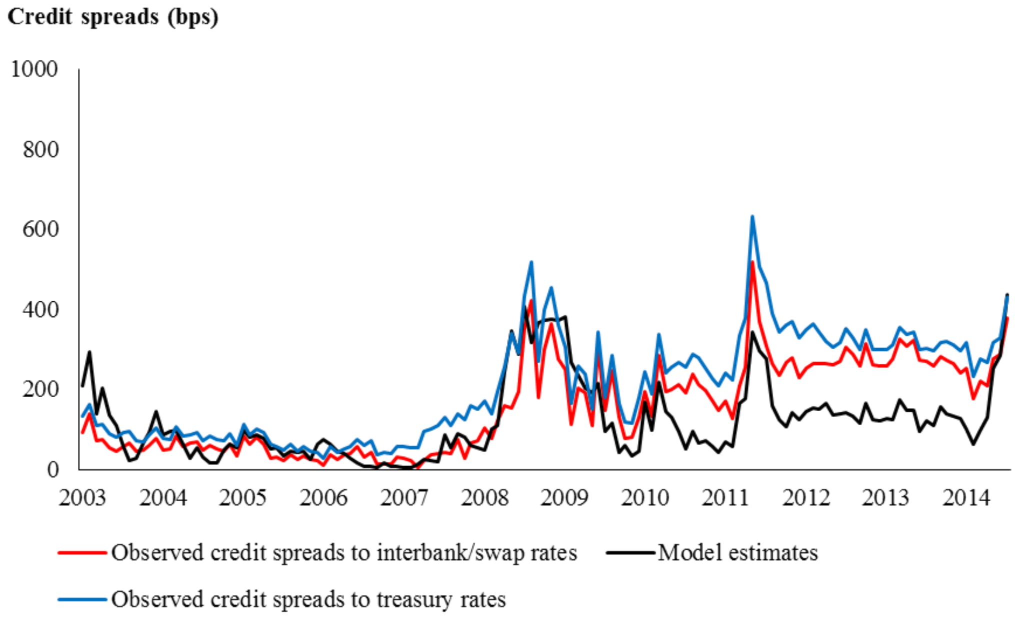


Graph 21: *The development in observed spreads for financial companies relative to model estimates, using either a default boundary of 1.00 or a recalibrated default boundary to Moody`s (2011). We use the recalibrated default boundary for financial firms in our thesis, as explained in the methodology. We calculate credit spreads as monthly averages for our financial companies.*

Despite the improvement following the changes in the default boundary, some systematic biases remain for financial sector, particularly the overestimation of spreads in periods of financial turmoil. Similar to previous arguments, we believe that parts of the explanation relate to the fact that asset volatility might change over the investors holding periods of the bonds. Nagel and Purnanandam (2015) emphasize the fact that the equity payoff of banks resemble a mezzanine claim on the firm`s assets, rather than a call option as assumed in the Merton model. The consequence is that the asset volatility of financial firms will be low in good periods, whereas it increases substantially once the market conditions worsens. In addition, both Nagel and Purnanandam (2015) and Eisfeldt (2015) recognize several particular characteristics of banks that further complicate the modeling of credit spreads. For example, the presence of features such as deposit insurances and state implicit/"too-big-too fail" bailout guarantees, can cause banks to build up excessively large risk during periods were they perform well. If Norwegian investors take these moral hazard related issues into account, they have incentives to charge a higher credit risk pricing. Furthermore, banks are exposed to asset-liabilities interactions that might accelerate both down-ward and up-ward movements in asset values, which also make the case of bank credit risk a somewhat distinctive case.

5.3.4 The choice of risk-free reference rate matters

The credit spread of a bond is the difference between the yield of a corporate bond and the risk-free rate. However, as the risk-free rate is not directly observable in the market, we have to use other interest rates as proxies to calculate real-life credit spreads. In the methodology, we explained that three alternatives have emerged in the literature; 1) the government bond yield, 2) the interbank/swap rates and 3) AAA-rated corporate bond yields. In our thesis, we ultimately decided on the interbank/swap rates as our risk-free reference rate.



Graph 22: *The development in model estimates to observed spreads, where we show the effect of using either treasury rates or interbank/swap rates as the risk-free rate. The graphs shows credit spreads as monthly averages for our total data sample.*

Traditionally, government bonds have been the natural choice for a risk-free reference rate, and graph 22 illustrates our model`s estimates relative to observed credit spreads using either treasury rates or interbank/swap rates. In our view, the alternatives are quite similar, and do not affect the overall conclusion of our thesis. The correlation is 0.73 with the government bond spreads, which is slightly higher than 0.69 for interbank/swap rates. However, government bond yields are on average 50-60 bps lower than interbank/swap rates, and so the under-pricing of the Merton model would have been stronger if we used treasury rates instead.

