Norwegian School of Economics
Bergen, Fall 2013

Predicting default in the Norwegian High Yield bond market

A study of defaults in the years 2006-2013

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Master thesis in Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

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Abstract

This thesis studies determinants of defaults experienced in the Norwegian High Yield bond market from 2006 to 2013. This is done by finding defaulted issuers from the bonds registered in the Norwegian Trustees database Stamdata. The information about defaulted and non-defaulted companies is coupled with financial and other characteristics available at the time of the bond issue.

From a univariate assessment, the typical issuer that defaulted in the Norwegian High Yield bond had lower profits relative to their debt already before issuance, was significantly smaller than a non-non defaulted issuer, the issue had higher coupon rates adjusted for the level of interbank interest rates, and the issued amount was higher relative to the issuer's total assets. Of the defaults found in the final sample of 176 issuers, 35 of the 59 (59%) observed defaults involved issuers that founded their companies less than six years from the issue year. Some of the rather surprisingly results regarding the liquidity ratios and the book equity ratio must be seen in connection with the relative high amount of start-up firms defaulting. Logistic regressions were carried out with default as the dependent variable using the variables in the SEBRA-basic bankruptcy prediction model developed by the Central Bank of Norway. The model performs decent when classifying the non-defaulted companies, but breaks down when classifying the defaulted companies. The logistic regressions back up the conclusions from the univariate analysis regarding profits relative to debt level, the size of the company, and that a start-up firm are more prone to default on their bond issues than more matured companies.

I would like to thank my supervisor Aksel Mjøs for answering important questions, and for providing critical reviews throughout the whole process. Thanks to the Norwegian Trustee for giving me access to their database Stamdata. I would also like to thank Jonas Osland at Gabler Investment Consulting for introducing the Norwegian High Yield bond market, and for providing me with literature and tips where to look for data. Thanks to the Holberg Funds for sending me introductory information from presentations held about the Norwegian High Yield bond market. I would also like to thank my family and those around me for putting up with, a sometimes, frustrated student. Writing a thesis about the Norwegian High Yield bond market is certainly a challenge, especially when it comes to gathering sufficient data.

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1. Introduction

What factors are important when explaining why certain issuers in the Norwegian High Yield bond market experience financial distress, and later default on their bond issues? Could investors identify especially risky firms when they lack updated credit rating information? Do we find some characteristics about the issuers that can provide warning signs that are available when the investor choose, or choose not to participate in a new bond issue? Are the markets participants aware of the risks involved in High Yield bonds? These are some of the questions that thesis tries to answer.

Recent Master thesis's at NHH have provided studies on performance of the Norwegian High Yield bond market (Bakjord and Berg, 2012), determinants of the outcomes of financial distress (Knapstad and Skarvøvik, 2012), and studies of recovery rates (Brekke and Haugland, 2010). Since the major credit rating agencies assign ratings to a small part of the issuers in the Norwegian market, it is of interest to dig into which type of High Yield issuers that is more likely to experience financial distress and subsequently default on their bond issues.

The lack of transparency and public available data was both encouraging and challenging when writing a thesis about the Norwegian Bond market. The Norwegian Fund and Asset Management Association is currently collaborating with the Norwegian Trustee to form a new company, Nordic Bond Pricing (2013). Nordic Bond Pricing shall deliver a weekly pricing service based on all the bonds listed and traded in the Norwegian bond market. The formation of Nordic Bond Pricing implicitly shows that it is costly for investors to update prices and measure to the risk of their portfolios when many bonds trade infrequently. The formation of Nordic Bond Pricing, as well as the experienced growth in the Norwegian corporate bond market, makes credit risk, with this market as a platform, an interesting subject to dig further into.

The corporate bond market in Norway is likely to continue to grow and strengthen its influence as a source of capital for both domestic and foreign companies. The main reason for this expected development is the legislation put forward by the Norwegian government that requires banks to hold more equity capital behind their lending activities. This could cause Norwegian banks to be more careful with lending to the more risky firms, which causes these firms to obtain cheaper financing in the corporate bond market (Halvorsen, 2013) than through bank borrowing. This possible evolution also warrants a better understanding of credit risk from a Norwegian market perspective.

The primary objective of this thesis is to provide evidence from the Norwegian High Yield market that can help investors in doing the default risk analysis when credit ratings are absent. This is done by collecting a sample of possible High Yield firms from the Norwegian Trustees database Stamdata. Defaulting and non-defaulting firms are identified and matched with information about the issuer available at the time of issuance.

The choice to use information available at the issue date is made because many of the bonds in the Norwegian market trade infrequently, and because many investors hold their bonds to either maturity, or default occurs. A clear focus is given to what separates the defaulted companies from the non-defaulted companies in a quantitative way. It is worth to notice that a qualitative assessment of the issuers business, its primary product market, and the comparative advantages of the issuer have a place in the analysis of default risk. The content in this thesis is also relevant for companies that wish to use the corporate bond market for gaining access to debt capital, in that it can help new issuers to look into which type of issuers that have fallen into trouble historically.

The structure of this thesis is the following: Chapter 2 gives a brief description of corporate bonds and bond markets in general. Chapter 3 gives an overview and description of central parts of the Norwegian corporate bond market. Chapter 4 examines bankruptcy- and default prediction literature. Chapter 5 describes the data gathering process. Chapter 6 discusses statistical methods used to analyse the final sample, while chapter 7 reports the findings and conclusion from the statistical analysis.

2. Bond theory

This chapter will start with some basic bond theory, which provides the necessary background for the analysis of default risk. Different designs of bond contracts, credit ratings, and the difference between default and bankruptcy, are among the topics being covered.

2.1 Bond basics

2.1.1 Bond types

A bond is a type of security that a borrower issues in connection with a borrowing arrangement. The borrower is selling bonds for cash directly to the investors instead of bank borrowing. Bonds are part of a wider asset class called fixed income securities. The principal, par value, or face value of the bond, is the amount that becomes due to the bondholder at the maturity date. A typical bond would obligate the borrower to pay semi-annual interest to the bondholder. An interest rate, called the coupon rate, multiplied by the principal amount determines the total interest payments owed to the bondholder. There is also a possibility for a floating interest rate on the bond. A floating rate bond links the coupon rate to a reference rate like the NIBOR[1], or the LIBOR[2] rate of interest. There are also bonds that do not pay any coupons before the maturity date. The investor's return on these zero-coupon bonds occurs entirely because the bond is sold at a price below the face value (Bodie, Kane et al., 2011).

Large issuers of bonds include governments, municipalities, government agencies, and corporations. In the private sector, the purpose of a bond issue is to finance an investment at an interest rate lower than the rate of return on the investment. An issue can also have the purpose of changing the capital structure of the company, or as a financing arrangement for the daily operations of the business. The most important difference between a corporate bond and a government bond, at least when the government is considered a solid debtor, is that the former exhibits default risk. An important aspect of bond financing is that the bondholder has a status of a creditor, unlike an equityholder, who is in fact an owner of the corporation in

[1] Norwegian Interbank Offered Rate.

[2] London Interbank Offered Rate.

which he holds stocks. This fact, and because a bond promises a fixed stream of payment, generally makes bonds less risky than equity (Martellini, Priaulet et al., 2003).

Corporate bond markets can be quite illiquid opposed to equity and other securities markets. The borrower can apply for listing at a bond exchange to improve the liquidity of the issue. In the US corporate bond market, most bonds trade over-the-counter (OTC) by a network of dealers, linked together by quotation system. Even bonds that are listed on the largest centralized bond market, NYSE[3] Bonds, trade mostly in the OTC market. The dealers do not carry bonds in their inventories and instead tries to match a possible seller with a possible buyer, when a sale or buy order is registered. This makes the market for some issues very thin, and makes liquidity a major risk factor when investing in corporate bonds (Bodie, Kane et al., 2011).

2.1.2 Bond pricing

The basis for pricing a simple coupon bond is given by the present value formula:

$$P = \sum_{i=1}^{n} \frac{C}{(1+r)^t} + \frac{FV}{(1+r)^n}$$

Where P is the price of the bond, C is the coupon payment, FV is the face value of the bond, n is the number of payment dates measured in years, and r is the appropriate discount rate for the bond.

The yield to maturity (YTM) is the constant discount rate, which makes the present value of the promised cash flow equal to the price of the bond:

$$P = \sum_{i=1}^{n} \frac{C}{(1+YTM)^t} + \frac{FV}{(1+YTM)^n}$$

A simple numerical example will illustrate how the probability of default and the loss to the investor in case of default, affects the price of the bond. Since the yield to maturity is the constant discount rate that makes the present value of payments equal to its current price, it

[3] New York Stock Exchange.

follows that the bonds yield will also change due to a change in the perceived probability of default, and the severity of a possible default:

Consider, for the purpose of simplicity, a risk free zero coupon. The price of the bond is currently 95.2381 one year before the principal of 100 becomes due. The yield of the bond is currently equal to the risk free rate of 5%. If investors instead now believe that it exists a 50% probability that the payment in one year only will come in at 50, the risk adjusted expected cash flows to the investors in one year is:

$$E(CF) = 0{,}5 \cdot 100 + 0{,}5 \cdot 50 = 75$$

Since this cash flow is risk adjusted, and the systematic risk of the bond is assumed zero, we can still discount the bonds cash flow by the risk-free rate of 5%:

$$P = \frac{75}{1 + 5\%} = 71{,}4286$$

Consequently, the yield to maturity of the bond will change according to equation 2):

$$71{,}4286 = \frac{100}{1 + YTM}, YTM = \frac{100}{71{,}4286} - 1 = 40\%$$

We see from the simple example that changes in the credit risk of the borrower affects the price of bonds and make yields volatile. The example above is off course simplified. In reality, many factors affect the price and yields of bonds. Some of the factors that one need to consider when valuing a bond is the contractual feature of the bond indenture, the liquidity of the issue, and the rate of return one can achieve on investments of similar systematic risk. However, when things start to get more complicated, it is useful to keep in mind the basic relationship between the price of a bond and its yield.

2.1.3 Contractual features of bonds

Below follows a description of several features that are especially important when it comes to understanding and valuing corporate bonds. The brief survey on contractual features concentrates on expressions, and contract specifications, that one typically encounter when analysing bonds in the Norwegian market.

Seniority and safety: Fabozzi (2013) describes the priority structure of different claims as the following rank, where senior secured debt is the safest claim in a default situation:

1. Senior secured debt
2. Senior unsecured debt
3. Senior subordinated debt
4. Subordinated debt

If the debt claim is backed by specific collateral, other than the general earnings power of the firm's assets, the debt is said to be secured. Similarly, debt not backed by a pledge of assets is referred to as unsecured. Subordinated debt ranks after claims that are more senior when distributing proceeds to creditors if the firm is liquidated. Subordinated debt can also be senior or junior within the subordinated class. Secured bank debt is generally the claim in a company's capital structure that is on top of the priority rank. Similar, junior subordinated bonds is at the lower end of the priority scale (Håvik, 2012).

Convertible provisions: A convertible bond is a regular bond with a conversion right attached. The bondholder typically has the option to convert the face value of the bond into a specified number of common shares in the issuing corporation. The bondholder becomes upon conversion a shareholder, and the price the bondholder is paying is effectively the face value of the bond divided by the number of shares that the bondholder gets upon conversion. This price is referred to as the conversion price. Commonly, borrowers issue convertible bonds deep out of money, meaning that the face value of the bond is greater than the market value of the common stocks that the bondholder gets if converting the issue. Consequently, a convertible bond can be thought of as a regular bond plus a package of warrants[4] (Berk and DeMarzo, 2011).

Put Provision: A put provision gives the bondholder the right to sell the issue back to the issuer for par at a specified date. This kind of provision is beneficial for the bondholder, because if interest rates have risen since the issue date, the bondholder is to receive par value, and can reinvest the proceeds in securities that promise higher coupon payments (Berk and DeMarzo, 2011).

[4] Warrants are similar to stock options, except that they are written on new stocks of the issuer.

Callable provisions: A call feature gives the issuer the right to repurchase the bond before the maturity date. The price is usually equal to face value plus a call premium that compensates the bondholder for the loss of interest. In a new issue, there often exists a grace period where the issuer cannot redeem the bond. The call feature is valuable for the issuer because if interest rates have fallen, or if the credit assessment of the company has improved, the company can refinance its debt and thus lower its future interest payments. The bondholder receives a disadvantage if the bond exhibits a call feature for three reasons: The cash flow structure is not known with certainty, the buy and hold investor is now exposed to reinvestment-risk, and the potential for price increases will be limited because the price will not rise much above the call price (Fabozzi, 2013).

Covenants: Covenants are restrictions on the borrower's future actions or performance that is explicitly included in the bond's indenture. Covenants can be either affirmative or negative. An affirmative covenant requires the borrower to do certain things to honour the loan agreement, while a negative covenant prohibits the borrower from actions that benefits shareholders at the expense of the bondholder. It is either common that the indenture specifies some limits to the absolute debt level outstanding, or that the indenture specifies a ratio in which the company's debt level must comply. Performance ratios, and restrictions on allowed dividends are also common covenants included in the bond indenture (Bodie, Kane et al., 2011). One common negative covenant in the Norwegian bond market is a negative pledge covenant, which prohibits the borrower from the pledging its assets to a new lender in a way that alters the security of the specific bond in which the negative pledge clause is included (Fabozzi, 2013).

Special High Yield bond features: In the High Yield bond market, many firms issue bonds to finance leveraged buyouts (LBOs) and to recapitalize (Fabozzi, 2013). Some of these financing arrangements provide high debt levels that make the interest payment burden substantial. To reduce interest payments, these bonds sometimes exhibit deferred coupon structures. There are three common kinds of deferred coupon structures: Deferred-interest bonds, step-up bonds, and payment-in kind (PIK) bonds. Deferred-interest bonds do not pay interest for an initial period from the issue date. Step-up bonds pay coupons that grow with the under the bond's life. A payment in kind (PIK) provision gives the issuer the option to pay interest and instalments in cash, or issue new bonds to the bondholders with a face value equal to the payment that is due.

One can see from the discussion on various bond characteristics that bonds, and other debt instruments, are generally complex securities. It is therefore important to factor in the specifics of the debt contract for both credit assessments and for valuation purposes.

2.2 Credit risk and credit ratings

Credit risk can be divided into to three distinct risk categories: default risk, credit spread risk, and downgrade risk. Since this thesis concentrates on default risk, the description will mainly centre on this type of risk factor. This part will also cover a description of the credit ratings that participants in the bond market use as relative indicators of credit risk.

2.2.1 Credit spread and default risk

Credit spread: The credit spread is the difference in yields between a treasury security and the yield of a security that is similar in all other ways except for its credit quality. The yield on the treasury security serves as a proxy for the riskless rate. The spread is supposed to measure the required compensation that the investor requires to bare the credit risk of the issue.

Fisher (1959) was the first to investigate the determinants of the risk premiums observed on corporate bonds. His hypothesis was that the risk premium depended on the liquidity of the bonds, and on the risk that the borrower will default. He measured the risk of default by three variables: A variable that measures the variation in the net earnings of the borrower[5], the length of time the firm had been operating without forcing its creditors to incur a loss, and the ratio of the market value of equity to the par value of the firm's debt. As a proxy for the bond's liquidity, he used the market value of all the bonds the firm has outstanding. With the help of these four variables, Fisher tried to explain the variation in the cross section of observed risk premiums on three different trading days. Fisher defined the risk premium to be the difference between the yield to maturity of the corporate bond and the yield to maturity of a treasury security of the same maturity. Fisher was able to explain 81,1 % of the variation in corporate bond spreads by his independent variables for the entire estimation sample, which was made up by 366 observations.

Fridson and Garman (1998) examine the determinants of credit spreads of newly issued High Yield bonds. They find that the spread on newly issued bonds is sensitive to quantifiable characteristics of the issue, and conditions prevailing in the financial markets around the time of the issue. Some of the factors that the authors find to contribute to a higher credit spread

[5] The coefficient of variation in the net earnings of the issuer from the last 9 years.

are longer maturity, if a first time issuer issues the bond, and if the bond is callable until maturity. When it comes to the market environment, the spread is likely to be higher if the secondary market spreads between BB rated bonds and B rated bonds are higher, and if the yields on Treasury bonds rose the month before the issue date. The authors are able to explain 56% of the variance in spreads by variation in their covariates.

Default risk: can be defined as the risk that the borrower is not able to make timely payments of interest and principal to honour the debt obligation of the issue (Fabozzi, 2013). Expected default loss is one way one can calculate the default risk component. The formula for expected loss is stated is:

$$Expected\ default\ loss = PD \cdot LGD = PD \cdot (1 - RR)$$

Where PD is the cumulative probability of default, and RR is the recovery rate given a default.

Longstaff, Mithal, and Neis (2005) examine the components of the credit spread by the use of Credit Default Swap(CDS)-spreads[6], and reduced form credit models, as measures of default risk. They find that default risk accounts for the majority of observed credit spreads. The default risk component grows as one move down to bonds with lower credit ratings. The researchers also find that it exist important non-default components in observed credit spreads.

Duffie and Singleton (2003) provide evidence that default rates depends strongly on the current state of the economy. The overall default rate is high when economic growth is low and correspondingly low when economic growth is high. As a concrete measure of the correlation between the business cycle and defaults, they measure the four-quarter moving average default rates, and compare this measure to GDP growth rates for a sample period from 1983-1997. The correlation between the two measures over the period is -0.78, indicating a strong negative correlation between GDP growth rates and defaults.

Ilmanen (2011) states that a reasonable recovery for senior debt is around 40%, but that it is important to remember that the recovery rate typically varies with time, seniority, and security. Typically, default rates and recovery rates move together in recession periods. The historical

[6] Credit Default Swaps are derivative instruments that provides protection for default risk.

default rate has followed the High Yield-treasury spread quite close in the United States of America since 1978, with an average spread of about 5.30 % compared with an annual average default rate of 4.3 %. When factoring in the recovery rate, the average default loss over the period has been around 2.6 %, thus investors have realised about half of the promised credit spread.

Sæbø (2011) examines credit spreads in the Norwegian market for the years 2008-2009. He identifies that roughly a quarter of the observed credit spreads from 2793 trades registered at the Oslo Stock Exchange (OSE) is due to compensation for expected loss. He uses the expected default frequency (EDF) from the Moody’s Creditedge model, and uses fixed recovery rates assumptions for the sectors finance, utilities and industry, as estimates of the cumulative probabilities of default and expected recovery rates. He also examines which factors that can explain the variation in credit spreads beyond annualized expected loss. Among the factors, that Sæbø finds to explain credit spreads is the size of the issuer, the issuers sector, and a measure of the general liquidity level in the bond market. Sæbø also states that it is difficult to find a proxy for the liquidity of an individual bond, and that some of the size factor could in fact be attributable to a liquidity premium.

