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Predicting spreads in the Nordic High Yield bond market

A study of credit pricing in the years 2000-2012

Adrian Gystad Ytterdal

Bjørn Halvard Knappskog

Supervisor: Thore Johnsen

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ABSTRACT

The main objective of this thesis is to identify and measure explanatory factors of observed credit spreads in the Nordic corporate high yield bond market in the period 2000 – 2012. From literature on credit pricing, we found three sources of risk compensation worth investigating; default risk, liquidity risk, and market risk. Our high yield sample consists of 323 bond issues, whereas 49 defaulted during the period.

Our spread analysis is twofold. First, we utilize an extended structural credit risk model based on the classic model of Merton (1974) to estimate fair bond spreads based solely on the expected loss from defaults. Loss given default was attempted to be modeled separately, but no systematic relationship was identified, and a static estimate was used instead.

Second, we attempted to explain the part of the observed credit spreads not explained by credit risk using a multivariate OLS-regression. This was done by instrumenting liquidity and market risk.

Our main findings are that default risk can explain as much as 65 percent of the observed credit spreads on average. Furthermore, the credit model has significantly lower relative mispricing for bonds involved in a credit event, implying that structural characteristics are good predictors of credit risk. The part of the credit spread not explained by default risk was 178 basis points (bps) on average in absolute terms. Our attempt at explaining the variation in mispricing with liquidity and market risk was less conclusive, but liquidity proved to be significant with a premium of 110 bps for illiquid issuers.

We would like to thank our counselor Thore Johnsen for answering important questions, and providing thorough reviews. We would also like to thank Mads T. Solberg at Stamdata for providing us with access to their database, and for answering key questions regarding the Nordic corporate bond market.

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1 INTRODUCTION

The Nordic corporate high yield bond market represents new and exciting opportunities for both investors in search of yield and firms seeking debt financing. However, many questions regarding the Nordic market remains unanswered, as the vast majority of existing research focus on the US market. Which factors are important when explaining credit spreads for Nordic high yield bonds? What types of risks are the investors facing and what are they compensated for? Answers to these questions would give valuable guidance to market participants, and will be the focus of this thesis.

The Nordic high yield market has for the last decade transformed from a small regional market to a highly developed bond market, and is now the third largest market for corporate High Yield bonds in the world. During the period 2005-2014 a total of NOK 660 billion has been issued by non-financial corporations in the Nordic market[1]. Yet, very few issuers are rated by a public agency. The practice is that arranging banks' credit research department publish a "shadow rating” based on international rating agency methodologies. The financial crisis in 2008 and the European sovereign debt crisis served as a reminder to investors of the downside of investing in risky debt securities. At the same time, these periods have resulted in increased regulatory requirements and increased funding costs. This has fueled the corporate HY bond market's growth by becoming an increasingly competitive source of debt capital, in addition to an exciting asset class for private and institutional investors in search for yield.

While a significant amount of research has been done on the US corporate bond market, the number of studies on the Nordic bond market is limited. The majority of bonds in the Nordics are traded over-the-counter (OTC), which makes the market less transparent due to retention of price quotes and trade details by the intermediary. Access to sufficient data is therefore a challenging process and is likely a reason for the relatively limited number of studies on the Nordic bond market.

Former master theses have studied interesting aspects of the Norwegian bond market, such as the performance of the market, default and recovery rates, and prediction of defaults. For instance, Luo and Tegnander (2012) analyze the performance of the Norwegian HY market in

[1] Source: Stamdata database

the period January 2008 – June 2012, by creating a HY index and measuring holding period returns. They find that their index yielded a compounded annual growth rate of 4.50 percent and outperformed the Oslo Stock Exchange Benchmark Index. Haugland and Brekke (2010) identified and analyzed default and recovery rates in the period January 2005 – June 2010 and found that a great number of bonds were involved in credit events in the wake of the financial crisis, and that the oil service sector experienced the highest default frequency and loss given defaults. Grøstad (2013) studies determinants of defaults in the period 2006-2013, where he uses a multivariate statistical model to predict default events with explanatory variables from the SEBRA-basic bankruptcy prediction model developed by the Central Bank of Norway. When reading through previous theses, we discovered that several studies touched upon core parts of credit spreads. Nevertheless, none of the previous master theses' investigates the explanatories of the actual bond pricing, measured by the coupon rate above the risk-free rate. This is however done by Sæbø (2015), Chief Treasurer at Folketrygdefondet. He investigates credit spreads for a sample containing both high yield and investment grade bonds in the Norwegian market for the years 2008 and 2009. The limited amount of research in the field and the opportunity given by access to a new and exciting dataset from Stamdata evoked our interest to analyze this aspect of the bond market.

The main objective of this thesis is to identify and measure explanatory factors of observed credit spreads at issue in the corporate HY bond market in the period 2000 – 2012. The area of research is highly relevant for credit market participants. For bond issuers it is beneficial to have knowledge of the credit spread dynamics to reduce the funding cost, and to better evaluate the most viable source of finance. For bond investors as for equity investors, it is critical to secure sufficient compensation related to the risk carried, which in the credit market is a function of the credit spread and the underlying credit risk. A deep understanding of the two is therefore crucial to succeed with credit investments.

The spread analysis is twofold. First we create a structural credit model to estimate fair spreads based only on the expected loss from defaults. We also attempt to model loss given default (LGD) separately to improve the credit model. Subsequently, we subtract the model spreads from the actual spreads to separate the part of the spread that is explained by default risk from the part that is due to other factors. The unexplained part is argued to include compensation for risk aversion, illiquidity, migration, and market risk, and is attempted to be explained with a multivariate regression analysis. This analytical method follows that performed by Sæbø (2015) and Eom, Helwege, and Huang (2004) among others, but is differentiated by its attempt to do an individual estimation of LGD for each issue of debt.

Due to lack of data on trading prices, the analysis is based only on observed spreads at issue. We assume that the bond is issued at par, and hence that credit spread can be derived from the coupon rate. Only bonds issued by public companies are included, as the structural model applied in the spread estimation requires equity market variables. The final HY sample consists of 323 bonds, whereas 49 defaulted during the period.

Our main finding is that default risk can explain as much as 65 percent of the observed credit spreads on average, which is significantly higher than the mispricing of 21.5 percent found by Sæbø (2015). Furthermore, the credit model has significantly lower relative mispricing for bonds involved in a credit event, implying that structural characteristics are good predictors of credit risk. The part of the credit spread not explained by default risk was 178 basis points (bps) on average in absolute terms. Explaining the variation in mispricing with liquidity and market risk was less conclusive, but liquidity proved to be significant with a premium of 110 bps for illiquid issuers.

The structure of this thesis is as following: Chapter 2 presents basic bond theory required to follow the discussions and analysis in the paper. Chapter 3 gives a description of the Nordic bond market, with main emphasis on the Norwegian market. Chapter 4 presents more advanced concepts and literature on credit pricing. Chapter 5 describes the data used in the analysis. Chapter 6 describes the methodology used to reach estimated bond spreads. Chapter 7 presents and analyzes the estimated credit spreads from our model, before we conclude in chapter 8.

2 BASIC BOND THEORY

In this chapter we will present basic bond theory in order to set the backdrop for the coming analysis. Theory regarding bond characteristics and credit risk will be covered.

2.1 What is a bond?

A bond is a debt security where an investor (bond holder) loans money to an entity (issuer), most often a corporation, a government, or a local government structure. The issuer of the bond makes periodical payments (coupons or interest) to the bond holder, and pays a principal through installments or at the end of the period called the maturity date. The owner of a bond can often trade the bond in the secondary market.

2.2 Bonds in relation to firms' capital structure

Firms are able to choose from a range of different options to finance their operations. The two main categories are debt and equity, whereas debt is always repaid before equity in case of bankruptcy. There is also a difference in priority within the debt category in case of default, which affects the amount expected to recover at default and the cost of capital of each type. The most secure form of debt is senior secured, which is secured with collateral. This means that the creditor has the right to certain assets in case of bankruptcy. The full capital structure priority ranking is summarized in table 2.1 below.

Table 2.1: Capital structure characteristics

Capital structure ranking	Priority in a default	Expected recovery in a default	Capital cost
Senior Secured	Highest	Highest	Lowest
Senior Unsecured	↓	↓	↓
Subordinated			
Preffered Stock			
Common Stock	Lowest	Lowest	Highest

2.3 Types of bonds

Bonds are often classified according to three main characteristics; their maturity, convertibility, and return type.

A bond with a defined maturity of more than one year is simply called a bond, while bonds with maturity of less than a year is called a certificate. A bond without a defined maturity date is called a perpetual bond. Bonds can similarly to a mortgage have both a fixed and floating rate payment structure. Floating rate bonds are normally linked to a benchmark government interest rate, like the NIBOR in Norway or LIBOR in GB. However, floating rate bonds can also be linked to other economic indicators such as inflation, macroeconomic indicators, stock indices, and so forth.

Other, more exotic bonds, include convertible, callable, and puttable bonds. The bondholder of a convertible can choose at maturity whether to redeem their bond for principal or equity shares. This enables bondholders to gain an upside, and hence such bonds pay less interest than similar plain bonds. A callable bond can be redeemed by the issuer prior to its maturity, while a holder of a puttable bond can force the issuer to repurchase the bond at predetermined dates and price prior to maturity.

2.4 Credit spread

A credit spread is defined as the difference between the yield on two debt securities with the same characteristics, but different credit risk. For bonds issued at par, the norm is to calculate the spread between the coupon of the corporate bond and a corresponding government bond. The latter is used as a proxy for a risk free rate. This way, the spread is a measure of the market premium of the risky debt security. We make the assumption that all bonds are issued at par as we have a cross-sectional dataset with only observations at issue and eventual default. If we had observations of continuous bond prices, a spread between the yield to maturity of the bond and a relevant government bond would be more suitable, as the assumption that the yield to maturity is equal the coupon would not be valid.

2.5 Credit risk

Credit risk is defined as the risk of the bond issuer failing to meet a contractual payment obligation. The failure to meet a promised payment is a default.

Moody´s define default in four distinct types (Sun, Munves, & Hamilton, 2012)

1. A missed or delayed disbursement of interest and/or principal, including delayed payments made within a grace period

2. Bankruptcy, administration, legal receivership, or other legal blocks (perhaps by regulators) to the timely payment of interest and/or principal
3. A distressed exchange occurs where: (i) the issuer offers debt holders a new security or package of securities that amount to a diminished financial obligation (such as preferred or common stock, or debt with a lower coupon or par amount, lower seniority or longer maturity); or (ii) the exchange had the apparent purpose of helping the borrower avoid default.
4. Government bailouts enacted to prevent a credit event

By buying and holding a risky bond, bond holders require to be compensated for credit risk, i.e. what they can expect to lose from holding the bond. This can we viewed as a function of 3 factors; (1) The cumulative probability that the issuer defaults during its bonds lifetime, (2) the percentage amount recovered should the bond default, and (3) the bond holder's exposure at default. As we are only looking at bullet bonds[2], we assume that exposure at default always is equal to 100 %. This compensation is formulated as the expected default loss of the bond, and is often defined as the product of the probability of default and loss given default.

$$\text{Spread} \approx \text{Expected default loss} = \frac{1}{\mathrm{T}} \times \mathrm{CPD} \times \mathrm{LGD} = \frac{1}{\mathrm{T}} \times \mathrm{PD} \times (1 - \mathrm{RR})$$

Where CPD is the cumulative probability of default from 0→T, LGD is loss given default, and RR is the recovery rate given default. The formula intuitively shows that the product of the probability that you will not be paid back in full and what you risk to lose, equals the expected loss. By using the *cumulative* probability of default and dividing by years until maturity T the formula expresses expected default loss per year.

In addition to the expected default loss given in the simple model above, in reality several other factors also affects the spread of bonds. Longstaff et al. (2005) examines the components of credit spreads, and finds that credit risk accounts for the majority of the spread, and that the relative size of this component grows as credit rating declines. This result is part of our motivation for focusing on the expected default loss, as credit risk is the major

[2] A bond where the entire principal is paid at once at maturity date

component of bond spreads, and that our sample solely consists of high yield bonds. However, we will also examine other possible components of the credit spread, as explained in chapter 4.3.

2.6 Credit ratings

A credit rating is an assessment of the credit worthiness of a borrower or a specific issue of debt. The best known are the credit ratings done by dedicated rating companies like S&P and Moody´s. The ratings performed by banks are called "shadow ratings". The rating firms are paid by the entity that is seeking rating either for itself or one of its debt issues.

A rating is a relative measure of the riskiness of the borrower or issue. Hence, a AAA rating is not a guarantee against default, it only implies that it is less probable that the firm will default than another firm with lower rating. The same scale is used for all types of issuers, should it be a government, a municipality, or a firm. As seen from table 2.2, the rating classifications used by different rating companies are very similar, even though they use different rating methodologies. A common factor is that the probability of default is a key factor for credit rating (Berk & DeMarzo, 2011). Bonds are divided into two main credit risk categories, *i*nvestment grade (low risk) and high yield (high risk). Investment grade is defined as bonds with a credit rating of BBB- or higher, while high yield is bonds with credit rating BB+ or lower.

Table 2.2: Credit ratings

Risk class	Moody´s	S&P/Fitch	Definition
INVESTMENT GRADE	Aaa	AAA	Best quality
	Aa1	AA+	Strong ability for timely payments.
	Aa2	AA	
	Aa3	AA-	
	A1	A+	Somewhat more exposed for negative changes.
	A2	A	
	A3	A-	
	Baa1	BBB+	Adequate ability to meet payments. Some elements of protection missing.
	Baa2	BBB	
	Baa3	BBB-	
SPECULATIVE GRADE / HIGH YIELD	Ba1	BB+	Speculative risk. Future not well secured.
	Ba2	BB	
	Ba3	BB-	
	B1	B+	Timely payment at the moment. Very exposed to any negative changes.
	B2	B	
	B3	B-	
	Caa1 …	CCC+ …	Default a likely option.
	Ca-C	CC-C	
	D	D	Default has occured.

Source: Håvik (2013)

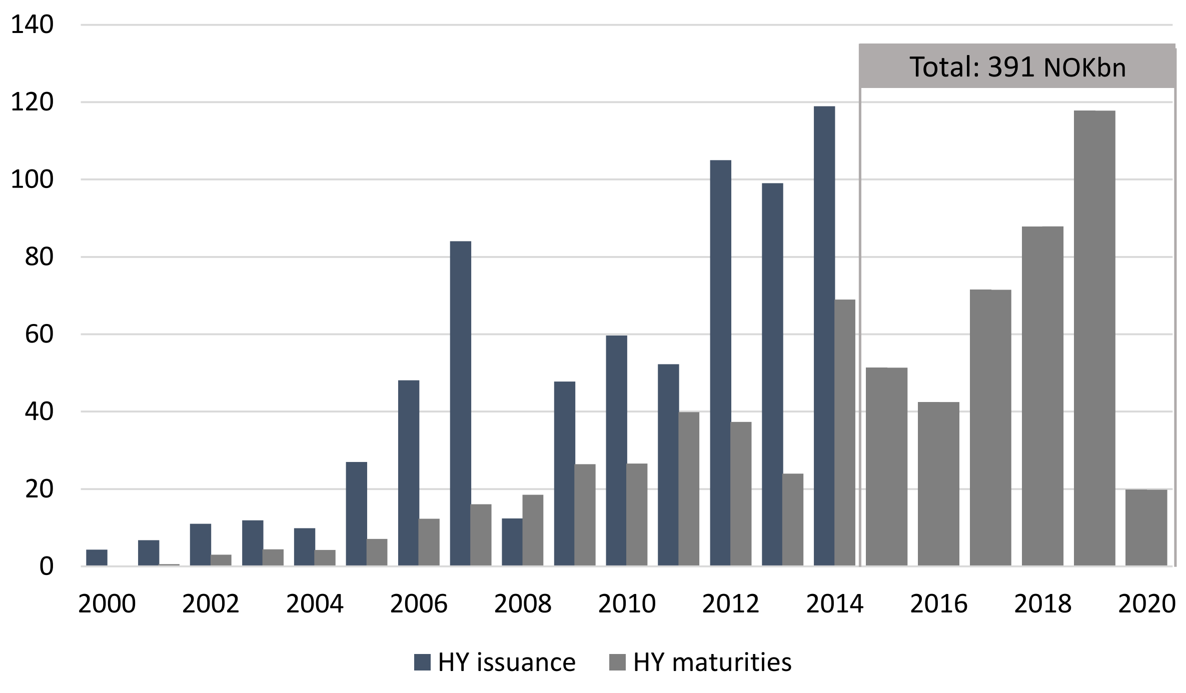
3 THE NORDIC CORPORATE BOND MARKET

This chapter will briefly introduce the Nordic corporate High-Yield market, present descriptive statistics and general characteristics, discuss bond trading and transparency, and the role of Nordic Trustee. The main focus will be dedicated to the development of the Norwegian bond market as it is dominating in size, representing almost 70 percent of total issued volume in 2014 (DNB, 2014).

During the last decade, the Norwegian corporate bond market has transformed from a small national market dominated by domestic utilities into a global market with large issue volumes of high yield corporate bonds (Lind, 2014). The transformation has made the Oslo Stock Exchange and the Nordic Alternative Bond Market the world’s third largest market place for high yield corporate bonds. Along with the substantial growth of the Nordic HY market, a large number of international issuers and international investors have entered the market. The percent of bonds issued by foreign companies have increased from 10 percent in 2005 to almost 50 percent in 2014 (DNB, 2014).

Figure 3.1 displays total issue and maturity volume in the period 2000 to 2014. The Norwegian High Yield market experienced significant growth prior to the financial crisis in 2008. The real economy was severely hit by the crash in the worldwide financial system. Equity and debt capital markets nearly froze overnight and banks were reluctant to offer capital and provide liquidity. The Nordic bond market was no exception and was significantly affected, declining from an all-time high issue volume of ~ NOK 80 billion in 2007 to less than a fifth of that in 2008. In the following years, the Nordic bond market recovered in a high pace, reaching new all-time high levels in 2012 and 2014. The significant growth is due to several factors. The global monetary policy implemented to address the credit crisis has led government bond yields to historically low levels, and has forced institutional investors down the credit ladder in the search for yield. Furthermore, as a consequence of the financial crisis and the European sovereign debt crisis, institutional banks are under stricter regulation and face increased funding cost, which reduces the availability of bank financing. Consequently, the Nordic HY market has satisfied both bond issuers and investors, as bank lending deteriorated and the search for yield intensified.

Figure 3.1: High yield bond issue and maturing volume (NOK billions)



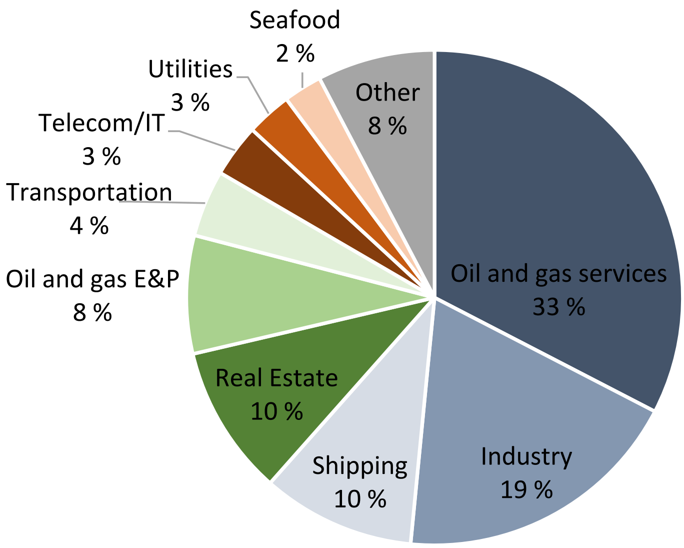
Source: Stamdata database

Figure 3.1 illustrate significant refinancing needs in the years to come, and that a large part of the outstanding debt is exposed to the current low oil price. Over 40 percent of the Nordic bond market originates from oil and gas related issuers, and from the time of issue the oil price has declined from levels around $100 per barrel to below $60 per barrel. In the coming five years, from 2015 to 2020, a total of NOK 391 billion of outstanding debt matures. Two challenges lay ahead for bond issuers in the Nordic credit market. First to be able to pay the principal and then to find refinancing at acceptable terms.

3.1 Corporate bond issuers

Due to the nature of Norwegian business, the issuers in the Nordic corporate bond market have originated from capital intensive industries such as oil and gas, offshore, and shipping. In figure 3.2, we see that oil and gas related industries represented over 40 percent of the total outstanding amount in 2015. However, in the recent years also other industries, such as fishery, food and service industry, real estate, and other industries, have begun to use the bond market as a source of debt financing.

Figure 3.2: Percentage bond issue volumes by industry (2000-2014)



Source: Stamdata database

Issuers have become increasingly diverse over the last decade. Today, issuers of all risk classes, newly established and matured firms, small and large caps, are represented in the market.

3.2 Listing of bonds in Norway

Today there exists two marketplaces for issuing debt in Norway, both offered by Oslo Børs; Nordic ABM and Oslo Børs. Nordic ABM is a more flexible offering, enabling companies to list debt in less than one week, with no need of approval from The Financial Supervisory Authority Norway and only on the basis of existing company information (Oslo Børs, 2015). According to the MIFID[3] definitions, Nordic ABM is an unregulated marketplace and the issuer does not need to prepare their annual reports according to IFRS standards. Oslo Børs is considered a regulated marketplace by MIFID. A larger degree of transparency is demanded from the issuer, and the issuer must prepare an EEA-prospectus approved by The Financial Supervisory Authority Norway.

3.3 Nordic Trustee and Stamdata

Nordic Trustee, previously Norwegian Trustee, is the leading supplier of trustee services in the Nordics, and has been a central market player since its establishment 20 years ago. The trustee´s main services are to monitor that issuers complies with agreed bond covenants, makes their scheduled payments in time, and acts as a communication channel between the issuer and the bond holders. The trustee manages third-party contractual rights on the basis of individual assignments, and mainly offers these services to bond holders. The company itself was established as a collaboration between Norwegian banks in order to offer a neutral trustee service to the bond market, and is now primarily owned by Nordic banks, life insurance companies, and security brokers (Nordic Trustee, 2015).

The use of a trustee can prove to be a major benefit both for issuers and bondholders. For the issuer, the trustee functions as single negotiation partner when discussing terms and issues with bond holders, and makes the process easier than having to approach each individual bond holder. It also makes it harder for single bond holders to steer negotiations to their own self-interest that violates the wishes of the majority. There exists no legal obligation for issuers to use a trustee, but the vast majority of firms in the market choose to do so.

Stamdata is a subsidiary of Nordic Trustee, and is the leading provider of reference data for Nordic debt securities. They supply information on loan documents, the letters sent from the

[3] Markets in Financial Instruments Directive of the EU

trustee to the bondholders, in addition to a detailed statistical database. The database covers Nordic debt securities, covering information on bonds, certificates, and structured debt securities. Nordic Trustee started Nordic Bond Pricing AS in 2013, who collects continuous prices of bonds. The service is currently not available, but should provide interesting research possibilities in the future.

3.4 Bond trading

The majority of corporate bonds are traded over-the-counter. This means that trades are done via a dealer network as opposed to a centralized exchange. In practice, a transaction is negotiated directly over computer networks, or by phone, with a broker-dealer. This is the reason why the corporate bond market is less transparent than the equity market, as price quotes and trade details are retained by the intermediary.