The other alternative is AAA-rated corporate bonds. Due to lack of public available credit ratings for Norwegian companies, we were not able to calculate this reference rate in the same way as Feldhütter and Schaefer (2015). Nevertheless, we can illustrate the effect this rate has on the results of Feldhütter and Schaefer (2015). In figure 1 and figure 3 of Feldhütter and

Schaefer (2015), they compare the results of different reference rates. In their baseline model they use AAA-rated bonds as their proxy for the risk-free rate. Here, the Merton model estimate for BBB-rated bonds tracks the development in actual credit spreads very well with correlations between 84% and 92%. However, when Feldhütter and Schaefer plots the model against government bonds (treasury yield) and swap rates, they find an underestimation of the Merton model similar to our results. "*For example, the average long-term AAA-treasury spreads is 77bps and only 10bps in the model (…) the actual spread to the swap rate is 25bps versus 11bps in the Merton model*" (Feldhütter and Schaefer, 2015, p. 14). These results are very important. First, because they indicate that out results are not that far from Feldhütter and Schaefer (2015) when we use the same benchmark rate. Second, because they imply that our Merton model could potentially have a stronger fit to actual credit spreads if we were able to use AAA-rated bonds as the risk-free reference rate.

The reason why the choice of reference rate matters is that interbank/swap rates and government bonds have very different liquidity from corporate bonds, as we saw in graph 16. Therefore, when we use interbank/swap rates or government bonds as risk-free reference rates we naturally include a liquidity premium to the credit spreads of corporate bonds. If we had used the AAA-rated corporate bonds instead, we would be able to get a closer look at default risk isolated, as we then compare corporate bonds to corporate bonds. This benefit of AAA-rated bonds as the risk-free reference rate for credit spreads is documented in other literature. For example, Leland (2004) points to a study by Cooper and Davydenko (2004) that tries to predict expected default losses from observed credit spreads in the market, i.e. the inverse calculation of what we are doing. Cooper and Davydenko (2004) find that the preferred spread that matches the actual default probabilities of companies is not the Government – corporate spread, but rather the spread to the AAA-rated corporate bonds.

Since credit ratings for Norwegian bond issuers are not available to us, we cannot check what effect the AAA-rated risk-free reference rate has on ability of the Merton model to predict Norwegian bond spreads. Nevertheless, Sæbø (2015b) lists his results according to "shadow-ratings" for Norwegian bonds, and so we conduct a thought-experiment to illustrate the effect of changing the reference rate. In table 21, we list the results of Sæbø (2015b) with the swap rate as a risk-free rate versus A-rated bonds as a risk-free rate. Note that there were no AAA-rated bonds in Sæbø`s results, and so as an approximation we use the highest rated A bonds. Table 21, illustrates that if we use A-rated bonds, the explained amount from the Merton model becomes higher, probably, as we are more able to isolate the effect of credit risk.

Having said that, A-rated bonds are not risk-free, and the actual AAA-rated risk-free rate would be much lower, It is therefore not necessarily true that the changes in interest rate leads to much of an improvement. In fact, a large portion of the spread to A-rated bonds is unexplained by the Merton model of Sæbø (2015b). Consequently, the choice of risk-free reference rate, although important, cannot be the whole explanation for the credit spread puzzle in the Norwegian bond market.

Table 21:
Illustrating the impact of using A-rated bonds as reference rates instead of swap rates. Example from Sæbø (2015), which include the "shadow-rating" for each issue.

	Bond "shadow rating"				
	A	**BBB**	**BB**	**B**	**CCC**
Swap rate as reference:					
Actual spread to swap	107	148	389	833	1214
Model estimate in Sæbø (2015)	10	20	76	466	1081
% explained	**9 %**	**14 %**	**19 %**	**56 %**	**89 %**
A-rated bonds as reference:					
Actual spread to A-rated bonds[1]		41	282	726	1107
Model estimate in Sæbø (2015)		20	76	466	1081
% explained		**49 %**	**27 %**	**64 %**	**98 %**