2.2.2 Credit ratings

The three major credit rating agencies; Moody’s Investor Services, Standard & Poor’s Corporation (S&P), and Fitch Investors Service publish credit assessments of large corporations and sovereign issuers. The credit rating agencies assign a letter grade to each corporation, municipality, or sovereign issuer that is supposed to reflect their ability to make timely payment of interest and principal. Ratings are relative assessments of an issuer’s ability to honour the obligation of the bond indenture over a cycle. Moody’s states that, as a rule of thumb, they are looking through the next economic cycle, or longer, when rating an issuer. Consequently, poor short-term performance will not make Moody’s downgrade an issuer if they believe that the issuer will continue to maintain its credit quality in the future (Moody's, 2013c).

Below is a table of the rating scale that the two largest credit rating agencies, Moody’s, and S&P use for their publications of credit ratings. The description to the left of the table is Moody’s brief description of the quality and risk of the issuer. Moody’s modifies the ratings with the numbers 1, 2, 3 from rating Aaa to Caa, where 1 is off the highest quality. Similarly, Standard & Poor's use + and – to modify their ratings. Bonds issued by an entity rated below Baa (Moody's), or below BBB (S&P), are commonly thought of as High Yield bonds[7](Bodie, Kane et al., 2011).

Table 1 Credit ratings

	Moody's	*S&P*	*Description*
Investment grade	Aaa	AAA	Judged to be off the highest quality, subject to the lowest level of credit risk.
	Aa	AA	Judged to be off high quality and are subject to very low credit risk.
	A	A	Judged to be upper-medium grade and are subject to low credit risk.
	Baa	BBB	Judged to be medium-grade and subject to moderate credit risk and as such may possess certain speculative characteristics.
High Yield	Ba	BB	Judged to be speculative and are subject to substantial credit risk.
	B	B	Considered speculative and are subject to high credit risk.
	Caa	CCC	Judged to be speculative of poor standing and are subject to very high credit risk.
	Ca	CC	Highly Speculative and are likely in, or very near, default, with some prospect of recovery of principal and interest.
		C	
Default	C	D	The lowest rated and are typically in default, with little prospect for recovery of principal or interest.

Source: Moody's (2013b) and Bodie, Kane and, Marcus (2011)

Very few of the issuers in the Norwegian market have an official rating assigned by the three largest credit ratings agencies. This constitutes a problem when one need to define which bonds that is considered High Yield. Market participants and portfolio managers therefore rely on the ratings assigned to the issue by the credit analysts at various investment banks. The market participants commonly speak of these internal ratings as "shadow" ratings. There is currently no available database in Norway where one can find regularly updated information on "shadow" ratings. Some of the largest investment banks in Norway publish weekly credit reports that investors, and other asset management institutions, can subscribe to for updated credit assessments on some of part the market. However, unfortunately, the credit reports do

[7] Sometimes speculative-grade bonds or junk bonds are used as a synonym for High Yield bonds.

not show the big picture of the distribution of ratings. As an example, in the weekly credit report published by DNB Markets for week 35 (2013), only thirty-nine industrial companies were included with either an official rating, or an internal credit rating.

In his book about expected returns, Ilmanen (2011) provides statistics that show that from 1973 to 2009, BB rated bonds average excess return over treasury bonds are higher than lower rated bonds, and that the BB category is the top performing bond rating class. This is rather surprising from common financial theory, and shows to some extent that higher risk does not generally imply higher expected average returns if we look at how the various bond-rating classes have performed historically. One explanation for this phenomenon is that many bond investors, such as pension funds and low risk bond funds, are constrained to invest in Investment Grade (IG) bonds only. When an issue gets downgraded this means that the majority of the portfolio managers are forced to sell the newly downgraded High Yield bonds[8]. The sale of these fallen angels causes a market segmentation effect, which causes the price of these bonds to fall, and accordingly their yields to go up.

2.2.3 Migration risk and credit spread risk

For bonds with issuers rated Investment Grade, the probability of default is relatively low and the risk of a rating downgrade is the most relevant risk factor. Downgrade risk, or migration risk, is the risk that one or more of three major credit rating agencies assign a lower credit rating to an issuer, or an issuer's debt obligation. Downgrades frequently leads to a widening of the credit spread, and subsequently to a capital loss. Credit spread risk refers to the risk that a bond's price will fall due to the widening of the credit spread. A widening of the credit spread can also occur because the industry in which the issuer competes suffers a downturn, or if the investors in bond markets think that the general level of credit risk in the market has become worse. Thus, the underlying reasons for the widening of the credit spread are not necessarily captured by the ratings of the rating agencies (Fabozzi, 2013).

[8] Bonds that are issued as Investment Grade and subsequently falls into the High Yield category are sometimes spoke of as fallen angels.

2.3 Definition of default

When performing a study on defaults, one must have a clear opinion of what type of event that constitutes a default. For this thesis, the Moody’s definition of default from Moody’s Corporate Default Risk Service (2013a) was used when determining which bonds that had been involved in a credit event. Moody’s divides a default incident into three broad categories:

1. A missed or delayed distribution of interest and/or principal, including 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 equity 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.

In defining the sample of defaulted bonds, the Moody’s definition of default is used to determine if the bond has experienced a default, and to distinguished between the three types of broad default categories that the Moody’s definition covers. The motivation to choose the Moody’s definition is because it is one of the broadest definitions available, and because it is possible to split observed defaults into the three categories above in an efficient manner.

Cross default clauses refers to a situation in which the bond agreements states that if the issuer defaults on another borrowing arrangement, the bond would be in default and the face value of the bond immediately becomes due. The defaulted amount on the other borrowing arrangement is regularly required to be above a certain threshold before the other bonds of the issuer falls into default (Fabozzi, 2013).

One example of a cross default situation from the Norwegian bond market is the default of the secured USD bond issued by the oil company Interoil Exploration and Production ASA. From the loan agreement the company had an obligation to pay an amount of 10 000 000 USD which, was due the 4th of May 2009. The company failed to honour this obligation and the Norwegian Trustee declared the bond into default and due for immediate payment. The issuer had also issued two unsecured Bonds, which according to a cross default clause in their loan agreements subsequently went into default.

2.4 Default versus bankruptcy

From the Moody's definition of default, one can immediately see that bankruptcy and liquidation are only two categories off possible credit events. Of the 160 defaults that were found in the preliminary sample of this thesis, only fourteen were defaults in which the first event was an event of either which consisted of a bankruptcy filing, by the company itself, or by its creditors. However, the outcome of several of the defaults was eventually bankruptcy and/or liquidation.

One possible solution when the issuer default on the loan agreement is to restructure out of court by postponing obligations, reduce principal or interest, or by forming another restructuring mechanism which might include converting the whole or a part of the debt into equity. The bankruptcy incidents that were found in this thesis have mainly been Chapter 11 filings in the United States, or the companies have filed for bankruptcy according to Norwegian law. If it is unlikely that an out of court restructuring will be successful, then either the company or its creditors files for bankruptcy petition[9].

In the United Sates the two most important chapters in the bankruptcy act, which includes fifteen different chapters, are Chapter 11 and Chapter 7. Chapter 11 is the most common form of bankruptcy and deals with the reorganization of the firm so that the firm can emerge from bankruptcy as a going concern. When in Chapter 11, the corporation receives protection from creditors who seek to collect their claims, and continue their daily operations. The purpose of the process is to put forth a reorganization plan for the company so that the company can continue its business, and that each creditor is treated fairly. If the bankruptcy court, and the creditors, do not deem the reorganization plan acceptable, the court may force a chapter 7 liquidation of the firm.

Chapter 7 deals with the liquidation of the company. When liquidating a company, the company cease to exist, and its assets are sold to cover the claims of the creditors. The distribution rules to creditors shall comply with the absolute priority rule. The absolute priority rules states that senior creditors are to be paid in full before the junior creditors receives any

[9] When the company files for bankruptcy, it is referred to as a voluntary bankruptcy filing. When the creditors file for bankruptcy, it is referred to as an involuntary bankruptcy filing.

payment. This priority rule grants both secured and unsecured creditors priority over the shareholders of a company in the case of liquidation (Fabozzi, 2013).

Although Norway has a bankruptcy legislation similar to Chapter 11 in the United States, it is of little use, and companies tend to restructure out of court when default is unavoidable. In Norway, the company needs to both insolvent and insufficient, for a full opening of bankruptcy and/or liquidation. Insolvent means, by Norwegian law, that the company is not able to pay its obligations when their obligations are due. Insufficient means that the value of the company's liabilities exceeds the value of its assets. Bankruptcy proceedings is initiated by an application to the probate court, and both insolvency and insufficiency must be documented (Gisvold, 2012).

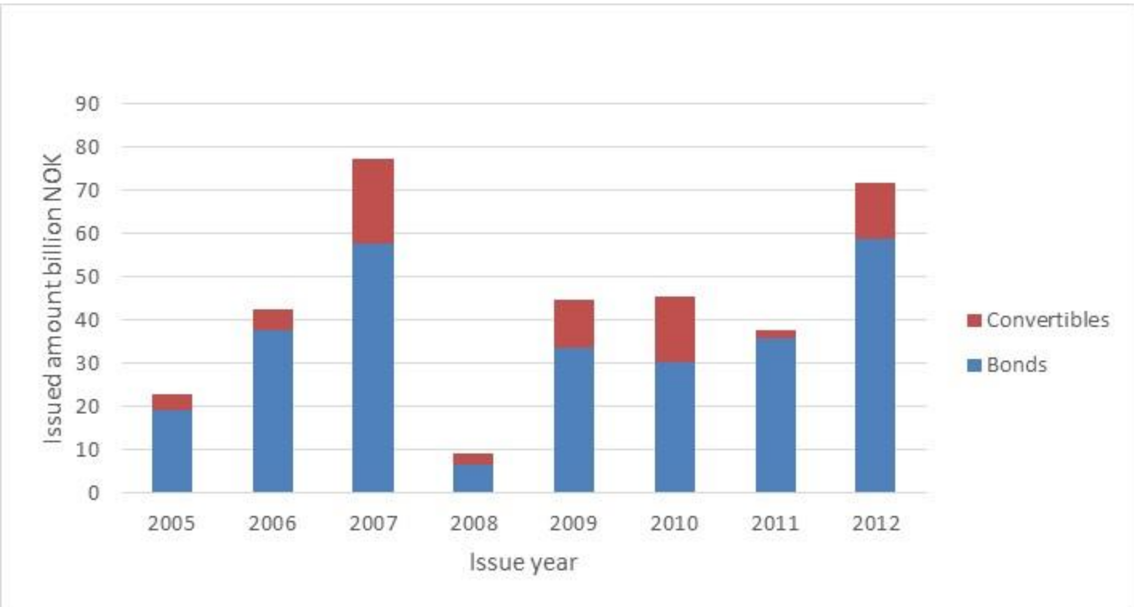
3. The Norwegian corporate bond market

In this chapter, the Norwegian corporate bond market is introduced by going through some general characteristics, the exchanges which these bonds trade, and the role of the Norwegian Trustee. Bonds registered in the Norwegian Trustees database Stamdata is used as a starting point to define the Norwegian corporate bond market.

3.1 Market description

Figure 1 below shows issued amount in billion NOK over the years 2005 and 2012, of regular bonds and convertibles. The industries banking, energy and utility, insurance, and the public sector are left out of the figures. Issues made by corporations that are government guaranteed and owned by the government, are left out the figures as well. Thus, the figures give an overview of issued amount in the corporate bond segment over the period. We see that most of the bonds issued are regular bonds, but that does not mean that the contractual features are simple. There are still a myriad of different structures on the issued bonds including deferred coupon structures, different bond covenants, and the bonds being callable in some part of the bond’s tenor.

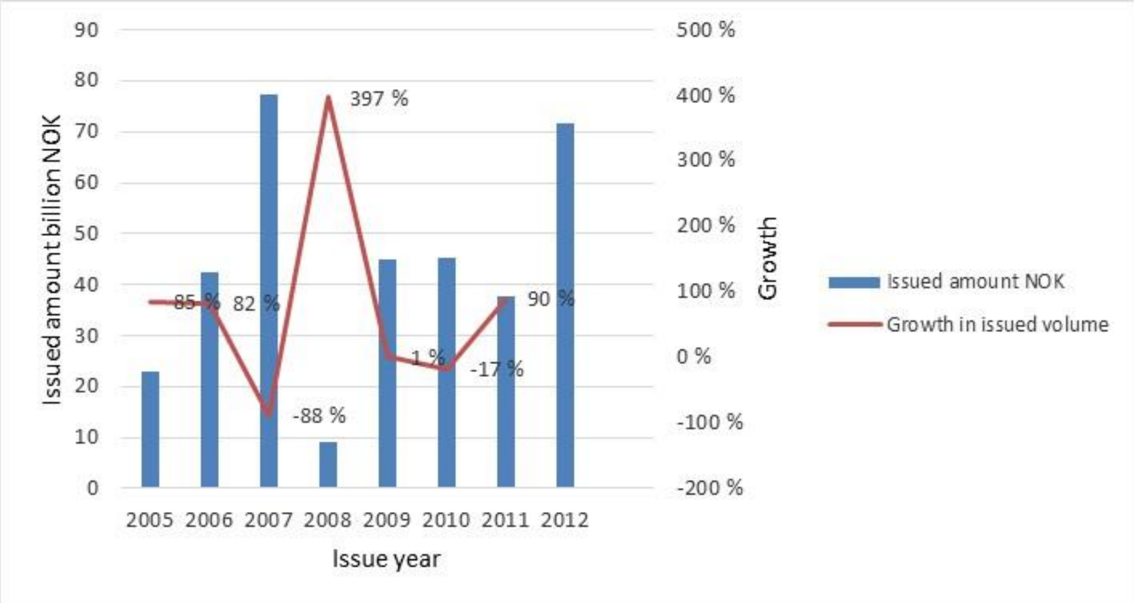
Figure 1 Issued amount by year and issue type



Source: Stamdata statistics

Figure 2 shows total issued amount in billions NOK registered in Stamdata per year from the period 01.01.2005 to 31.12.2012. The figure also shows the growth rate from year to year in issued amount. The cumulative average growth rate in issued amount per year (CAGR) for this part of the bond market has been 15.4%, but we see that the growth rate in issued volume has varied a lot over the years. As can be seen, there were high issue volumes coming up to the financial crisis period of late 2008 and 2009. During the financial crisis, few bonds were issued, but the market regained and passed its 2006 volume already in 2009.

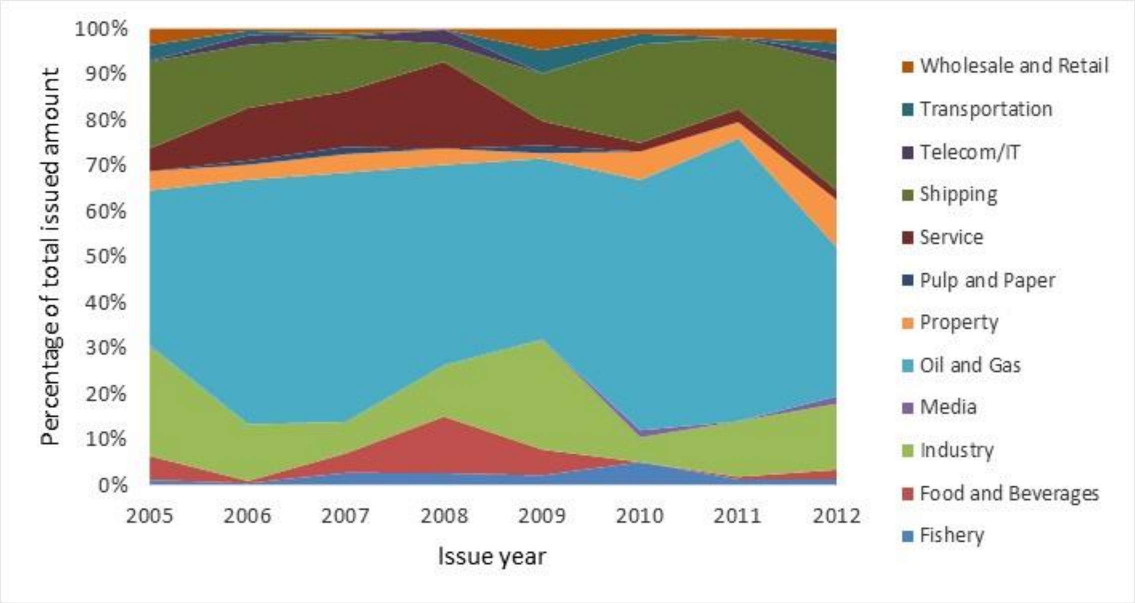
Figure 2 Issued amount and growth 2005-2012



Source: Stamdata statistics

Figure 3 shows which industries that dominate the market, using the industry classification assigned in the Stamdata database. Not surprisingly, issues made by the oil and shipping industry dominate the issues of corporate bonds in Norway. These industries are capital heavy industries, and industries that generally dominate the business landscape of Norway. Oil- and shipping companies also dominate the equity market at the Oslo Stock Exchange.

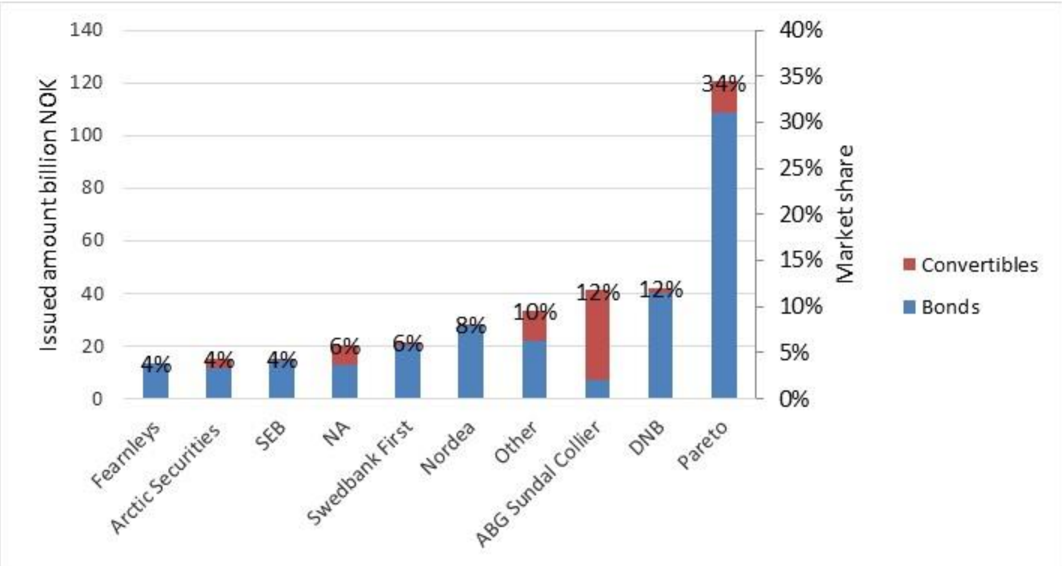
Figure 3 Issued amount by industry 2005-2012



Source: Stamdata statistics

Figure 4 shows total issued amount split up by the investment bankers that acted as a managers when designing and marketing these issues to investors.