3.5 Uniqueness of the Nordic corporate bond market

The Nordic bond market has several characteristics that distinguishes it from its larger US and European international counterparts, and that makes it a convenient market to raise debt capital. First, the Nordic market has no public rating requirements from agencies such as Standard & Poor’s, Moody’s, or Fitch. The practice is rather that the arranging banks’ credit research department publish a "shadow rating” based on international rating agency methodologies.

Second, the documentation requirements are far looser and the timeline for a bond issue is far shorter than international standards. The documentation generally consist of a term sheet of 5 – 8 pages followed by a standard agreement of 30 – 35 pages between the issuer and the trustee (Lind, 2014), resulting in a far simpler origination process than bonds issued under US or UK laws (Fitch Ratings, 2014). The timeline for a bond issue is normally less than five weeks for first time issuers and even shorter for frequent issuers.

Finally, the transaction costs are lower compared to the UK and US (Lind, 2014). After the bond has been issued, listing is optional.

The characteristics mentioned above have contributed to regional, and increasingly more international issuers and investors, preferring the emerging Nordic product over the cumbersome and costly international HY process (Fitch Ratings, 2014).

4 BOND PRICING THEORY

We will here present literature, theory, and our model choices done to estimate bond spreads. We implement a credit pricing model using individual estimates of recovery rates in order to provide an estimate of bond spreads. We begin by reviewing literature and theory of credit pricing and follow with reviewing recovery rate prediction.

4.1 Credit pricing

There are today three main approaches to credit modelling and the pricing of credit risk. The first, and maybe best known, is based on Merton's structural model (Merton, 1974). The second is the so called "reduced-form models", with Jarrow et. al (1995) being one of the earliest examples. The third is purely statistical models like the SEBRA model used by Norges Bank (The Norwegian central bank) (Bernhardsen & Larsen, 2007) and Altman's Z-score method (Altman E., 1968).

The structural models are all based on a contingent-claims approach to valuing corporate debt using the option pricing theory proposed by Black & Scholes (1973) and Merton (1974). These are mainly used to estimate the spreads of bonds issued by public firms, as stock prices are a major component of the model input parameters, and the use of e.g. comparables would introduce new major sources of error. They are the models most used by practitioners today, with CreditMetrics and Moody´s KMV both using this methodology, and are favored for their economic intuition. The reduced form method models a company's time to default as a stochastic process whose price parameters are estimated by fitting the model to past bond price data. Hence, no assumption regarding the firm assets is made, and the dynamics of default is exogenously specified. The model's main difference from the structural model is its assumption of a limited information set, in contrast to the comprehensive set assumed by structural models. It is assumed to be a more theoretically correct model due to this fact, but is limited by the need of detailed bond price data. Statistical models use various forms of econometric techniques to identify determinants of default. They are less reliant on economic theory as their model framework, but are limited by their poor out-of-sample-power.

We have chosen to use a structural model based on the Merton (1974) model in our paper, and motivate this choice by the model's economic intuitiveness, ease of interpretation, and our existing knowledge of the Black & Scholes and Merton framework. Furthermore, the absence of sufficient high yield bond price data disables us from implementing a reduced form model, and a statistical approach would make it difficult to separate the effect of credit risk and other factors. We will thus focus on the structural models in the theory and literature review, but we will also provide a brief review of reduced form models and statistical models.

4.1.1 Basic Merton model

The basic Merton model uses the market value of equity of the firm, equity volatility, and the risk free rate to evaluate the assets and debt of a firm. The model builds upon the fact that debt and equity value can be replicated using options on the firm's assets and uses option pricing to value the company's debt under the no-arbitrage argument. We briefly present the intuition to why equity and debt can be replicated with options.

Equity holders only have a claim on the company when the value of the firm is higher than the value of the debt. The value can be described as $E_t = Max[0, V_t - D]$, meaning that if the value of the firm exceeds the value of the debt at maturity, equity holders receive the residual claim. But if the firm value is below the debt value the equity is worthless. The value of an equity position is thus exactly the same as a call option on the firm's assets with exercise price equal to the face value of debt (FV):

$$Equity = Call\ Option(FV) \tag{4.1}$$

The same approach can be used to define the debt value using options on the firm's assets. The payoff to debtholders at maturity can be defined as a portfolio of a risk free zero coupon bond with face value equal to the face value of outstanding debt and a short position in a put option on the firm's assets with strike price equal to the face value of the outstanding debt at maturity:

$$Debt = Riskfree\ Bond - Put\ Option\ (FV) \qquad (4.2)$$[4]

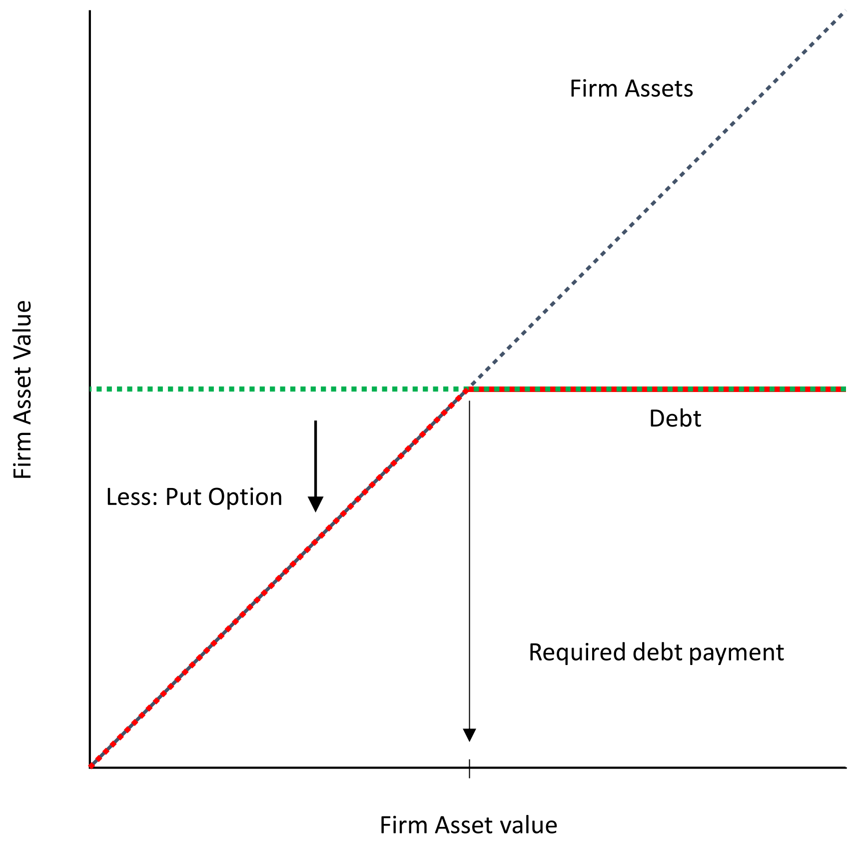
If the firm's asset value exceeds the required debt payment, the put is worthless, and debtholders receive the principle payment in full. If the firm's assets is below the required payment, the owner of the put will exercise it. The debtholder will then receive the principle

[4] See appendix 6C for a derivation of equation 4.2

of the risk-free bond minus the difference between the asset value and the principle, leaving the debtholder with only the assets of the firm.

The payoff to debtholders at maturity is illustrated in figure 4.1 and gives an intuitive understanding that the replicating portfolio in equation 4.2 equals the debt value.

Figure 4.1: Debt value as a of a risk free bond minus a put option on the firm's assets



Source: Berk & DeMarzo (2011)

A useful application of the above, besides valuing risky debt, is that it can be used to derive the probability of default. From (4.2) we see that the only case where the debt is not paid in full, i.e. default, is when the put option is exercised. In other words, the probability of default equals the probability that the put option is exercised. We will discuss this further when presenting the Black & Scholes option pricing model.

The section above gave insight to how equity and debt can be valued using options on the firm’s assets, which will be useful to follow the presentation of the basic Merton model in the following.

In the basic Merton model, Merton uses the insight that the difference between a risk free bond and a risky bond is simply a put option[5] on the underlying asset and applies a classic Black & Scholes model for valuation. The model assumes that the firm has issued one zero coupon bond, and that if the value of the firm's assets A_t falls below the default point B at the time of maturity T then the firm defaults. If not, then the firm pays their debt in full, and the remaining value of the equity is $E_t = \max(A_t - D, 0)$.

The model is based on several assumptions (Merton, 1974).

1. There are no transactions costs, taxes or indivisibilities of assets
2. There are a sufficient number of investors with comparable wealth levels such that each investor believes that he can buy and sell as much of an asset as he wants at the market price
3. There exists an exchange market for borrowing and lending at the same rate of interest
4. Short sales of all assets, with full use of the proceeds, are allowed
5. Trading in assets take place continuously in time
6. The Modigliani-Miller (MM) theorem that the value of the firm is invariant to its capital structure obtains.
7. The term structure is flat and known with certainty; i.e., the price of a riskless discount bond that promises a payment of $1 at time T in the future is $P(t,T) = e^{-r}(T-t)$, where r is the (instantaneous) riskless rate of interest, the same for all time
8. The dynamics for the value of the firm, V, through time can be described by a diffusion-type stochastic process.

Merton (1974) notes that the first four assumptions, regarded as the perfect market assumptions, can be significantly weakened, as they are not necessary for the model to obtain. Assumption seven is made to focus on default risk rather than interest rate risk. Sundaresan (2013) discusses the assumptions and their use in evolving literature. Several strands of literature incorporate stochastic interest rates, which directly break assumption 7.

[5] In practice a credit default swap (CDS)

Merton notes that this is a fairly harmless modification of his main insights. Sundaresan (2013) further notes that assumption 5 regarding continuously traded assets in time is used in practically all papers in the literature, and assumption 8 has been relaxed in some papers.

The model assumes that the asset value, A_t, follows a geometric Brownian motion (GBM)

$$dA = \mu_A \cdot A \cdot dt + \sigma_A \cdot A \cdot dW \tag{4.7}$$

Where μ_A is the expected continuously compounded return on A, σ_A is the volatility of asset returns and dW is the standard Wiener process, which is a continuous-time stochastic process, i.e. a random process. A Brownian motion assumes that there are two parts to a random movement. The first is a constant drift, illustrated by the first addend in equation above. The second is a random component, illustrated by the second addend in the equation. The movement of the asset is thus a result of a constant drift plus a random movement. Consequently, as the asset can increase or decrease at any random rate, the central limit theory in statistics tells us that the periodic return will be normally distributed, which is the foundation of the Black-Scholes-Merton model. Merton utilizes the Black & Scholes formula to calculate the value of equity as the value of a call on the firm's underlying assets A with maturity at time T and exercise price equal to the debt value B. The value of equity is then given by the following formula:

$$E = A\,N(d_1) - Be^{-rT}N(d_2) \tag{4.8}$$

where

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

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

N(·) represents the cumulative normal distribution function. Here r is the continuously compounded risk free interest rate, σ_A is the asset volatility, and T is time to maturity. The formula above is the basic Black & Scholes formula for pricing a European call option.

In simplified terms, equation (4.8) can be interpreted as what one would expect to receive minus what one would expect to pay from buying the call option. The variables d_1 and d_2 are derived from the formula for calculating the standard Z-score, which is a statistical measurement used to derive probabilities from a normal probability distribution[6]. In fact, $N(d_2)$ is equal to N(-Z) from a normal probability distribution and is simply the probability that the asset value A will be at or above the debt value B at maturity. A direct result from the previous is that $N(d_2)$ represents the probability that the option is exercised. $N(d_1)$ is what is known as a conditional probability. When multiplied with the asset value, A$N(d_1)$ is the expected value of the firm if, and only if, the asset value is above the strike price at expiration. From these interpretations, the Black & Scholes formula can be described as the expected value of the assets, given that it's above the debt value, minus the present value of what is to be paid multiplied with the probability of exercising. In other words, what one would expect to receive minus what one would expect to pay.

Merton (1974) then utilize the Black & Scholes formula to value debt as a risk free bond minus a put option on the firms underlying assets A with maturity at time T and exercise price equal to the debt value B. The value of the put option, or risky debt is given by the following formula:

$$D = P = Be^{-rT}\, N(-d_2) - A\, N(-d_1)$$

$AN(-d_1)$ is now the expected value of the assets if, and only if, the value is below the strike price at expiration. $N(-d_2)$ is the probability that the asset value is below the strike price at expiration and consequently also the probability of the put option to be exercised, which we earlier found to be the same as the probability of default when valuing debt using options in the theory section.

4.1.2 KMV extension of the Merton model

In their paper, Crosbie & Bohn (2003) gives the reader insight into the KMV model, which enables an intuitive explanation of the transition from the Merton model to estimates of credit spreads. With the estimate of probability of default, it is easy to see the transition from the Merton model to an estimate of credit spread by multiplying probability of default with the recovery rate, and adjusting for maturity. They use the credit risk measure *distance to default* and defines it as the number of asset standard deviation moves the asset value must make in order for a firm to default. Crosbie & Bohn (2003) explains how distance to default can be estimated through the observed values of stock prices, long term and short term debt,

[6] See appendix 6A for a presentation of the normal probability distribution and Z-scores

the risk free rate through government treasury rates, and time to maturity T. They estimate the asset value A, asset volatility σ_A, expected asset return μ_A, and default barrier B, and use the estimates[7] to calculate distance to default (DD) as follows

$$DD = \frac{\ln\left(\frac{A}{B}\right) + \left(\mu_A - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}}$$

The expression shows the change in continuously compounded returns measured in standard deviations, which needs to change in order for the firm to reach default. Thus, $\ln\left(\frac{A}{B}\right)$ can be interpreted as the return the firm can afford to lose, and $\left(\mu_A - \frac{1}{2}\sigma_A^2\right)T$ can be interpreted as the return the firm is expected to earn before the debt matures. The sum of the two expressions is therefore the maximal negative change in returns possible without reaching default. Again, this is measured in terms of standard deviations. If we assume that DD is normally distributed, i.e. that the asset value follows a geometric Brownian motion, the probability of default can then be calculated using the normal probability distribution[8]:

$$PD = N(-DD)$$

Moody´s KMV has created their own distribution based on historical defaults. This distribution is created by matching a certain company's DD with other companies with the same DD and time to maturity, and observe how many defaulted. This makes it possible to create a default frequency distribution. With this approach, the model is independent of any theoretical assumption of probability distribution. However, a problem does arise when assuming that historical defaults has predictive power, which has been a major point of criticism of structural models. Critics are skeptical of using past events as predictions of the future, and instead promote the use of forward looking variables such as prices. However, Moody´s KMV has shown that their model has good predictive power (Crossen & Zhang, 2011).

Crosbie & Bohn (2003) illustrate how their measure EDF is estimated. EDF, or estimated default frequency, may be defined as the probability of default within 1 year and is calculated

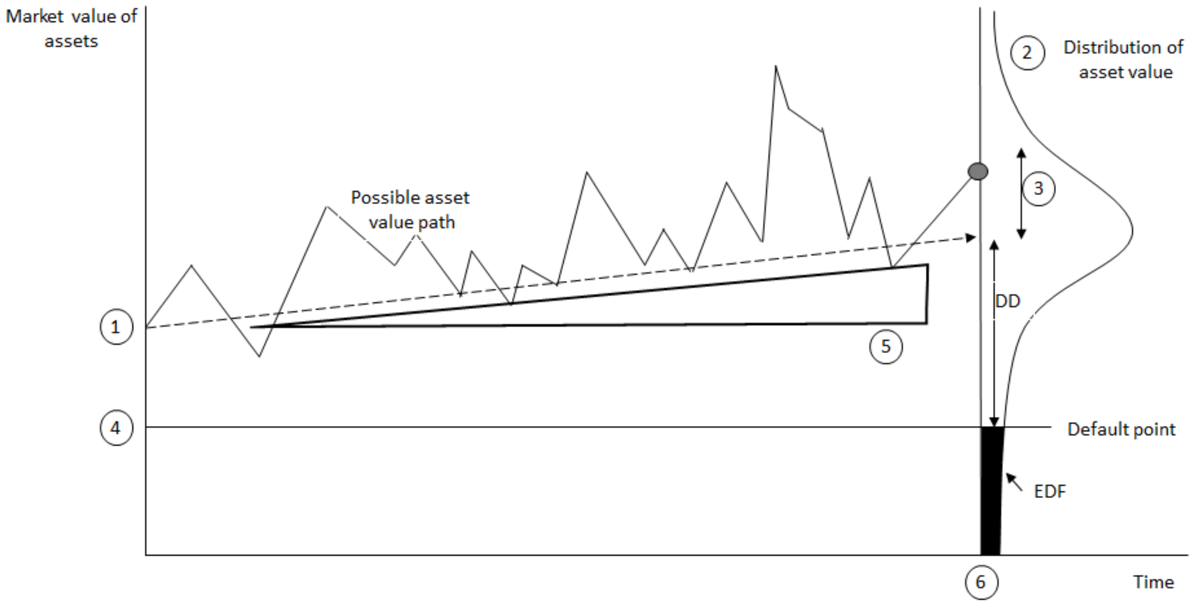
[7] How asset value, asset volatility, expected asset return, and default barrier are estimated is explained in the methodology section

[8] As explained in appendix 6A

using the method described above. The figure 4.2 explains how EDF is calculated using 6 input variables:

1. The current asset value
2. The distribution of the asset value at time H
3. The volatility of the future asset value at time H
4. The level of the default point, determined by the book value of total liabilities
5. The expected rate of growth in the asset value over the horizon
6. The length of the horizon, H

Figure 4.2: Illustration of distance to default and probability of default



The figure visualizes the intuition behind their model, with asset value at time 0 (1) growing at an expected rate (5) with a certain degree of volatility (3). If the asset value falls below the default barrier (4), here assumed to be the book value of liabilities, the firm defaults at time H (6). Given a distribution (2) around the expected value of assets, the probability of default can intuitively be calculated as N(-DD) given the normal distribution, visualized as the shaded area under the graph.

4.1.3 Adaptations of the Merton model

The Merton (1974) model spawned a large amount of theoretical literature on risky debt pricing. In this section, we will review some of the extensions and adaptions of structural models done in the literature. According to Eom et al. (2004), one motivating factor of the large amount of literature is the perception that the Merton model cannot predict sufficiently high spreads to match those observed in the market. The resulting papers have included various extensions and improvements in order to correct for this underpricing. Examples include allowing for coupon payments (Eom et al. (2004), Black & Cox (1976), Bielecki & Rutkowski (2002)), stochastic interest rates (Longstaff & Schwartz (1995)), allowing default prior to maturity (Gekse (1977), Jarrow & Protter (2004)), including the effect of covenants (Black & Cox (1976)), taking account of taxes and bankruptcy costs (Leland (1994)), and implementing a stationary leverage ratio (Collin-Dufresne et al (2001)). However, even with extensions, most of the models still underestimates spreads.

There has been developed several adaptations of the Merton model in recent times, and hence several multi-model analysis´ have been performed in order to measure the accuracy of the new models. Eom et. al (2004) is one such study. They tested the accuracy of 5 models; an extended version of the Merton (1974) model allowing for coupons through the modelling of the bond as a portfolio of ZCB, in addition to the models of Geske (1977), Leland & Toft (1996), Longstaff & Schwartz (1995), and Collin-Dufresne et al (2001).

They found that all models tested have bias issues, over predicting spreads for high yield bonds and underestimating spreads for safer, investment grade bonds. The Merton (1974) and Geske (1977) models both tend to underestimate spreads on average, while on the other hand, Leland & Toft (1996) overestimates spreads.

We try to minimize the problem of underestimation by implementing an extended version of the Merton model, as described by Eom et al (2004). This model incorporates coupons, payout ratio[9], and default before maturity. This is done by valuing a bond as a portfolio of zero coupon bonds, thus incorporating coupons and default before maturity at once. Payout ratio is included to incorporate the cash outflow to bond and equity holders. This eliminates some of the simplifying assumptions in the simple model, and should in theory produce more accurate estimates. More details on the model are shown in the methodology section. Given that the previous literature shows that most structural models under predict spreads even with the extensions mentioned, we try to give insight into what this difference consists of

[9] Defined as the sum of dividends to equity holders, share repurchases adjusted for stock splits, and interest paid to equity and bond holders, divided by asset value

through a regression analysis of the mispricing, thus enabling us to use a model that in the base case underestimates spreads.

4.1.4 Reduced form models

Another major strand of credit risk modelling research focuses on reduced form models of default. One of the earliest examples of reduced form models are first found in a 1995 paper written by Jarrow & Turnbull (1995). The reduced form models' flexibility in their functional form is one of the main traits differentiating the model from structural models. Their flexible form entails that it is easy to fit a narrow collection of credit spreads. You are left with a model with strong predictive power within the sample, but low predictive power outside the sample. This is in strong contrast to structural models, which functional form is static (Arora, R. Bohn, & Zhu, 2005). The method models a company's time to default as a stochastic process with price parameters estimated by fitting the model to past bond price data. This contrasts with the structural models, where no assumption regarding firm assets is made and the dynamics of default is exogenously specified.

Jarrow et al (2004) compares structural and reduced form models, and highlights their differences. They point out that structural models assumes complete information about a very detailed information set, thus assuming that a firm's default time is predictable. In contrast, reduced form models assume knowledge of a less detailed information set, more like what is actually observable in the market place. This information assumption implies that the firms default time is inaccessible. This is the main part of the discussion and conflict between researchers favoring one or the other model. Followers of reduced form models argue that their information assumption is more realistic, and should be used because it is the same information set used by the market (Jarrow & Protter, 2004). On the other hand, users of structural models (Arora, R. Bohn, & Zhu, 2005) argue that the complete information assumption of structural models is an approximation designed to facilitate a simpler way of capturing the various economic nuances of how a firm operates.

There has been an increase in research regarding reduced form models in recent times, motivated by the fact that the framework utilizes bond prices as input. Comprehensive information regarding bond prices has been, and still is to a certain degree, hard to obtain. Nevertheless, as information access is improved, we might see an increase in popularity of these models.

4.1.5 Statistical models

A third strand of literature is based on using econometric techniques to find determinants of default and with them create a model for predicting default. One such model is the SEBRA model of Norges Bank (Bernhardsen & Larsen, 2007). This model uses key figures calculated on the basis of firms' annual reports, in addition to data on the firms' age, size, and industry. The model has been revised and improved over the years by researchers at Norges Bank, and is mainly used to estimate the vulnerability of the banking sector.

A better-known model is the so-called Z-score model developed by Altman (1968). He performed multiple discriminant analysis as a tool to predict bankruptcy, which is an econometric technique used to categorize an observation into several predetermined categories. He used a sample of 33 companies that went bankrupt during the years 1946-1965 and paired them with 33 companies of the same industry and size. He collected financial data from the year previous to the year of default, and collected in total 22 various variables, out of which 5 were deemed significant in predicting corporate default. The variables were; earnings before interest and taxes divided by total assets, working capital divided by total assets, market value of equity divided by book value of total debt, retained earnings divided by total assets, and the ratio of sales divided by total assets. Altman continued his research, and developed a new model in 1977 (Altman, Haldeman, & Narayanan, 1977), using the same methodology, but now with a larger sample.

Statistical models has been popular as they are less reliant on specific assumptions about the dynamics of default, but are limited by their poor out-of-sample-power. This means that the coefficients estimated by Altman using American data is not universally applicable to all markets and industries.