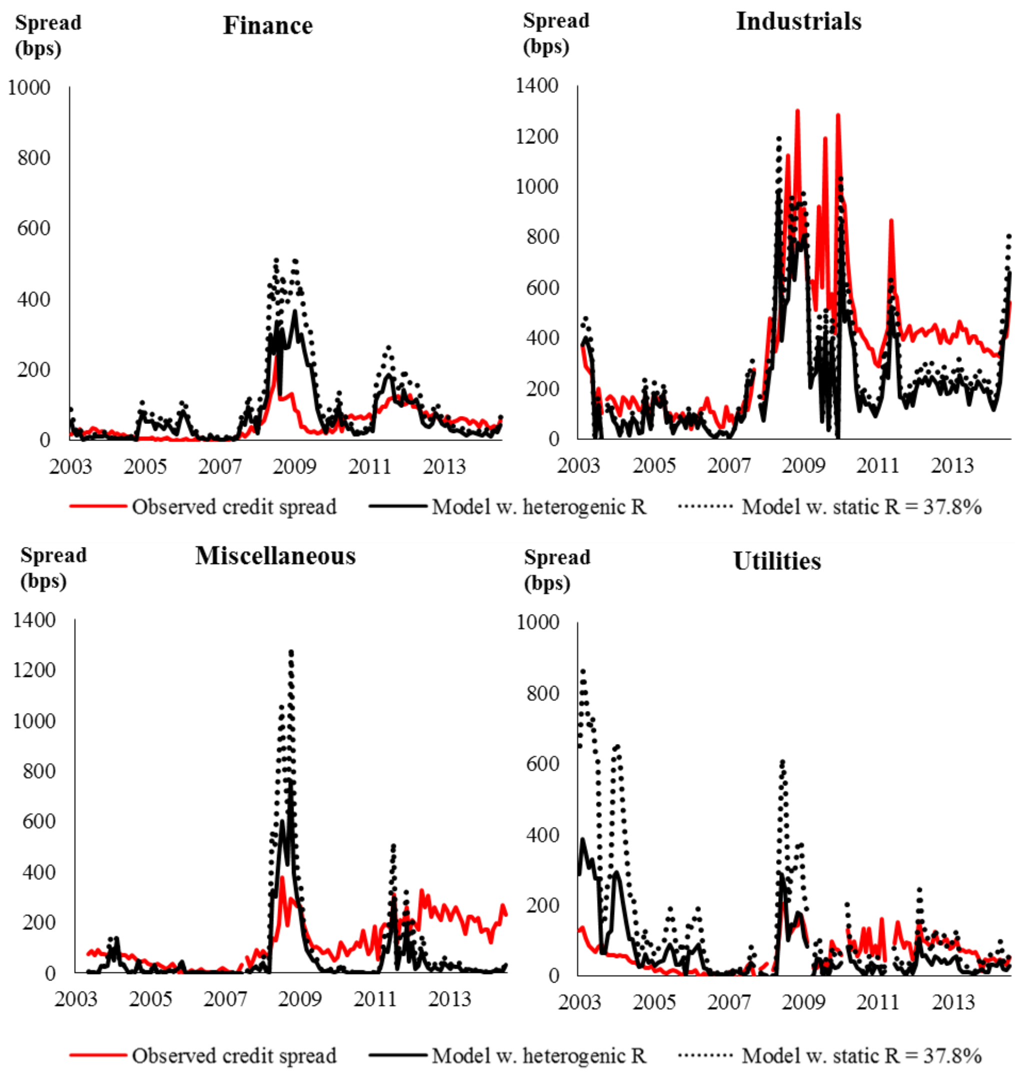
The numbers are based on table 2 in Sæbø (2015), and illustrate the average credit spread and model estimate for his total sample of 10,595 credit spreads from 2008-2013.
Note 1: We calculate the A-rate spread as the difference between the actual spread to swap for each category to the actual spread to swap for the A-rated bonds.

5.4 Explanation 3: Issuer specific uncertainty

In our thesis, we have identified several possible explanations for the credit spread puzzle. Still, the potentially largest explanation remains, i.e. the issuer-specific uncertainty. One attempt to quantify this effect is to look at the baseline regression model in part 4.3. The model has an adjusted R^2 measure of 38.4% and a standard error of regression of 183.9bps, and it incorporates the proxy variables for those explanations of the credit spread puzzle that we found economically viable. Clearly, a large part of the credit spread puzzle remains unexplained, and we attribute this factor to issuer specific uncertainty. In this term, we include the factors that are specific to each particular observation that we are not able to control for in our analysis. In this section, we take a closer look at what these factors could be.