Figure 4 Bond managers 2005-2012



Source: Stamdata statistics

As we can see, Pareto Securities is by far the dominant manager in the Norwegian bond market, with a market share of 34%. DNB Markets and ABG Sundal Collier follow with market shares of 12 %. It is also worth noting that ABG Sundal Collier has specialized on convertible bonds and has the leading role in this sub-segment.

3.2 Listing of bonds in Norway

In Norway, there exist two exchanges where bonds and other fixed income securities are listed for trading, at the Oslo Stock Exchange (OSE), or at the Nordic Alternative Bond Market (ABM). In addition, Norwegian issuers may also list their bonds abroad.

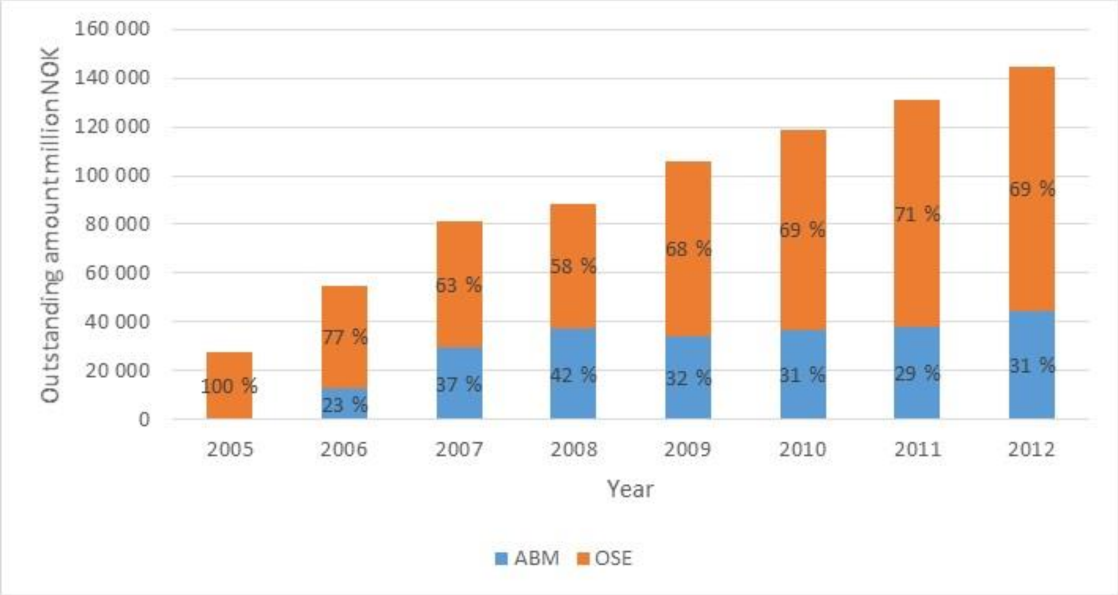
Oslo Stock Exchange is a regulated marketplace according to EUs MiFID[10] directive, making the listing process on OSE more comprehensive than the listing process on the ABM exchange. OSE requires the lender to make a prospectus according to EU-law, and the Financial Supervisory Authority of Norway must approve the prospectus before the issue is available for trading. The issuer is also obliged to use International Financial Reporting Standards (IFRS) when preparing its annual accounts.

On the other hand, the Nordic Alternative Bond Market is an unregulated marketplace where the rules of the exchange adjust to the demands of the market participants. The listing process is quicker and easier, and the issuer is not obliged to use IFRS in their annual reports (Oslo Børs, 2013). The process for listing is thus faster, and requires less documentation from the issuer, which cause some foreign firms that finds the process in their home country tedious to use the Norwegian corporate bond market as a source of capital of instead. Some see this as an undesired evolution, which causes the average credit quality of the borrowers in the Norwegian market to go down. As an example, the well-known portfolio manager Peter Warren is cited by the online business newspaper E24 (2012) that he do not see it as a positive sign that foreign companies issue bonds in the Norwegian High Yield bond market because of little documentation requirements. Another concern according to Warren is that investors in the Norwegian High Yield bond market, in many cases, do not require official credit ratings on the issues.

Figure 5 shows the evolution in outstanding amount by year-end from 2005 and 2012 at the OSE exchange and the ABM exchange. We can see that the ABM exchange has taken good share of the listings since its inception in 2005.

[10] Markets in Financial Instruments Directive.

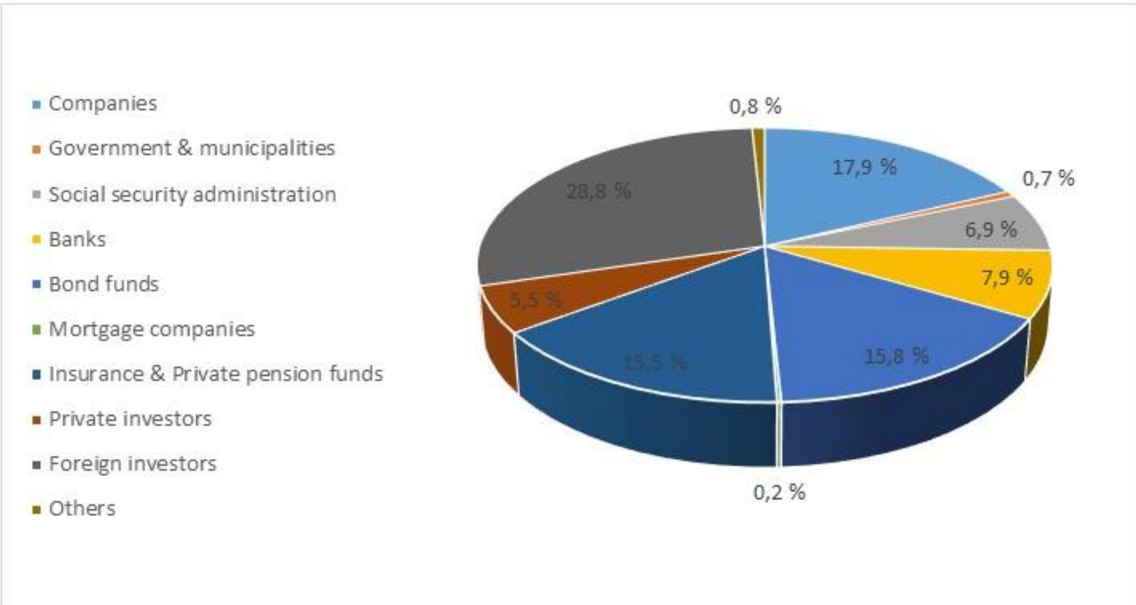
Figure 5 Year-end volume OSE and ABM 2005-2012



Source: Oslo Stock Exchange Annual Statistics (2013)

There is also a possibility that the bonds registered in Stamdata trades on a foreign exchange. However, in the preliminary sample of this thesis, none of the bonds were reported as being listed on a foreign exchange. The bonds were either listed, delisted, should apply for listing later, had applied for listing, or were not supposed to apply for listing in Oslo or abroad. To get a sense of which investors who hold bonds on the OSE exchange, figure 6 shows the percentage distribution of different investors in corporate bonds listed at the OSE.

Figure 6 Ownership structure OSE 2012



Source: Oslo Stock Exchange Annual Statistics (2013)

The investors in the bond market are generally institutional investors like pension funds and bond mutual funds. We also see that foreign investors are by far the biggest investors in listed bonds at the Oslo Stock Exchange, followed by bond funds, insurance & private pension funds, and regular companies. Thus, the bond market in Norway is certainly a global market, and bonds are being sold to investors all over the world. If we look at the ownership structure at the ABM exchange we find a similar structure, expect that insurance & private pension funds have a bigger share together with foreign investors at around twenty-five to twenty-six percent.

3.3 Norwegian Trustee and Stamdata

The main purpose of the Norwegian Trustee is to act as a trustee in the Norwegian fixed income securities market (Sandvik, 2010). The company is organized as a private enterprise owned by Norwegian banks, life insurance companies, and investment funds. The Group, Norwegian Trustee, has subsidiaries in Denmark, Finland, and in Sweden. The trustee monitors that the issuer complies with covenants in the bond agreement, that the issuer makes scheduled payments in time, and acts as an information channel between the issuer and bondholders. The trustee can also take legal actions against the borrower if the borrower does not act according to the bond agreement, and discusses matters with the borrower when there is no a need for a bondholders meeting. An advantage of using the Norwegian Trustee from the perspective of the issuer is that the borrower can negotiate with one party rather than approaching each individual bondholder, this process also makes it harder for a bondholder to steer a solution to his advantage if he has interests that are different from the other bondholders. There is no legal obligation to use a trustee when issuing a bond in the Norwegian market, but 95% of the issued volume currently have a trustee arrangement.

Stamdata, which is a database owned and updated by the Norwegian Trustee, is the main source of data for this thesis. Stamdata is the leading provider of bond reference data in the Norwegian bond market. In Stamdata, one can find information covering loan documents, the letters that are sent from the trustee to the bondholders, and a large statistics service where one can extract information on all the issues and tranches registered in the database. Stamdata covers information on all the bonds, convertibles, and commercial papers where the Norwegian Trustee has the trustee role[11], which compromises about 90% of the bonds registered in the security register in Norway. Pricing information is currently not included in the database, but may be included in the future with the establishment of Nordic Bond Pricing.

[11] Some bonds where another institution has the trustee role are included in the database as well.

3.4 The Norwegian High Yield bond market

The Bergen based asset management company the Holberg Funds, measures the current size of the corporate bond market in Norway to be around 300 billion NOK (2013). S&P, Moody's, and Fitch, or credit analysts at the major Norwegian investment banks rate about half of the issues below Investment Grade according to the Holberg Funds. There is generally no agreed upon definition of the High Yield bond market in Norway because many issuers that certainly can be thought of as High Yield, lack credit ratings at all. Oil companies, offshore companies and shipping companies dominate the Norwegian High Yield market. Consequently, the lack diversification may be a concern when building a High Yield debt portfolio including only companies issuing bonds in the Norwegian market.

A special characteristic of the Norwegian High Yield bond market compared to other more well-develop bond markets, is the high level of liquidity risk. Credit spreads are generally higher in Norway than in the global High Yield bond markets. One possible explanation for this difference is the presence of a substantial liquidity premium on a good part of the issues.

Gabler (2012) notes that there is a tendency towards that the Norwegian High Yield market is used as a capital source primarily by publicly listed firms who needs to fund their daily operations. A few years ago, firms that needed project funding mainly used the market, and the uncertainty around their earnings and the value of the bonds were much higher than it is today. In the big issue year of 2007, almost half of the issues were rated CCC according to Gabler. Gabler also states that while the average credit quality in the High Yield bond market has gone down in the United States, it has improved in the Norwegian market as the market has matured in recent years. Another concern about the Norwegian market is the lack of an available benchmark index. It is therefore positive that Nordic Bond Pricing is thinking of establishing a reference index when they begin their pricing service in the future.

4. Prediction of distress.

As noted by Marchisini, Perdue and Bryan (2004), although bankruptcy and default represent different phases of financial distress, it is still worth exploring the bankruptcy prediction models as a starting point when the purpose is to predict default on bonds. This chapter will include a description of the early bankruptcy models that use accounting and cash flow information, a brief overview of the background of the more theoretically motivated Merton-model, and a description of the SEBRA-model used by the Central Bank of Norway for bankruptcy predicting purposes.

4.1 Litterature review on bankrupcty prediction

4.1.1 Statistical models

Beaver (1966) was the first to perform a study of financial ratios as possible predictors of corporate bankruptcy. His sample was made up by financial statements for 79 firms, which had failed in the years 1954-1964 and had adequate financial data for the accounting year prior to the bankruptcy event. The sample of failed firms operated in 38 different industries. He then compiled a list of non-failed firms, which he paired with the failed firms according to industry and the size of their balance sheets. Beaver compared the means of several financial ratios for the failed firms and the non-failed firms, and tested if there were significant differences in the means of important financial ratios between the two groups. Beaver found that the ratio distribution of the failed firms deteriorated markedly as the firms approached failure. One of the ratios that Beaver found especially useful in separating non-failed firms from failed firms, was the cash flow to total-debt ratio.

In 1968, Edward Altman (1968) developed the Z-Score by the help of multiple discriminant analysis as a tool for predicting corporate bankruptcy. An advantage of a multivariate analysis is that the interaction between the variables is taking into consideration. Multiple discriminant analysis (MDA) is a statistical technique used to categorize an observation into several categories dependent on the characteristics of the specific observation. MDA tries to derive a linear equation which best discriminates between the categories. Altman's sample was made up by 33 manufacturing companies that filed for bankruptcy petition during the years 1946-1965. He then paired this sample with 33 companies of equal industries and size. Financial data was collected from the financial statements one reporting period prior to bankruptcy.

Altman collected twenty-two financial ratios, which were possible predictors of failure. Five of the ratios proved to be doing the best job in predicting corporate bankruptcy. The variables that Altman found to do the best job were working capital divided by total assets, retained earnings divided by total assets, earnings before interest and taxes (EBIT) divided by total assets, the market value of equity divided by the book value of total debt, and the ratio of sales divided by total assets.

In 1977, Altman, Haldeman and Narayanan (1977) came up with a new model, the ZETA-model, or the ZETA-score. 54 bankrupt firms, and 58 non-bankrupt firms, made up the sample from the period 1967-1975. The sample also covered larger firms than in the Z-score study, took into account recent advances in accounting rules, and included retailers as well as manufacturers. The independent variables in the ZETA-model are EBIT divided by total assets, stability of earnings[12], EBIT divided by total interest payments, retained earnings divided by total assets, current assets divided by current liabilities, 5 year average market value of equity divided by total capital ,and the firms total assets. Altman and the co-authors found that the single most important variable to discriminate bankrupt firms from non-bankrupt firms was retained earnings to total assets.

James A. Ohlson (1980) was the first to use logistic regression analysis to predict corporate bankruptcy using financial ratios. He argued that the use of a probabilistic measure of the risk of corporate bankruptcy is more useful than the Z-score derived by Altman because the estimated probability of bankruptcy is possible to interpret directly. Ohlson gathered financial data up to three years prior to the bankruptcy event for 105 bankrupt companies, and coupled this information with 2058 data points of non-bankrupt companies, from the years 1970-1976. Only industrial companies in the United States are analysed in Ohlson's study. A requirement for the inclusion in his sample was that the equity of the firm had to be traded, either on a public exchange or in the OTC equity market. A list of nine independent variables were used to predict bankruptcy within one year, within two years given that the company did not file for bankruptcy in the subsequent year, and within one or two years from the financial information period. One important conclusion from Ohlson's study is that the predictive power of any model depends on when the information used in the model is made available to the public. Ohlson only incorporates information that was available prior to the bankruptcy event

[12] Measured by the standard error of estimate around a ten-year trend in EBIT divided by total assets.

when estimating his prediction model. He criticize previous bankruptcy predicting studies because they implicitly assume that the annual accounting information was available at the end of the fiscal year. This is not necessarily true because the company needs to prepare the financial statements, and an auditor needs to finish the audit process before the company releases the annual reports to the public.

There is also models that tries to use a cash flow based approach for predicting corporate default. Aziz, Emanuel and Lawson (1988) use the Lawson identity[13] to motivate the choice of independent variables. The researchers use both logistic regression analysis and multiple discriminant analysis within the same set of independent variables to predict corporate bankruptcy. They find that the Logit model performs marginally better compared to a multiple discriminant analysis approach for predicting bankruptcy one to five year before the event. Similarly, Gentry, Newbold and Whitford (1985) use a flow of funds approach to predict failed and non-failed firms using multiple discriminant analysis, the Probit model, and the Logit model. The authors get the best predictive results using the Logit model on their sample of failed firms from 1970- 1981 in the United States.

4.1.2 Structual models

While there had been several models that used accounting ratios to predict the probability of default and bankruptcy, there was no general theory of pricing bonds when there is a significant probability that the bond would default before 1974. Robert C. Merton (1974) suggested that it is possible to use the option pricing formula proposed by Black & Scholes (1973) to price risky debt. Merton suggested that the levered equity of the firm could be valued as a call option on the firm assets, with a strike price equal to the face value of the required debt payment of the firm. This relationship occurs because the shareholders enjoys limited liability and that it is irrational, at least in theory, for the shareholders of the firm to pay off its debt when the asset value of the firm is below the value of the firms debt. Consequently, the bondholders are long the borrower’s assets and short a call option written on the borrower’s assets.

[13] The identity says that the company’s total cash flow is the sum of the total cash flows to lenders and the total cash flows to shareholders, and splits this cash flow stream by its various origins.

Merton explicitly derives a formula for the valuation of risky zero-coupon bonds, and risky-coupon bonds when the term structure of interest rates is given. By the help of relationships from the Black & Scholes option-pricing model, one can estimate the market value of the firm's assets and its asset volatility with the help of information from equity markets. From the Merton-model the probability that the call option will expire out of the money can be derived, this is the risk neutral probability that the firm will default. When the value of the assets falls below the default point, the firm will default on their debt and the debt holders becomes the owners of the corporation.

KMV Corporation, which Moody's acquired in 2002, has extended the Merton model to become a standard for default-risk measurement. KMV has derived an ordinal measure of a company's default risk named the distance to default (DD) (Kealhofer, 2003):

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

Where DD can be thought of as being roughly the number of standard deviations, (σ_A) the market value of the company's assets (A) is above the default point (DPT) . The default point is the face value of the debt maturing at horizon (h). If the market value of the company's assets is lower than the face value of the company's liabilities, the company defaults on its debt. DD is an ordinal measure of default and is not directly useful for valuation purposes in the sense that it only ranks companies default risk. KMV has been tracking defaults on all publicly traded companies in the United States since 1973, and uses their proprietary database to substitute the theoretical default probabilities on can derive from the Merton model with an empirical distribution of default rates from the KMV default database using the distance to default measure. Companies with similar DDs are predicted to have the same probability of default by the KMV-model. Differences between individual companies are accounted for by the estimated asset value, the volatility of the assets, and the company's capital structure. The measure is not brought in as a covariate in this thesis, but provides a useful theoretical framework to keep in mind when analysing default risk.