4.1.6 Our model choice

In this paper, our focus is on the structural models of default and we have chosen to apply an extended version of the Merton model. This model does not need two of the simplifying assumptions of the simple model; no coupons and that default only can happen at maturity. These two assumptions are taken into account by modelling coupon bonds as a portfolio of zero coupon bonds, and through this improvement, we reduce some of the bias of the simple model. In addition, the model implements the simple modification of adding payout ratio[10] as part of the drift term of assets. We further motivate the choice of this model with its economic intuitiveness, ease of interpretation, and our existing knowledge of the Black & Scholes and Merton framework. How we implement this model is described further in chapter 6.1.1.

4.2 Predicting recovery rates

The previous section gave a thorough presentation of the theory behind our model framework that will be used to price the bonds in our sample. An important factor in the model is the recovery rate in the case of default. Hence, precise estimates of recovery rates would strengthen the model's accuracy in predicting spreads. In 6.2 we perform an individual analysis of recovery rates in attempt to attain individual recovery rate estimates. In this section, we will review theory and literature regarding modelling of recovery rates to motivate our recovery rate analysis.

There are generally two types of literature on recovery rates: (i) Theoretical papers on credit risk models that makes various assumption about recovery rates, and (ii) empirical papers that studies historical recovery rates on defaulted bonds.

Theoretical papers on recovery rates are, for obvious reasons, closely linked to the various credit risk theories presented earlier in this paper. Creating a credit risk model without making explicit or implicit assumptions regarding the recovery rate is inevitable. Second generation structural models, which is what is used in this paper, treat the recovery rate as an exogenous variable. The recovery rate is thus independent from the probability of default and needs to be estimated separately. This is partly the motivation for performing a complete analysis on recovery rates before running the credit model.

Empirical papers on recovery rates are generally data intensive studies attempting to identify driving factors of recovery rates using various statistical methods. For instance, Altman and Kishore (1996) analyze recovery rates with respect to industry, and find that public utilities, chemical, and petroleum companies has the highest average recoveries. Furthermore, they find that bond rating has almost no effect when adjusting for seniority, which is the same

[10] Payout ratio is defined as the sum of dividends, share repurchases, and interest paid to debt and equity holders.

conclusion of a similar study by Hanson & Schuermann (2004). Other studies have found that recovery rates and default rates are negatively related (Altman, Brady, Resti, & Sironi, 2005). On the other hand, one may find researchers who argue that there is no need to systematically model recovery rates. The argument is that the recovery rate is the outcome of a bargaining process between the creditor and the debtor, which is assumed to be unsystematic (Longstaff & Schwartz, 1995).

The recovery rate analysis in section 6.2 will test several of the driving factors found in earlier research. The results will form an independent view of which factors that are applicable for the Nordic market.

4.3 Credit risk premium

The previous sections gave a thorough insight in relevant theories for predicting *expected loss* (EL) through the two factors *Probability of default* (PD) and Loss given default (LGD). While the typical textbook assumption is that default risk is the only inherent risk investors are compensated for, several researchers and practitioners claim that it is only one of several sources, and that default risk alone is not sufficient to explain the full spread observed in the market. (See for instance Hull, Predescu, & White (2012), and Elton, Gruber, Agrawal, & Mann (2001)).

The unexplained part of the credit spread, when relying solely on expected default risk, is often referred to as *the credit spread puzzle* and has received a lot of attention among researchers in later time[11]. A recent study by Sæbø (2014), find that a credit puzzle is highly present in the Norwegian fixed income market, but state that the word *puzzle* is misleading as it implyes that investors are risk neutral. In other words, if the average investor are willing to accept credit spreads equal to the expected loss, the expected return is equal to an otherwise similar risk free bond. This means that the investor does not demand a premium for the uncertainty inherent in the expected loss; hence the investor is risk neutral. Based on the more realistic assumption that most investors are risk averse, Sæbø (2014) conclude that there should be a *credit puzzle*, i.e. a compansation for risk aversion. In line with other well known research (Hull et al. (2012), and Elton et al. (2001)), he also conclude that part of the *puzzle* may be explained by compensation for bearing non-default related risk factors. The

[11] See for instance Feldhütter & Schaefer (2014), and Sæbø (2014)

most common factors examined by researchers are tax premium, liquidity premium and risk premium.

Tax premium originates mostly from studies on the US market, as interests on corporate- and government bonds are taxed differently in the US. In the Nordic market, on the other hand, interests on corporate- and government bonds are taxed equally, and the tax effect will hence not be an issue in credit spreads in the Nordic market, or in this paper.

Liquidity premium stems from the fact that part of the corporate bond market suffer from low trading volumes, which leads to higher and more volatile bid ask spreads. The result may be delays in finding a counterparty for a transaction and lower realized price in the case of a sale, and investors demand compensation for these risks.

Another source of premium is migration risk, which may be defined as the risk that the credit quality of the issuer deteriorates. For bonds, this implies the risk that the credit quality of the issuer deteriorates within the lifetime of the bond. Migration risk and the incremental loss for each fall in credit rating can be understood much in the same way as probability of default and recovery rates earlier described. Migration risk can be shown as a the product of the probability that the rating falls within a set time period multiplied by the expected loss for the investor from the incremental change in rating. The Merton (1974) model does not incorporate this risk, and hence it might be one of the factors explaining the difference between estimated model spreads and actual observed spreads

Risk premium stems from the bond's sensitivity to systematic risk factors and there are several reasons to why a risk premium exist. First, bonds often do not default independently. In fact, it can be shown that defaults tend to cluster in time which implies that there is a non-diversifiable risk that investor should demand compensation for bearing. (Hull, Predescu, & White, 2012). Second, the lower the quality of the bond, the more it becomes like equity. Theoretically, when the asset value is below the debt value, debtholders have a full claim in the company and the debt converts to equity. As the debt become more like equity, the bond price will be more affected by the same market factors as the equity and should be compensated by the same non-diversifiable risks as equity investors do.

5 DATA

This chapter will first present the various sources of data on bond issues, recovery rates, financial and market data, and discuss assumptions and methods used to define the final sample. We then present descriptive statistics of the bond sample and recovery rates.

5.1 The high yield sample

The data used to define the Nordic High-Yield market in this thesis was retrieved from the Stamdata database. Stamdata is a subsidiary of Nordic Trustee and is the leading provider of debt securities data in the Nordic market, with coverage of almost all bond issues in the market place. Bond characteristics in the database are only given for the time of issue. The analysis is therefore limited to observed spreads at issue. We assume that the bond is issued at par, and hence that credit spread can be derived from the coupon rate.

When analyzing credit spreads, it is important to use a relatively homogenous bond sample to avoid biased results. For instance, the spread for a convertible bond will on average be lower than an otherwise similar bond, as part of the compensation is paid with an embedded call option on the company. Hence, the same model would not be valid to analyze and compare spreads for the two types of bonds. This is the reason why we filter the bond dataset from initially over 23,500 to 323 bonds. The following section will motivate the high number of exclusions from the preliminary sample.

5.1.1 Determining the high-yield sample

First, issue-based statistics for the entire Nordic bond market were extracted from the Stamdata database, which comprises over 23,000 investment grade and high-yield bond issues from 1950 to 2015 with an aggregate issued amount of 16,176 NOK bn. The data include close to all corporate bonds issued in the Nordics, but has lower coverage of government bonds, where only Norwegian government bonds are covered until the mid 2000s.

Table 5.1 presents a summary of the preliminary sample sorted by industry. The majority of the issuers are government entities, finance institutions, and banks.

Table 5.1: Overview preliminary sample

Industry	Issued amount (NOKbn)	% of total	Average issue size (NOKm)	N
Government	5,344	33.0 %	16,242	329
Finance	3,851	23.8 %	2,647	1,455
Bank	3,218	19.9 %	372	8,644
Public Sector	1,212	7.5 %	190	6,368
Utilities	592	3.7 %	302	1,963
Real Estate	330	2.0 %	256	1,288
Industry	307	1.9 %	487	630
Oil and gas services	249	1.5 %	594	419
Transportation	181	1.1 %	275	660
Telecom/IT	167	1.0 %	592	283
Convenience Goods	164	1.0 %	330	496
Shipping	101	0.6 %	643	157
Auto	94	0.6 %	888	106
Consumer Services	88	0.5 %	353	249
Pulp, paper and forestry	79	0.5 %	652	121
Oil and gas E&P	77	0.5 %	532	145
Insurance	47	0.3 %	881	53
Seafood	24	0.2 %	532	46
Media	22	0.1 %	392	55
Pharmaceuticals	11	0.1 %	788	14
Health Care	11	0.1 %	518	21
Agriculture	7	0.0 %	461	15
Total	16,176	100 %	688	23,517

Source: Stamdata database

Table 5.2: Percentage share of Investment grade vs High Yield

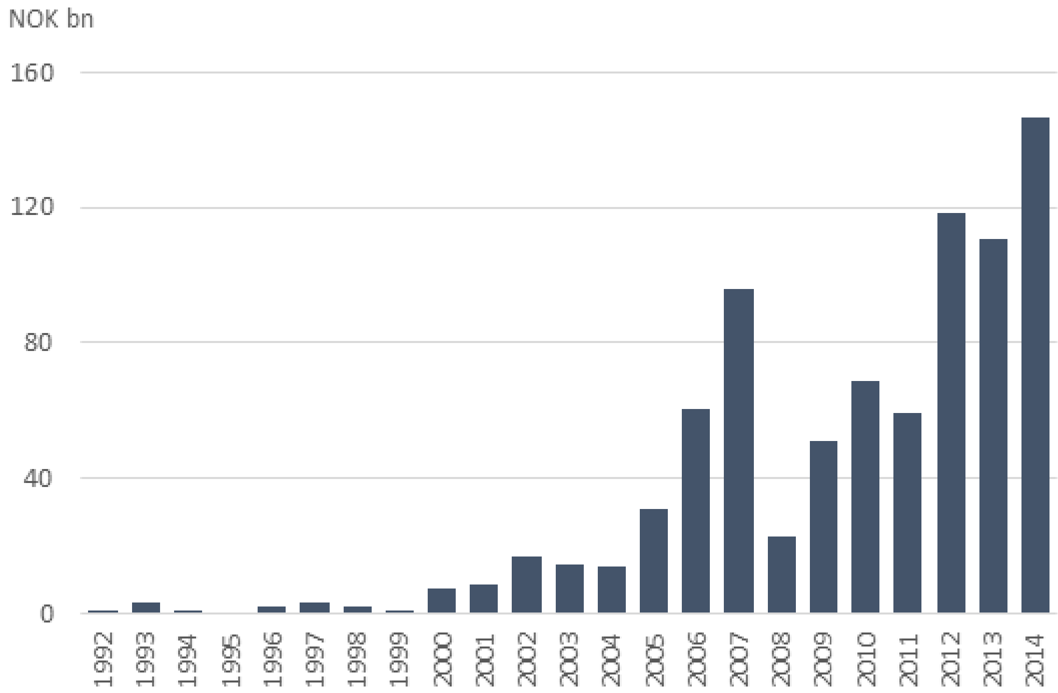
	Issued amount (NOKbn)	# of issues	% of issues
High Yield	848	2,004	9 %
Investment Grade	15,328	21,511	91 %
Total	16,176	23,515	23,515

Source: Stamdata database

Table 5.1 presents the breakdown of high yield and investment grade bonds in the preliminary sample. Total issued volume of investment grade bonds and corporate high yield bonds in the period was 16,179 and 848 NOK billion respectively, illustrating that the high yield market is a minor part of the overall bond market. However, the focus in this thesis is on high-yield, rather than investment grade bonds. All 21,511 investment grade issues were therefore excluded from the final sample.

As illustrated in figure 5.1, the Nordic high yield bond market did not really emerge before the beginning of the new millennium. Limited number of issues before this time makes the data unsuitable for statistical analysis. For this reason, in addition to poor visibility of default and recovery data, all issues before the year 2000 were left out from the final HY sample.

Figure 5.1: Nordic high yield issues



Source: Stamdata database

The analysis in chapter 7 is highly data intensive and requires data from several different financial markets, as well as financial data. The data gathering process was thus time consuming.

The initial focus in our thesis was planned to be on the difference in credit spreads for defaulted bonds and non-defaulted. Such an analysis would not need issues in the recent years, as we would not have the grounds to distinguish between defaulted and non-defaulted bonds before they are realized. We therefore used a great amount of time to collect a complete dataset on all relevant bonds issued before 12/12/12. Later in the process, we decided to extend the scope of the paper to analyze other explanatory factors than default. However, we did not have the time nor the capacity to collect data on the remaining high yield bonds and the final high yield sample thus only include bonds issued before the end of 2012.

In order to define the final high yield sample, other criteria were also used to filter out certain bond issues to achieve a more homogenous dataset. Bonds issued by banks, finance institutions, and companies that was state owned were excluded. Convertibles, linked and credit linked notes, capital content securities, and warrants were also excluded from the sample. As will be described in detail later, our credit model require market data, such as market cap and volatility, which is only available for publicly listed firms. We therefore only include bonds issued by public companies to reach the final bonds sample in our analysis. We present a full overview of the number of bonds excluded per criteria are in appendix 2.

5.1.2 Describing the High yield Sample

To sum up, the final high yield sample (hereafter called HY sample) consist of plain vanilla bonds issued by public non-financial companies that are not state owned in the timeframe 2000-2012. The HY sample comprises of 323 bond issues, amounting to 188 NOK billion in total issued volume.

Table 5.3 summarizes the sample divided by industry. The oil and gas constitute by far the largest issuer group, followed by pulp, paper and forestry, industry, shipping, telecom/IT, seafood, real estate and transportation. These are broad industry classifications. For instance, “Oil and gas” include E&P, drilling, floatels, FPSO, service, supply, subsea and surveying companies.

Table 5.3: Final HY sample overview

Industry	Issued volume (NOKm)	%	Average issue size	N
Oil and gas	88,101	47 %	518	170
Pulp, paper and forestry	28,377	15 %	2,027	14
Industry	22,022	12 %	512	43
Shipping	17,533	9 %	474	37
Telecom/IT	14,228	8 %	949	15
Seafood	5,850	3 %	390	15
Real Estate	3,991	2 %	307	13
Transportation	2,051	1 %	410	5
Other	6,817	4 %	620	11
Total	188,971	100 %	585	323

Source: Stamdata database

Table 5.4 below presents the distribution of fixed vs floating coupon rates in the sample.[12] 64 percent of the 323 bonds in the final sample have floating coupon rates, where the reference rate is usually set to the interbank rate of the respective currency's home country. The remaining 36 percent have fixed coupon rates. The distribution is more even when measured in issued volume, where floating rate bonds account for 54 percent of the issued volume.

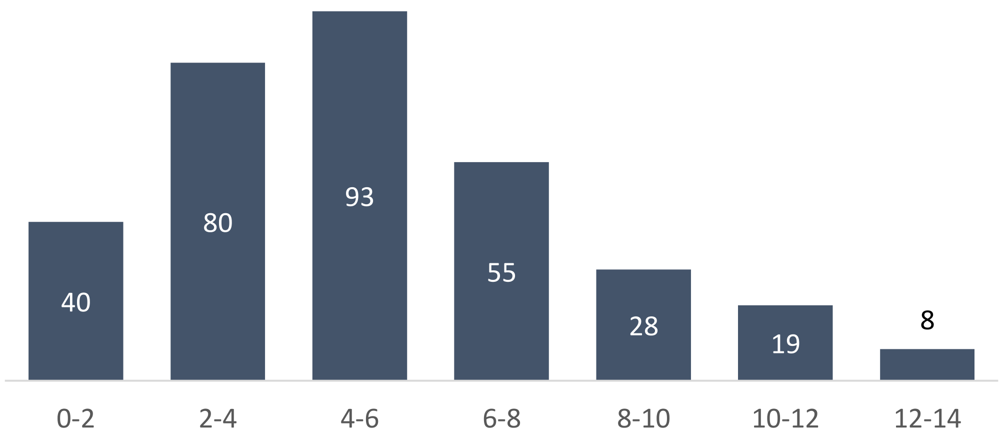
Table 5.4: Fixed vs Floating coupon rates[7]

Coupon type	Avg. coupon	Std	Avg. spread	Std	% of value	% of N	N
Fixed	9.1 %	3.1 %	6.2 %	3.2 %	46 %	36 %	115
Floating	6.9 %	2.6 %	4.6 %	2.4 %	54 %	64 %	206
Total	7.7 %	7.7 %	5.2 %	2.9 %	100 %	100 %	321

Source: Stamdata database

The coupon spread above risk free rate varies from close to zero to 14 percentage points within the sample (Figure 5.2). While spreads for floating rate bonds are given directly as the spread above a reference rate, spreads for fixed coupon bonds needed to be calculated. A more detailed discussion of spread calculations are presented later in the paper, but in short, the spread is calculated by subtracting the rate of government bonds with matching currency and duration. The full distribution of coupon spreads are summarized below in a histogram with # of shares on the y-axis and spread intervals on the x-axis. The average spread within the sample is 5.2 percentage points, and the distribution is centralized around this area (Figure 5.3)

Figure 5.2: Coupon spread histogram (Bins in percent)

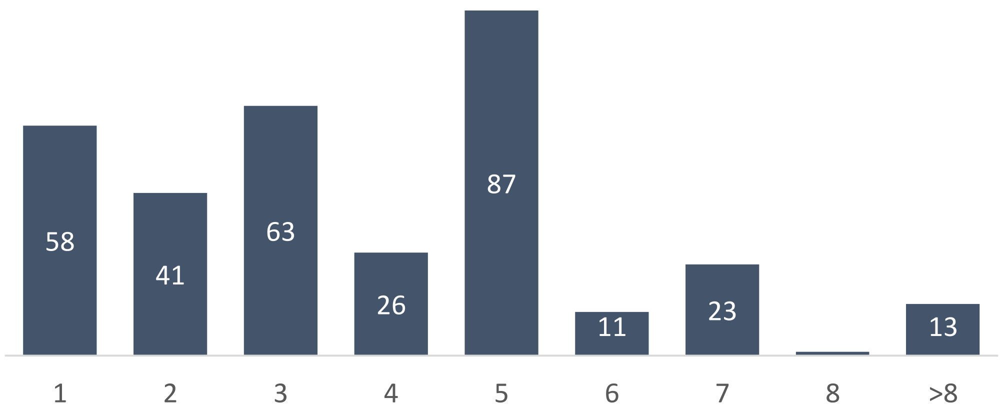


[12] The sample also includes two zero-coupon bonds and are left out of table 5.4

Source: Stamdata database

The typical maturity in the sample is around 5 years, and the utmost bonds have a maturity of less than seven years (Figure 5.3). A complete list of the bond sample is presented in appendix 1.

Figure 5.3: Maturity histogram



Source: Stamdata database

5.2 Default and recovery rate data

To date, there are no official statistics on default and recovery rates in the Nordic market. This is due to both the bond market's generally low transparency and the complicated process of calculating precise recovery rates. Former master theses written by business students, have attempted to find and analyze default and recovery rates (Haugland & Brekke (2010), Grøstad (2013)), but comparison of descriptive statistics show significant deviations in their estimated recovery and default rates, as well as with ours. It is important to note that this is most likely due to the numerous ways of defining and calculating default and recovery rates, and not poor research. It is therefore important to assess default data with a critical view and be well aware of which methods, definitions, and assumptions used in the underlying material.

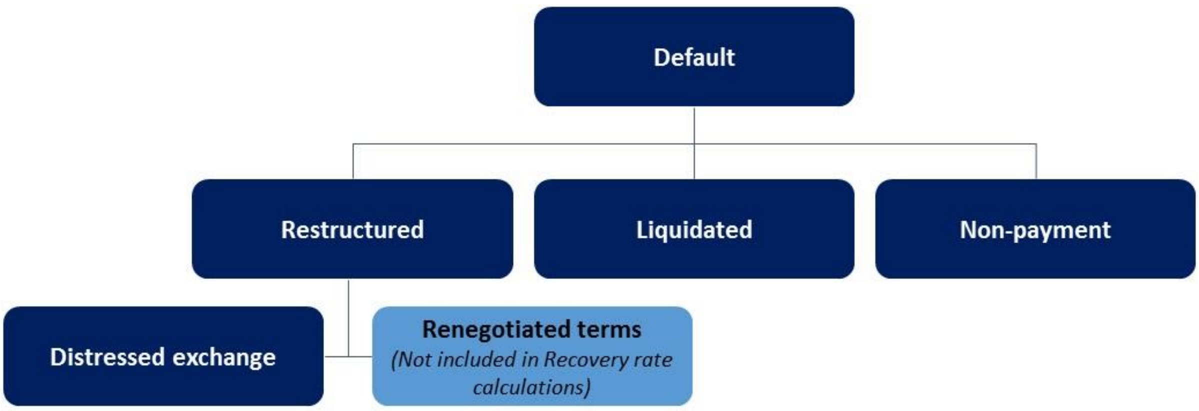
Nordic Trustee is daily monitoring the majority of bonds in the Nordic market, and have an especially active role in cases of default. Hence, they possess the greatest amount of key information about default history and payments to bondholders in the market. Stamdata has therefore now created a proprietary dataset on ultimate recovery rates, which is intended to be released in the Stamdata database at a later stage, covering defaults from 2007 to 2015. The dataset is a preliminary version, but is arguably still the most comprehensive and precise dataset on recovery rates in the Nordic market created to date, and this study will be the first to utilize it in an academic paper.

5.2.1 Definition of default events in the sample

By assuming a "buy and hold" strategy throughout the analysis, we also assume a yearly yield equal to the annualized coupon yield, unless the bond defaults. Defining and identifying defaulted bonds is therefore critical for the ex-post analysis of bond performance, and hence, bond pricing. The underlying definition of defaults in the dataset will be presented in the following.

Initially, Stamdata identify defaults according to the following definition: "An issuer is by definition in default when it is in breach of the legal obligations between issuer and bondholders as set out in the bond indenture" (Nordic Trustee, 2014). Stamdata further define defaults in the following three categories: Restructured, liquidated and non-payments.

Figure 5.4: Nordic trustee default event classification



A Restructuring is a process that allows the issuer to reduce and renegotiate its debt obligations. The result is often significant updates of the bond indentures, in order to restore liquidity and the ability to continue its operations to avoid bankruptcy. Liquidation is when the firm's assets are sold, and the proceeds are paid to creditors (bondholders) after a bankruptcy. Any leftovers will be distributed to shareholders. A non-payment is when the issuer is unable to make coupon payments or installments. Defaults where the issuer is in breech with covenants, so-called technical defaults, are not included in the dataset. As illustrated in Figure 5.5, restructurings are further defined as “Distressed exchanges” and “Renegotiated terms”. The former is a restructuring where the bond’s outstanding amount is exchanged for new securities with lower priority, e.g. options, debt for equity swaps, new debt, and PIK bonds. Renegotiated terms is when the issuer is allowed to renegotiate bond-terms, such as maturity profile, bond priority, and security with the intention of preventing immediate distress. Defaults classified as “Restructured: Renegotiated terms” are not included in the recovery rate dataset. Stamdata argue that including these defaults will deteriorate the quality of the results when calculating recovery rates in a bond market (Nordic Trustee, 2014). For instance, bonds with renegotiated longer maturities or with lower priority will have the same payout as promised at issue, even though increased duration and riskiness could lead to notable disadvantages at a later stage. Renegotiated lower coupons are, however, more debatable. Lower coupon rates will result in a lower cash flow to bondholders than promised and will therefore have a theoretically recovery rate of less than 100 percent. However, based on observed market prices the changes are often less than significant (Solberg, 2015), and including renegotiated terms defaults in the recovery dataset would only bias the estimates upwards. Another argument for exclusion is that renegotiated terms is often the first step towards a distressed exchange, or even worse, a liquidation. Including these defaults would thus lead to repetitive observations of the same bond default. In the following analyses, we therefore ignore renegotiated terms restructurings, and assume that these bonds pay investors as promised at issue, unless a more severe credit event occurs.