5.4.1 Recovery rates should be issuer-specific

One of the changes in our model from Feldhütter and Schaefer (2015) is that we use heterogenic recovery rates instead of a static estimate. We use sector estimates of recovery rates 1971-2011 from Altman and Kuehne (2012), and set the recovery rate to 49.2% for financials, 70.0% for utilities, 48.0% for industrials and 39.7% for miscellaneous companies. Graph 23 presents our model estimates relative to a model with a static recovery rate similar to Feldhütter and Schaefer (2015) of 37.8%.



Graph 23: *The development in observed spreads relative to model estimates, using either heterogenic recovery rates or a static recovery rate.*

For industrial companies, the effect of the changed recovery rate is limited. Yet, for the other sectors there is a clear benefit of using heterogenic recovery rates. In the static recovery rate model, the Merton model strongly overestimates the credit spread for the companies at some time-periods, where the companies are close to default and recovery rates matters. This illustrates that the model can be improved if we get better estimates of a company`s true recovery rate. In our view, the recovery rates should be determined for each particular issuer, since the asset composition and collateral ability may differ for each company. It therefore seems that a potential cause of the credit spread puzzle is that Norwegian investors have much more precise estimates of the recovery rate, than what is possible for us to include in the Merton model.

5.4.2 Bond pricing is a complex exercise with extreme demands to a structural bond model such as the Merton (1974)

Recovery rates are not the only potential factor that can be issuer specific. Covenants are another factor that we are not able to investigate further. Many bonds include additional restrictions or rules in the loan contract, and these alter the credit risk of the bond investors. Examples include minimum requirements for key metrics for the company, such as the leverage ratio or the interest coverage, or prohibitions for the firm to raise new debt with the same seniority. In addition, the maturity structure of the company's liabilities may be important, as well as any agency-costs between the equity holders and the bondholders. The latter stems from the fact that bond investors and equity shareholders may have different objectives and views on the future of a company, particularly the degree of risk a firm should have on its investments. Sundaresan (2013) also points out that in reality many firms do not default directly, and instead they restructure their debt or renegotiate the terms in the loan contract. Since the Merton model only considers direct bankruptcy, the model may forget the implications of such options for the bondholders. Relationships among the investors and the management can also be another cause of deviations from the model, as previous good or bad experience with one another may be important for the risk perception of the investors. At last, we must not forget that our thesis relies on public available data, and that our augmented Merton model is estimated from simple formulas on accounting data or market data. It may therefore be the case that the Merton model is correct, but that we cannot obtain the same estimates of input parameters as those used by real-life investors.

In total, our study on the credit spread puzzle of the Merton model shows the complexity of bond pricing. This complexity may be particularly large in Norway, as studies of the Norwegian market seems to have a greater problem explaining actual credit spread observations. Having said that, it seems hard for any structural risk model to be able to perfectly explain market prices, since there is an enormous amount of changing risk factors to take into consideration. At this point, credit risk pricing of corporate bonds therefore remain a mostly case-by-case exercise, where simple models such as the Merton cannot replicate the risk analysis of professional real-life bond investors.

5.5 Limitation to our data sample, and some interesting aspects for future studies of the credit spread puzzle

It is important to note some characteristics about our data sample. In part 1.3, we illustrated the massive size of the Norwegian bond market, and despite the fact that we have one of the largest data sets in any study of the credit spread puzzle in Norway, we only include a small part of this market. On the one hand, we have only looked at public traded bonds at the Oslo Stock Exchange and the Nordic ABM, where the issuers are large companies with listed stocks. We can therefore not know with certainty that the drivers of the credit spread puzzle is the same among other companies. Interesting areas for future studies can be to examine non-public bonds or those from smaller companies. In addition, we only look at senior unsecured bonds, and it could be interesting to see what effect seniority or collateral has on the pricing of credit risk. Thus, we urge future papers to compare the effect of senior unsecured bonds to those with collateral claims. Finally, as the Norwegian bond market is relatively new, future studies might be able to get hold on much more detail data than our thesis. This may include credit ratings for bonds, implied volatilities on call options on stocks or quarterly accounting data instead of annually. Stamdata has made available a new service called Nordic Bond Pricing. This will give shadow-prices for Norwegian bonds, and it will be interesting to see future studies make use of these data to explain credit risk pricing.