A clear problem with these models is that they only apply to publicly traded companies. One need the market value of equity, and the volatility of equity, to estimate the market value of the firm's assets and the asset volatility. Both publicly traded companies and companies appears in the final sample of this thesis. Hence, there is not possible to derive a market-based probability of default measure as an explanatory variable for the whole sample. Several researchers have used the distance to default as a covariate in studies of default risk. It has for example been used by Hillegeist et al. (2004) to compute the probability of bankruptcy, and by Das, Hanoun, and Sarin (2009) to explain the variation of the cross-section of CDS-spreads.

4.2 Application to default on bonds

Marchesini, Perdue, and Bryan (2004) examine how the most famous bankruptcy prediction models perform in predicting default on High Yield bond issues. They examine four different models which includes two accounting models: The Altman Z-score and Ohlson’s Logit model, and the two cash flow based models developed by Gentry, Newbold and Whitford (1985) and Aziz, Emanuel, and Lawson (1988). Their dataset consist of High Yield bond issues in the years 1997-2000 and defaults from the years 1997-2002. Of the 104 High Yield bonds in their sample, 44 bonds experienced a default before March 2002 and the remaining 60 bonds were still viable traded assets. The result they obtain from the use of the bankruptcy models is discouraging. The best accuracy rate is obtained by the model developed by Gentry, Newbold, and Whitford, which had an accuracy rate for their sample of 61,5% one year before default. That is, 61,5 % of the issues were predicted to be in the correct category, defaulted, or non-defaulted. The authors also suggest a different model that is more suitable for predicting default on High Yield bonds. The model include six variables: the log of total assets, total equity divided by total assets, EBIT divided by sales, operating cash flow divided by sales, operating cash flow divided by total assets, and EBIT divided by interest expense. This model exhibits an accuracy rate applied to their sample of 79,6% one year prior to default, 72,6% two years prior to default, and 68,2% 3 years prior to default.

Grammenos, Nomikos, and Papaostoulo (2008) estimate the probability of default for High Yield bonds in the shipping industry by using financial ratios and industry specific variables available at the time of issue. Fifty High Yield bonds issued in the period 1992-2004, whereas thirteen bonds that had defaulted by the end of 2004, make up their sample. The authors find that the key variables explaining default at issuance is a measure of gearing, the amount raised in the issue divided by total assets, working capital divided by total assets, retained earnings divided by total assets, and an industry specific variable that captures the shipping market conditions at the time of issuance.

This thesis mostly relates to the study of Huffman and Ward (1996). They use a sample of 171 High Yield bond issues, including 54 bonds that defaulted during the period covered. The authors estimate a Logit model that uses financial ratios from the accounting year prior to the year of issuance. This is last available financial report before the respective bond issues. 121 of the observations are used to estimate the parameters of the model, while a randomly selected holdout sample of 50 issues are used to explore the predictive capacity of the model. The variables that are found to indicate a higher default probability is a higher growth in total assets prior to issuance, larger changes in liquidity, a higher share of collateralized assets, and a smaller operating profit margin. The predictive power of their final model is higher compared with an alternative model that employs Altman's original covariates.

4.3 The SEBRA-model

Eivind Bernhardsen (2001) at Norges Bank developed in his master thesis a model of predicting bankruptcy in Norway based on information from firm's financial statements. Bernhardsen applies the logistic regression technique to accounting information from the SEBRA-database held by the Central Bank of Norway and couples the financial data with information about bankrupt firms in Norway. Dun and Bradstreet provided the bankruptcy data from the period 1990-1999. The model is the best-known model for predicting corporate bankruptcy in Norway and is a natural starting point for the choice of variables when performing credit risk analysis on Norwegian data. The dependent variable in the model is corporate bankruptcy within 3 years from the accounting year, given that the observed financial statement is the last reported statement of the firm. The model has been revised and improved over the years by researchers at the Central Bank of Norway and is primarily used to estimate the vulnerability of the banking sector.

Although, the model is mainly used for estimating bankruptcy probabilities for Norwegian limited liability companies, it is interesting to see how the independent variables of the model performs when the purpose is to predict default on bonds and when foreign firms are included in the analysis. The latest available article describing the SEBRA-model, found in Economic Bulletin nr. 3 2007 (Bernhardsen and Larsen, 2007), is used as a starting point in the analysis section of this thesis. The different articles describing the SEBRA model over the years are also used. More will be said about the SEBRA-model in chapter five of this thesis.

5. Data

In this chapter, the data gathering process is described. This process was a two-step process, first finding defaults and non-defaulted bonds in Stamdata, and second matching these observations with relevant accounting and market information. This chapter also includes a description of the variables tested as predictors of default, and descriptive statistics for the final sample.

5.1 Stamdata

From Stamdata, Issue based statistics was used as the starting point for finding High Yield firms[14].To make the sample as large as possible, all issues from 01.01.1993-31.12.2012 were extracted from the database. However, to make the manual process of going through the loan documents manageable, the sample was narrowed down by filtering out issues that matured before 01.01.2005. This was also done because the Norwegian High Yield bond market was rather small prior to 2005. Issue types other than bonds were also filtered out, like commercial papers and warrants. Energy companies, companies classified to be in the public sector, banks, insurance companies, and other financial companies were excluded because these firms are not generally thought of as being part of the Norwegian corporate bond market. Issues made by firms were Stamdata reported the issuer to be owned by the government, to be an unlimited liability company, or issues that were categorized as government guaranteed, were also removed.

A list of possible defaulted firms was received from the investment-consulting firm Gabler. This list was complemented with a list of defaulted firms found by Brekke and Haugland (2010) in their thesis, to create a list of possible defaults. Ninety-six companies appeared on this list before searching through Stamdata. As mentioned earlier, since few of the bonds in the Norwegian market have an official credit rating, it can be difficult to determine which issuers who are considered High Yield and which who are Investment Grade issuers. I had access to credit reports published by two Norwegian investment banks, but either the major rating agencies, or the respective investment banks had rated many of the firms that appeared

[14] The alternative is Tranche-Based Statistics where each tranche registers separately.

in Stamdata. I decided to use the list of High Yield firms determined by Pareto Securities found in the thesis written by Brekke and Haugland to filter out Investment Grade issuers. Since this list was determined fall 2010, issuers that issued bonds after this period do not appear on the list. It is a risk that some of the issuers in the final sample are rated investment grade by some credit analysts. Nevertheless, when looking through the distribution of issuers, an approximation that these firms are High Yield issuers, seem reasonable. After the filtering process was finished, 646 bond issues and 270 issuers made up the sample before digging into the letters archived in Stamdata.

The next step was to go through the letters sent from the trustee to the bondholders to search for defaults covered by the Moody's definition. The analysis in this thesis are conducted per issuer. An alternative would have been to include all the issued bonds in the final sample, but the observations for each company now become highly dependent on each other, and the advantage of a larger sample was not deemed big enough to justify a per bond approach. A concern was that many borrowers had issued multiple bonds in the period covered, and that some of the defaulting firms had defaulted on several bonds. When multiple defaults are present, the default date is set as the default date on the first bond where default is noticed. The default date was set to be either the date of the letter in Stamdata for a bondholders meeting regarding the incident, or a letter of information providing evidence that default had occurred. One company, Northland Resources AB, had to be withdrawn from the sample because a letter from the company to the bondholders proposing a restructuring was missing in Stamdata.

For the companies that had not defaulted on a bond issue, the first bond issued by the borrower is used when comparing non-defaulted firms with defaulted firms. This choice is important because it determines the period for which information is supposed to be collected. The rule has been circumvented in some cases because of little adequate financial data for some firms in the beginning of the period. In some cases, issues made when the company was completely different from what it is today, have been filtered out.

When going through the bonds and issuers it soon became evident that some of the firms were linked together in group structures, or in a more complex business setting. Some issues in the Norwegian market are issues made by special purpose companies. Typically, a rig or a vessel is incorporated in a wholly owned subsidiary by the parent company. In cases like this, the parent company is taken to be real debtor. For some issues it is explicitly stated in the loan documents that a parent company is guaranteeing the issuer. After accounting for such relationships, the sample was narrowed to a preliminary sample of 253 issuers. A brief overview of the filtering process, and a list of some firms left out because of such connections, can be found in the appendix of this thesis. In addition, some adjustments were made based on the weekly credit reports. One company, Aker Solutions was added back to the sample because of updated rating information. Tele 2 AB was also left out because it was rated Investment Grade at the issue date (DNB Markets, 2012).

5.2 Accounting information

Most of the accounting information used in this thesis has been collected from the Centre for Applied Research at NHHs (SNF) accounting database. The SNF database covers accounting information from 1993 to 2011 of nearly all the companies registered in the Brønnøysund Business Register Centre. As described earlier, this thesis concentrates on using information available around the issue date to help investors with the default risk analysis. The timing of the information gathering is thus important for the purpose of prediction. As a base year for information, the accounting year prior to the issue year is chosen as the year in which balance sheet and income statement- information is collected. For some firms, this was not manageable, mainly because the issuing company was founded in the issuing year. There is generally evidence from the default incidents that this involves a good deal of companies that financed its start-up phase. Consequently, some adjustments had to be made to gather a sample that was large enough to perform a statistical analysis[15].

All foreign firms and a good part of the Norwegian companies lacked adequate data in the SNF database. Thus, financial data was collected manually for fifty-nine companies, which did not appear in the SNF database, or had figures that were not reliable. Accounting information for seven companies was extracted from the international accounting database Orbis. For these companies, I could not find the annual reports by searching through Newsweb[16], or on the respective company's website.

It is also useful to include group figures when a group structure exist, because pure accounting numbers for subsidiaries or parent companies tends to be quite misleading of what is actually going on in the business. The group as a whole is considered the real borrower if a subsidiary or a parent company in the group is registered in Stamdata as the borrower. Of the manually collected annual reports, some were cases where only the annual report from the subsidiary or the parent company was available in the SNF database.

For the manually collected annual reports, many of the firms reported their annual accounts in foreign currency. Year-end exchanges rates were extracted from DataStream to convert the

[15] A list comparing the issue year and the accounting year is found in the appendix.

[16] Newsweb is a webpage operated by the Oslo Stock Exchange that archives information disclosures from listed issuers.

balance sheet numbers into NOK. To convert the numbers from the income statements, daily average exchange rates were calculated and used to convert the line items. The method used is similar to the current-method used in both US. GAAP[17] and in IFRS to translate financial statements of subsidiaries reporting in another currency into the financial statements of the parent company (Goedhart, Koller et al., 2010). The accounting information extracted from Orbis was translated from USD into NOK using the same exchange rates as for the manually collected reports. The accounting numbers from the manually collected annual reports have been defined in the same way as in the latest documentation and quality check on the database performed by Berner, Mjøs and Olving (2013).

Finally, it is worth noting that if more time had been available for this thesis, then perhaps a couple of companies could have been supplemented to the final sample, and a more detailed set of variables could have been collected. It is unlikely that the sample would have been any larger if a different base year had been chosen. The decision to use information available at the time of issuance was chosen for both practical reasons, and because of the low liquidity in many of the bond issues in Norway.

[17] United States Generally Applied Accounting Principles.

5.3 Choice of independendt variables

As previously mentioned, the data gathering of financial variables has been quite challenging because of little available and sometimes thin financial data for a large part of the preliminary sample. This sets a clear limitation of what variables that can be included as predictors of default. For each issued bond, issue specific variables are collected. This is done because an issue can be perceived more or less attractive depending on the contractual features of the bond's indenture. This type of information was extracted from the Stamdata database.

The variables contained in the different versions of the SEBRA-model have been used a starting point for finding issuer specific variables predicting default. The end of this chapter describes the chosen variables from the SEBRA-model in more detail. Several other possible explanatory variables of default were also collected. The inspiration for the other possible explanatory variables were taken from the previous mentioned studies on default and bankruptcy prediction. These variables are extracted from the balance sheet and income statement line items, as well as combining the issue specific variables extracted from the Stamdata database with accounting figures.

Ideally, it would have been useful to extract averages and standard deviations for some of the variables prior to issuance, for example to measure corporate performance over time, and to get a sense of the fluctuations in earnings. However, this has not been possible due to many firms being start-ups, or firms being very different from year to year due to the presence of merger and acquisitions.

Another concern that came while looking through the distribution of the variables was that many companies were start-ups that made their first real debt financing through the High Yield bond market. Thus, some of the firms had debt levels and equity ratios that were not representative for their ratios after the bond issue. Investors will generally only invest in the bonds of a company if they think that the company can handle the debt level they receive after the bond issue is made. To correct for this problem, the issued amount in each issue is added to both the debt level and the total assets of each company. This correction affects both the reported debt level, equity ratios, and liquidity ratios. Since the different business performance measures are supposed to measure the historical performance of each issuers, the original debt level and the original size of the company, are used when computing these ratios. I recognize that this correction are not a perfect substitute for the equity ratios and debt levels after the bond issue. It could be that some of the firms issued a mixture of debt and equity at the same time to finance their investments, or that a later bond issue was already planned and marketed to the investors with a later issue date.

5.3.1 Issue specific variables

Coupon: One should expect that the more risky the issuing firm is perceived, the larger the coupon rate of the issue. Coupon rates will generally vary with the overall interest level prevailing in the financial markets. To correct for the general interest rate level at the time of issuance, the relevant reference rate for the currency in which the bond is denominated is subtracted from the observed coupon rate. The most common reference rates used in the Norwegian bond market is the 3-month NIBOR interest rate for issues in NOK, and the 3-months LIBOR interest rate for issues in USD. The final sample consists of issues in NOK and issues in USD only[18].

Two of the bonds in the final sample were zero-coupon issues, a bond issued by Petrolia ASA, and a bond issued by Banetele AS. For the Banetele bond, it was impossible to calculate the yield to maturity of the bond because the loan documents were missing in Stamdata. The yield to maturity at the issue date was used as a proxy for the coupon rate in the Petrolia case.

Convertible versus non-convertible: Convertible bonds will generally carry a coupon rate that is lower than a regular bond issue, if the issue is similar in all other aspects (Berk and DeMarzo, 2011). In order to adjust for a convertible provision in the bond indenture, a dummy variable is generated that exhibits one if the issue has a convertible provision. Firms that find it difficult to raise equity at a fair price frequently use convertible bonds, typically high growth and start-up firms. This makes it interesting to test if convertible bonds issues are more prone to default. However, some firms issue a mixture of convertibles and regular bonds. This could cause this effect to be less obvious.

Issued amount: Grammenos, Nomikos and Papaostoulo (2008) found that the amount raised divided by total assets was a significant variable when predicting the probability of default for shipping High Yield bond issues. Although their sample was a small one, and consisted only of shipping companies, the variable is included as a supplement to the pure issuer specific

[18] In the preliminary sample, one bond was issued in DKK and another bond was issued in EUR.

variables. One should be cautious when interpreting the results regarding this variable because some firms issue series of bonds at different dates, and the time-period between the issues can seem arbitrarily. Going through these details, and finding out the total issue volume of debt financing that is communicated to investors at the issue date, is an almost impossible task.

Not Matured: In order to perform the analysis on a sample with both matured issues and issues that are still viable assets, a dummy variable is generated. The variable is one if the issue is still a viable asset as of 01.10.2013.

Seniority and type of security for each bond are also clearly relevant when gauging the potential for possible losses in case of default. According to Håvik (2012), expected default frequency is constant across seniority and rating class. Consequently, the security and seniority of each bond is not included as potential determinants of financial distress. These contract specifications are certainly highly relevant when one is to conduct a recovery rate analysis. It is also rather difficult to extract these specifications from Stamdata in a consistent way without having to look into each loan document manually.

5.3.2 SEBRA variables

The starting point for choosing the issuer specific variables is the before mentioned SEBRA-model. The SEBRA-model has performed well in predicting bankruptcy on Norwegian companies through several periods and applications. However, the model has not been directly applied to defaults. In fact, Bernhardsen, Eklund and Larsen (2001) states that they originally wanted to estimate the probability of a company defaulting, but due to data limitations they decided to estimate the probability of bankruptcy instead. As noted by Bernhardsen (2001), his choice of explanatory variables in the original SEBRA-model must be viewed as suggestions. Bernhardsen also states, that any model of default or bankruptcy-prediction should contain a measure of liquidity, a measure of solidity, and some measure of business performance. In this thesis, the predictive variables are defined as in the publication in Economic Bulletin 3.2007 published by the Central Bank of Norway. In this publication, the authors propose two versions of the SEBRA-model, SEBRA-basic and SEBRA-extended. Some of the variables in SEBRA-extended proved to be difficult to define in a consistent way from the manually collected annual reports. However, the variables of the basic version of the model proved to be much more accessible to foreign companies and companies reporting under different reporting standards. It is also worth noting that the dependent variable is different in the SEBRA-model compared to how the dependent variable is defined in this thesis. The dependent variable in this study is simply issued in the Norwegian bond market and defaulted, or non-defaulted, before October 2013. A description of the SEBRA variables that are used follows:

Business performance: In the SEBRA model the variable measuring business performance is the ratio of ordinary profit before depreciation and write-downs divided by total debt. It is not totally clear what is meant by ordinary profit, and the definition of what is considered extraordinary items can vary between firms and reporting standards. The definition that is used for generating the variable is the following:

$$Performance = \frac{Ordinary\ profit\ after\ tax + depreciation\ and\ amortization}{Total\ debt\ before\ bond\ issue}$$

From the SNF database, the variable *"aarsrs"* is used as ordinary profit after tax, *"anlvurd"* is used as depreciation and amortization, and "*gjeld"* is used to measure total debt before the bond issue.

Leverage: The measure of leverage in SEBRA-model is the book value of equity divided by total assets:

$$Equity\ ratio = \frac{Book\ value\ of\ equity}{Total\ assets + bond\ issue}$$

From the SNF database, the variable "*ek"* is used as the book value of equity, and the variable *"sumeiend"* is used for total assets.

Liquidity: The chosen liquidity measure of the SEBRA- model is the following:

$$Liquidity = \frac{Liquid\ assets - short\ term\ debt}{Operating\ revnues}$$

Due to the presence of firms being in an establishment phase, a good part of the final sample had operating revenues equal to zero. To overcome this problem, and to avoid cutting observations, the variable is adjusted to the following:

$$Liquidity = \frac{Liquid\ assets - short\ term\ debt}{Total\ assets + bond\ issue}$$

The adjusted variable measures in essence the same phenomenon, that a smaller cash reservoir of the company relative to its size will predict a greater likelihood of financial distress. From SNF, “*cash”* is used for liquid assets, “*kgjeld”* is used for short-term debt, and “*sumeiend”* is used for total assets.

Lost equity: An indicator variable is included which is supposed to measure if the observed equity ratio is due to accumulated earnings, or if the ratio is maintained by the raising of new equity. This indicator variable is one if the book value of equity is less than paid in equity, and zero otherwise. When the book value of equity is less than paid in equity it indicates to some degree that the firm has not been able to accumulate profits and is badly run. From SNF, “*inn_ek*” is used as paid-in equity capital.