5.2.2 Describing the recovery rate dataset

The recovery rate dataset consists of 150 defaults in the time span from 2007 to 2014. Table 5.5 presents the distribution among liquidated, Restructured (distressed exchange), and non-payments.

Table 5.5: Breakdown of credit events

	Distressed Exchange	Liquidation	Non-payment	Total
Bonds	62	36	11	109
CDs	1	2	1	4
Convertibles	21	6	10	37
Total	84	44	22	150

Source: Stamdata recovery rate database

With the exception of 2007 and 2008, the distribution between the different types of defaults have remained relatively similar each year. The majority of defaults result in restructurings, in the form of distressed exchanges as defined above. Figure 5.5 and 5.6 below present the number of defaults and defaulted volume respectively from 2007 to 2014.

Figure 5.5: Number of defaults in the period 2007-2014

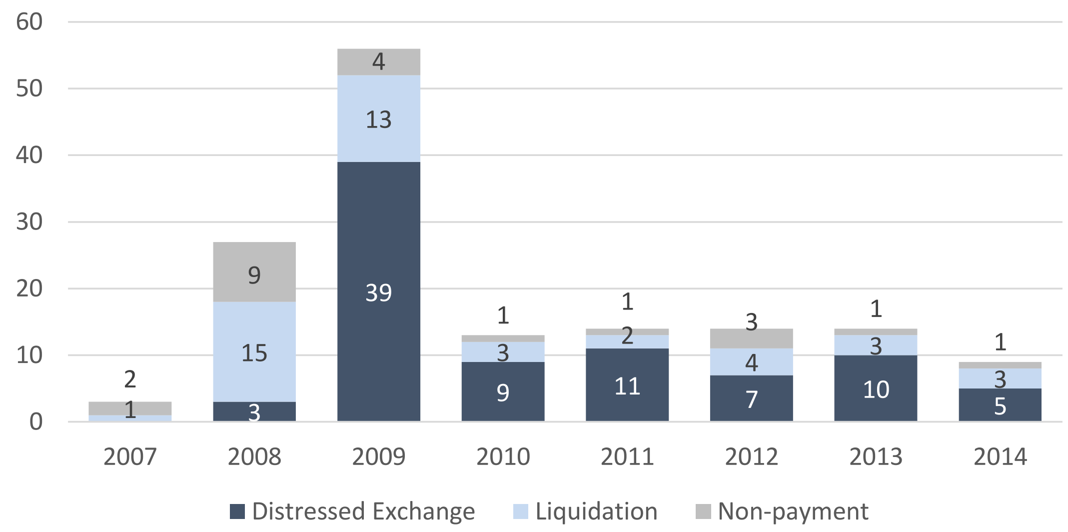
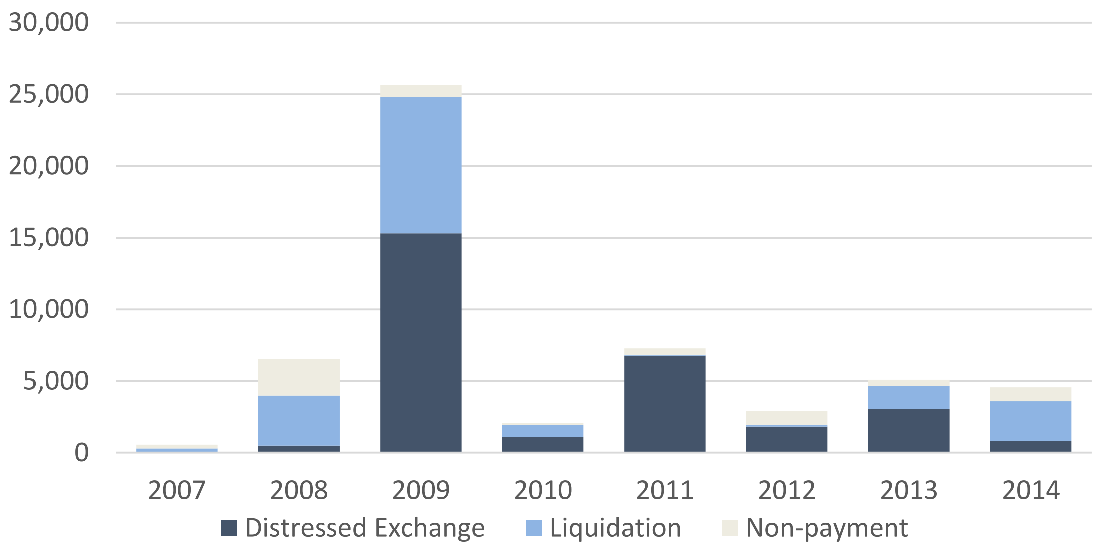


Figure 5.6: Defaulted volume (NOKm)



Source: Stamdata recovery rate database

The financial crisis in 2008 clearly impacted the high-yield bond market, leading to a high number of defaults in 2008 and 2009. The number of defaults has remained fairly stable at lower levels the continuing years. However, when measured in defaulted volumes, figure 5.6 show more variation in the aftermath of the crisis.

Table 5.6 shows recovery statistics divided in seniority within the capital structure and whether the bonds are secured or not. Subordinate bonds, as expected, experienced a notably lower of average recovery rate than the secured bonds. Surprisingly, senior unsecured bonds have experienced slightly higher recovery than senior secured, with an average recovery of 47% and 44% respectively, which is not in line with what one would expect. However, this is may be explained the fact that the majority of oil service bonds in the sample are senior secured and experienced much lower recovery rates than the E&P sector, where the majority of bonds were unsecured.

Table 5.6: Breakdown of recovery rated by seniority

	Volume weighted	Average	Median	N
Senior Secured	43 %	44 %	39 %	83
Senior Unsecured	47 %	49 %	48 %	52
Subordinated	5 %	16 %	0 %	15
All bonds	42 %	42 %	35 %	150

Source: Stamdata recovery rate database

Table 5.7 and 5.8 presents evidence in favor of this explanation for higher average recovery for unsecured than secured bonds. The two tables show the number of defaults and the value weighted average recovery rate respectively, distributed in the two largest sectors and by security/seniority. The two largest sectors in the default sample are E&P and Oil services, which together account for two thirds of the defaulted bonds. We see that 49 out of the 73 bonds issued in the Oil service sector are secured, whereas within the E&P sector the majority is unsecured, though more evenly distributed. As the value weighted average recovery rate within oil service is significantly lower than within E&P, the average rates for the overall sample indicate that secured bonds recover less than unsecured, but the reason is more likely to be that the companies with secured bonds had lower expected recovery independent of security. In fact, when we look at the difference between secured and unsecured within the two sectors, the value weighted average recovery is higher for the secured bonds. For the industries defined as “other”, the result is still counter-intuitive. The explanation is likely due similar to the previous, but the industry dispersion is too high to perform the same analysis.

Table 5.7: Breakdown of credit events on industry and seniority

Industry	Senior Secured	Senior Unsecured	Subordinated	Total
E&P	12	15		27
Oil Services	49	17	7	73
Other	23	20	7	50
Total	84	52	14	150

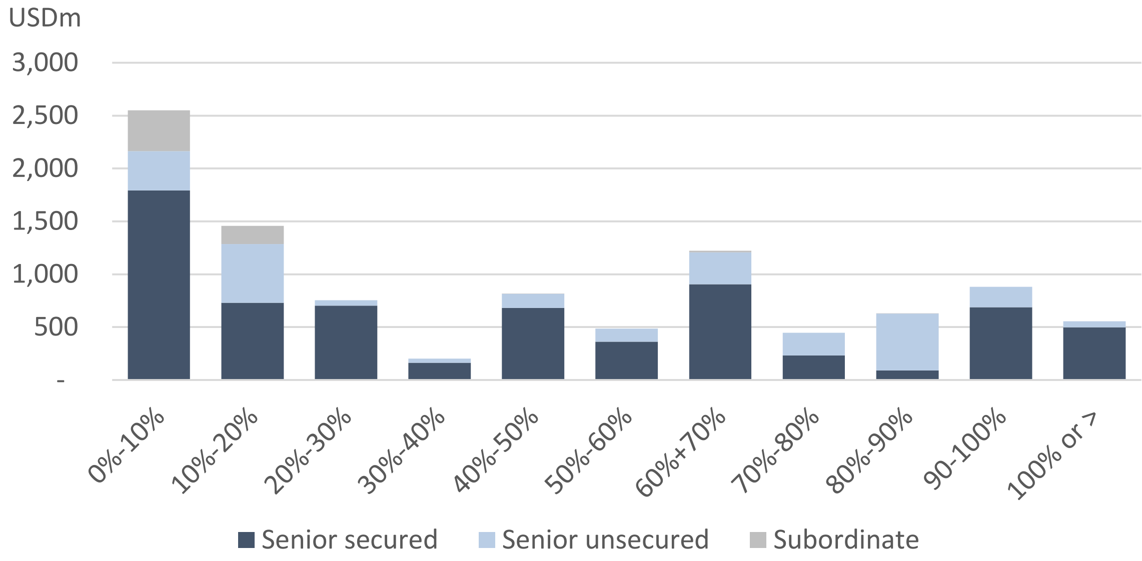
Table 5.8: Breakdown of Value weighted average recovery rates on Industry and Seniority

Industry	Senior Secured	Senior Unsecured	Subordinated	Total
E&P	64 %	61 %		62 %
Oil Services	47 %	42 %	7 %	43 %
Other	20 %	44 %	1 %	27 %
Total	43 %	47 %	5 %	42 %

Source: Stamdata recovery rate database

Figure 5.7 below illustrate that the recovery rates fluctuates widely around its mean. The sample has a clearly non-normal distribution, which makes average a less informative measure to describe the sample and will cause challenges for statistical analyses. The distribution can appear to be approximately a bimodal distribution, meaning that bondholders are likely to recover either close to nothing, or close to everything.

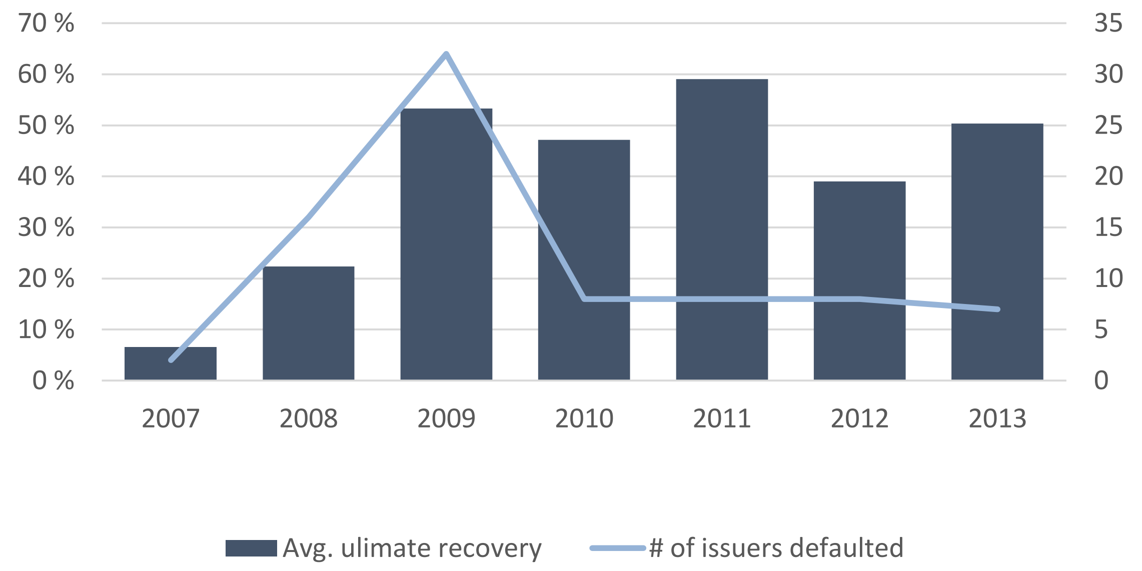
Figure 5.7: Recovery rate distribution



Source: Stamdata recovery rate database

Average recovery rates have varied between 40 and 60 percent after 2009 and well above levels during the financial crisis in 2007-2008. The extremely low recovery rate in 2007 should be interpreted with care due to the low number of observations, nevertheless, recovery rates in the Nordic market has improved notably in the aftermath of the financial crisis. Figure 5.8 below shows the number of defaulted issuers and the average ultimate recovery of the value weighted recovery of the issuers' defaulted bonds per year.

Figure 5.8: Average Recovery rate development



Source: Stamdata recovery rate database

5.3 Financial and market data gathering

This section explains where we have gathered the financial and market data for our dataset.

We have naturally found that company observations are in various currencies, and so we make sure that all observations are converted to NOK for variables listed in absolute terms, while variables listed in ratios, we make sure that all variable observations is in the same currency within the same company.

5.3.1 Financial data

We have gathered financial data from a variety of sources in order to obtain a comprehensive set of input variables for our models.

We have mainly used The Norwegian Corporate Accounts database issued by The Norwegian School of Economics and their subsidiary SNF. The database contains corporate and financial information for all Norwegian companies for the years 1992-2011. Documentation, description, and quality assurance can be reviewed in a paper by Berner et al (2013).

For observations of all public and available private Norwegian companies in 2012, we have extracted data manually from the website www.forvalt.no, which is a searchable engine that gathers corporate information from a variety of sources. For further information regarding the sources used by www.forvalt.no, please visit (forvalt.no, 2015).

For non-Norwegian companies without data in The Norwegian Corporate Accounts database or forvalt, we have gathered information from Bloomberg, Orbis, and directly from annual reports.

For data on payout ratio (dividend, share repurchases etc.) and volume traded data has been collected from Compustat.

5.3.2 Market data

Market data cover stock price quotes and total shares outstanding. A significant share of the market data in our dataset has been gathered from Børs Databasen (NHH, 2015), a part of Børsprosjektet at NHH, which is a database containing detailed market data on Norwegian firms, available for students and faculty members.

Non-Norwegian firms and firms not found in Børsdatabasen has been found in yahoo finance and Bloomberg, in addition to some observation of companies listed on Nasdaq OMX Nordic, which has been extracted directly from their website www.nasdaqomxnordic.com. For these observations, shares outstanding have been extracted directly from company annual reports.

6 METHODOLOGY

In this section, we will elaborate on our method used to calculate credit spreads. To do the estimation, we combine a credit model based on the extended Merton model described by Eom et al (2004) with individual estimation of loss given default, to estimate the spread of individual bonds. We begin by describing the credit model in section 6.1, continue with a thorough review of parameter estimation in 6.2, and finally describe in 6.3 how we try to estimate recovery rates.

6.1 Method of estimating spread

In the extended model we follow the same procedures as Eom et al (2004), who utilizes the Merton model and models a coupon paying bond as a portfolio of zero coupon bonds. They also do the simple modification of including payout ratio, defined as dividends, share repurchases, and interest paid to equity and bondholders. This reduces the drift of the assets in the standard Merton model, and so increases the chance of default and predicted spreads.

The model uses both variables directly observable in the market place, in addition to unobservable variables that must be estimated. These include asset value, asset volatility, and default barrier. How they are estimated is described in section 6.2. Observed variables used as input includes bond coupon, firm equity price quotes, book value of liabilities, government treasury rates, time to maturity, dividend payout rate, share repurchases, and interest paid to equity and bond holders. Recovery rate enters the model as either a modeled or a static estimate as further elaborated in chapter 6.3. We chose to use a static estimate, due to our failure to create a recovery rate model with significant predictive power, further explained in chapter 7.1.

6.1.1 An extended Merton model

The model (Eom et al (2004)) consider a defaultable bond with maturity T and unit face value that pays semiannual coupons at an annual rate c. For simplicity, we assume that 2T is an integer, and let $T_n, n = 1, \dots, 2T$, be the n*th* coupon date. We assume that the default barrier K is constant and that default is triggered if the asset value is below K on coupon dates. We may then price a coupon paying bond as the present value of expected payoffs from coupons and the principle:

$$P(0,T) = \sum_{i=1}^{2t-1} D(0,T_i)E^Q\left[\left(\frac{C}{2}\right)I_{\left(V_{T_i}\geq K\right)} + \min\left(\frac{wc}{2}, V_{T_i}\right)I_{\left(V_{T_i}<K\right)}\right]$$

$$+ D(0,T)E^Q\left[\left(1+\frac{C}{2}\right)I_{(V_T\geq K)} + \min\left(w\left(1+\frac{C}{2}\right), V_T\right)I_{(V_T<K)}\right]$$

Where $D(0,T_i)$ is the time 0 value of a default-free zero-coupon bond maturing at time T_i, $I_{(.)}$ is the indicator function, and E^Q represent the expected value under the risk netural measure, and w is the recovery rate. The top part of the formula is simply the risk-neutral expected present value of all future coupons of the bond; $D(0,T_i)$ is the discount factor, $\left(\frac{c}{2}\right)I_{\left(V_{T_i}\geq K\right)}$ is the value of the semiannual coupon times the risk neutral probability that the asset value is above the default barrier at time T_i, and $\min\left(\frac{wc}{2}, V_{T_i}\right)I_{\left(V_{T_i}<K\right)}$ is the minimum value of the asset value and the value of semiannual coupon multiplied with the recovery rate, adjusted by the risk neutral probability that the asset value is below the default barrier. Similarly, the bottom part is the risk-neutral expected present value of the principal and the last coupon paid at maturity. For a more thorough walkthrough of the intuition of the equation and its components, see appendix 6B.

To complete the model, it can be shown that

$$E^Q I_{\left(V_{T_i}\geq K\right)} = N(d_2(K,t))$$

$$E^Q\left[I_{V_t<K}\min(\psi, V_t)\right] = V_0 D(0,t)^{-1}e^{-\delta t}N\big(-d_1(\psi,t)\big) + \psi\left[N\big(d_2(\psi,t)\big) - N(d_2(K,t))\right]$$

where $\psi \in [0,K]$ and N(.) represents the cumulative normal function and

$$d_1(x,t) = \frac{\ln\left(\frac{V_0}{x * D(0,t)}\right) + (-\delta + 0{,}5\sigma_A^2)t}{\sigma_A\sqrt{t}} \qquad (6.1)^{13}$$

$$d_2(x,t) = d_1(x,t) - \sigma_A\sqrt{t}$$

[13] For a given risk free rate r, equation (6.1) can be rearranged to: $d_1(x,t) = \frac{\ln\left(\frac{V_0}{x}\right)+(r-\delta+0{,}5\sigma_A^2)t}{\sigma_A\sqrt{t}}$, which is the same as d_1 in the Black & Scholes formula but adjusted for a lower drift due to the payout ratio.

Given the term structure of $D(0, T_i)$ given by the Nelson-Siegel-Svensson model[14], the given equations can be used to calculate the price of a risky coupon bond under Merton's assumptions.

The yield spread of the bond can then be calculated as the difference of the implied yield of the risky bond and a risk free bond:

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

6.2 Parameter estimation

We will explain how we estimate the various input parameters of the equation in the following sections.

6.2.1 Implied asset value and implied asset volatility

The asset value and asset volatility are unobservable values, and needs to be estimated. We can imply these values by simultaneously solving two functions derived from the Black-Scholes-Merton framework. In the theory section, we explained how we can use option pricing to model a call option on a firm's assets as a function asset value A, asset volatility σ_A, time to maturity T, debt B, and risk free rate r. The only endogenous variables in this equation is the asset value and volatility. This relationship is expressed in equation 6.2.

$$E = A\,N(d_1) - Be^{-rT}N(d_2) \tag{6.2}$$

$w$here

$$d_1(x,t) = \frac{\ln\left(\frac{V_0}{x * D(0,t)}\right) + (-\delta + \sigma_A^2)t}{\sigma_A\sqrt{t}}$$

$$d_2(x,t) = d_1(x,t) - \sigma_A\sqrt{t}$$

and N() represents the cumulative normal distribution function.

Furthermore, using Black and Scholes' framework, it can be shown that

[14] See section 6.2.3 for an explanation of the Nelson-Siegel-Svensson model and our choice of risk free rate

$$\sigma_E = \frac{A}{E} \times N(d_1) \times \sigma_A \tag{6.3}$$

We now have two equations, equation 6.2 and 6.3, and two endogenously determined variables, asset value and asset volatility. This enables us to solve the two equations simultaneously using excels solver function.

The absence of debt volatility in equation 6.3 can be explained by the fact that equity can be described as a portfolio of the firm's assets and risk free debt. Likewise, it is also possible to define the equity volatility as a function of the volatility of assets and the volatility of risk free debt. As the volatility of risk free debt is zero, it is intuitively possible to show the volatility of equity purely as a function of asset volatility. It is worth mentioning that debt volatility is in reality a part of asset volatility, but as we do not need to separate the two, the issue is irrelevant in our model.

6.2.2 The default barrier

The default barrier is defined as the level the assets must reach for default to happen. How the default barrier is modeled varies between models. Some models assume maturity of 1 year, and for these model's consensus seems to be that directly using the book value of liabilities proves faulty. This is because firms often are allowed to renegotiate or postpone debt with longer maturities, and all debt is rarely due within the estimation period. Hence a natural choice of default barrier is one less than total debt. Many studies has chosen the same default barrier approach as the KMV model (Crosbie & Bohn, 2003), and used short term debt plus half of the long term debt as the default barrier.

$$B = Current\ debt + k \times Non - Current\ Debt$$

(Afik, Arad, & Galil, 2012) tests the Merton model with various values of k, i.e. the share of -noncurrent debt included into the default barrier. They find that the specification of the default barrier relative to the market standard of 0.5 has a relatively small effect on the models accuracy.

For papers utilizing greater variation of issue maturities, the norm is different. Feldhütter & Schaefer (2014) assume that the default boundary is the book value of liabilities. This assumption is also used by Eom et al (2004) and Cremers et al (2008), but Chen et al (2009) and Huang & Huang (2002) use a lower boundary more in line with the KMV methodology.

Eom et al (2004) explains the use of book value of liabilities instead of the face value of the bond. They explain that in most structural models, including the one we use, equity holders earn the residual value of the firm first when all debt has been paid off. As this residual only begins to accrue once the par value of the bond is paid and all other debt is paid off, all debt must be paid off before equity has any value. As the majority of firms has several sources of debt, which also is true for our sample, the book value of liabilities rather than the face value of the bond is the correct measure of the default boundary.

Previous research thus shows various practice, but again it does not seem to impact results significantly. To simplify our analysis, we have in our model defined the default barrier as the total book value of liabilities at issue date, both with regards to defaults on coupons and on the principal payments.

6.2.3 Choice of risk free rate

We have chosen to use government treasuries with various maturities as our risk free rate. These are not completely without risk, but are considered the asset class with the lowest risk. This is especially true for the Scandinavian countries, the EU, and the US, which is the source countries in our paper and are considered some of the safest government bonds attainable. Some choose to use the bank swap rate less 20-30 bps, but the choice does not seem to impact the results significantly in previous research papers.

We have gathered government bonds from Norway, Sweden, Denmark, the European Union, and the US. We have gathered all available maturities between 1 and 10 years. We have then used the Nelson-Siegel-Svendsson model to interpolate and extrapolate the missing dates. For the longest maturities, e.g. bonds with maturity of more than15 years, we have manually checked that the model estimates are plausible. This method of modeling the yield curve was first developed by (Nelson & Siegel, 1987), and later extended by (Svensson, 1994). The method involves reducing the sum of residual of the actual observations and the model estimates.