6. CONCLUSION

In this thesis, we have implemented an augmented Merton model inspired by Feldhütter and Schaefer (2015) on Norwegian corporate bonds 2003-2014. Previous literature have illustrated that the Merton model have problems predicting real-life observations of credit spreads, a phenomenon called the credit spread puzzle. Yet, few studies exist on the Norwegian corporate bond market, and in our thesis, we expand the dataset of previous studies by Sæbø (2015a, 2015b) to include a longer time-horizon and a broader sector diversity. The goal of our thesis is to answer the following two questions: 1) Does the credit spread puzzle still exist in the Norwegian corporate bond market when implementing a model similar to Feldhütter and Schaefer (2015)? and 2) if a mispricing exists, which factors can explain the deviations between the model's estimates of credit risk and the pricing of Norwegian investors 2003-2014?

Our results uncover the strong presence of the credit spread puzzle in the Norwegian corporate bond market. Not only are there large uncertainties regarding the model`s predicting ability depending on which observation we actually investigate, but the general trend is a strong underestimation with 75% of observations explaining less than 88% of actual spreads. However, the results are not surprising, and the median level of 26% is close to previous studies of the Norwegian market in Sæbø (2015a, 2015b). Apparently, the Feldhütter and Schaefer (2015) model cannot change this general trend in the data.

Our further analysis reveals that multiple systematic biases may explain the credit spread puzzle. Sector seems to be the single most important factor for the difference we observe between the credit spreads estimated by the Merton model and observations of actual credit spreads in the Norwegian bond market. Controlling for other factors, we find that Norwegian bond investors charge a higher premium above the Merton model for industrial companies than companies in the financial or utilities sector. As several of these companies are in cyclical industries such as oil & gas production, oil services and shipping, the risk premium can reflect a particular risk aversion towards cyclical companies. On the other hand, risk aversion towards high-yield issuers in general or systematic biases in the leverage ratio for these companies are other potential explanations.

Moreover, the Merton model seems to have systematic biases that relates to the input parameters for debt leverage and volatility. The finding corresponds with Eom, Helwege and Huang (2004) that the Merton model underestimates actual spreads for safe bonds with low leverage or volatility, whereas overestimating spreads for bonds with the opposite characteristics. The problem with debt leverage ratio relates to the sector premiums, and we argue that the Merton model disregards the possibility that some companies keep low debt levels due to precautionary motives, and in some cases low leverage may in fact be risk symbol. We suggest that other measures of debt levels should be considered in structural models, and cash-flow measures such as debt-to-EBITDA are a potential candidate. The reason is that cash flow ultimately is what pays the bond holders, and therefore cash flow risk is at the core of the credit risk analysis. On top of that, historic volatility measures are problematic, and in our thesis, we implement an exponentially weighted moving average (EWMA) volatility that proves better than simple rolling volatility measures. Still, some problems of volatility remains, and we argue that the Merton model`s assumption of a constant volatility is not consistent with empirical observations. The model should instead take into account the fact that stock prices go steady upwards, but fall quickly and dramatic once crises hits the economy.

Risk factors such as liquidity and the Fama & French (1993) factors for issuer size or growth are other potential explanations that relates to the credit spread puzzle. We find that these factors are present in the Norwegian corporate bond market, but that their overall effect is limited compared to the aforementioned factors. Instead, these characteristics could be important on a case-by-case basis, where bonds or companies with abnormal size, liquidity or growth may deserve an additional risk premium on the Merton model. Furthermore, the choice of risk-free reference rate matters, and when we use interbank/swap rates or government bonds we naturally impose liquidity premiums on corporate bond spreads.

Despite the many potential explanations of the credit spread puzzle, issuer specific uncertainty proves to be the most important driver of the mispricing in the Norwegian bond market. The high complexity of corporate bond valuation makes it hard for any structural model to ever attain a perfect prediction of credit spreads. For that reason, our thesis illustrates the complexity of credit risk pricing. To a large degree, the valuation of Norwegian corporate bonds remains an activity for professional investors, whose analysis of the particular issuer can incorporate a far more detailed level of risk characteristics than what is possible to incorporate in a simple credit risk model.