Size: Previous studies have found that the probability of default and bankruptcy, are lower for larger companies. Hence, a measure of size is included as a possible alternative explanatory variable. This variable is included in the SEBRA-extended model by taking the logarithm of total assets:

$$Size = \ln(Total\ Assets + bond\ issue)$$

From the SNF database, “*sumeiend”* is used as a measure of total assets.

The variables trade accounts payable as a percentage of total assets, as well as unpaid taxes and public dues as a percentage of total assets, that appears in SEBRA-extended had to be dropped because of difficulties finding the relevant items in the manually collected annual reports. They were present in some of the collected annual reports, but these balance sheet figures were often consolidated under items like other short-term debt, making it impossible to determine their presence and size. The relevance of these variables for large multinational corporations is also up for discussion. Bernhardsen (2001) states that the main reason for including public dues and unpaid taxes is that bankruptcy proceedings are often initiated by the revenue authorities, and that the level of trade credit varies a lot between industries.

Industry variables: In the SEBRA-model, yearly industry effects is captured by the industry mean of the book equity ratio, as well as the industry mean and the standard deviation of the business performance measure. These ratios are calculated from the yearly-consolidated annual report dataset found in the SNF database. The 2-digit industry NACE[19] code version published in 2007 is used for grouping the observations by industry. Foreign companies, and some of the Norwegian companies, did not have NACE codes registered. These companies are compared with a comparable firm when defining the missing codes. Thus, all the firms in the sample are classified by the 2-digit NACE code.

5.3.3 Other possible explanatory variables

Tangibility: One should suppose that the greater the value of tangible assets compared to the total assets of the company, the greater is the capacity for generating cash flow from operations and thus for the company to avoid financial distress. However, Huffman and Ward (1996) found that the larger the value of collateralized assets to the book value of assets, the greater is the probability of default. The opposite can also be true, in that market participants generally speak of companies that have a larger share of standardized assets with proven technology to be safer bets than companies that is more dependent on intangible assets for generating their stream of revenue (Håvik, 2012). The ratio is also highly relevant when the bond investor assess the expected recovery rate of an issue. The ratio used is the following:

$$Share\ of\ Tangible\ Assets = \frac{Property, plant\ and\ equipment}{Total\ assets}$$

From SNF, the variable, "*vardrmdl"* is used to measure property, plant and equipment. An alternative to this measure is to calculate the share of intangible assets to total assets. Note that the issued amount is not added to the total assets of the issuer.

Alternative measure of performance: EBITDA divided by total assets is included as an alternative measure of corporate performance. This is done for two reasons, the first being that the measure of performance in the SEBRA-model can be highly inflated if the debt level prior to the first bond issuance is low compared to EBITDA, and second because EBITDA is a measure that is more suitable when comparing companies with different capital structures. EBITDA serves as a proxy for the operating cash flow generated by a company. The ratio is calculated as follows:

[19] The NACE standard is the standard used by the EU to classify companies into industries.

$$\frac{EBITDA}{Total\ Assets} = \frac{Operating\ profit + Depreciations, Amortization\ and\ Write\ downs}{Total\ assets}$$

For ordinary profit, "*driftrs"* is used. "*anlvurd"* is the variable used for deprecations, amortizations, and write-downs.

Interest coverage: An interest coverage measure is included. This measure can be defined in several ways. One possible financial indicator is EBITDA divided by interest expenses, but for this particular sample, there is a problem with generating missing values if the variable is constructed in the usual way. This is because many of the firms reported their interest rate cost to be zero in the last available financial statement before the issue date. The inverse of the interest coverage ratio is applied instead. It captures the same information, but one must interpret the outcome of the analysis in a different way:

$$\frac{1}{Interest\ covereage} = \frac{1}{\frac{EBITDA}{interest\ expenses}} = \frac{interest\ expenses}{EBITDA}$$

A concern is that many of the start-up companies had debt levels and subsequently interest expenses that were not representative of the interest expense going forward because the bond issue was the first major debt financing arrangement of the company. The variable is therefore calculated by adding a computed interest payment, after the bond issue to the interest expense from the annual reports. This is done by multiplying the coupon of the issue by the issued amount.

From SNF "rentekost" is used for interest expense, and EBITDA is applied as before.

Other accounting ratios: In addition, three accounting ratios are collected with inspiration from Altman (1968). Current assets divided by current liabilities (commonly known as the current ratio), working capital to total assets, and EBIT divided by total assets.

Start-up: One should suspect that start-up companies would exhibit a greater probability of default on their debt. Older companies are typically larger, use more recognized and well-known technology, have more experience with internal control, and the managers are usually more experienced. It could be that a merger or an acquisition dampens these effects for some companies. Nevertheless, it is likely that the risk of default is greater for start-up companies than for companies with a longer operating history. The variable is constructed by subtracting the establishment year from the accounting year, and grouping companies with an age lower or equal to four years in a start-up phase category. This dummy variable exhibits zero if the company is older than four years, and one otherwise. Similarly, SEBRA-extended use indicator variables for up to eight years since establishment. The SEBRA specification is not used because of the problem with applying too many covariates relative to the sample size.

Crisis: Many defaults occurred in the years 2008 and 2009 after the record issue year of 2007. The main reason for this wave of defaults was the financial crisis, which caused cyclical high-leveraged companies to fall into financial distress. Since defaults also have been found to be highly correlated with economic growth, a dummy variable is generated that is one if the bond is issued in 2006 or 2007, and zero otherwise. The reason for imposing a variable like the crisis dummy variable is to test if the issues made in the years preceding the crisis were issues that exhibited a greater likelihood of defaulting. If this variable turns out to be positive and significant, then maybe investors misgauged the credit risk in many of the issues in the high volume issue years preceding the crisis. A different method of correcting for macroeconomic factors would have been a yearly dummy variable, but in the final sample, there is a problem of applying such a specification because of the small sample size.

Market value of equity for publicly traded firms: 89 of the companies that makes up the final sample had publicly traded equity around the time of their respective bond issues. However, it is not a good idea to mix book values of equity with market values of equity when analysing default risk. As an example, Altman (2002) prefers estimating the Z-score with two different models, with the book value of equity for private firms, and using the market value of equity for publicly traded firms. Although two distinct samples are not possible because of the already small sample size, a measure of market-based equity-ratio is used to collect a subsample of companies that had available data for the market value of equity at the end of the accounting year prior to issuance. These market values are the reported values of “Market Value of Capital” (MVC) or “Market Value” (MV) from the last trading day observed in the accounting year. The information is extracted from DataStream.

As explored in the Merton and KMV-model, market based leverage compared to the asset volatility of the firm gives us a market based assessment of the likelihood of default. Asset volatility can be estimated from the company’s equity volatility and the company’s debt to value ratio. To estimate equity volatility with reasonable accuracy, one need at least a couple of years of equity prices. Because of some firms that went public the year before issuance, and because of an already low sample size, the asset volatility and the corresponding distance to default is not brought in as a possible covariate. The book value of debt is used as a proxy for the market value of debt. The market based leverage measure is calculated as:

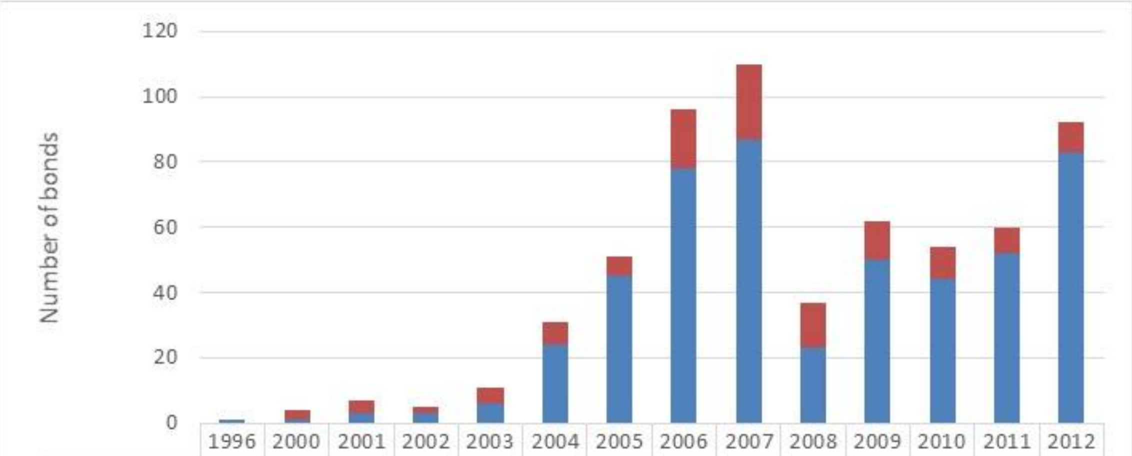
$$Market\ leverage = \frac{Book\ value\ of\ debt + bond\ issue}{Market\ value\ of\ equity + (Book\ value\ of\ debt + bond\ issue)}$$

5.4 Sample overview

5.4.1 Preliminary sample of bond issues

Figure 7 gives an overview of what type of bonds that are included in the preliminary sample, along with the issue year of the bonds. Most of the issuers in the sample issued bonds after 2003, and there is not much data on bonds issued in previous years in Stamdata. Most of the bonds are bonds without a convertible provision. This does not mean that the contractual features of the regular bonds are simple. Many bonds are callable, and include a variety of covenants that sets limits on financial ratios, and/or possible actions taken by the borrower. These details are not explicitly listed in the Stamdata database, so one need to go through each loan document to gather such information. Since the scope of this thesis is to examine the default risk of the borrowers, I chose not to dig into these details. A total of 253 issuers and 621 bonds make up the preliminary sample. 500 of the bonds are regular bonds without a convertible provision, and 121 of the bonds are convertible issues.

Figure 7 Issue year and issue types-preliminary sample



	1996	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Convertibles		3	4	2	5	7	6	18	23	14	12	10	8	9
Bonds	1	1	3	3	6	24	45	78	87	23	50	44	52	83

Table 2 gives an overview of the observed defaults by year and a split up by the type of default covered by the Moody's definition. Credit events covered by the Moody's definition were found for 160 bonds in the preliminary sample.

Table 2 Defaults by year and category preliminary sample by bonds

Type of default	2006	2007	2008	2009	2010	2011	2012	2013	Total
Moody's category 1)		1	9	16	5	7	6	2	46
Moody's category 2)			6	7	1				14
Moody's category 3)	1	3	13	52	12	9	5	5	100
Sum	1	4	28	75	18	16	11	7	160
Percentage	0,6 %	2,5 %	17,5 %	46,9 %	11,3 %	10,0 %	6,9 %	4,4 %	100,0 %
Average days to default									685

We can see that the majority of the defaults in the Norwegian High Yield bond market have been a Moody's category 3) default. This category is rather broad, and exhibits both complex restructurings, and other simple amendments to the bond contract, like postponement of the maturity date. Some judgement was involved in classifying the observed defaults in one of the category. In cases were the category was not very clear, the category judged to be the best description of the incident was chosen. Generally, if there exists a restructuring proposal, which both consists of a delayed payment and a proposal of exchange of debt into equity, the credit event was classified as being in the distressed exchange category. It is worth noting that some of the firms that had credit events categorized in category 1) and 3), also filed for bankruptcy at a later stage. Only fourteen of the observed defaults were incidents where a bankruptcy filing was the first possible information about the default. Finally, it is worth noting that 86 issuers compromise the 160 different bonds that is found to be involved in a default.

We see that most of the defaults occurred when the financial crisis was at its worst in 2008 and 2009, especially the year of 2009, which accounts for nearly half of the defaults found. Much of the outstanding volume of High Yield bonds that were issued in the big issue years of 2006 and 2007 went into trouble because of the financial crisis. The average time from issuance to default is 650 days, or slightly under two years from the issue date. This result must be seen in conjunction with the large volume in 2006 and 2007. If another period had been covered, it is likely that the average time to default would have been lower.

We can also see which industries that make up the preliminary sample based on the industry classification in Stamdata. The industries Oil and Gas, Service, Shipping, and the broad Industry classification, are the industries that have experienced most of the defaults. In addition, these industries dominate the issuer landscape in the Norwegian corporate bond market and the business landscape in Norway in general. An industry overview per issue is provided in table 3.

Table 3 Industry overview preliminary sample by issues

Industry	Number of issues	Percentage of total	Defaulted issues	Percentage of issues defaulted
Oil and Gas	219	35,3 %	62	28,3 %
Shipping	142	22,9 %	16	11,3 %
Industry	94	15,1 %	23	24,5 %
Service	59	9,5 %	32	54,2 %
Property	25	4,0 %	7	28,0 %
Telecom/IT	23	3,7 %	9	39,1 %
Fishery	22	3,5 %	8	36,4 %
Transportation	12	1,9 %	1	8,3 %
Pulp and Paper	10	1,6 %	1	10,0 %
Media	6	1,0 %	0	0,0 %
Wholesale and Retail	5	0,8 %	1	20,0 %
Food and Beverages	4	0,6 %	0	0,0 %
Total	621	100,0 %	160	25,8 %

The oil and gas industry, and the shipping industry, dominate the total number of issues in the final sample with a percentage share of around 35% and 23%. As previously mentioned, these industries dominate the issuer landscape in the Norwegian bond market, and are thought of as being capital heavy industries. Shipping bonds appears to be relatively safe compared to the other industries if we look at the percentage number of bonds defaulting. 11,3% of the bonds issued by shipping companies in the preliminary sample have experienced a default. This is significantly lower than the percentage of defaults experienced by other large groups of companies like the oil and gas sector, the service sector, and the industry sector. The service industry has the highest default rate by number of issues. Companies that are classified in this industry are mostly oil-service companies. About a quarter of the issues that is included in the final sample have been involved in a default, this high default rate is not surprising given that the final sample covers firms assumed to be High Yield issuers.

Table 4 provides the same sort of industry classification broken down by issued amount and the percentage of issued amount defaulting. The average size per issue is also shown.

Table 4 Industry overview preliminary sample by issued amount

Industry	Issued amount MNOK	Defaulted amount MNOK	Percentage of amount defaulted	Average size per issue
Oil and Gas	151171	30893	20,4 %	690
Shipping	65535	4783	7,3 %	462
Industry	43898	9387	21,4 %	467
Service	21390	12024	56,2 %	363
Property	8337	826	9,9 %	333
Pulp and Paper	7980	385	4,8 %	798
Fishery	7960	2545	32,0 %	362
Transportation	6549	150	2,3 %	546
Telecom/IT	1981	517	26,1 %	86
Media	1900	0	0,0 %	317
Food and Beverages	1450	0	0,0 %	363
Wholesale and Retail	640	40	6,3 %	128
Total	318790	61550	19,3 %	513,35

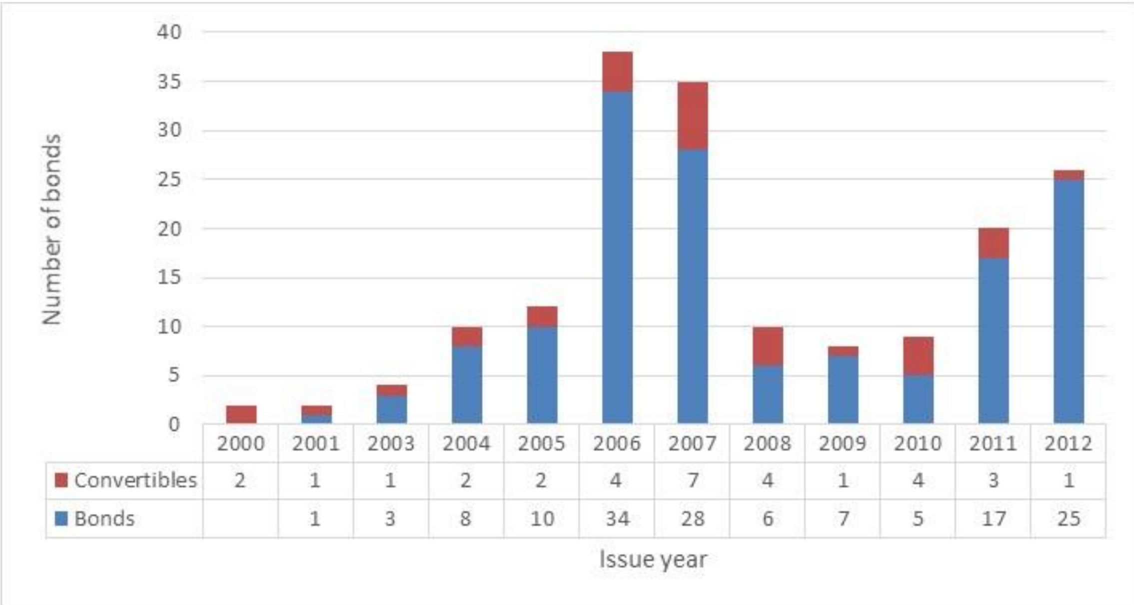
The service industry also has the highest percentage defaulted amount if the default rate is measured in terms of issued amount. The average issued amount per bond in the final sample is about 500 million. We also see that the average issued amount of the oil and gas industry comes in second. Only pulp and paper has a higher average issued amount per bond, but this calculation is based on only ten issues. About one-fifth of the issued volume in the final sample have experienced a default by October 2013. The measure of defaulted amount do not coincide with the actual losses to investors, because one need to factor in the recovered amount in each of the observed default. It is beyond the scope of this thesis to calculate recovery rates for the defaulted bonds.

Nearly all of the bonds in the preliminary sample were fixed coupon issues (306 bonds), or floating rate notes (299) bonds. Thirteen of the issues were zero coupon issues and one bond was a step up interest issue. 466 of the bonds were registered in Stamdata as issued by companies domiciled in Norway (75%).

5.4.2 Final sample of issuers

After coupling the information from Stamdata with accounting information, the final sample shrank to 176 issuers and 176 bond issues, according to the process described earlier in this chapter. A list of the firms excluded due to unavailable financial data can be found in the appendix of the thesis. The final sample includes 59 firms that experienced a default during the period covered. Although it was not possible to gather financial information from around the issue date for 77 companies, the final sample is still quite representative for the issuers, and the issue characteristics in the Norwegian High Yield bond market. The final sample includes companies within all the industries observed in the preliminary sample. The distribution of bonds and issue years present in the final sample are given in figure 8.

Figure 8 Issue year and issue types-final sample



Of the 176 issues, 144 bonds were regular bond issues without a convertible provision, and 32 bonds were convertibles. We see that the final sample provides fairly the same distribution of issue years and bond types compared to the preliminary sample.

Table 5 gives an overview of defaults by year, and a split up by the type of default given by the Moody's definition, observed in the final sample.