The model itself is given as

$$D(0,x) = \beta_1 + \beta_2 * \frac{1 - e^{-\left(\frac{x}{\lambda_1}\right)}}{\frac{x}{\lambda_1}} + \beta_3 \left(\frac{1 - e^{\left(-\frac{x}{\lambda_1}\right)}}{\frac{x}{\lambda_1}} - e^{\left(-\frac{x}{\lambda_1}\right)} \right) + \beta_4 (\frac{1 - e^{\left(-\frac{x}{\lambda_2}\right)}}{\frac{x}{\lambda_2}} - e^{\left(-\frac{x}{\lambda_2}\right)})$$

The maturity of each coupon/principal has been matched with relevant government bond in terms of both currency and maturity.

6.2.4 Standard deviation of equity

The equity standard deviation is calculated from 5 years of monthly data. The asset standard deviation is derived from the black & Scholes framework as described in detail earlier.

6.2.5 Payout ratio

We calculate payout ratio as explained by Eom et al (2004). . Observation time is year before issue, in line with previous papers (Feldhütter & Schaefer (2014), Eom et al (2004)). We calculate the payout ratio as the sum of dividends, share repurchases adjusted for stock splits, interest payments to debt- and equity holders, and then divide by total assets.

$$Payout\ ratio = \frac{Dividends\ to\ equity\ holders\ +\ share\ repurchases\ +\ interest\ paid\ to\ bond\ and\ equity\ holders)}{Assets}$$

Estimates of payout ratios are based on historic observations. It is naturally to assume that firms will adjust their payout policy according to future investment plans and current profitability. If a firm is experiencing solvency issues, we expect it to reduce its payout to equity holders. To incorporate this effect, we set dividends and share repurchases to zero for issuers with estimated asset value less than two standard deviations from debt value.

6.3 Predicting loss given default

Section 6.2 introduced the model that will be used to predict spreads in the analysis later in this paper. The model depends on several variables, of which an estimate of the recovery rate in the case of a default is especially important. This section will explore the possibility of modelling recovery rates, so that individual estimates of recovery rates for each bond can be incorporated in the credit model presented previously.

To estimate loss given default, or 1 – recovery rate, we create a statistical model based on the recovery rate dataset of initially 150 defaulted bonds. The model is based on a multivariate OLS regression, which incorporate industry-, issuer-, as well as bond-specific information. This part will present the statistical methods applied and the motivation behind them. Subsequently, we test potential explanatory factors, before we analyze and discuss the power of the recovery rate model.

6.3.1 Selecting statistical framework

The first step to create a Recovery rate model (RR model) is to decide on the most suitable statistical framework, given the properties of our data and the model's objective. In the literature review, we found that recovery rate modeling have changed over time, and also that there still is significant variation in later studies' assumptions and choice of statistical framework, and hence it was not straightforward for us to find an approach for our model. The various techniques has specific strengths and weaknesses, but we found no consensus in the literature of what type of model to be the most precise. Furthermore, it was a criteria for us that we use a statistical framework reasonably within our econometric capabilities. With this in mind, we decided to use an ordinary least squared regression (OLS)[15], but to adjust for default clusters by only including one defaulted bond per issuer within one month time period.

The model itself is not bound to any specific interval. Predicted values must therefore be transformed to ensure that the recovery rate is bound between 0 and 1 if they are to be used in the credit model.

6.3.2 Exclusion of observations

Many of the issuers in the recovery dataset have multiple defaulted bonds around the same dates. To avoid biased estimators due to double counting in the regression, we excluded all 44 repetitive bond defaults, defined as bonds defaulted in the same year, from the same issuer, and with equal security.

In addition, we excluded 7 issuers due to inaccessible financial data, reducing the final default sample to 95 bonds [16.]

[15] See appendix 3A for an introduction of OLS regression theory

[16] See appendix 5A an overview of excluded issuers.

7 ANALYSIS AND FINDINGS

This analysis has three main objectives: First, to estimate issue specific recovery rates. Second, to estimate and analyze the credit risk component of Nordic high yield bond spreads. Third, to identify and measure additional factors affecting the credit spreads.

The analytic procedure is performed in three steps. First, we use a multivariate OLS regression to attempt to create a model suitable for estimating individual recovery rates. Second, we use our structural credit model to predict spreads, which are compared to actual spreads to test the model's predictive power and to measure the share of the credit spread explained by default risk. Third, we subtract the predicted spreads from the actual spreads observed in the market. We perform a multivariate regression to identify and measure sources of this residual. The residual is argued to include compensation for risk aversion and extra risk premium for non-default related risks, illiquidity and migration risk. We start off with a more detailed motivation for the twofold analytic procedure.

The previous chapter gave a detailed description of the methodology used to predict spreads. The model spread equals the predicted expected loss of the bond, and hence, the expected total return of the bond investment equals the risk free rate. The model therefore implies that credit investors are risk-neutral and are only to be compensated by the expected loss. As discussed earlier in this paper, the average investor is more likely to have some degree of risk aversion and will demand compensation for the uncertainty of the expected return inherent in the investment. Furthermore, we presented several non-diversifiable risk-factors that investors demand compensation for bearing.

The actual spread levels are therefore expected to be above the predicted spreads, as the latter only account for default risk. This implies that the structural credit model may not be adequate to predict the absolute level of spreads. However, default risk constitute a significant part of the total risk and should thus be a good predictor of relative differences in credit spreads. The former statement relies on the systematic risk premium to be relatively constant among the issuers in the sample. For instance, if the issuers' exposure to systematic risk factors vary greatly, the variation in spreads may just as likely be explained by different sensitivity to systematic risk as default risk levels. The third part of the analysis will attempt to explain the variation in these risk premiums. We start by attempting to estimate issue specific recovery rates, and continue by comparing and analyzing the predicted and actual spreads.

7.1 Predicting recovery rates

Our analysis starts by attempting to estimate issue specific recovery rates, as it is an important input factor for our credit risk model. We begin by giving a rational for the explanatory variables included in our regression, and continue with a presentation and analysis of the regression results.

7.1.1 Explanatory variables

To explain the variation in recovery rates we include a set of both issuer and bond specific variables in addition to industry dummy variables.

Of the issuer specific variables, five are financial ratios representing firm fundamentals that we believe have an effect on recovery rates. The relative amount of intangibles and receivables are included as these balance sheet items has lower collateral value than tangible assets and liquid funds and will thus lead to lower recovery at default.

Book equity ratio value is included to instrument the financial solidity of the firm. The argument for inclusion is that with a high equity ratio the firm can suffer a larger loss before debt holders are severely affected. The profitability of the firm prior default is likely to indicate what condition the firm is in at default. For instance, if a firm default due to temporarily liquidity issues, the outcome of a restructuring process is likely to yield higher recovery for profitable firms. Also, the share of long term debt relative to total debt was included, which is motivated by the fact that long term debt is a more stable funding source, less likely to cause default, short term, and more likely to cooperate to a restructuring.

Distance to default is the same variable as the one introduced in section 4.1.2, and is included to account for a potential inverse relationship between default risk and recovery rate. Furthermore, it is also arguably a proxy for the market's expected asset value, which obviously affects the recovery rate in a default event.

In addition to firm fundamentals, bond specific factors are believed to contribute additionally to explain recovery rates. Even bonds issued by the same firm may have varying recovery rate depending on the priority in the capital structure and collateral security. We therefore include dummy variables for senior secured, senior unsecured, and subordinated bonds.

Finally, we include industry dummy variables to account for industry specific effects. Previous literature has found industry to be an important indicator of recovery rates, and practitioners often rely on refined industry averages as recovery estimates (Gupton & Stein, 2005). Due to low number of observations in some industries, we only include the five industries with the most default observations[17].

Other explanatory variables could be included to improve the model. For instance, credit rating was found to be significant in Jankowitsch, Nagler, & Subrahmanyam's (2014) study on recovery rates in the US market. However, very few Nordic bonds have official credit ratings, and we were not able to attain shadow rating for Nordic arranging banks.

Type of credit event was tested to be have significant explanatory power and would likely improve the model. However, to ensure the out-of-sample power of this analysis it is important that only information available to an investor at the time of issue is used. It would be difficult, if not impossible, to predict if a potential credit event results in a liquidation, or a distressed exchange, every time one would use the model.

Table 7.1 presents an overview of the variables included in the OLS-regression.

Table 7.1: Explanatory variables

Variable	Definition	Variable	Definition
Equity ratio:	$\frac{Equity}{Total\ Assets}$	Seniority and security:	$Dummy\ variable$
Receivables:	$\frac{Receivables}{Total\ Assets}$	Profitability:	$\frac{EBITDA}{Total\ revenue}$
Long term debt (LTD):	$\frac{LTD}{Total\ Debt}$	Distance to Default (DD):	$Distance\ to\ default$
Intangibles:	$\frac{Intangibles}{Total\ Assets}$	Industry:	$Dummy\ variable$

All financial variables are defined as ratios in order to make them comparable across different

[17] See Appendix 5B for an overview of number of default per industry in the regression sample

currencies, and are calculated using financial statements one year prior the initial credit event.

7.1.2 Regression Results

We performed multiple regressions to test the significance, direction, and magnitude of the explanatory variables for recovery rates we motivated above. The regression outputs are summarized in table 6.1 below.

Table 7.2: Recovery rate regression outputs

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
LTD	-0.0935				-0.115	
	(-0.668)				(-0.866)	
Intang	0.187				0.0110	
	(1.297)				(0.0657)	
Receiv	0.569				0.558	
	(1.554)				(1.328)	
EqRatio	0.105				0.0487	
	(0.621)				(0.284)	
Prof	0.155				0.218	
	(1.047)				(1.511)	
DD		-0.0398			-0.0175	
		(-1.185)			(-0.532)	
SeniorUS			0.0317		0.0655	
			(0.423)		(0.871)	
Subordinated			-0.258**		-0.251**	-0.304***
			(-2.268)		(-2.220)	(-2.941)
EandP				0.212	0.117	
				(1.631)	(0.826)	
OilService				0.0931	0.0291	
				(0.789)	(0.247)	
Shipping				-0.301*	-0.427**	-0.458***
				(-1.738)	(-2.460)	(-3.369)
Industry				0.132	0.0789	
				(0.828)	(0.487)	
TelecomIT				0.160	-0.0227	
				(1.038)	(-0.121)	
Constant	0.376***	0.411***	0.459***	0.348***	0.414**	0.505***
	(2.750)	(9.433)	(9.362)	(3.285)	(2.531)	(13.91)
Observations	95	95	95	95	95	95
R-squared	0.092	0.015	0.065	0.119	0.267	0.166
Adjusted R-squared	0.0409	0.00429	0.0445	0.0696	0.149	0.148

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The dummy variables for subordinated bonds and shipping are the only significant explanatory variables, and are consistent across the models. However, the number of observations within the dummy subsamples are small, and should be interpreted with care. If we were to rely on model (6), it implies that all else equal, subordinated bonds on average recover 30.4 percentage points less than senior secured bonds, which is the benchmark with respect to seniority. Furthermore, it implies that defaulted bonds within the shipping sector recover 45.8 percentage point lower than other sectors.

Unfortunately for the predictive power of the model, only the two dummy variables were proven significant. Consequently, the result is a model that is no more advanced, or precise than using a table of averages as estimates. Furthermore, the variance within the sub samples created by the dummy variables are too high to infer any valid relationship, except for subordinated bonds and shipping. These facts raise concerns about the predictive power of the recovery rate model.

The reason to the less conclusive results is likely to be both low degrees of freedom after correcting for default clusters, and the fact that the outcome of a default event is the result of a bargaining process between debt holders and debt issuer, which may be unsystematic and difficult to model.

In the subsequent anaylysis of bond spreads, as mentioned before, a key criteria is to only utilize information availible at the time of issue. If the recovery model mostly rely on industry and seniority averages from realized default events, the problems of overfitting is likely to be present and result in information that investors was likely to not have. For these reasons and to secure the validity of our bond spread analysis, we rely on static LGD estimates in line with litterature and practicioners when applying the credit model in the following analysis.

Even with low predictive power, the previous recovery rate analysis may shed some interesting light to the analyses of credit spreads in the following. First, we should pay attention to significant results related to the shipping sector, as low expected recovery may be a contributor. Second, if an unsystematic process in fact drives recovery rates, we should be careful to use recovery rates as a major explanatory factor for variation in spreads within subsamples of bonds. For instance, we did not find firm fundamentals to explain the recovery rate variation within any of the industry subsamples.

Lower recovery for subordinated bonds would initially also be an interesting factor to apply. However, the high yield sample in the following analysis only include two subordinated bonds.

7.2 Comparisons of predicted and actual spreads

This section will present descriptive statistics of the predicted spreads from our structural model. We compare them to actual spreads for the respective bond sample, and use the results to differentiate the credit loss part of the credit spread from other risk factors.

Note that observed spreads throughout the analysis are based on one observation for each bond at issue and is assumed issued at par. The credit spread is therefore calculated using the coupon rate as the yield to maturity.

Table 7.1 presents a summary of predicted and actual spreads measured in basis points (bps) for the sample overall and for two sub-samples of defaulted vs non-defaulted bonds. The predicted spreads are lower than actual spreads, with an average spread of 340 and 518 bps respectively. This is in line with the prior expectations, that default risk does not explain the credit spread in full. However, our model spreads are higher compared to what Sæbø (2014) finds in his analysis, even though his sample has higher average actual spreads then ours. The predicted sample has a larger range of spreads, from close to 0 to around 1,650 bps, and has notably higher variance than the actual spread sample. Observing some cases of predicted spreads close to 0 bps is in conflict with reality. The explanation is that some firms in our sample has a very low leverage ratio. The structural model then calculate the probability of default to be almost absent, resulting in severely under prediction.

By looking more closely on the subsamples of defaulted vs non-defaulted bonds, it is evident that the market is able to price defaulted bonds lower on average, i.e. with higher spreads. The bonds that defaulted have significantly higher spreads than those who did not. Interestingly, the model attains similar results. In fact, the model spreads infer an even larger relative difference in spread between defaulted and non-defaulted bonds, which will be examined in more detail when we analyze the mispricing between model and actual spreads.

Table 7.3: Overview of model spreads and actual spreads at issue (bps)

	Model spread				Actual spread				
	Mean	STD	Max	Min	Mean	STD	Max	Min	N
Defaulted bonds	610	481	1647	64	788	278	1342	300	49
Non-Defaulted bonds	291	351	1699	0	469	260	1406	35	274
All	340	390	1699	0	518	286	1406	35	323

We rely on both absolute and relative measures to analyze the mispricing between model and actual spreads, using similar definitions as Sæbø (2014). Absolute mispricing is defined as the model spread subtracted from the actual spread. Relative mispricing is defined by the following formula:

$$Relative\ mispricing_{i,t} = 1 - \frac{Model\ spread_{i,t}}{Actual\ spread_{i,t}}$$

The two measures basically describes the same. However, the relative measures is more easily comparable between different dimensions. An important distinction arise when using mispricing to estimate risk premiums. Absolute and relative measures of mispricing may lead to the opposite conclusion regarding which sample of bonds that has the highest/lowest risk premium compensation. For instance, Sæbø (2014) finds that the relative mispricing was the highest for high quality bonds, and declined with lower quality, and that the complete opposite was true when measured in absolute terms.

The appropriate measure to use depends on how risk premium is assumed to be incorporated in the total spread prediction. If the risk premium was to be a factor to be multiplied with the expected loss, the relative measure would be the correct one. However, if the risk premium is a term that is to be added to the expected loss, then the absolute mispricing would be the correct measure. Due to the fact that the risk premium contain non-default related risks, e.g. non-diversifiable market risk and liquidity risk, we argue that it should not be affected by the initial level of the spread, as is the case for the relative measure. We will therefore rely on the relative measure only when comparing spreads, and use the absolute measure when we discuss the level of risk premium inherent in the observed spreads, and assume the following relationship:

$$Spread_i = EL_i + \lambda_i$$

Where EL_i is the predicted expected loss and λ_i is the risk premium for bond i. Consequently, the model defines the risk premium as the absolute difference between the observed spread and the expected loss:

$$\lambda_i = Spread_i - EL_i$$

The average transaction-by-transaction relative mispricing for the sample overall is 35 percent (table 7.2). This indicates that, on average, as much as 65 percent of the credit spread is explained by default risk according to our extended structural model. In absolute terms, the average mispricing is 178 bps. However, note that variation in mispricing is large and does suffer influence from a small number of extreme differences. The table also show that the minimum mispricing is below -400 bps, which may seem odd as first. Such observations simply mean that the model spread is higher than actual spread, i.e. the predicted *expected loss* is higher than what can be implied in the observed spread.

Table 7.4: Relative and absolute mispricing

	Relative mispricing (%)				Absolute mispricing (bps)				
	Mean	STD	Max	Min	Mean	STD	Max	Min	N
Defaulted bonds	15	78	93	-198	178	535	999	-1079	49
Non-Defaulted bonds	38	73	100	-404	178	341	1269	-984	274
All	35	74	100	-404	178	376	1269	-1079	323

The average relative mispricing within the two sub-samples of defaulted and non-defaulted bonds is 15 and 38 bps respectively. The model has significantly (p=0.025)[18] lower relative mispricing for defaulted than for non-defaulted bonds. This means that, on average, predicted spreads are significantly closer to actual spreads for bonds that defaulted, than for those who did not. An interesting interpretation of the preceding is that, in isolation, the structural model was better to estimate the default risk than the market. This bold claim require a robustness check.

Firstly, we observed earlier that the majority of defaulted bonds belong in the high spread environment. Hence, the findings above may simply be due to better prediction ability in this area. In table 7.3 we have divided the sample in two groups according to spread level at issue. The “High spread environment” group consist of all bonds with spreads higher than the median of 475 bps, and the “Low spread environment” consist of the remaining bonds with

[18] Using a two-sample student t-test assuming equal variance

lower spreads at issue. The relative mispricing does not seem to be any notably different between the two groups. This implies that the model has equal prediction power for high spread bonds as for low spread bonds, and that this is not the source of lower mispricing for defaulted bonds.

Secondly, one may propose that this finding could be due to differences in non-default related risk premiums. However, there is no intuitive explanation for defaulted bonds to be less exposed to non-diversifiable risks than those who did not default. The issue of accounting for non-diversifiable risk premiums will be the focus in the next sub-chapter.

Table 7.5: Breakdown of relative mispricing in high and low spread environment

	Model spread (bps)		**Actual spread**		**Relative mispricing**		
	Mean	STD	Mean	STD	Mean	STD	N
High spread enviroment	485	450	746	223	33	66	158
Low spread enviroment	200	256	299	120	36	82	165
All	340	390	518	286	35	74	323

We further examine the effect of the financial crises in 2008 on average spreads at issue and the explanatory share of the credit model. Table 7.4 divides the sample in bonds issued prior and post the financial crisis, defined by the fall of Lehman Brothers on 15. September 2008 (similar approach as Sæbø (2015)). As expected, the average spreads in the market are notably higher in the aftermath of the financial crises. The model also responds to lower equity values and increased volatility by predicting higher spreads on average. In fact, the part of the credit spread explained by the model increases to 71 percent from initially 59 percent. This is in line with the findings of Sæbø (2015), that the part explained by default risk increased after the financial crisis. However, in absolute terms, the mispricing increases. Even though the model responds to the increased risk, it seems that the uncertainty in the financial markets increased credit spreads even more.

Table 7.6: Breakdown of mispricing prior and post the financial crisis

	Predicted spreads	Actual spreads	Relative mispricing	% explained	Absolute mispricing
Prior financial crisis	258	399	41	59	141
Post financial crisis	413	624	29	71	211
All	340	518	35	65	178

In this section we found that our model explain 65 percent of the observed spread on average, leaving 35 percent unexplained. In absolute terms, the unexplained credit spread amount to

178 bps, both within the default- and non-default sample. This represent an estimate of the average compensation for non-diversifiable risks, illiquidity and migration risk. The estimate may also contain random errors or market mispricing. The following section will attempt to identify and measure sources of the observed premium.

7.3 Identifying sources of risk premium

This section will use the absolute mispricing between expected loss and observed spreads found in the previous analysis as an estimate of risk premium, and attempt to identify and measure sources to explain the variation within the sample. The theory section described four main sources of none-diversifiable risk premiums in bond spreads; Risk aversion, migration, illiquidity, and market risk.

We choose to do a regression analysis of the difference between our model spreads and actual spreads in order to explain the content of the mispricing. We do this through an OLS regression and use absolute mispricing as our dependent variable[19]. The method follows that of Sæbø (2015) and Eom et al. (2004), and we will throughout this section compare our results with those of previous studies.

To get an overview of which explanatories could be important, we divide the sample in one group with mispricing higher than the median, and one group with mispricing lower than the median. We continue by performing simple t-tests to determine variation in 14 selected variables among the two groups[20]. We find that observations with high mispricing has significantly lower maturity, size, and market leverage, and significantly higher coupon. We also find that the oil price were significantly higher at the time of issue for bonds with high mispricing.

We start by explaining our rational for the explanatory variables chosen to be included in our OLS-regression.

7.3.1 Industry

We have included dummy variables for the major industries represented in our sample. As shown in appendix 4B, the industry groups “Oil and gas services”, “Oil & gas E&P”, “Industry”,

[19] See section 6.3.2 for details on how and why an OLS regression is performed, and the underlying assumptions of the OLS regression method.
[20] See appendix 4H for t-test outputs

and “Shipping” are the groups most heavily represented. The remaining industry groups are included as the omitted dummy variable. Sæbø (2015) finds that industry group is able to explain a significant amount of variation between firms. The reason is likely to be that some industries are more sensitive to market risk than others and that the industry dummy variables account for the related premium. Additionally, investor’s may require compensation for industry specific downside risk, and so we expect our dummies to be significant.

7.3.2 Size

Size is a risk factor well known as one of the Fama-French factors (Fama & French, 1993). There are several intuitive reasons to why larger companies often are perceived less risky. For instance, large companies often have a broader customer base, more stable bank financing, more diversified products etc. We measured size as market capitalization of equity at the time of issue, denominated in million NOK. Both Sæbø (2015) and Eom et al. (2004) show that this is an important factor to include, and that the variable explains a significant amount of variation in the mispricing. We expect larger companies to have lower spreads due to lower sensitivity to market factors, and hence that the sign of the coefficient to be negative.

7.3.3 Market leverage

Market leverage is one of the key inputs of our spread model, and hence is important to test. We define market leverage as Market capitalization divided by total book value of liabilities. Eom et al. (2004) found that all the 5 structural models they tested had systematic errors related to leverage. They highlight that the models do a poor job of pricing safer bonds with low leverage, which to us is a good result as we only study high-risk bonds in this paper. They further note that this might indicate that leverage is poorly estimated or that the models fail to assign the appropriate risk to each level of leverage. As stated by Eom et al. (2004), the model has a tendency to severely under predict spreads for low leveraged companies. The model sometimes estimate spreads close to zero, while observed spreads always are higher. If this tendency appears to be systematic, we would expect to see a negative sign for this variable, i.e. the structural model under (over) estimates spreads for low (high) leveraged companies. Otherwise, if our structural model is the “true” model, it is expected to be insignificant.

7.3.4 Oil price

We include a variable representing the oil price on the date of the issue. Oil price is regarded as a significant factor for the real economy and especially for the Norwegian. Furthermore, as about 70 % of our sample consist of bonds issued in NOK (appendix 4E), the reason for including it is even greater. Hence we are curious to see the effect this variable might have on mispricing. Sæbø (2015) tests the significance of the oil price on the Norwegian bond market, but his results are inconclusive.