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8. APPENDIX

Appendix A1: Sources for our data

Table A1:
Sources of data used in this master thesis

Variable	Description	Source	Code
Input data in the augmented Merton model:			
Book value of debt	Accounting data for the sum of non-current and current interest bearing liabilities. Annual observations.	Datastream	WC03255
Market value of equity	Daily observations of traded market capitalisation	Datastream	MV
Number of shares	Daily observations of number of shares	Datastream	NOSH
Stock price	Adjusted default price in Datastream. Used in the volatility calculation.	Datastream	P
Interest expense on debt	Annual accounting data for the interest expense on debt.	Datastream	WC01251
Dividend per share	Daily observations of dividend per share	Datastream	DPS
Interbank/Swap rate	Interpolation of yield curve from a combination of swap and interbank rates. Daily observations. NIBOR rates: 2, 3, 6 months Swap rates: 2, 3, 5, 6, 8, 9, 10 years	Macrobond	
Recovery rate	From Altman & Kuehne (2012) figure 27: *Recovery Rates by Industry and Seniority 1971-2011*	Altman & Kuehne (2012)	
Time-to-maturity	The number of years between the maturity date and the issue date specificed in the loan contract.	Stamdata	
Historic default distributions	Moody`s (2011). Exhibit 38: *Average Cumulative Issuer-Weighted Global Default Rates by Broad Industry Group, 1970-2010.*	Moody`s (2011)	
Market data for yield & credit spread calculation:			
Settlement date	The settlement date registered for the bond price on the Oslo Stock Exchange.	Datastream	SETT
Turnover	We only include prices were we identify an actual trade volume. Either turnover by value or turnover by volume.	Datastream	VA/VO
Prices (different alternatives)	We include bond prices were one of the following were registered at Datastream. In preferred order: 1) Clean Price, 2) Market Price, 3) Price Datastream default	Datastream	CP/MP/MPD
Yield-to-maturity	Control-check of yield calculation with Datastream (where available)	Datastream	RY
Coupon rate, frequency and other loan data	Important loan contract data as specified in the Stamdata database	Stamdata	
Risk-free reference rates	Interbank/Swap rates calculated as above. Government bond yields from the following rates: 3, 6, 9, 12 months, 3, 5, 10 years	Norges Bank	
Other data:			
Book value per share	Annual accounting data for book value per share.	Datastream	WC05476
Price-to-book value	Datastream defined value	Datastream	PTBV
Option implied volatility	At-the-money interpolated implied volatility for call options	Datastream	VI
Number of issues	Aggregate statistics from the Norwegian bond market from Stamdata	Stamdata	
Outstanding volume on Oslo Stock Exchange	Aggregate monthly and annual statictics from the Oslo Stock Exchange	Oslo Stock Exchange	
Turnover/Outstanding volume	Aggregate monthly and annual statictics from the Oslo Stock Exchange	Oslo Stock Exchange	
Bond size	Specified in the loan contract	Stamdata	
OSEAX level	The OSEAX index level. Monthly observations	Macrobond	
OSEAX return	Calculated as the monthly y/y return on the OSEAX index.	Macrobond	

In this master thesis, we use the following databases:

1. **Stamdata:** Provider of reference data for the Nordic bond market
   URL: http://www.stamdata.no/
2. **Thomson Reuters` Datastream:** Database for accounting data and market prices
   URL: http://thomsonreuters.com/en.html
3. **Macrobond:** Macroeconomic data
   URL: https://www.macrobond.com/
4. **Oslo Stock Exchange:** Statistical data for listed bonds
   URL: http://www.oslobors.no/Oslo-Boers/Statistikk/
5. **Norges Bank:** Interest rate data for government bonds from the Norwegian Central Bank
   URL: http://www.norges-bank.no/Statistikk/Rentestatistikk/

Appendix A2: Assistive calculation for the determination of the equity volatility measure

Table A2:
Model fit characteristics for different volatility measures

Volatility measures:	**Our choice EWMA (0.98) cap 80%**	EWMA (0.98)	EWMA (0.96)	1 year rolling volaitlity	2 years rolling volaitlity
Correlation between all observed spreads and model estimate	**0.625**	0.623	0.607	0.605	0.597
Correlation between observed spreads and model estimate for monthly aggregated data	**0.693**	0.654	0.607	0.596	0.565

The paranthesis for the expontially weighted moving average (EWMA) volatility indicate the λ value

Table A3:
Model fit characteristics for different restrictions on maximum volatility in the EWMA (0.98) model

Volatility measures:	**Our choice EWMA (0.98) cap 80%**	Cap 70%	Cap 60%	Cap 55%	No cap
Correlation between all observed spreads and model estimate	**0.625**	0.615	0.602	0.595	0.623
Correlation between observed spreads and model estimate for monthly aggregated data	**0.693**	0.717	0.737	0.733	0.654

Appendix A3: Comparison of model spread and actual spread for selected companies