Table 5 Defaults by year and category-final sample

Type of default	2006	2007	2008	2009	2010	2011	2012	2013	Total
Moody's category 1)		1	1	7	1	3	2	1	16
Moody's category 2)			2	2					4
Moody's category 3)	1	2	7	19	4	2	2	2	39
Sum	1	3	10	28	5	5	4	3	59
Percentage	1,7 %	5,1 %	16,9 %	47,5 %	8,5 %	8,5 %	6,8 %	5,1 %	100,0 %
Average days to default									773

The industry distribution is pretty much the same in the final sample as in the preliminary sample. Table 6 reports various issuers and defaulted issuers by industry.

Table 6 Industry overview-final sample

Industry	Number of issuers	Percentage of total	Defaulted issuers	Percentage of issuers defaulted
Oil and Gas	50	28,4 %	17	34,0 %
Shipping	39	22,2 %	8	20,5 %
Industry	29	16,5 %	10	34,5 %
Service	16	9,1 %	11	68,8 %
Telecom/IT	13	7,4 %	5	38,5 %
Property	10	5,7 %	2	20,0 %
Fishery	8	4,5 %	4	50,0 %
Transportation	4	2,3 %	0	0,0 %
Food and Beverages	3	1,7 %	0	0,0 %
Pulp and Paper	2	1,1 %	1	50,0 %
Media	1	0,6 %	0	0,0 %
Wholesale and Retail	1	0,6 %	1	100,0 %
Total	176	100,0 %	59	33,5 %

All the industries that were present in the preliminary sample are still present in the final sample. Twenty-seven defaulting firms were lost during the financial gathering process, and fifty non-defaulting firms had to be omitted from the final sample due to unavailable financial data. About one-third of the issuers in the final sample experienced a default during the period covered.

132 (75%) of the issuers were reported to have their domicile in Norway, while the rest of the firms were reported to be domiciled in foreign countries like Bermuda (14 issuers) and Sweden

(6 issuers). The rest of the issuers were spread in small numbers across different countries. It should be noted that it was generally more difficult to gather financial information for the foreign issuers This causes a slightly biased sample towards Norwegian issuers, but the final sample has a share of issuers that is representative with the observed share of foreign versus Norwegian companies found in the preliminary sample. We can see that although many cases were lost due to insufficient data, much of the variation in the preliminary sample is captured by the final sample. A list of all the issuers that are included in the final sample can be found in the appendix.

5.4.3 Descriptive statistics

Table 7 shows descriptive statistics for the collected SEBRA variables. Skewness and Kurtosis are reported to gauge the normality of the ratio distributions. A positive skewness indicates that the distribution is skewed to the right, while a negative skewness indicates that the distribution is skewed to the left. On the other hand, kurtosis measures the degree of fat tails in the distribution. The value of the skewness measure is zero if the variable is drawn from the normal distribution. Similarly, kurtosis should come out with a value of three if the variable is drawn from a normal distribution (Bodie, Kane et al., 2011).

Table 7 Descriptive statistics SEBRA variables

Variable	N	Mean	Median	Max	Min	Std. Dev	Skewness	Kurtosis
Performance	176	-0,42	0,04	5,79	-71,06	5,40	-12,86	168,94
Liquidity	176	-0,05	-0,04	0,43	-0,52	0,18	-0,11	3,12
Equity Ratio	176	0,32	0,31	0,88	-0,17	0,18	0,18	3,17
Size of Company	176	14,52	14,52	18,03	10,39	1,55	0,01	2,62

The variable measuring business performance includes some heavy outliers, especially at the left tail of the distribution, and the distribution is skewed to the left. Many of the firms that exhibits extreme values on this variable are categorized as start-up companies that, as expected, experienced operating losses in their first years. For the rest of the variables, assuming normality seem reasonable.

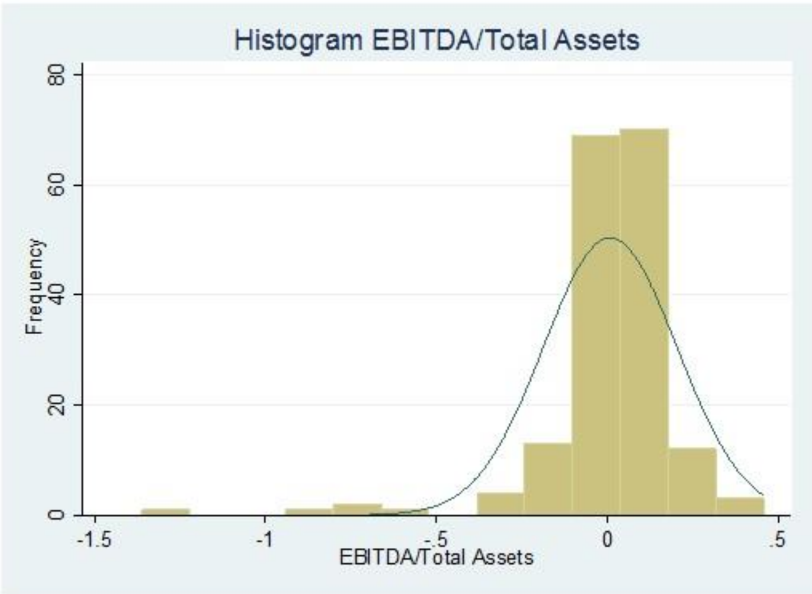
Table 8 shows descriptive statistics for each of the proposed alternative variables:

Table 8 Descriptive statistics Alternative variables

Variable	N	Mean	Median	Max	Min	Std. Dev	Skewness	Kurtosis
Share of Tangible Assets	176	0,47	0,51	0,97	0,00	0,32	-0,14	1,54
EBITDA/Total Assets	176	0,01	0,03	0,46	-1,36	0,20	-3,16	19,81
Interest Coverage Ratio	176	-0,64	0,17	21,64	-46,24	5,48	-4,18	34,47
Coupon	175	0,05	0,05	0,15	-0,04	0,03	0,27	3,49
Issued amount/ Total Assets	176	0,81	0,21	38,39	0,00	3,35	9,37	98,25
Working Capital Ratio	176	0,07	0,07	0,58	-0,45	0,15	0,05	4,16
EBIT/Total Assets	176	-0,03	0,01	0,29	-1,43	0,20	-3,57	21,28
Current Ratio	176	4,30	1,47	148,92	0,07	13,08	8,48	88,39
Market Leverage Ratio	89	0,47	0,49	0,91	0,02	0,20	-0,13	2,62

Six variables stands out from the kurtosis and skewness measure as being clearly non-normally distributed; the SEBRA performance ratio, EBITDA divided by total assets, the interest coverage ratio, issued amount divided by total assets, EBIT divided by total assets, and the current ratio. A graphical distribution for EBITDA/Total Assets is provided in figure 9 as an example of the distribution of one of the collected variables.

Figure 9 Histogram EBITDA/Total Assets



The distribution is skewed to the left, and we find some extreme values at the left of the distribution. The normal curve is drawn to compare the distribution with the distribution that appears if we assume normality. The presence of outliers could constitute a problem when performing regression analysis, and when performing other statistical analysis. Assuming normality, or not, also serves as a guideline for choosing the right statistical tool.

Frequencies for each of the indicator variables are provided in table 9.

Table 9 Frequency table indicator variables

Lost Equity	Frequency	Percent	Not Matured	Frequency	Percent
0	111	63,07	0	115	65,34
1	65	36,93	1	61	34,66
Total	176	100	Total	176	100
Start-up			Convertible Bond		
0	103	58,52	0	144	81,82
1	73	41,48	1	32	18,18
Total	176	100	Total	176	100
Crisis					
0	103	58,52			
1	73	41,48			
Total	176	100			

Sligthly over 40% of the sample is made up by companies that were founded less than five years from the accounting year[20]. The presence of many start-up companies, together with the relative high amount of issues coming up to the financial crisis, make the sample particulur risky in terms of default risk. It is also worth noting that 65% off the issues have either matured, have been called, or the issuer has filed for bankruptcy.

[20] Or less than six years from the issue year.

6. Methodology

In this chapter, the statistical tools were are used to analyse the sample of defaulting, and non-defaulting companies, from the Norwegian corporate bond market are introduced.

6.1 Wilcoxons rank-sum test

One possible way to compare the difference between variables of different groups is to perform the student t-test, which tests if there is statistically significant difference between the means of two groups. As mentioned in the previous chapter, the sample is clearly not normally distributed among some of the variables. One test that is more robust to outliers, and still can be used to compare the values of variables between two populations, is the Wilcoxon rank-sum test (Keller, 2012). The test technically ranks the observation of the two groups that we wish to compare from the smallest observed value to the largest observed value. It then sums the rank number of these two groups two form a test statistic that is set arbitrarily to be the rank sum of one of the groups. The following hypothesis can then be tested:

H_0: The location of the two populations is the same
H_1: The location of one population is different from the location of the other population.

For a sample size larger than ten observations, the test statistic is approximately normally distributed with a mean of $E(T)$ and a standard deviation of σ_T:

$$E(T) = \frac{n_1(n_2+n_2+1)}{2} \text{ And } \sigma_T = \sqrt{\frac{n_1 n_2(n_1+n_2+1)}{12}}$$

$E(T)$ is the expected value of the test-statistic (T), n_1 is the number of observations in group one, and n_2 is the number of observations in group two.

The standardized test statistic becomes:

$$z = \frac{T - E(T)}{\sigma_T}$$

The Rank-sum test is used in the analysis section as a tool when comparing the medians of the chosen independent variables between the defaulting and non-defaulting issuers.

6.2 Regression analysis

6.2.1 The Linear Probability Model

Default is a binary dependent variable, thus we cannot use ordinary multiple regression analysis when predicting default. One way to deal with a binary dependent variable is to use the linear Probability model (LPM). If the zero conditional mean assumption holds[21], then it is true that:

$$E(y|\boldsymbol{x}) = \beta_0 + \beta_1 x_1 + \cdots \beta_k x_k$$

Where $\boldsymbol{x}$ is a vector of covariates, β_k are the coefficients of each of the independent variables. If the dependent variable is binary, that is taking on the values zero or one, it is always true that:

$$P(y = 1|\boldsymbol{x}) = E(y|\boldsymbol{x}) = \beta_0 + \beta_1 x_1 + \cdots \beta_k x_k$$

Which says that the probability of the dependent variable taking on the value one is linear in the set of explanatory independent variables. The most important drawbacks with a model like this is that the predicted probabilities can come out with a value greater than one, and that the effect of a change in the predicted probability of similar changes in the explanatory variables are constant no matter what the initial value of the other independent variables (Wooldridge, 2009). This is particular a problem in the collected final sample because of the presence of outliers. The predicted probabilities from the analysis are very likely to be above one, or negative for some of the companies, and the corresponding predictions become meaningless.

[21] $E(u|x_1, \dots, x_k = 0)$ In words: The expected value of the residual is zero regardless of the value of the predictors.

6.2.2 The Logit Model

One way to avoid some of the LPM limitations is to define a function who assures that the predicted probabilities takes on values between zero and one. In general:

$$P(y = 1|\boldsymbol{x}) = G(\beta_0 + \beta_1 x_1 + \cdots \beta_k x_k) = G(\beta_0 + \boldsymbol{x\beta})$$

Where $\boldsymbol{x\beta} = \beta_0 + \beta_1 x_1 + \cdots \beta_k x_k$

There are two specific forms of the function G that have dominated the applications when researchers needs to deal with a dichotomous variable; the Logit model, and the Probit model. The Probit model is not discussed further, but the analysis of the Probit model is quite similar compared to the Logit model. The primary difference is that the function G is the cumulative normal function in the Probit model, while the function G in the Logit model is the logistic function:

$$G(z) = \frac{e^z}{1 + e^z} = \frac{1}{1 + e^{-z}}$$

Where z is any real number. One can see from this function that whatever the value of z, the function $G(z)$ returns a value between zero and one (Wooldridge, 2009). The above equation returns a value between zero and one because, the limit of the function $G(z)$ as z approaches infinity is one, and the limit of the function $G(z)$ as z approaches negative infinity is zero.

The logistic model estimated is:

$$P(y_i = 1|\boldsymbol{x}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_{1i} + \cdots \beta x_{ki} + u_i)}}$$

Where $P(y_i = 1|\boldsymbol{x})$ is the probability that observation y_i, given the vector of independent variables, will take on the value of one.

Since a model like this is nonlinear, the coefficients cannot be estimated by ordinary least squares (OLS). Instead, the model is estimated by maximum likelihood estimation (MLE). The basic principle of maximum likelihood estimation is that the parameters of the model are chosen to maximize a function called the log-likelihood function. The log-likelihood function in the Logit model can be set up as the following function (Brooks, 2008):

$$LLF = -\sum_{i=1}^{N}[y_{\,i}\ln(1+e^{-z_i}) + (1-y_i)\ln(1+e^{z_i})]$$

Maximizing this equation with respect to the parameters in z_i can be done by taking the derivative of LLF with respect to the parameters, and using an iterative process of solving the corresponding equations (Bernhardsen, 2001). In the statistics software program STATA, one can see how the log-likelihood drops at each iteration.

6.2.3 Interpretation of the Logit model

Interpreting the coefficients: Since the logistic function is a non-linear function one must rely on calculus to find the partial effect of a change in one of the independent variables on the dependent variable. However, the direction of the effect is possible to interpret directly. A positive coefficient would imply that a change in the variable would result in a higher probability of $y_i = 1$, and a negative coefficient would imply a lower probability of $y_i = 0$ (Wooldridge, 2009)

Percent correctly predicted: This is a goodness-of-fit measure where we define the predicted value of y_i to be one if the predicted probability is greater than some defined cut-off value, and zero if the predicted probability is less than the cut-off value. Given a set of observation, we can see how well the model predicts the observations to be in the right category. This type of goodness of fit measure can be quite misleading, especially if the model performs poorly in predicting one of the outcomes. Suppose for example that we have a sample of 200 observations with 160 $y_i = 0$, and 40 $y_i = 1$. If we predict 140 of the 160 $y_i = 0$ to be zero (87.5 % correct prediction), we will still get an overall accuracy rate of 70% even if none of the predictions of $y_i = 1$ is correct. It is therefore recommended to gauge the predictive capacity of the model with respect to both categories of observed outcomes.

Pseudo R-squared: Pseudo R^2 is a goodness of fit measure, based on the log-likelihood function. If $L_0$is the log-likelihood function in a model with only the intercept, and L_1 is the log-likelihood function for our estimated model, a Pseudo R-squared goodness of fit measure can be calculated as:

$$\text{Pseudo } R^2 = 1 - \left(\frac{\ln L_1}{\ln L_0}\right)$$

This measure can only take on values between zero and one. The measure has no direct interpretation as the regular R^2 for ordinary least squares. Pseudo R-squared can be used to measure if the model's fit is improved by substituting a model by another, holding the sample constant (Tufte, 2000).

Likelihood ratio-test: The likelihood-ratio test can be used to test if there is a significant change in the model when adding a new independent variable. It is based on the log-likelihood function. Suppose that we call a the log-likelihood of a model with only the intercept L_0, and that we name the log-likelihood of a model including one explanatory variable as L_1.We can then perform a test which tests the following null-hypothesis (H_0), against the alternative hypothesis (H_A):

$$H_0: L_0 = L_1 \;\; H_A: L_0 \neq L_1$$

In words, the log-likelihoods of the two models are the same, or the log-likelihoods of the two models are different from each other. The test statistic is obtained by multiplying the difference in log-likelihoods between the two models by-2:

$$G^2 = -2(L_0 - L_1)$$

Which is approximately chi-squared distributed with degrees of freedom equal to the difference in variables between the two models. It is important that two samples are identical. Hence, one must be careful with missing values when calculating this statistics between different sets of independent variables

Statistical inference: The standard errors provided by maximum likelihood estimation are asymptotic standard errors for which the formula is quite complicated. However, once the standard errors of the estimators are obtained, one can construct z-tests as with ordinary least squares. The test statistic is:

$$z = \frac{\widehat{\beta_J}}{ASE\left(\widehat{\beta_J}\right)}$$

The null hypothesis $H_0: \beta_j = 0$, and the corresponding alternative hypothesis $H_a: \beta_j \neq 0$[22], is kept or rejected, based on the chosen level of significance. With five percent significance level, the critical value becomes 1,96. With a chosen significance level of ten percent, the critical value becomes 1,64.

ROC analysis: An alternative measure of the predictive power of a model is the area under the Receiver Operating Characteristic (ROC) curve. The ROC-curve graphs the sensitivity versus the 1-specificity of a diagnostic test, based on different cut-off values. Sensitivity is the fraction of the positive outcomes that are identified by the diagnosis test, while specificity is the fraction of negative cases that are correctly classified by the diagnosis test. The closer the area under the ROC-curve comes to one, the greater is the predictive capacity of the model.

[22] In a two-sided test.

7. Findings

7.1 Univariate analysis

In this section, the suggested explanatory variables are compared between the groups of defaulted and non-defaulted firms. This is done with the help of the Wilcoxon rank-sum test. The rank-sum test actually tests if a variable drawn from two independent samples comes from a population with the same distribution, but in the following, the results are presented by speaking of median values as the central tendency measure of the two groups. Because of the relatively small population, and correspondingly small sample size, a significance level of ten percent is chosen when performing the analysis. The median and mean values of the SEBRA variables and the Z-statistics from the Wilcoxon rank-sum test are reported in table 10. The difference calculated is the difference between the median value of the non-defaulted group, and the median value of the defaulted group. A positive number, and a positive Z-value, correspond to a median value of non-defaulted group that is higher than the median value of the defaulted group.

Table 10 Rank-sum test SEBRA variables

Variable		Performance	Liquidity	Equity Ratio	Size of Company
Non-defaulted	Median	0,09	-0,06	0,30	14,98
N	Mean	0,13	-0,08	0,30	14,95
59					
Defaulted	Median	-0,04	0,02	0,35	13,51
N	Mean	-1,49	0,01	0,35	13,66
117					
Total	Difference	0,13	-0,08	-0,05	1,47
N	Z-Value	5,80	-3,36	-1,832	5,373
176	P-value	0,0000	0,0008	0,0670	0,0000

All the differences in medians of the SEBRA-basic variables are significant at the ten percent level. The difference in median values of the size and the performance measure is what you would expect from earlier studies and common economic reasoning. Larger companies are often more diversified in terms of economic exposure, use more recognized technology, and have more experienced managers than smaller companies. This could be plausible explanations of why the median value of the size measure is lower in the group of defaulted firms. Firms that do not generate earnings relative to their debt are clearly in danger of falling into financial distress. The median value of the SEBRA performance measure is around 9% in the non-defaulting category, compared to around -4% in the defaulting category. Consequently, the typical defaulted firm performed significantly lower already before the bond issue.