7.3.5 Years until maturity

Years until maturity has been shown to be a significant factor for the structural models, and tells us to expect that structural models especially struggle with predicting high enough spreads on short maturity bonds as there is not a sufficient timespan for the volatility to come into play (Eom et al., 2004). Maturities in our sample have great dispersion, with the majority between 0.5 and 5 years. Hence; we expect the sign of the coefficient to be negative.

7.3.6 Price/book value

We have included market capitalization divided by book value of equity as an explanatory variable. The inclusion of this variable is motivated by being one of the Fama-French risk factors, where low price/book ratios represent value stocks, and high price/book ratios represent growth stocks. Value stocks are perceived to represent the risk factor of the two. This is motivated by a higher exposure to "business-cycle-risk", which means that value stocks as a group are more affected in a downturn (Fama & French, 1993). Sæbø (2015) found this variable to be significant in many of the models he ran, but highly unstable and hence deemed as a non-relevant variable. Eom et al. (2004) did not include price/book-value as a variable in their analysis. Nevertheless, the high importance of the factor for the equity market, makes this variable interesting to test.

7.3.7 Illiquidity

Liquidity is important for bond investors. A larger part of the corporate bond market suffer from low trading volumes, which leads to higher and more volatile bid ask spreads. The result may be delays in finding a counterparty for a transaction and lower realized price in the case of a sale. Due to these reasons, liquidity premium is one of the most common explanatories of the extra risk premium investigated in literature and is naturally included in the regression analysis. There are, however, different ways to define and incorporate the variable.

Sæbø (2015) includes the bid-ask spread of government treasuries, as a proxy on the general liquidity in the market, but this variable does not incorporate the liquidity of individual bonds. He also points to the possibility of including issue size as a proxy, but this would probably generate problems of multicollinearity with the firm size variable. A third option he mentions is the use of bond bid/ask spreads. However, we were not able to obtain detailed historic data on these spreads

As a fourth option, included in order to capture some of the individual variation between bonds, we include a variable measuring days with registered trades in the issuer's equity. We define this variable as the number of days with registered trades in the year prior to issue divided by possible trade days in said year. With further investigation, we find that the majority of the observations are close to 100%. Another shortfall is that there might be a multicollinearity problem with the included size variable[21]. Hence, we instead wish to highlight those firms with what we define as a high liquidity ratio vs. those with a low ratio. We set this limit to 90 %, as we have a significant cluster above 90 %, and with significant dispersion of those below 90 %, and include the variable as a dummy. Hence, a dummy value of 1 indicates a high liquidity bond, and dummy value of 0 indicates a low liquidity bond.

We use this ratio as an indicator of bond liquidity because we believe that if the related stock of a bond has low liquidity, it is also likely that the bond itself has low liquidity. Using a bond liquidity proxy from the equity market is partly motivated by limited alternatives, but also by the fact that other research have found interesting results using similar methods[22].

7.3.8 Time dummy

To test time varying effects, we include a dummy indicating whether an issue was made post or prior the financial crisis. A widely accepted definition of the beginning of the crisis is 15. September 2015, which marks the fall of the Lehman Brothers. This is also the same date used by Sæbø (2015), making our results more comparable. Increased general risk and uncertainty in the market after the crisis motivates an expectation of higher absolute mispricing after the crisis. The dummy is defined as 1 if the observation is after the crisis, and 0 if it is before.

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[21] See plot illustrating potential multicollinearity in appendix 4J

[22] See for instance de Jong & Driessen **Invalid source specified.**

7.3.9 Security

We have included a dummy indicating whether the bond is senior secured or senior unsecured. An overview can be seen in appendix 4D. Our structural model does not incorporate security in its spread prediction, and hence we expect unsecured bonds to have a higher degree of absolute mispricing than secured bonds. A dummy of 1 indicates a senior secured bond, while a dummy of 0 indicates a senior unsecured bond.

7.3.10 Floating vs. fixed rate bonds

We have included bonds with both fixed and floating coupon in our sample, despite Merton's assumption of fixed rate bonds. Furthermore, we observe that fixed interest rates have been consistently higher than floating interest rates during the sample period. We have included a dummy variable indicating whether the bond is of floating or fixed rate due to this fact. This is done as a corrective measure for the regression analysis, and will not be interpreted as an explanatory factor of risk premium. A dummy of 1 indicates a fixed rate bond, while a dummy of 0 indicates a floating rate bond.

7.3.11 Variables not included in our analysis

We have limited our choice of variables due to both data availability, time restrictions, and to avoid over-fitting a small sample with too many independent variables. However, we are aware that previous research has tested a number of additional variables that could be significant for our analysis. Eom et al. (2004) implements a wide array of variables, but a reason for this is that they test not only the Merton model, but also four other structural models, all incorporating different factors. They test all variables included in their Merton model; coupon, payout ratio, asset volatility, market leverage, and size. They also test for several other variables theory predict might have an impact on spreads; most notably are term structure (defined as the difference between the 2 year and 10 year treasury yield), credit rating, and PPE/Assets. Of variables not included in our analyses, Sæbø (2015) includes excess return of OSEBX and relative bid/ask spread on treasuries

Of the variables present in our spread model, we have only included maturity and market leverage. This is because previous studies have shown that these variables are the ones structural models have the most trouble incorporating. Including credit (shadow) rating from a bank could give interesting insight, but were unfortunately not available to us. The excess return of OSEBX was deemed insignificant by Sæbø (2015) and were hence not included. We were unable to find data easily implementable for relative bid/ask spreads of treasuries.

7.4 Regression analysis

In this section we perform multiple regressions to test the significance, direction, and magnitude of the explanatory variables motivated in the previous section. Selected regression outputs are summarized in table 7.1 below. As previously reasoned, we have chosen to use absolute mispricing as the regressions' dependent variable, defined as actual observed spread subtracted predicted model spread. The interpretation of the coefficient will therefore be as follows: A positive coefficient will indicate a higher premium related to the variable. A negative coefficient will indicate a discount related to the variable.

In model 1 we start by running a regression only including industry dummies, in order to get an initial view of their significance. In model 2 we continue by running a regression omitting maturity and leverage, to test a model without variables included in our structural model. In model 3 we include all discussed variables, and in model 4 we add a time dummy indicating if the issue observation was made before or after the financial crisis. For a discussion of the OLS assumptions in conjunction with the regression, see appendix 3C.

Table 7.7: Regression outputs

VARIABLES	Model 1	Model 2	Model 3	Model 4
Industry	68.80	64.61	103.4	107.8
	(63.65)	(65.65)	(64.52)	(67.11)
Oil and gas services	26.77	60.49	108.7**	137.5***
	(59.19)	(56.30)	(48.74)	(50.66)
Oil and gas E&P	49.35	52.92	11.01	18.48
	(77.74)	(81.19)	(74.05)	(72.70)
Shipping	232.0***	249.1***	231.8***	238.7***
	(68.14)	(70.07)	(66.19)	(62.69)
Size		8.28e-05	-0.000162	-0.000604
		(0.00102)	(0.00144)	(0.00153)
Price/book		2.093	-11.08**	-5.549
		(7.032)	(5.173)	(5.348)
Security		-147.2*	-100.6	-94.80
		(80.09)	(72.10)	(71.01)
Oil price		0.648	1.431*	-0.238
		(0.912)	(0.816)	(1.118)
Liquidity		-95.42	-114.7*	-113.5*
		(74.46)	(68.05)	(67.97)
Return Type		157.9***	164.2***	160.9***
		(52.96)	(47.79)	(47.79)
Maturity			-23.91**	-20.52**
			(10.05)	(10.10)
Market Leverage			-70.43***	-76.54***
			(10.15)	(11.11)
Financial Crisis Dummy				172.8**
				(67.73)
Constant	35.41	24.14	220.5*	238.9**
	(38.27)	(122.2)	(118.8)	(119.1)
Observations	310	310	310	310
R-squared	0.027	0.078	0.221	0.242

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We begin by taking a look at the industry dummies. In model 1 we see that the Shipping dummy is significant at the 1 % level, a result consistent throughout all our models. This might imply that the shipping industry group is more exposed to systematic market risk than other industries in the sample. The shipping industry is well known to be a highly volatile and cyclical industry, which might be why we find this variable to be significant at such a consistent level. However, this may also be explained through the findings from our LGD regression[23], which finds the Shipping industry group to have significantly lower recovery rates than other industries. This indicates that we use a too high recovery rate in our spread prediction model, which in turn causes underestimation of spreads in the form of an underestimation of credit risk.

The remaining industry group dummies for Industry, Oil and gas Services, and Oil and gas E&P is not consistently significant across our models. Oil and gas services is significant in model 3 and 4, but we observe again in section 6.3.6 that this group has a lower recovery rate than the rest of the sample, although not as low for the Shipping group. With inconsistent significance and biased recovery rate coming into play, it is difficult to draw any conclusions. Such a low significance of industry dummies is quite contrary of Sæbø`s (2015) finding, which is that industry can determine a significant amount of the mispricing. A reason might be that we use a too small sample both in our spread and recovery rate regression to find significant results, and another reason might that industry group determines less of the variation in spreads for high yield bonds than for investment grade bonds (which constitutes the majority of Sæbø's (2015) sample). This can be explained by the economic intuition that a relatively larger percentage of the observed spreads are explained by credit risk for high yield than for investment grade bonds, giving motivation to claim that factors like industry group has a smaller absolute impact on the spread of high yield bonds.

We find both the two variables already included in our spread model, Market Leverage and time until maturity, to be significant in the regression. The first variable, Market leverage, is significant and with a negative sign. This is the same result as Eom et al. (2004), who found market leverage to be significant for a range of different structural models. As high yield bonds are mainly issued by firms with high leverage, this might be an indication that the spread model is better at predicting spreads for high yield bonds than for investment grade bonds, and that higher leverage in turn means lower mispricing. It also implies that our structural model is struggling to assign the proper amount of risk for different leverage levels, especially true for low leverage issuers. The second variable we test that also is a part of our

[23] See section 6.3.6

credit model is Maturity, which is shown to be significant and negative in both model 3 and 4. The negative relationship found indicates that high maturity bonds have the lowest degree of mispricing, which also is in line with the findings of Eom et al (2004), and the common perception that structural models struggles with predicting high enough spreads on low maturity bonds. In model 2, we include all explanatory variables except those already included in our spread model, and witness that the R-squared changes significantly from 7.8 % in model 2 to 22.1 % in model 3. This gives further motivation to claim that market leverage and maturity indeed are important correctional factors to include in the regression, and highlights the structural models difficulty of properly incorporating them.

Our next factor of consideration is liquidity. The dummy included as a proxy for bond liquidity is shown to be significant, and implies that high liquidity has a negative impact on mispricing. The result is true for all models except in model (2), where we remove variables included in the spread model. It is difficult to conclude why the removal of the variables leverage and years until maturity, whereas leverage is the main source of effect, has this impact. Note that we do not find any indications of multicollinearity between Liquidity, Leverage, and Years until maturity in the correlation table in appendix 3C. Nevertheless, the finding that the market leverage and years until maturity are significant variables motivates the conclusion that model 2 might be a biased regression by omitting these variables. Our findings regarding the liquidity ratio implies that the structural model predicts more accurate results for firms with high liquidity, or possibly that these firms entail a larger degree of migration risk[24]. Although it is not possible to separate the effect of migration risk and liquidity risk, the finding supports the view that liquidity is of significance to investors, and that they demand a premium for low liquidity issues. Our results indicate a liquidity premium of up to 110 bps, which is within the range of what is found in previous studies[25].

In model 4, we include a dummy indicating whether the observation is prior or post of the financial crisis[26]. The dummy is significant, and indicates higher mispricing after the crisis.

[24] Migration risk and liquidity risk is linked by the fact that if a firms rating drops, and its debts liquidity in addition is low, the price impact on the bond will be higher.

[25] An example is de Jong & Driessen **Invalid source specified.** who found the premium to be 150 bps per annum for speculative grade bonds.

[26] An effort was made to sort the sample in two group divided by the start of the financial crisis. However, the individual sample sizes proved too small to produce significant results

From table 7.4, we observed that the model predicts higher spreads after the fall of Lehman Brothers, and that default risk explained a greater part than before. This is broadly in line with what Sæbø (2015) finds regarding the effect of the financial crisis. A potential explanation is that even though equity prices declined, and the model's default risk increased, the uncertainty in the capital markets raised credit spreads even more, resulting in a net increased average mispricing in the aftermath of the financial crisis.

Price/book value provide an interesting and significant effect in model 3. The negative coefficient implies that growth stocks (high P/B) has lower risk premium than value stocks (low P/B). This is in line with the theoretical motivation presented by Fama and French (1993). Although interesting, the variable is unstable and becomes insignificant once leverage and maturity are removed or the time dummy is added. It is difficult explain exactly why this is. Sæbø (2015) has similar findings in his analysis.

We find that the oil price is a significant variable with a positive effect on mispricing in model 3. We do however witness that the variable is unstable, as it becomes insignificant when market leverage and maturity are removed in model 2. One would expect that an increased oil price would be risk reducing, especially for oil related companies. The sign of the coefficient in our regression may thus seem odd. The explanation may be that we rely solely on observations at issue and not the trailing spread developments. Once issued, the bond spreads are likely to be reduced when oil prices increase, as a result of increased profitability and lower default risk. The effect of oil prices in absolute levels at issue are, on the other hand, less obvious. Sæbø's (2015) conclusion regarding the effect of the oil price is inconclusive, but his main regression finds oil price to have a negative effect on mispricing, which is more in line with our previous expectation.

However, the inclusion of a time dummy representing the financial crisis pushes the oil price variable out of significance. The issue dates in our sample and the oil price on the respective dates, creates an evident linear relationship with a steady increase from the early 2000 and until our last issue observation in 2012[27]. Even with the abrupt drop in oil price late 2008, the mean oil price in our sample is significantly higher post the financial crisis than prior, which poses a collinearity problem. This can also be seen from the correlation matrix in

[27] See scatterplot in appendix 4I

appendix 3C, which shows a correlation factor of about 60 % for the time dummy and oil price. This observation might explain the positive coefficient of oil price discussed earlier in this section and might explain our wonder for why this is. It might simply be due to the fact that the oil price indicates the financial crisis, which in itself represents radical changes in several dimensions of the economy. Hence, the positive coefficient of oil price does not have to represent a relationship between spreads/mispricing and the oil price, but rather the increased risk premium demanded after the financial crisis, as discussed in the previous section.

Sæbø (2015) finds company size to be a significant factor in the spreads of Norwegian corporate bonds (in a sample of both HY and IG). However, we do not find this variable to be of significance in our sample. This might be due to the typical Nordic high yield issuer being relatively small. As seen from the firms in our sample, over 75 % of the firms have a market capitalization below 1 billion NOK.

In this section we have given a thorough analysis of our regression outputs. Our findings indicate that there is a liquidity premium in the Nordic high yield bond market of about 110 bps, and that the size of the issuer measured by the market value of equity does not entail a premium or discount. Furthermore, we find that investors demand a premium for investing in high yield shipping bonds of about 230 bps while industry classification in general has minor explanatory power. We support previous research done by Eom et al (2004) indicating that structural models struggles with properly incorporating the full effect of the leverage ratio and time to maturity, and Sæbø's (2015) finding that the risk premium of HY bonds increased in absolute terms after the financial crisis. We do however note that the sample size is small, and out of sample testing has not been possible due to this fact. Hence the validity of our results must be interpreted with care.

7.5 Criticism

In this chapter, we will present limitations of our thesis, points of improvements, and suggestions to future research.

The main limitations of writing a master thesis is time, a fact also true for this one. Collecting data has been an extensive process, and a challenge in terms of the pure existence of data, in addition to their availability. This challenge has forced us to use several sources, thus creating challenges in terms of sorting and aligning different datasets, in addition to increasing the risk of measurement error. Lastly, choosing and understanding the models has been an exciting, but time-consuming maturation process.

The novelty and limited size of the Nordic corporate high yield bond market is challenging in terms of obtaining a complete and bias-free dataset. This paper joins others in making the first steps to describe and understand this market. We have three points of improvement that can be done at a future time when the market is more mature, and a greater population of bonds is available for analysis. First of all, an increase in sample size and the ability to draw a truly random sample would better the robustness of our results. Second, we would be more likely to find significant determinants of loss given default. Third, we would be able to test the predictive power of our models in an out of sample test with observations not included in our sample.

We have only used observations at the time of issue for our structural model, and time of issue and default for our recovery model. Using point estimates causes a risk of measurement error, as the time of observation could be highly significant for the output of our models. We have been forced to use point estimates, as comprehensive, continuous price data currently is unavailable for the Nordic high yield bond market. Nordic Bond Pricing AS is a subsidiary of Nordic Trustee with future plans to make continuous prices of corporate bonds available to the public. Future researches should make sure to utilize such a dataset when, or should, it become available.

As elaborated in the theory section, many different variations of the original Merton model exists, most of them focusing on including different factors economic theory predicts should have an effect on credit risk. There are two additional factors we would especially like to test given more time. The first being an endogenously defined default barrier, as first done by

Black & Cox (1976). As explained in section 6.2.2, the default barrier is often defined as a value less than the book value of liabilities, due to the intuition that all debt rarely is due within the estimation period. As our sample consists of bonds with maturity ranging from 6 months to 30 years, we think that being able to differentiate the default barrier, also between coupons and principal, could improve our models accuracy. The second factor we would like to include is stochastic interest rates, studied by Longstaff & Schwartz (1995) among others. The significance of their inclusion has been debated, but differing interest rate environments in world markets would make it interesting to test its inclusion in our study of the Nordic market.

The structural models are criticized for utilizing unobservable variables and so we run the risk of biased input variables. An example is asset value/volatility, which is estimated using equity volatility. For low liquidity firms, equity volatility might be underestimated due to few observed price quotes. This would again cause underestimated asset volatility, which would cause too low modeled spread estimates.

8 CONCLUSION

The main objective of this thesis was to identify and measure explanatory factors of observed credit spreads in the Nordic corporate HY bond market in the period 2000 – 2012. From literature on credit pricing, we found three sources of risk compensation worth investigating; Default risk, liquidity risk, and market risk.

We started off with creating a credit model to measure the part of the credit spread that could be explained by default risk, i.e. loss related to a default event. The spreads were estimated using an extended version of the Merton (1974) model, as found in Eom et al (2004). Loss given default, an important input variable in the credit model, was first attempted to be estimated individually for each stock. This was done by creating a model based on a multivariate OLS regression on a recovery dataset of 150 defaulted bonds in the market. However, the power of the recovery analysis was low, which might be due to two possible explanations. First, it might be due to low degrees of freedom after correcting for default clusters. Second, it might be due to the fact that the outcome of a default event is the result of a bargaining process between debt holders and debt issuer, which may be unsystematic and difficult, if not impossible to model. An interesting observation, nevertheless, was that subordinated and shipping bonds recovered significantly lower than the other subsamples. Due to the inconclusive results from the recovery analysis, the credit model were run using static recovery estimates of 40 percent, which is in line with other research papers and our recovery sample.

The average spread predicted by the credit model was 340 basis points (bps), whereas the average actual spread in the sample was 518 bps. The average relative mispricing on a bond-by-bond basis was 35 percent, which implies that the credit model explained as much as 65 percent of the credit spread on average. Furthermore, the mispricing was found to be significantly lower for the bonds that were involved in a default event. We also discovered that default risk accounted for a greater part of the credit spread after the financial crisis in 2008, and that the absolute value of the risk premium increased as well.

The average relative mispricing is considerably lower compared to prior studies like Sæbø (2015), who finds an average relative mispricing to be 78.5 %. This is probably due to his inclusion of investment grade firms in his sample, where credit risk has a smaller relative impact than on high yield bonds. The direction of the difference of our and Sæbø's (2015) findings should be no surprise for market participants, but rather the surprisingly large magnitude. Our findings implies that more than twice as much of the spreads of high yield bonds are explained by credit risk relative to the bond market as a whole (Sæbø, (2015)), which gives an indication that structural models are more suitable for predicting spreads on high yield bonds, than on investment grade bonds.

The unexplained part of the observed spreads amounted to 178 bps on average in absolute terms. With a multivariate OLS, we attempted to explain the part of the credit spread not explained by default risk using instrument variables for the other two sources of risk premium, i.e. liquidity and market risk. The R-squared we obtain with our regressions is about 22 %, and with a relative mispricing of 35 % this implies that still at least 27.3 % of the actual spreads remain unexplained.

The results from the regressions performed are mainly in line with previous research, although with some deviations. “Shipping” is the only industry group in our sample proved to be consistently significant. Our analysis indicates that investors demand a risk premium of about 240[28] bps for investing in HY shipping bonds relative to other industries, although the coefficient may be biased by our finding that the “Shipping” group has significantly lower recovery rates relative to the market average. Contrary to prior research by Sæbø (2015) we do not find industry grouping in general to be a major source of variation in mispricing.

Our finding regarding the importance of the size of the issuer, a well-known Fama—French factor, is also deviating from the findings of Sæbø (2015), who found this variable to be of importance. We find this variable to have no significance on the mispricing of Nordic high yield bonds. However, this result may partly be explained by the relatively small issuer size in our sample, with 70 % having an equity market value of less than 1 billion NOK.

A result more in line with theory, is our finding that investors demand a premium for investing in companies with low liquidity. Our coefficient implies a premium of ca 110 bps for investments in low liquidity bonds. We furthermore support earlier research done by Eom et al (2004) indicating that structural models struggles to correctly incorporate the impact of the firms leverage ratio and time until maturity. These variables are critical components of our credit risk model, which is the same model used by Eom et al (2004), and so the bias is

[28] Highest estimate is 249.1 and lowest is 231.8 bps. See table 7.1 for more details.

indicated as we find both market leverage and maturity to be highly significant variables in our mispricing regressions.

Although we note several interesting findings, our small sample size causes questions to be raised regarding the robustness of our results. Due to a large degree of heterogeneity in the preliminary sample, we have been forced to reduce the sample size significantly. Our results could be improved if the initial amount of eligible issues had been larger, and a random sample could be drawn. A larger sample would also have made it possible to split our sample in two in order to further test the robustness of our regression model.

9 APPENDIX

APPENDIX 1: HIGH YIELD SAMPLE OVERVIEW (SORTED BY DATE)

Issuer	Issue Date	Issuer	Issue Date
Seadrill Norge AS	03.10.2000	DNO International ASA	03.11.2004
DOF ASA	24.10.2000	DNO International ASA	03.11.2004
Crystal Production AS	27.11.2000	DOF ASA	07.12.2004
Frontier Drilling AS	20.12.2000	DNO International ASA	02.02.2005
Marine Harvest ASA	20.12.2000	Farstad Shipping ASA	07.02.2005
Marine Harvest ASA	20.12.2000	Aker ASA	02.03.2005
Marine Harvest ASA	20.12.2000	Aker ASA	02.03.2005
Marine Harvest ASA	15.03.2001	Prosafe SE	09.03.2005
Seadrill Norge AS	03.04.2001	Prosafe SE	09.03.2005
Northern Offshore LTD	06.04.2001	Odfjell SE	17.03.2005
DNO International ASA	01.06.2001	Sevan Marine ASA	31.03.2005
DNO International ASA	01.06.2001	DNO International ASA	06.06.2005
Marine Harvest ASA	14.06.2001	Seadrill Norge AS	22.06.2005
Fred Olsen Energy ASA	21.06.2001	Sinvest AS	22.06.2005
Bourbon Offshore Norway AS	16.07.2001	Norse Energy Corp. ASA	13.07.2005
UPM-Kymmene Oyj	23.01.2002	Eastern Drilling ASA	15.07.2005
UPM-Kymmene Oyj	21.11.2002	Sinvest AS	15.08.2005
UPM-Kymmene Oyj	21.01.2003	Songa Offshore SE	08.09.2005
DOF ASA	24.04.2003	Dof Subsea AS	16.09.2005
DNO International ASA	02.06.2003	Blom ASA	05.10.2005
Ocean Rig ASA	29.08.2003	DNO International ASA	12.10.2005
Fred Olsen Energy ASA	26.03.2004	DNO International ASA	12.10.2005
Prosafe SE	26.03.2004	I. M. Skaugen SE	14.12.2005
Fred Olsen Energy ASA	30.03.2004	Sinoceanic Shipping ASA	28.12.2005
DNO International ASA	03.05.2004	Deep Sea Supply AS	23.01.2006
TGS Nopec Geophysical Company ASA	05.05.2004	Sevan Marine ASA	31.01.2006
DNO International ASA	01.06.2004	Ignis AS	03.02.2006
DNO International ASA	01.06.2004	Norwegian Car Carriers AS	03.02.2006
I. M. Skaugen SE	02.06.2004	Wintershall Norge AS	15.02.2006
STX Europe AS	23.06.2004	Stora Enso Oyj	22.02.2006
DOF ASA	15.07.2004	COSL Drilling Europe AS	28.02.2006
Ocean Rig ASA	15.10.2004	DNO International ASA	02.03.2006
Ocean Rig ASA	15.10.2004	Odfjell SE	17.03.2006

Issuer	Issue Date	Issuer	Issue Date
Songa Offshore SE	24.03.2006	Telio Holding ASA	15.12.2006
Ocean Rig ASA	03.04.2006	Norgani Hotels AS	18.12.2006
STX Europe AS	05.04.2006	Sevan Marine ASA	20.12.2006
Stora Enso Oyj	13.04.2006	MPU Offshore Lift ASA	22.12.2006
Stora Enso Oyj	13.04.2006	Songa Offshore SE	22.12.2006
Stora Enso Oyj	23.05.2006	PetroProd Ltd	12.01.2007
PetroMena ASA	24.05.2006	Seadrill Ltd	23.01.2007
Vmetro ASA	29.05.2006	Seadrill Ltd	23.01.2007
Petrojack ASA	30.05.2006	Ability Drilling ASA	13.02.2007
Petrojack ASA	30.05.2006	Seabird Exploration PLC	14.02.2007
DOF ASA	13.06.2006	Island Drilling Company ASA	27.02.2007
I. M. Skaugen SE	19.06.2006	American Shipping Company ASA	28.02.2007
Tandberg Data ASA	27.06.2006	American Shipping Company ASA	28.02.2007
Tandberg Data ASA	27.06.2006	Nexus Floating Production Ltd	07.03.2007
Belships ASA	04.07.2006	Dof Subsea AS	09.03.2007
Interoil Exploration and Production ASA	11.07.2006	Odfjell SE	19.03.2007
Norse Energy Corp. ASA	13.07.2006	Remedial (Cyprus) Public Company Limited	28.03.2007
Seabird Exploration PLC	14.07.2006	Austevoll Seafood ASA	29.03.2007
Aker ASA	29.08.2006	Interoil Exploration and Production ASA	29.03.2007
APL ASA	20.09.2006	Norwegian Air Shuttle ASA	19.04.2007
MPF Corp Ltd	20.09.2006	Petrojack ASA	19.04.2007
Axel Springer Norway AS	27.09.2006	Kverneland AS	27.04.2007
Oceanteam Shipping ASA	27.09.2006	Kverneland AS	27.04.2007
Deepocean AS	04.10.2006	Interoil Exploration and Production ASA	02.05.2007
Eitzen Chemical ASA	04.10.2006	Reservoir Exploration Technology ASA	11.05.2007
Eitzen Chemical ASA	04.10.2006	Sevan Marine ASA	14.05.2007
Electromagnetic Geoservices ASA	02.11.2006	Norwegian Car Carriers AS	23.05.2007
DNO International ASA	29.11.2006	PetroProd Ltd	24.05.2007
Akastor ASA	01.12.2006	TTS Group ASA	24.05.2007
Akastor ASA	01.12.2006	Songa Offshore SE	01.06.2007
Akastor ASA	01.12.2006	I. M. Skaugen SE	06.06.2007
Akastor ASA	01.12.2006	Northern Offshore LTD	13.06.2007
Havila Shipping ASA	13.12.2006	Oceanteam Shipping ASA	18.06.2007

Issuer	Issue Date	Issuer	Issue Date
Aker Floating Production AS	05.07.2007	Hurtigruten ASA	06.03.2009
COSL Drilling Europe AS	06.07.2007	I. M. Skaugen SE	11.03.2009
Norse Energy Corp. ASA	06.07.2007	I. M. Skaugen SE	11.03.2009
Norwegian Energy Company ASA	13.07.2007	Austevoll Seafood ASA	30.03.2009
Norwegian Energy Company ASA	13.07.2007	Austevoll Seafood ASA	30.03.2009
Norgani Hotels AS	23.07.2007	Austevoll Seafood ASA	30.03.2009
Wega Mining AS	02.08.2007	Nokia Oyj	07.05.2009
Prosafe SE	15.08.2007	Bergen Group ASA	13.05.2009
Sevan Marine ASA	24.10.2007	DOF ASA	15.06.2009
EMS Seven SEAS AS	19.11.2007	Kverneland AS	17.06.2009
PetroMena ASA	19.11.2007	Kverneland AS	17.06.2009
DNO International ASA	29.11.2007	Akastor ASA	26.06.2009
Reservoir Exploration Technology ASA	13.12.2007	Akastor ASA	26.06.2009
Songa Offshore SE	17.12.2007	Bergen Group ASA	06.07.2009
DOF ASA	20.12.2007	Nattopharma ASA	10.07.2009
Aker Floating Production AS	24.01.2008	I. M. Skaugen SE	01.09.2009
Northern Offshore LTD	12.03.2008	Havila Shipping ASA	14.09.2009
Roxar AS	22.05.2008	EMS Seven SEAS AS	22.09.2009
Songa Offshore SE	16.06.2008	EMS Seven SEAS AS	22.09.2009
Petrolia SE	20.06.2008	Blom ASA	25.09.2009
Dof Subsea AS	28.08.2008	Prosafe SE	14.10.2009
I. M. Skaugen SE	16.09.2008	Seadrill Ltd	10.11.2009
Songa Offshore SE	22.09.2008	Norwegian Energy Company ASA	20.11.2009
Norse Energy Corp. ASA	25.09.2008	Norwegian Energy Company ASA	20.11.2009
Seadrill Ltd	30.09.2008	Odfjell SE	04.12.2009
Norse Energy Corp. ASA	05.12.2008	Bonheur ASA	15.12.2009
DNO International ASA	08.12.2008	Norwegian Air Shuttle ASA	17.12.2009
DNO International ASA	08.12.2008	Rem Offshore ASA	27.01.2010
DNO International ASA	08.12.2008	YIT Oyj	26.03.2010
Reservoir Exploration Technology ASA	11.12.2008	Eltek ASA	08.04.2010
Norse Energy Corp. ASA	19.12.2008	Kungsleden AB (publ)	30.04.2010
Scan Geophysical ASA	29.12.2008	Transocean Norway Drilling AS	30.04.2010
Nokia Oyj	04.02.2009	Sevan Marine ASA	04.05.2010

Issuer	Issue Date	Issuer	Issue Date
AB Sagax (publ)	20.05.2010	Det Norske Oljeselskap ASA	28.01.2011
Amer Sports Oyj	11.06.2010	Morpol ASA	03.02.2011
Corem Property Group AB	08.07.2010	Transocean Norway Drilling AS	24.02.2011
Bergen Group ASA	09.07.2010	Transocean Norway Drilling AS	24.02.2011
Havila Shipping ASA	19.07.2010	Prosafe SE	25.02.2011
Electromagnetic Geoservices ASA	21.07.2010	Kungsleden AB (publ)	09.03.2011
DOF ASA	22.07.2010	I. M. Skaugen SE	15.03.2011
Sevan Marine ASA	10.08.2010	Cecon ASA	18.03.2011
Sevan Marine ASA	10.08.2010	Dannemora Mineral AB	22.03.2011
Stora Enso Oyj	01.09.2010	Havila Shipping ASA	30.03.2011
Stora Enso Oyj	01.09.2010	Havila Shipping ASA	30.03.2011
Interoil Exploration and Production ASA	14.09.2010	Blom ASA	04.04.2011
Lemminkäinen Oyj	14.09.2010	DNO International ASA	11.04.2011
I. M. Skaugen SE	17.09.2010	DNO International ASA	11.04.2011
Farstad Shipping ASA	27.09.2010	Amer Sports Oyj	13.04.2011
Norwegian Car Carriers AS	29.09.2010	CLS Holdings Plc	27.04.2011
Seadrill Ltd	05.10.2010	Norwegian Energy Company ASA	27.04.2011
FastPartner AB (publ)	06.10.2010	Norwegian Energy Company ASA	27.04.2011
Austevoll Seafood ASA	14.10.2010	Fred Olsen Energy ASA	12.05.2011
Kungsleden AB (publ)	18.10.2010	RusForest AB (publ)	12.05.2011
Bonheur ASA	29.10.2010	Electromagnetic Geoservices ASA	26.05.2011
Havila Shipping ASA	08.11.2010	Corem Property Group AB	30.05.2011
Panoro Energy ASA	15.11.2010	Keskisuomalainen Oyj	03.06.2011
Panoro Energy ASA	15.11.2010	YIT Oyj	20.06.2011
Aker ASA	23.11.2010	Stolt-Nielsen Limited	22.06.2011
Aker ASA	23.11.2010	Havila Shipping ASA	30.08.2011
Teekay Offshore Partners LP	29.11.2010	I. M. Skaugen SE	30.09.2011
Havila Shipping ASA	02.12.2010	EMS Seven SEAS AS	25.10.2011
Norwegian Energy Company ASA	06.12.2010	Songa Offshore SE	17.11.2011
DOF ASA	09.12.2010	Teekay Offshore Partners LP	27.01.2012
Sevan Marine ASA	22.12.2010	Aker ASA	30.01.2012
EMS Seven SEAS AS	23.12.2010	Austevoll Seafood ASA	07.02.2012
EMS Seven SEAS AS	23.12.2010	DOF ASA	07.02.2012

Issuer	Issue Date	Issuer	Issue Date
Prosafe SE	08.02.2012	Havila Shipping ASA	30.08.2012
Bonheur ASA	10.02.2012	Stolt-Nielsen Limited	04.09.2012
Bonheur ASA	10.02.2012	Aker ASA	07.09.2012
Seadrill Ltd	13.02.2012	Tethys Oil AB (publ)	07.09.2012
Farstad Shipping ASA	15.02.2012	DOF ASA	12.09.2012
YIT Oyj	17.02.2012	Stora Enso Oyj	19.09.2012
Pacific Drilling S.A.	23.02.2012	Cermaq ASA	21.09.2012
I. M. Skaugen SE	27.02.2012	FastPartner AB (publ)	28.09.2012
Stora Enso Oyj	07.03.2012	Aker Solutions ASA	09.10.2012
BWG Homes ASA	12.03.2012	Fastighets AB Balder (publ)	10.10.2012
Amer Sports Oyj	15.03.2012	Austevoll Seafood ASA	15.10.2012
Amer Sports Oyj	15.03.2012	Oceanteam Shipping ASA	24.10.2012
BW Offshore Limited	15.03.2012	Millicom International Cellular S.A.	30.10.2012
Aker ASA	16.03.2012	Millicom International Cellular S.A.	30.10.2012
Stolt-Nielsen Limited	19.03.2012	Norwegian Energy Company ASA	30.10.2012
Stolt-Nielsen Limited	19.03.2012	Consilium AB (publ)	01.11.2012
Hurtigruten ASA	20.03.2012	Dolphin Group ASA	14.11.2012
Sanoma Oyj	20.03.2012	Stockmann Oyj Abp	19.11.2012
AB Sagax (publ)	22.03.2012	Odfjell SE	03.12.2012
Arise AB (publ)	23.03.2012	Odfjell SE	03.12.2012
Blom ASA	04.04.2012	BWG Homes ASA	12.12.2012
I. M. Skaugen SE	11.04.2012	Navigator Holdings Ltd	18.12.2012
Odfjell SE	11.04.2012	Havila Shipping ASA	20.12.2012
Norwegian Air Shuttle ASA	13.04.2012	Rem Offshore ASA	20.12.2012
Björn Borg AB	17.04.2012	Grieg Seafood ASA	21.12.2012
Teekay LNG Partners L.P.	03.05.2012	Northland Resources AB (publ)	21.12.2012
Blom ASA	23.05.2012		
Aker Solutions ASA	06.06.2012		
Songa Offshore SE	11.06.2012		
Stora Enso Oyj	26.06.2012		
Stora Enso Oyj	26.06.2012		
Swedish Orphan Biovitrum AB (publ)	26.06.2012		
Arendals Fossekompani ASA	06.07.2012		

APPENDIX 2: NUMBER OF BONDS EXCLUDED FROM HY-SAMPLE PER CRITERIA

Exclusion criteria	# of bonds excluded by criteria	# of bonds left in HY sample after exclusion
Initial Nordic bond sample		**23,515**
- Investment grade bonds	21,511	2004
- Bonds issued before 01/01/2000	112	1892
- Public sector, Financial institutions	603	1289
- Convertibles, linked notes, warrants	200	1089
- Non-public issuers or unavailible financial data	701	388
- Bonds issued after 31/12/2012	65	**323**

APPENDIX 3: ORDINARY LEAST SQUARED REGRESSIONS (OLS)

APPENDIX 3A: OLS THEORY

Ordinary least squares (OLS) regression was used both to model recovery rates and to analyse credit spreads. We will therefore include a brief summary of the method and the assumptions required to attain unbiased and efficient estimators.

OLS is a statistical method for estimating the parameters of a multiple linear regression model. The OLS estimates are obtained by minimizing the sum of squared residuals, and thereby the name. Mathematically, in the general case of *k* explanatory variable, the method generate estimates of $\hat{\beta}_0$, $\hat{\beta}_1$, …, $\hat{\beta}_k$ in the equation:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_k x_k$$

By defining residuals u as the difference between the observed value y and the predicted value $\hat{y}$, the estimators are found by minimizing the following expression:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_k x_k$$

For the OLS estimators to be unbiased and efficient, i.e. that the estimator's expected value equals the population value and has the least variance attainable, five assumptions regarding the model must hold:

1. Linear in Parameters

   The *true model* is linear in the parameters and can be defined as equation (2)
2. Random sample

   The sample of n observations is random

3. No perfect colinearity

   There are none perfect linear relationship among the regressors.

4. Strict exogeneity

   The explanatory variables are exogenous. Consequently the errors have zero mean ($E[\varepsilon|X] = 0$) and are uncorrelated with the regressors ($E[X^T\varepsilon] = 0$).

5. Homoscedasticity

   The error u has constant variance for any values of the explanatory variables, i.e. $Var[u|x_1, \dots, x_k] = \sigma^2$

It can be shown that under assumption 1-4 the OLS estimates are unbiased and under 1-5 they are also the estimates with the lowest variance among competing methods[29]. In other words, under assumption 1-5 OLS is the best linear unbiased estimator (BLUE) (Wooldridge, 2013).

APPENDIX 3B: TESTING OLS ASSUMPTIONS IN THE RECOVERY RATE REGRESSIONS

We have done tests to uncover potential violations of the OLS-assumptions in conjunction with the regressions performed to examine recovery rates in section 7.1. In tables and graphs below showing various regression specific statistics

We performed a visual examination of correlation matrixes (table 3B.1) in order to investigate possible multicollinearity. No major issues regarding multicollinearity with the included variables described in our models have been found, except for receivables and long term debt.

We have done visual examination of residual plots (table 3B.2), in addition to white-test in order to check for possible heteroskedasticity in our models but did not find indication of critical issues.

We have found some deviation in our models from the assumption of normally distributed residuals (table 3B.3). The model is still unbiased, but the deviation may affect the efficiency of the model.

[29] For explicit proofs of the OLS properties we refer to Appendix 3A in (Wooldridge, 2013). On page 682 he proves that OLS estimators are the best linear unbiased estimators when the OLS assumptions 1-5 are holds.

Table 3B.1 CORRELATION TABLE: EXAMINING MULTICOLLINEARITY

	UltimateRR	DD	LTD	Intang	Receiv	EqRatio	Prof	SeniorUS	Subordinated	EandP	OilService	Shipping	Industry	TelecomIT
UltimateRR	1.00													
DD	-0.12	1.00												
LTD	-0.19	0.10	1.00											
Intang	0.16	-0.10	-0.14	1.00										
Receiv	0.24	-0.18	-0.55	0.20	1.00									
EqRatio	-0.01	0.20	0.23	-0.05	-0.33	1.00								
Prof	0.07	0.03	0.07	-0.25	-0.05	0.16	1.00							
SeniorUS	0.11	-0.05	-0.11	0.03	0.05	0.09	0.00	1.00						
Subordinated	-0.25	-0.01	-0.02	-0.11	0.09	-0.07	-0.02	-0.28	1.00					
EandP	0.18	-0.05	-0.06	0.52	0.01	-0.13	-0.24	0.08	-0.19	1.00				
OilService	0.00	-0.12	0.14	-0.41	-0.15	0.05	0.20	-0.13	0.08	-0.46	1.00			
Shipping	-0.30	0.09	0.00	-0.16	-0.14	-0.02	0.17	0.24	-0.09	-0.13	-0.23	1.00		
Industry	0.03	0.07	0.16	0.08	-0.16	0.29	0.00	-0.08	-0.11	-0.16	-0.27	-0.08	1.00	
TelecomIT	0.06	-0.05	-0.36	0.21	0.63	-0.19	-0.03	-0.03	0.22	-0.17	-0.29	-0.08	-0.10	1.00

Table 3B.2 SCATTER PLOT: EXAMINING POTENTIAL HOMOSKEDASTISTITY

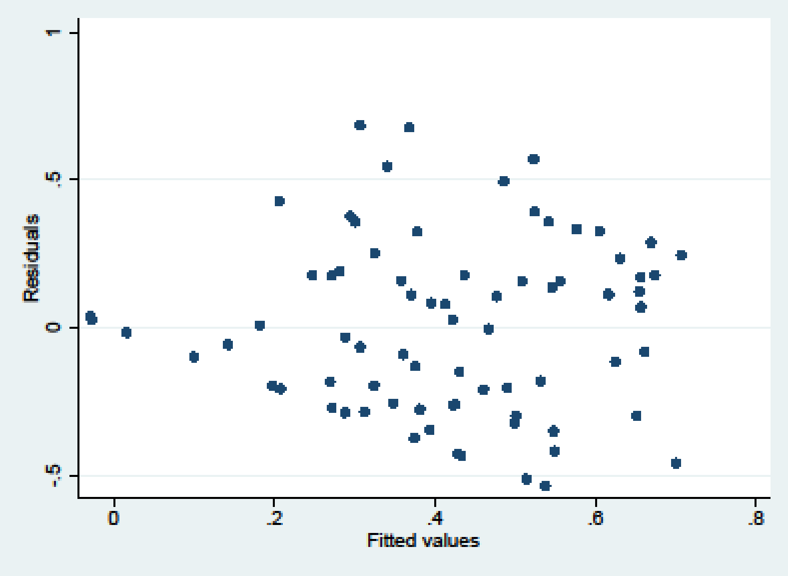
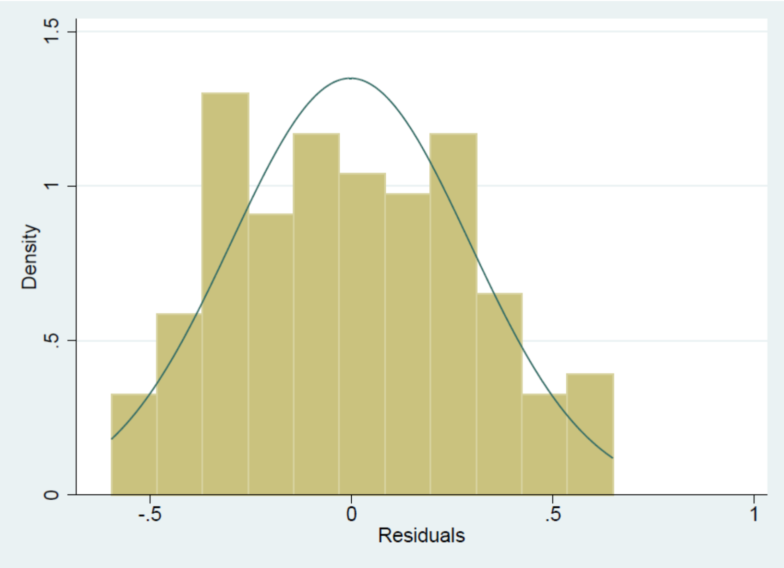


Table 3B.3 HISTOGRAM: EXAMINING NORMALITY OF RESIDUALS



APPENDIX 3C: TESTING OLS ASSUMPTIONS IN THE CREDIT SPREAD REGRESSIONS

We have done tests to uncover potential violations of the OLS-assumptions in conjunction with the regressions performed to examine mispricing. In tables and graphs below showing various regression specific statistics, model 3 is the source model, as shown in the analysis chapter 7.4.

We have performed VIF-tests, as well as visual examination of correlation matrixes (table 3C.1) in order to investigate possible multicollinearity. No major issues regarding multicollinearity with the included variables described in our models have been found, except for the time dummy and oil price, which is explained in detail in the analysis chapter 7.4.

We have done visual examination of residual plots (table 3C.2), in addition to white-test in order to check for possible heteroskedasticity in our models. Both tests indicated heteroskedasticity issues, and therefore robust standard errors were used.

We have found some deviation in our models from the assumption of normally distributed residuals, as can be viewed in the scatter plot (table 3C.3) on the following page. However, we assess the deviation to be sufficiently small to rely on the model framework.

We have done a thorough investigation of outliers in the sample. This is an especially important task as we have cross sectional data of the companies, causing the risk of short-lived time varying effects. E.g., Hurtigruten ASA went through a complex restructuring process at the time of their bond issue in 2009, which caused their equity market value to fluctuate greatly around the date of issue. We also choose to remove outliers with extreme market leverage ratios. Leverage is one of the key inputs of our spread model, and extreme values tend to massively overpredict or underpredict spreads. Hence, we have chosen to remove observations with leverage (total debt / market capitalization of equity) higher than 20 or lower than 0.1. We further remove variables with a market capitalization of more than 100 billion NOK, consisting of three issues. These firms massively dwarf the size of the rest of the sample, and have an extreme impact on our regression coefficients. This process led to the removal of 8 outliers.

We further found residuals, regression leverages, and the Cook's D measure, in order to check for additional outliers. The found outliers were examined according to their observed characteristics, as well as estimated factors not included in the model. This process causes us to remove in total 5 observations, which are shown and commented in appendix 4A.