The results from the median comparisons regarding liquidity and solvency are harder to interpret in a logical way. The median value of the liquidity measure is actually higher for the defaulted firms than for the non-defaulted firms. One cannot think of any valid economical explanation of why this result is observed. However, it is worth keeping in mind that the financial data is collected at the time of issuance. One should suppose that firms with a liquidity problem at the time of issue find it hard to issue bonds. The median equity ratio is also higher for the defaulting firms than for the non-defaulting firms. Although firms with less leverage are generally thought of as being more financially robust, a possible explanation for this result could be the relatively high amount of start-up firms defaulting. The equity ratio is higher both when the bond issue is added to total assets from the annual report, and when the bond issue is omitted. Table 11 shows a crosstable between the defaulted category and the start-up category.

Table 11 Crosstable Start-up and Default

Start-up	Non-default	Default	Total
No	79	24	103
Percentage	67,52	40,68	58,52
Yes	38	35	73
Percentage	32,48	59,32	41,48
Total	117	59	176

Thirty-five, or about 60%, of the companies with observed defaults are classified as being in the start-up category. Start-up firms are typically financed mostly by equity and with little use of debt. Hence, these firms have higher equity ratios before they go to the debt market for capital. The issuance of High Yield bonds is one way for these firms to grow and develop their business. Although the debt level from the relevant issue is included in the debt base of these ratio calculations, the ratios do not take into account any additional financing that the firm may acquire from banks etc. This is a reason why one should interpret these results with care.

What about the proposed alternative predictors of failure? Table 12 reports the Z-score from the Wilcoxon rank-sum test, together with the median and mean values of the first four suggested alternative explanatory variables.

Table 12 Rank-sum test alternative variables 1

Variable		Share of Tangible Assets	EBITDA/Total Assets	Interest Coverage Ratio	Coupon
Non-defaulted	Median	0,55	0,07	0,20	0,04
N	Mean	0,50	0,06	-0,30	0,05
59					
Defaulted	Median	0,37	-0,02	-0,39	0,05
N	Mean	0,42	-0,08	-1,32	0,06
117					
Total	Difference	0,18	0,09	0,59	-0,01
N	Z-Value	1,56	5,85	3,34	-2,34
176	P-value	0,1182	0,0000	0,0008	0,0193

The difference between the two groups is not statistically significant when it comes to the median value of the share of tangible assets. Thus, we cannot say from a univariate perspective that the non-defaulted companies had a higher share of tangible assets in their balance sheets compared to the defaulted group.

The median value of the coupon measure is statistically significant, and the difference is about one percent. That is, the defaulted firms had a median coupon rate, adjusted for interbank interest rates, which was one percent above the median value of the coupon rate observed for the non-defaulted firms. One interpretation of this result is that the investors and the managers of the bond issues are, in some degree, able to filter out which issue that require a high coupon as compensation for default risk. One should remember that this is a purely univariate exercise, and that it may be necessary to correct for contractual features, for example if the particular bond indenture includes a convertible provision.

The difference in median values of EBITDA divided by total assets is about nine percent, and the difference in population locations given by the Wilcoxon rank-sum test is significant. Given the former discussion that many of the companies that defaults are start-up companies, this should come be no surprise. Typically, these companies goes through an establishment phase with low or negative EBITDAs for a couple of years before generating positive cash flows from operations.

The median value of the interest coverage measure is higher for the non-defaulted issuers. This result should again be seen as indicating that the defaulted firms are typically start-ups with low debt levels, and correspondingly low interest payments levels before their first bond issue[23]. This result is the same, regardless of adding the computed interest cost of the issue to the interest expense taken from the annual reports or not.

Table 13 shows the performed Rank-sum test of the remaining proposed alternative variables.

Table 13 Rank-sum test alternative variables 2

Variable		Issued amount/Total Assets	Working Capital Ratio	EBIT/Total Assets	Current Ratio	Market Leverage
Non-defaulted	Median	0,14	0,04	0,04	1,29	0,46
N	Mean	0,66	0,05	0,02	2,19	0,45
59						
Defaulted	Median	0,36	0,12	-0,03	1,98	0,53
N	Mean	1,10	0,10	-0,11	8,47	0,53
117						
Total	Difference	-0,22	-0,07	0,07	-0,68	-0,07
N	Z-Value	-5,36	-2,00	5,63	-3,02	-1,65
176	P-value	0,0000	0,0461	0,0000	0,0025	0,0985

One of the more interest findings is that the defaulted firms have a median value of issue size to total assets that is around 22 % higher compared to the non-defaulted firms. This indicates that one should be careful with companies that issue bonds with an issue volume that is large compared to their current balance sheets. However, how large is a difficult question to answer. Certainly, there is a need evaluate each issue case by case regarding if the company is able to handle the proposed debt volume.

[23] Remember that the inverse of the traditional interest coverage ratio is calculated.

The EBIT to total asset ratio measures in essence the same thing as the EBITDA to total asset ratio, but also included the company's ability to generate earnings and cash flows when an amount equal to the accounting year depreciation and amortization is reinvested in the business. The sign of the difference between the two groups is positive, and this result is in line with what you would expect from traditional studies of credit risk.

Again, the working capital to total assets and the current ratio, has the opposite sign of what you would expect from a traditional analysis. Again, the likely explanation is that the accounting information of the newly started firms are not especially relevant going forward, and that the asset and liability structure is changed as the firms become older.

To bring a market value dimension to the analysis, the market-based leverage is compared between the two groups for a subsample of 89 companies that were public at the time of issuance, and where the market value of equity was possible to extract form DataStream. The result is now the opposite of what was found when comparing the book equity ratio between the two groups. The defaulted firms have a median market based leverage ratio of about 53%, compared to 46% for the non-defaulted firms. A possible explanation for this result is that the issuers that were public at the time of issuance are older companies that have a more normal debt level. Opposed to the firms that did not have publicly traded equity, which used mostly private equity financing before searching for financing in the public capital market.

It is also of interest to see if the issuers of the different categories of default identified by the Moody's definition differed around the issue date on several of the proposed explanatory variables. However, due to the now small sample size with few observations in each category, a statistical exercise is almost impossible to carry out in a proper way. Few of the differences in values of the variables are likely to be statistically significant.

From the univariate analysis, we can summarize that one can question the predictive power of the book equity ratio and the liquidity ratio from the SEBRA-model as possible predictors of default in the Norwegian High Yield corporate bond market, when using information available at the time of issuance. If these variables are used, one should be cautious with interpreting the variables as in a traditional credit risk model. The reason for some of the more strange results could be the relative high number of defaults by firms classified as newly started companies. These start-up companies have in some cases accounting figures that result in extreme values on many of the collected ratios. The results from the univariate analysis also support the inclusion of possible alternative predictors in a statistical model predicting default.

7.2 Logistic regressions

As a starting point, the SEBRA variables were used in a logistic regression model to predict default. The variables of interest is then added to the model one by one to see if the variable turns out to be a significant predictor of default. Because the population, and correspondingly the final sample of bond issuers in Norway are rather small, the chosen level of significance is ten percent. That is, the variables will be interpreted if the p-value is less than ten percent. Table 14 shows the logistic regression with the SEBRA variables, adding size to the model, adding the share of tangible assets, and correcting for coupon rates and convertibility.

Table 14 Logistic regressions 1

	(1) SEBRA-basic	(2) Added size	(3) Added tangibility	(4) Added coupon rates
Performance	-1.969^{***}	-1.395^{**}	-1.982^{***}	-1.712^{**}
	(-2.94)	(-2.11)	(-2.92)	(-2.46)
Equity Ratio	1.105	1.080	1.110	0.855
	(0.98)	(0.94)	(0.98)	(0.74)
Lost Equity	0.623	0.493	0.630	0.567
	(1.54)	(1.19)	(1.55)	(1.36)
Liquidity	1.899^{*}	1.985^{*}	1.879^{*}	1.892^{*}
	(1.70)	(1.75)	(1.67)	(1.69)
Mean Equity Ratio in Industry	4.206	3.635	4.197	4.303
	(1.21)	(1.03)	(1.21)	(1.23)
Mean Performance in Industry	-0.109	-0.0589	-0.105	0.0555
	(-0.16)	(-0.08)	(-0.15)	(0.08)
Standard Deviation of Performance in Industry	-0.0162	-0.0139	-0.0157	0.0158
	(-0.09)	(-0.08)	(-0.09)	(0.09)
Not Matured	-1.179^{**}	-0.877^{*}	-1.192^{**}	-1.309^{***}
	(-2.55)	(-1.82)	(-2.53)	(-2.68)
Size of Company		-0.357^{**}		
		(-2.32)		
Share of Tangible Assets			0.0890	
			(0.14)	
Convertible Bond				0.479
				(0.95)
Coupon				7.144
				(0.93)
Pseudo R^2	0.232	0.257	0.232	0.239
Observations	176	176	176	175

z statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The only variable that turns out to be a significant predictor of default in the SEBRA-basic variable model is the performance measure. However, the sign of the coefficient is what you would expect and the variable is significant in all of the four different model specifications. Consequently, lower performance as measured by ordinary profit after tax relative to the firm's debt level is a significant predictor of failure already at the issue date. The liquidity level also turns out to be a significant predictor of failure, although the sign of the coefficient is rather surprising. It may be necessary to correct for other variables to get a more logical result regarding the liquidity level prior to issuance. The coefficient of the size measure is negative, and significant when added to the SEBRA-basic model. The specification with the size measure is also the model specification, which gives the highest value of the Pseudo R^2 goodness-of-fit measure. Thus, the model predicts smaller companies to have a higher probability of default. This is not surprising if we look at the defaulting companies case by case, and is in line with former studies on bankruptcy and default prediction. However, one should interpret this variable with some care because it may be necessary to bring in the start-up characteristics of the firm.

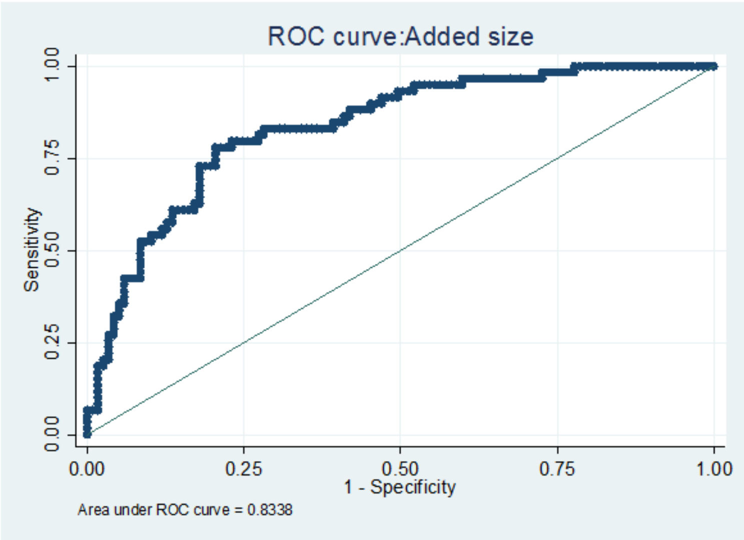
The classification table of the model including the size measure is provided in table 15.

Table 15 Classification table SEBRA-basic with size

	True group		
Classified	Defaulted	Non defaulted	Total
Defaulted	32	12	44
Non-defaulted	27	105	132
Total	59	117	176
Percentage correct	54,2 %	89,7 %	77,8 %
Percentage wrong	45,8 %	10,3 %	22,2 %

The classifications are based on a cut of value of 0,5. That is, the specific issuer is classified in the default category if the predicted probability of default is greater than 0,5. The choice of the optimal cut off value depends on the cost of classifying a defaulted firm wrong, versus to the cost of classifying a non-defaulted firm wrong. This issue is not explored further, but is a highly relevant question to ask for bond portfolio managers. The model including the size measure also provided the best overall classification accuracy by classifying 77,84% of the firms correct, but the model is not of much use because it classifies a great deal of the defaulted firms wrong. Only 54,24% of the defaulted firms are classified to be in the right group. The overall classification accuracy when using information around the issue date is in line with the classification results of the Marchesini, Perdue, and Bryan (2004) study. One alternative way to compare the predictive power of the models is to examine the area under the ROC curve. If the model has no predictive power, the area under the ROC curve would be 0,5, and the curve will lie close to the 45 degrees straight line. Perfect fit, and classification, would imply an area under the ROC curve of 1.The area under the ROC curve for this model specification is 0,8338 and the graph is depicted in figure 10. As a comparison, the area under the ROC curve estimated by the Norwegian Central Bank of Norway was 0,88 applied to the estimation period of 1990 to 2002 (Bernhardsen and Larsen, 2007).

Figure 10 ROC SEBRA-basic with size



The same exercise that was done in table 14 is carried out in table 16, but now the size measure is added to the SEBRA variables at instance. The start-up dummy and the crisis dummy are then added one by one to the model. The performance measure is again significant across all model specification, even when correcting for size, and with the inclusion of the start-up dummy. The dummy variable that is supposed to measure if the issue was issued in the wave of issues coming up to the financial crisis is significant, and the sign of the coefficient is positive. Thus, it seems that some of the companies that issued bonds for the first time coming up to the financial crisis were especially risky issuers. This result should of course be interpreted with great care because of the financial crisis being a highly unusual event, and becomes highly influential when analysing such a short issue period. It is also worth noting that the coefficient of the liquidity measure is not statistically different from zero when correcting for the issuer being a start-up company or not.

Table 16 Logistic regressions 2

	(1) SEBRA-basic with size	(2) Added start-up	(3) Added crisis
Performance	-1.395**	-1.227*	-1.674**
	(-2.11)	(-1.90)	(-2.47)
Equity Ratio	1.080	1.179	1.292
	(0.94)	(1.02)	(1.10)
Lost Equity	0.493	0.421	0.576
	(1.19)	(1.00)	(1.32)
Liquidity	1.985*	1.849	1.356
	(1.75)	(1.62)	(1.15)
Mean Equity Ratio in Industry	3.635	3.103	1.436
	(1.03)	(0.90)	(0.46)
Mean Performance in Industry	-0.0589	-0.0201	-0.0666
	(-0.08)	(-0.03)	(-0.09)
Standard Deviation of Performance in Industry	-0.0139	0.00205	-0.00876
	(-0.08)	(0.01)	(-0.05)
Not Matured	-0.877*	-0.884*	-0.181
	(-1.82)	(-1.83)	(-0.32)
Size of Company	-0.357**	-0.353**	-0.323**
	(-2.32)	(-2.30)	(-1.97)
Start-up		0.489	
		(1.19)	
Crisis			1.560***
			(3.29)
Pseudo R^2	0.257	0.264	0.310
Observations	176	176	176

z statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

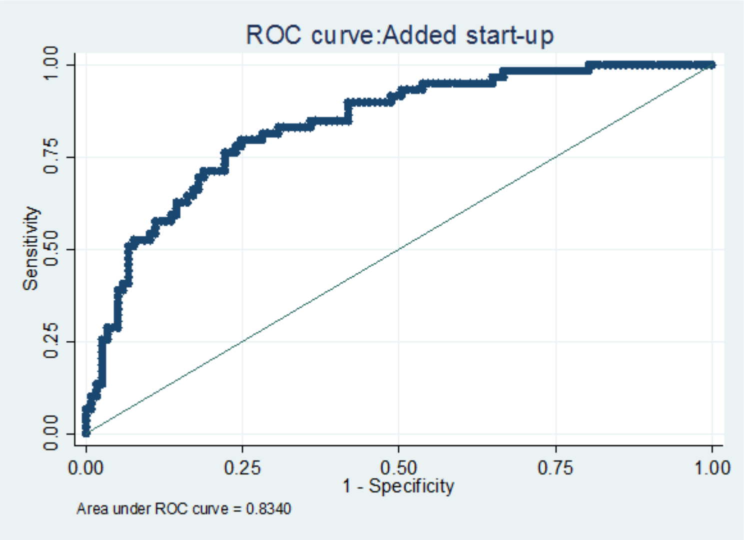
The model with the highest Pseudo R^2 goodness-of-fit, is the model containing the original SEBRA-basic variables including the crisis dummy and the size measure. The model with the crisis dummy is of little use when predicting bond defaults in future periods for the same reasons as explored earlier. The model including both the measure of size and the start-up dummy provides the highest classification accuracy of the three models, with an overall classification accuracy of 78,41%. Again, the model fails at classifying the defaulted firms in a decent way. 57,63% of the defaulted issuers are classified correctly by the model. The results obtained when the start-up dummy is included are slightly better than if the dummy is omitted. The classification table of the model is provided in table 17.

Table 17 Classification table SEBRA-basic with size and start-up

	True group		
Classified	Defaulted	Non defaulted	Total
Defaulted	34	13	47
Non-defaulted	25	104	129
Total	59	117	176
Percentage correct	57,6 %	88,9 %	78,41 %
Percentage wrong	42,4 %	11,1 %	21,59 %

The area under the ROC curve for the model including the start-up variable is 0,8340, slightly higher than the model which included only the size measure. This ROC curve is depicted in figure 11.

Figure 11 ROC SEBRA-basic with size and start-up



Finally, a stepwise estimation procedure was performed to find the best overall model. This is done by starting with all of the proposed explanatory variables, and then removing variables that does not provide significantly to the model according to the likelihood-ratio test described in chapter six. The chosen level of significance of the likelihood-ratio test is ten percent. The variables that make the cut are the SEBRA performance measure, the coupon of the issue corrected for the level of interbank interest rates, the dummy variable of issuance coming up to the financial crisis, and the dummy for being a convertible bond. All of the variables exhibits significant coefficients. The signs of the coefficients are what you would expect from the theoretical discussion, and from common economic reasoning. Nevertheless, one should be careful with interpreting these results as concluding that the stepwise estimation model is the best overall best model. It is a pure data mining exercise performed on this particular sample, and it is unlikely that the same results would have been obtained if performed on a different sample, or if the accounting information was collected in a different period of the bonds tenor. The regression table for the stepwise estimation procedure is provided in table 18.

Table 18 Stepwise estimation

	(1) Stepwise estimation
Not Matured	-0.509
	(-0.93)
Performance	-1.872^{***}
	(-2.85)
Coupon	24.11^{***}
	(2.94)
Crisis	2.488^{***}
	(4.52)
Convertible Bond	1.442^{**}
	(2.47)
Pseudo R^2	0.306
Observations	175

z statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The predictive relevance of such a model is also of doubt because of the inclusion of the crisis dummy. Although the model has the best overall classification accuracy when classifying the defaulted issuers, with an classification accuracy of 59,32%, it is not useful when predicting default going forward because of the financial crisis dummy.

Finally, it is worth noting that the overall results from the prediction exercise are rather disappointing, and that one should look at this analysis not primarily as a direct prediction exercise. Instead, the analysis should be thought of as providing some ideas to which type of firms that have fallen into trouble historically. I hope that the logistic regressions, together with the univariate assessment, are able shed some light on which characteristics that makes a bond issue especially risky in terms of default risk, and can provide some ideas to further research on default prediction models.