VIF TEST

Variable	VIF-stat
Oil and gas services	1.98
Oil and gas E&P	1.60
Shipping	1.52
Industry	1.44
Size	1.39
Leverage	1.23
Maturity	1.23
Security	1.17
Oil price	1.15
Price/book	1.12
Liquidity dummy	1.10
Return type	1.09

Table 3C.1 CORRELATION TABLE OF VARIABLES:

VARIABLE	Absolute mispricing	Maturity	Size	Financial Crisis	Price/ book	Oil price	Liquidity Dummy	Return Type	Market Leverage	Industry	Oil and gas	Oil and gas E&P	Shipping	Security
Absolute mispricing	1.00													
Maturity	-0.09	1.00												
Size	0.00	0.41	1.00											
Financial Crisis Dummy	0.09	-0.03	-0.02	1.00										
Price/book	0.00	-0.03	0.08	-0.34	1.00									
Oil price	0.04	0.05	-0.04	0.63	-0.17	1.00								
Liquidity Dummy	-0.11	0.01	0.10	-0.12	0.09	-0.18	1.00							
Return Type	0.12	-0.03	0.05	-0.02	0.01	-0.08	0.02	1.00						
Market Leverage	-0.34	-0.08	-0.19	0.28	-0.27	0.18	-0.10	0.02	1.00					
Industry	0.01	0.06	0.10	0.14	0.01	0.15	0.03	0.02	0.04	1.00				
Oil and gas services	-0.05	-0.10	-0.11	-0.18	0.04	-0.10	-0.09	-0.02	0.20	-0.31	1.00			
Oil and gas E&P	-0.01	-0.06	-0.13	-0.08	0.07	-0.12	0.10	0.17	-0.15	-0.16	-0.33	1.00		
Shipping	0.16	0.06	-0.09	0.06	-0.07	0.07	-0.14	-0.20	-0.08	-0.15	-0.29	-0.15	1.00	
Security	-0.14	-0.08	-0.19	0.01	-0.06	0.05	0.06	0.13	0.19	-0.08	0.24	0.05	-0.16	1

Table 3C.2 SCATTER PLOT: EXAMINING POTENTIAL HOMOSKEDASTISTITY

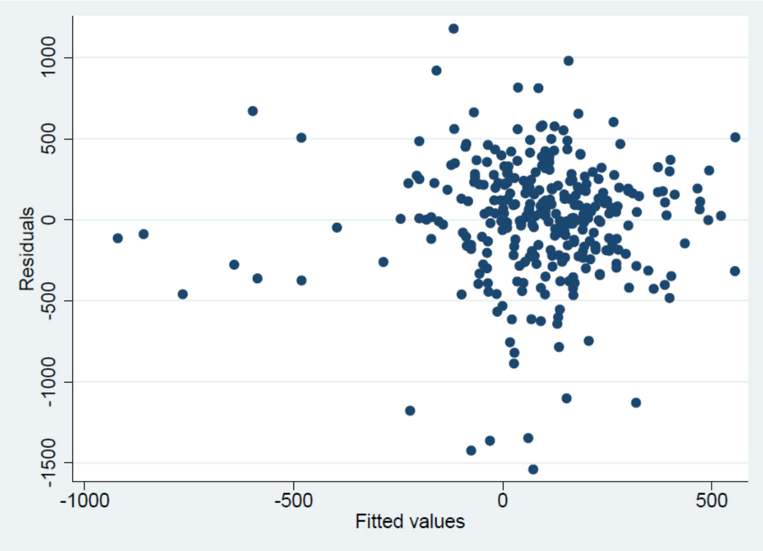
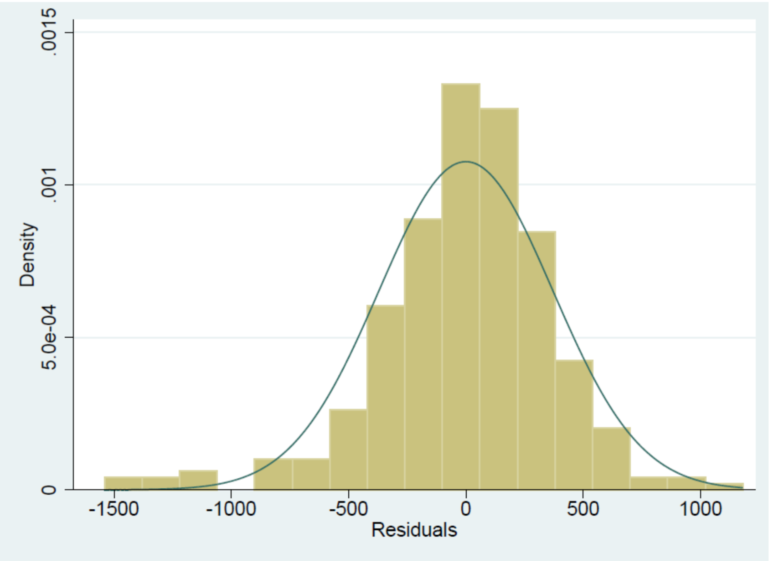


Table 3C.3 HISTOGRAM: EXAMINING NORMALITY OF RESIDUALS



APPENDIX 4: ADDITIONAL TABLES FROM THE CREDIT SPREAD REGRESSION

APPENDIX 4A OVERVIEW OF OMMITTED VARIABLES

Issuer	Issue date	Market Cap (MNOK)	Market-Leverage	P/B	Year until maturity	Model spread	Comment
Frontier Drilling AS	20.12.2000	157	0.82	1.11	3.00	1,876	Very high predicted spread close to our model roof. Together with a low/average leverage ratio, this indicates that something is wrong. We also observe an unrealistic high estimated asset volatility
Hurtigruten ASA	06.03.2009	56	94.71	0.01	3.00		Removed due to restructuring at time of issue (spread not calculated)
Oceanteam Shipping ASA	24.10.2012	64	17.87	0.10	5.00	1,506	Very high market leverage combined with an unrealistc high estimated asset volatility, which causes suspicion of measurement error
Stora Enso Oyj	13.04.2006	59,886	1.25	1.02	30.01	56	Very large market cap and very long maturity which significantly differentiate the observation from the remaining sample, thus causing major regression leverage and biased results
Stora Enso Oyj	13.04.2006	59,886	1.25	1.02	30.01	56	Very large market cap and very long maturity which significantly differentiate the observation from the remaining sample, thus causing major regression leverage and biased results

APPENDIX 4B: NUMBER OF BONDS PER INDUSTRY

Industry Group	Frequency	Percent	Cummulative percentage
Oil and gas services	120	38.71	38.71
Oil and gas E&P	45	14.52	53.23
Industry	42	13.55	66.77
Shipping	37	11.94	78.71
Other;	66	21.29	100
Seafood	15	4.84	
Real Estate	13	4.19	
Pulp, paper and forestry	12	3.87	
Telecom/IT	12	3.87	
Agriculture	4	1.29	
Transportation	4	1.29	
Media	2	0.65	
Pharmaceuticals	2	0.65	
Consumer Services	1	0.32	
Utilities	1	0.32	
Total	310	100	

APPENDIX 4C: NUMBER OF BONDS PER RETURN TYPE

ReturnType	Frequency	Percent
Floating rate = 0	205	66.13
Fixed rate = 1	105	33.87
Total	310	100

APPENDIX 4D: NUMBER OF BONDS PER SECURITY

Security	Frequency	Percent
Senior Unsecured	247	79.67742
Senior Secured*	63	20.32
Total	310	100

*Includes 2 subordinated bonds

APPENDIX 4E: NUMBER OF BONDS PER CURRENCY

Currency of issue	Frequency	Percent
NOK	218	70.32
USD	52	16.77
SEK	25	8.06
EUR*	15	4.19
Total	310	100

* Includes 2 bonds issued in GBP

APPENDIX 4F: NUMBER OF BONDS PER LIQUIDITY MEASURE

Liquidity Dummy	Frequency	Percent
High liquidity = 1	272	87.74
Low liquidity = 0	38	12.26
Total	310	100

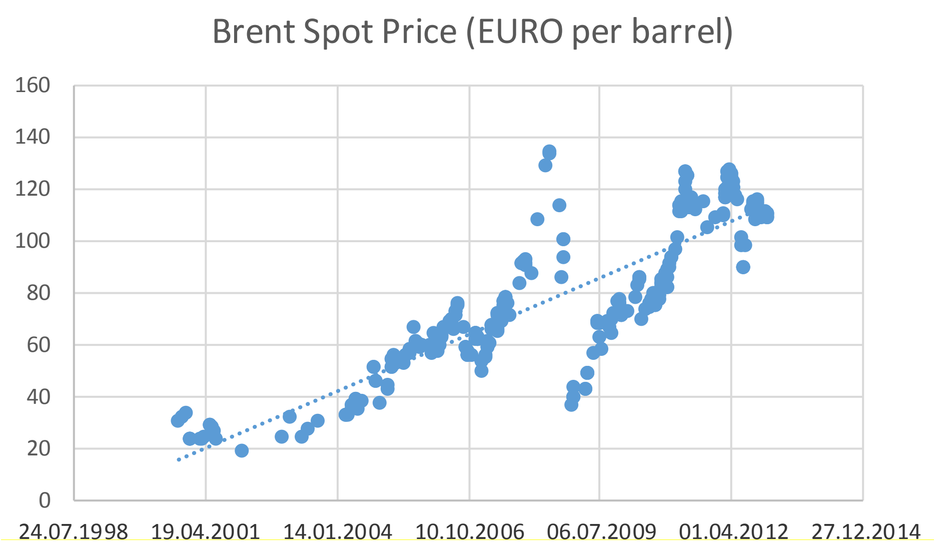
APPENDIX 4G: T-test of difference in maturity (equal variances)

Variable	Floating rate(Mean)	Floating rate SD	Fixed rate(Mean)	Fixed rate(SD)	P-value	T-stat
Maturity	3.84	2.07	3.70	2.73	0.64	0.47

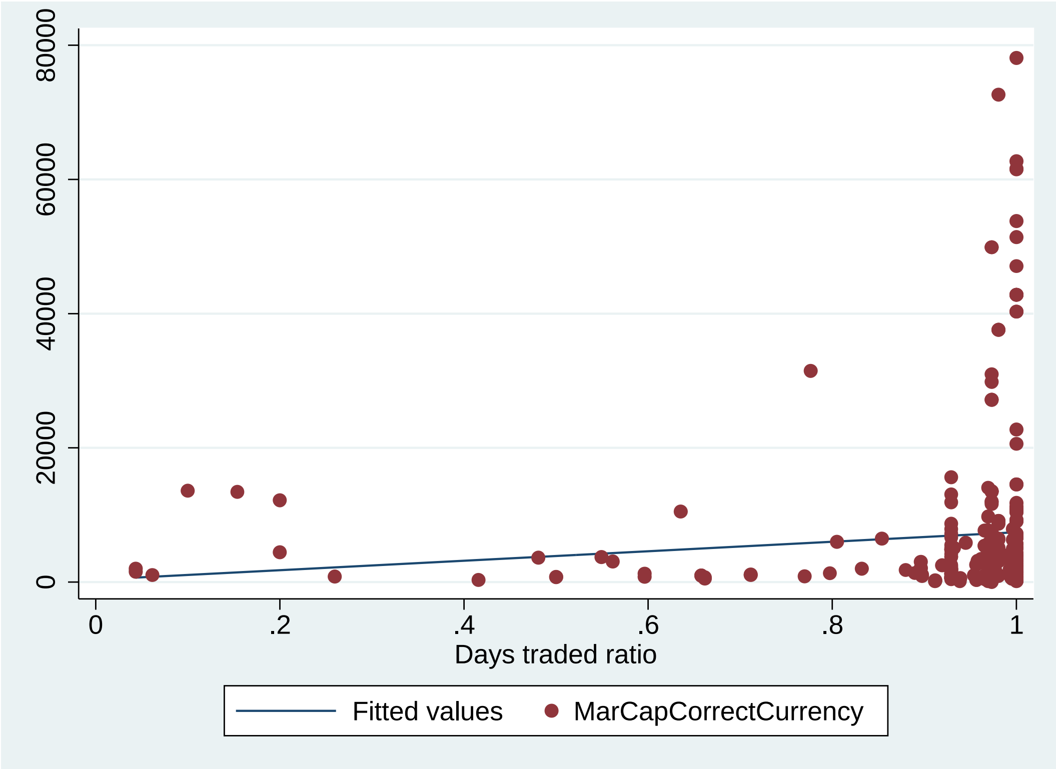
APPENDIX 4H: T-TEST OF MISPRICING FOR EXPLANATORY VARIABLES

Variable	Low Mispricing(Mean)	Low Mispricing SD	High Mispricing(Mean)	High Mispricing(SD)	P-value
Years until maturity	4.16	2.49	3.42	2.07	0.00
Coupon	6.87	2.83	8.38	2.88	0.00
Size	8789.20	14609.24	5044.21	9185.41	0.01
Price/book	1.88	2.68	2.07	3.48	0.60
Oil price	75.01	31.10	81.46	26.25	0.05
Liquidity dummy	0.90	0.30	0.85	0.36	0.18
Return Type	0.29	0.46	0.38	0.49	0.09
Market Leverage	2.58	2.94	1.67	1.52	0.00
Industry	0.14	0.35	0.13	0.34	0.71
Oil and gas EP	0.12	0.33	0.17	0.37	0.28
Oil and gas services	0.39	0.49	0.38	0.49	0.93
Shipping	0.08	0.28	0.15	0.36	0.06
Other	0.26	0.44	0.17	0.37	0.05
Financial crisis dummy	0.46	0.50	0.58	0.50	0.04
Security	0.19	0.40	0.20	0.40	0.93

APPENDIX 4I: SCATTERPLOT - OILPRICE VS DATES OF ISSUES



APPENDIX 4J: SCATTERPLOT - MARKET CAPITALIZATION OF EQUITY VS LIQUIDITY RATIO



APPENDIX 5: ADDITIONAL TABLES FROM RECOVERY RATE REGRESSION

APPENDIX 5A: EXCLUSIONS FROM RECOVERY RATE REGRESSION DUE TO UNAVAILIBLE FINANCIALS

Issuer	Fiscal year
Amarant Mining Ltd	2008
EOAL Cyprus Holdings Limited	2011
EOAL Cyprus Holdings Limited	2012
EOAL Cyprus Holdings Limited	2006
MPF Corp Ltd	2007
Oceanlink Ltd NUF	2013
OSA Goliath Pte.Ltd	2008
PetroProd Ltd	2008
PetroRig III	2011

APPENDIX 5B: NUMBER OF DEFAULTS PER INDUSTRY IN RECOVERY RATE REGRESSION

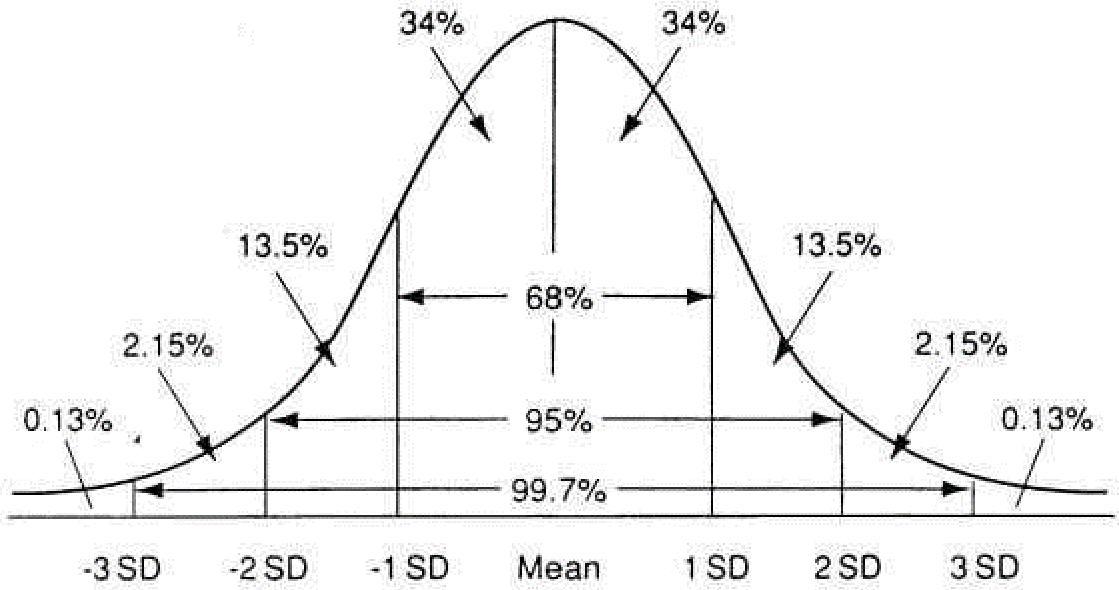
Industry	N
Oil Services	42
E&P	20
Other	10
Telecom/IT	9
Industry	8
Shipping	6

APPENDIX 6: THEORY

APPENDIX 6A: NORMAL DISTRIBUTION AND Z-SCORES

When we explained the Black and Scholes' framework for valuing options, we relied on normality assumptions, and further used the properties of a normal distribution to estimate probabilities using Z-scores.

The normal distribution is a very common and widely used probability distribution. The assumption that a sample's mean, e.g. stock returns, follow a normal distribution is explained by the central limit theorem in statistics, which states that the arithmetic mean of a sufficiently large number of independent random variables will be approximately normal distributed, regardless of the underlying distribution. The normal distribution is illustrated below:



The total area under the normal curve represents all probabilities of an event occurring, and is symmetrical about the mean. The x-axis represent the number of standard deviations from the population mean. The figure above illustrate that there is a 68 percent probability that a random observation will be within one standard deviation from the mean, and a 95 percent probability that it will be between two standard deviations. This property has many useful applications. In fact, by calculating the area under the curve, on can estimate the probability of any event occurring. Mathematically this is done using Z-scored, which is defined as:

$$Z = \frac{x - \mu}{\sigma}$$

Where μ is the population mean, σ is the standard deviation, and x is the score, or the event that the probability is to be calculated for. The Z score represent a point on the X axis above, and the probability to observe such an observation or lower is the total are under the graph to the left of this point. The probability is written as N(Z). The probability of observing and event larger than a given value is calculated as N(-Z), represented be the total area under the curve to the right of the given Z-score.

APPENDIX 6B: EXPLANATION OF EXTENDED MERTON MODEL FORMULAS

In the paper, we applied a relatively complex formula for pricing defaultable coupon paying bonds, which we will give an intuitive justification for in the following.

The applied formula is as follows:

$$P(0,T) = \sum_{i=1}^{2t-1} D(0,T_i) E^Q \overbrace{\left[\left(\frac{c}{2}\right) I_{\left(V_{T_i} \geq K\right)} + \min\left(\frac{wc}{2}, V_{T_i}\right) I_{\left(V_{T_i} < K\right)}\right]}^{\text{1. Expected payoff from coupon}} + D(0,T) E^Q \underbrace{\left[\left(1+\frac{c}{2}\right) I_{(V_T \geq K)} + \min\left(w\left(1+\frac{c}{2}\right), V_T\right) I_{(V_T < K)}\right]}_{\text{2. Expected payoff from principal + last coupon}} \quad (1)$$

As illustrated above, the formula is the simply the sum of the expected payoff from coupons and the principal, which is discounted to present value by multiplying with the discount factor $D(0,T_i)$. The only difference between the two addends is that the principal is included in the latter by adding 1 into the equation. We therefore explain the second additive in detail, as the first addend will be understood in the same way.

By multiplying E^Q into the brackets, the second addend can by written as:

$$\overbrace{\left(1+\frac{c}{2}\right)}^{\text{Expected payoff if not default}} \underbrace{E^Q I_{(V_T \geq K)}}_{\text{Probability of not default}} + E^Q \left[\overbrace{min\left(w\left(1+\frac{c}{2}\right), V_T\right)}^{\text{Expected payoff if default}} \underbrace{I_{(V_T < K)}}_{\text{Probability of default}}\right] \quad (2)$$

Where $\left(1+\frac{c}{2}\right)$ is simply the principle and coupon payment, and w is the recovery rate. The first addend in Eq. 2 is relatively straightforward. $E^Q I_{\left(V_{T_i} \geq K\right)}$ is the probability that asset value is at or above the default barrier at time T, i.e. the probability of not defaulting. In that case the full principle and coupon is paid. The formula is directly comparable to $N(-d_2)$ in the Black & Scholes formula, which is presented earlier in the paper:

$$E^Q I_{\left(V_{T_i} \geq K\right)} = N(d_2(K,t))$$

where:

$$d_1(x,t) = \frac{\ln\left(\frac{V_0}{x * D(0,t)}\right) + (-\delta + 0{,}5\sigma_A^2)t}{\sigma_A\sqrt{t}}$$

$$d_2(x,t) = d_1(x,t) - \sigma_A\sqrt{t}$$

The second addend in Eq. 2 represents the expected payoff for various default events, multiplied with the probability of the event occurring. Mathematically it is defined as:

$$E^Q\left[I_{V_t<K}\min(\psi, V_t)\right] = \overbrace{V_0 D(0,t)^{-1} e^{-\delta t} N\big(-d_1(\psi,t)\big)}^{\text{Expected value of } A \text{ if, and only if, A is below } \psi} + \underbrace{\psi}_{\text{Expected payoff if } \psi < \text{A} < \text{K}}\overbrace{\left[N\big(d_2(\psi,t)\big) - N(d_2(K,t))\right]}^{\text{Probability of } \psi < \text{A} < \text{K at maturity}}$$

Where ψ in this case represents the expected recovery value of the principle and the last coupon payment $\left(w\left(1+\frac{c}{2}\right)\right)$. The intuition is that the promised payments are paid in full when the asset value A is greater than the default barrier K. When asset value is lower than K, but higher than the expected recovery ψ, the payout is limited to ψ. Lastly, if the asset value is lower than the expected recovery, the payout is equal to the asset value.

The foregoing gave a detailed explanation of the second addend in Eq. 1, which calculate the expected payout of the principle and the last coupon payment. The same intuition and explanation can be used to explain the first addend, which relies on the same calculations, but only for the periodic payments and not the principal.

APPENDIX 6C: DERIVING DEBT VALUE USING OPTIONS

Recall that equity can be defined as a call option on the firms assets A with strike equal to the face value of debt.

$$Equity = Call\ Option(FV) \tag{4.1}$$

The value of the assets of a company can be defined as the sum of the equity and debt value:

$$Assets = Equity + Debt \tag{4.2}$$

From substituting equity from (4.1) in (4.2) and rearranging, we get:

$$Debt = Assets - Call\ option \tag{4.3}$$

From put call parity we know that Eq. 4.4 must hold, or else an arbitrage opportunity would be present.

$$Call\ option(Strike) + PV(Strike) = Underlying + Put\ Option\ (Strike) \tag{4.4}$$

The Present value of the *strike* can be thought of as a risk-free bond with the same face value as the strike price, i.e. at maturity you are certain to be paid the value K, without any inherent uncertainty. In this thought experiment, remember that the strike price can be thought of as the face value of the total debt (FV) that the firms owes at maturity. Consequently, Eq. 4.4 can be written as:

$$Call\ option(FV) + Riskfree\ Bond = Asset + Put\ Option\ (FV) \tag{4.5}$$

By substituting the Call option valuation from (4.5) in the debt formula (4.3), we get the following definition of debt:

$$Debt = Assets - [Asset + Put\ Option\ (FV) - Riskfree\ Bond]$$

$$Debt = Riskfree\ Bond - Put\ Option\ (FV) \tag{4.6}$$

The resulting function (4.6) is that debt value is the same as a risk free-bond minus a put option on the firm’s assets with exercise price equal to the face value of the firm’s deb.

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