7.3 Criticism

When preparing the dataset it became clear that the issuing firms were more diverse than first thought off. Especially when it comes to their age and the set of information that was possible to collect for each firm. The final sample exhibits a mixture of well-established companies, and companies that went through an establishment phase around the issue period. Ideally, the data quality of some of the firms would have been better, especially for the foreign firms. If a larger set of issuers were available, it would have been desirable to draw a random sample from the population to estimate a prediction model. The predictive power of the model could then have been tested in an out-of sample test with the observations that were not including when estimating the model.

One should be careful with interpreting the results from the regression to literally. First, they are based on few observations, a relatively short issue period, and the appropriateness of several of the proposed variables as predictors of financial distress on bonds could be further debated. The goal of this thesis was to see if financial variables from a statistical credit risk model, like the SEBRA model, were any good in predicting default on bonds using information available of newly issued bonds, and uncover some basic results between the characteristics of the issuers and the risk of defaulting. The results obtained in this thesis must be viewed as a supplement to a qualitative assessment of the issuer's credit quality. The diversity of these firms, and the fact that many of these firms had few years of available accounting information, could provide some explanation as to the failure of the different model specifications in classifying the defaulted and non-defaulted firms correctly.

Focusing almost solely on accounting information is also a relevant critique to the study. Accounting ratios are in essence backward looking and do not reflect expectations of future performance. Therefore, a blend of accounting information with information from equity markets, and perhaps other financial markets, could have been a boost to the predictive power of the model. The lack of publicly available data from the Norwegian bond market, and the need to bring in private companies in the analysis, has been challenging in this case.

Few of the coefficients in the logistic regressions come out as significant. The reason could be the already mentioned small sample size, or that it simply is very difficult to find any statistical relationship between information gathered around the issue period, and which firms that run into trouble. Certainly, a qualitative assessment of the issuers is still needed when performing analysis of default risk. The time period covered is also relatively short, and includes a highly unusual event like the financial crisis. It is possible that the period covered is not representative going forward due to the financial crisis creating a wave of defaults. It is also worth mentioning that the bond market is likely to continue its rapid change in the future, and relationships covered from historical data are not necessarily good predictors of failure in future periods and for a new set of issuers.

Certainly, there also exists a time effect in predicting financial distress. Almost every study of default, or bankruptcy, prediction reports better results when using information closer to the default incident. Although my focus has been on information available at the date of issuance, with more time and resources available, information from other periods of the bonds life could have been used in a prediction model. It turned out to be difficult to do this in a consistent way, and still get a decent size of the final sample. The choice to use information from the issue period was made because off the low liquidity in many of the bonds, and in the Norwegian bond market in general. It also turned out to be very time consuming to gather financial information, because financial information for many of the companies did not appear in an available database that was detailed enough to gather the necessary variables.

7.4 Conclusion

Although some problems were confronted during the data collection and the analysis of the collected dataset, there are still possible to draw some general conclusions about the characteristics that make an issuer more likely to default in the Norwegian High Yield bond market.

From the logistic regressions, one can conclude that companies with lower profits relative to their debt exhibits a greater probability of running into trouble with their debt payments, even when using available information around the issue date. A possible explanation for this result is that start-up companies, and firms in an establishment phase, experience negative profits in their first years. These firms are typically smaller and face greater uncertainty around their future earnings than older and more established companies face. The results are backed up by the significant positive coefficient of the SEBRA size measure, and the significant positive coefficient of the start-up dummy. Finally, a model with the SEBRA variables clearly breaks down when it comes to classifying the defaulted firms, but performs decent when classifying the non-defaulted companies.

If we consider the stepwise model, issues made coming up to the financial crisis exhibits a greater probability of default. This gives some merit to the hypothesis that the large volume of issues in 2006 and 2007 included some companies that were especially risky. The performance measure from the SEBRA model also proves to be a significant predictor of default in the stepwise model. A higher coupon rate, adjusted for the level of interbank rates, is a significant predictor of default. The median coupon rate of the bonds that defaults are also significantly higher than for the bonds that did not default. This could provide some merit to the bond market in assigning the highest coupons to the most risky bonds. These results are also significant when correcting for convertible provisions. The stepwise model provides some evidence that convertible bonds are more risky in terms of default risk than regular bonds. One explanation for this result could be that convertible bonds are typically issued by firms with lower profitability, consistent with the findings of Rauh and Sufi (2010) of a negative relationship between the profitability of the firm, and the use of convertible bonds from a sample of public firms in the United States.

Focusing solely on the univariate analysis, the typical issue and issuer that defaulted had lower profit margins, are smaller compared to a non-defaulting company, has a higher equity ratio, a higher reservoir of liquid assets compared to its total assets, lower interest expenses to EBITDA, a higher coupon, and a higher ratio of issued amount to total assets. Again, some of the results are surprising, and some might say absurd. One explanation of the observed results regarding the equity ratio, and the different liquidity ratios, could be that it is not appropriate to gather financial information from newly started companies prior to their first bond issue. If the population of issuers in the Norwegian market had been larger, and if I had access to a larger set of financial data, then the sample could have been divided into two. One sample that compromised more matured companies, together with one sample that was set up by newly started companies.

For a subsample of 89 public companies, the market-based leverage ratio was calculated. The median market-based leverage ratio is significantly higher for the defaulted firms than for the non-defaulted firms. This result is the opposite of the result when looking at the equity ratio in terms of book value. A possible explanation for this difference could be that the firms that were public at the issue date were more matured, and had a more "normal" capital structure, than the firms that goes to the bond market in an establishment phase before considering going public to raise equity. The market-based leverage is also less distorted by different accounting rules than the book equity ratio.

Further studies should look at how the financial ratios and information from the equity market changes when the firms approach default. This could possible provide some warning signs for investors from periods after the bond's issue date. Had a larger group of issuers been available, a statistical credit risk model could have been estimated with a random sample of firms, and the model could subsequently be up for a predictive power test with a holdout sample. It is also of interest to test if a different model specification is better to identify the defaulting firms.

It would also have been interesting to conduct an analysis when weekly price information is available from Nordic Bond Pricing. Then one can compare the implied probabilities from the observed credit spreads with predicted probabilities, and loss given default, from a credit risk model. An analysis that tries to explain the credit spreads by different variables observed in the Norwegian Bond market on a larger set of issuers can then be performed. It is of interest to conduct an analysis, which can answer if the investors in the Norwegian bond market systematically underestimates the credit risk of the issuers.

8. Appendix

Filtering process:

Filtering process	Bond issues	Issuers
Issue based statistics	12834	865
After removal of issue types other than regular bonds and convertibles	4332	700
After removal of Energy, Public sector, Banks, Insurance and other Financial companies	878	341
After removal of companies owned by the government, unlimited liability etc.	807	317
After removal of government guaranteed securities etc.	778	314
After removal of IG companies determined in Brekke & Haugland (2010)	646	270
Preliminary sample after further adjustments	621	253

Adjustments made to arrive at the preliminary sample:

Issuer	Excluding reason
Aker ASA	Removed issues made by Aker RGI Holding
Aker Solutions ASA	Rated below Investment Grade DNB Markets weekly credit report 35/2013
APL PLC	Use APL ASA instead. Change of jurisdiction after issuance
Bayerngas Produksjon Norge AS	Guaranteed by parent company PA Resources AB
Cecon ASA	First credit event registered by Cecon 1 AS and Cecon 2 AS
Det Norske Oljeselskap ASA	Removed issues made by Aker Exploration AS
Dof Subsea AS	Removed issued by made GEO ASA
Domstein ASA	First credit event noticed by R. Domstein & Co AS
DP Producer AS	Parent FPS Ocean AS bankrupt
Gamle Holding AS	Issue withdrawn just after registration in Stamdata
Global Investments Group Finance Ltd.	Financial company
Marine Subsea Cyprus Holding Ltd	Guaranteed by parent company Marine Subsea AS
Noreco Norway AS	Issuing company Altinex Oil Norway. Already present in final sample
Northland Resources AB	Missing letter in Stamdata
Northland Resources S.A.	Missing letter in Stamdata
PetroRig III	Single Purpose Company. Parent Petromena ASA
Polarcus Alima AS	Single Purpose Company. Parent Polarcus ltd.
Precise Prediction AS	Financial company
Remedial Cayman Limited	Credit event noticed by Remedial (Cyprus) Public Company Limited before issue date
Seadrill Norge AS/Smedvig ASA	Issues made by Seadrill Norge AS or Smedvig ASA removed
Tele2 AB	Investment Grade DNB Markets weekly credit report 19/2012
Tordenskjold ASA konkursbo	Bankrupt company. No letters in Stamdata
Transocean Norway Drilling AS	Issued as Aker Drilling. Use issues made by Transocean Norway Drilling instead

Issuers involved in at least one default:

Issuer	Issuer
Ability Drilling ASA	Neptune Marine Invest AS
Aker Biomarine ASA	Nexus Floating Production Ltd
Aladdin Oil & Gas Company	NOR Energy AS
American Shipping Company	Nordic Heavy Lift ASA
Apptix ASA	Norse Energy Corp. ASA
Austevoll Seafood ASA	Norwegian Energy Company
B+H Ocean Carrier Ltd.	Oceanlink Ltd NUF
Belships ASA	Oceanteam Shipping ASA
Bergen Group ASA	Oren Oil ASA
Bergen Oilfield Services AS	Peterson AS
Blom ASA	Petrojack ASA
Bluestone Offshore	Petrolia ASA
Camo Software AS	Petromena ASA
Cecon 1 AS and Cecon 2 AS	PetroProd Ltd
Club Cruise Entart. & Travel. N.V.	Primorsk International Shipping Ltd
Codfarmers	R. Domstein & Co AS
Crew Gold Corp	Realkapital European Opportunity AS
Dannemora Mineral AB	Remedial (Cyprus) Public Company Limited
Delphin Kreuzfahrten GmbH	Reservoir Exploration Technology RXT ASA
Eitzen Chemical ASA	Resitec AS
Eitzen Maritime Services ASA	Rocksource ASA
Emerging Europe Land Develo.	Rowan Drilling Norway AS
EOAL Cyprus Holdings Limited	Scan Geophysical ASA
Equinox Offshore Ltd	Seabird Exploration PLC
Estatia Resort Property AS	Sea Production Ltd
Fairstar Heavy Transport NV	SeaMetric International AS
FPS OCEAN AS	Selvaag Bolig ASA
Front Exploration AS	Sevan Marine ASA
Funcom N.V.	Songa Floating Production ASA
Hurtigruten ASA	Songa Offshore SE
IBB-Bygg AS	Svithoid Tankers AB
Ignis ASA	Tandberg Data ASA
Interoil E&P ASA	Tandberg Storage ASA
Krillsea Group AS	Thule Drilling AS
Kverneland ASA	TMG International AB
Malka Oil AB	Transeuro Energy Corp
Marine Accurate Well ASA	TTS Group ASA
Marine Subsea AS	Valhall Oil & Gas AS
Master Marine AS	Valiant Petroleum Holdings AS
Monitor Oil PLC	Viking Drilling ASA
MPF Corp Ltd	Wega Mining AS
MPU Offshore Lift ASA	Wentworth Resources Limited
Nattopharma ASA	Ziebel AS

Final sample inlcuding issue year and accounting year:

Name annual report	**Accounting year**	**Issuer**	**Issue year**
ABILITY DRILLING ASA	2006	Ability Drilling ASA	2007
AKER ASA	2004	Aker ASA	2005
Aker Biomarine ASA	2006	Aker Biomarine ASA	2007
AKER SOLUTIONS ASA	2005	Aker Solutions ASA	2006
AKER YARDS AS	2003	STX Europe AS	2004
ALADDIN OIL & GAS COMPANY ASA	2006	Aladdin Oil & Gas Company ASA	2007
ALTINEX ASA	2005	Altinex ASA	2006
American Shipping Company ASA	2006	American Shipping Company ASA	2007
APPTIX ASA	2004	Apptix ASA	2005
ATLANTIC OFFSHORE AS	2011	Atlantic Offshore AS	2012
AUSTEVOLL SEAFOOD ASA	2006	Austevoll Seafood ASA	2007
AVANTOR ASA	2002	Avantor AS	2003
B+H Ocean Carrier Ltd.	2005	B+H Ocean Carrier Ltd.	2006
BANETELE AS	2002	Banetele AS	2003
Belships ASA	2005	Belships ASA	2006
BERGEN OILFIELD SERVICES AS	2007	Bergen Oilfield Services AS	2008
BLOM ASA	2008	Blom ASA	2009
BOA OCV AS	2010	Boa OCV AS	2011
BOA OFFSHORE AS	2011	Boa Offshore AS	2012
Bonheur ASA	2008	Bonheur ASA	2009
BORGESTAD ASA	2008	Borgestad ASA	2009
BW GAS AS	2005	BW Gas AS	2006
BW Offshore Limited	2011	BW Offshore Limited	2012
BWG HOMES ASA	2011	BWG Homes ASA	2012
CALCULUS AS	2005	APL ASA	2006
CAMO ASA	2006	Camo Software AS	2007
CECON ASA	2008	Cecon 1 AS and Cecon 2 AS	2009
CERMAQ ASA	2011	Cermaq ASA	2012
Codfarmers ASA	2006	Codfarmers ASA	2007
COLOR GROUP ASA	2003	Color Group AS	2004
CRUDECORP ASA	2011	Crudecorp ASA	2012
DALANE BREIBAND AS	2011	Dalane Breiband AS	2012
DANA PETROLEUM NORWAY AS	2006	Dana Petroleum Norway AS	2007
Dannemora Mineral AB	2010	Dannemora Mineral AB	2011
DEEP SEA SUPPLY ASA	2005	Deep Sea Supply ASA	2006
DEEPOCEAN AS	2005	Deepocean AS	2006
DET NORSKE OLJESELSKAP ASA	2010	Det Norske Oljeselskap ASA	2011
DFDS A/S	2011	DFDS A/S	2012
DISCOVER PETROLEUM AS	2007	Front Exploration AS	2008
DNO ASA	2003	DNO International ASA	2004
Dockwise Ltd.	2006	Dockwise Ltd.	2007
DOF ASA	2002	DOF ASA	2003
DOF SUBSEA ASA	2006	Dof Subsea AS	2007

DOLPHIN GROUP ASA	2011	Dolphin Group ASA	2012
DOMSTEIN ASA	2009	R. Domstein & Co AS	2010
DSB	2008	DSB	2009
Eitzen Chemical ASA	2006	Eitzen Chemical ASA	2006
ELECTROMAGNETIC GEOSERVICES AS	2005	Electromagnetic Geoservices ASA	2006
EMERGING EUROPE LAND DEVELOPMENT AS	2010	Emerging Europe Land Development AS	2011
EMS SEVEN SEAS ASA	2006	EMS Seven SEAS ASA	2007
Fairstar Heavy Transport N.V.	2007	Fairstar Heavy Transport N.V.	2008
FARSTAD SHIPPING ASA	2004	Farstad Shipping ASA	2005
FJELLSTRAND AS	2007	Fjellstrand AS	2008
Floatel International Ltd.	2011	Floatel International Ltd.	2012
FPS Ocean AS	2007	FPS OCEAN AS	2008
Fram Exploration ASA	2010	Fram Exploration ASA	2011
FRED OLSEN ENERGY ASA	2000	Fred Olsen Energy ASA	2001
FREDENSBORG AS	2011	Fredensborg AS	2012
FRONTIER DRILLING ASA	2000	Frontier Drilling AS	2001
Frontline Ltd	2009	Frontline Ltd.	2010
Funcom N.V.	2010	Funcom N.V.	2011
GLAMOX ASA	2003	Glamox ASA	2004
GLOBAL RIG COMPANY ASA	2010	Global Rig Company ASA	2011
Golar LNG Ltd	2011	Golar LNG Ltd.	2012
Golar LNG Partners LP	2011	Golar LNG Partners LP	2012
Golden Ocean Group Ltd.	2006	Golden Ocean Group Ltd.	2007
GRIEG SEAFOOD ASA	2008	Grieg Seafood ASA	2009
HAVILA AS	2010	Havila AS	2011
HAVILA SHIPPING ASA	2005	Havila Shipping ASA	2006
HEXAGON COMPOSITES ASA	2005	Hexagon Composites ASA	2006
HOST HOTELEIENDOM AS	2010	Host Hoteleiendom AS	2011
Höegh LNG Holdings Ltd.	2011	Höegh LNG Holdings Ltd.	2012
I. M. Skaugen SE	2006	I. M. Skaugen SE	2007
IGNIS ASA	2005	Ignis AS	2006
INTEROIL EXPLORATION AND PRODUCTION ASA	2005	Interoil Exploration and Production ASA	2006
J. Lauritzen A/S	2009	J. Lauritzen A/S	2010
Jason Shipping ASA	2004	Jason Shipping ASA	2005
Jasper Investments Limited	2010	Jasper Explorer Plc	2011
Kistefos AS	2011	Kistefos AS	2012
KRAGERØ FJORDBÅTSELSKAP AS	2004	Kragerø Fjordbåtselskap AS	2005
KVERNELAND AS	2006	Kverneland AS	2007
Lightstream Resources Ltd.	2009	Lightstream Resources Ltd.	2010
LOFOTENS OG VESTERAALENS DAMPSKIBSSELSKAB ASA	2003	Hurtigruten ASA	2004
London Mining Plc	2006	London Mining Plc	2007
Lotos Exploration and Production Norge AS	2008	Lotos Exploration and Production Norge AS	2009
M PETERSON & SØN AS	2005	Peterson AS	2006
MARACC - Marine Accurate Well ASA	2007	MARACC - Marine Accurate Well ASA	2007
Marine Subsea AS	2007	Marine Subsea AS	2007

MERKANTILBYGG HOLDING AS	2011	Merkantilbygg Holding AS	2012
METALLKRAFT AS	2009	Resitec AS	2010
Monitor Oil Plc	2006	Monitor Oil Plc	2007
MORPOL ASA	2010	Morpol ASA	2011
MOSKING BOLIG AS	2011	Mosking Bolig AS	2012
MPF Corp Ltd.	2006	MPF Corp Ltd.	2006
NATTOPHARMA ASA	2008	Nattopharma ASA	2009
NERA ASA	2005	Eltek ASA	2006
NEXTGENTEL HOLDING ASA	2005	Nextgentel Holding ASA	2006
Nexus Floating Production Ltd.	2006	Nexus Floating Production Ltd.	2007
NJORD GAS INFRASTRUCTURE AS	2010	Njord Gas Infrastructure AS	2011
NORDIC MINING ASA	2006	Nordic Mining ASA	2006
NORSKE SKOGINDUSTRIER ASA	2003	Norske Skogindustrier ASA	2004
NORTECHS FPSO ASA	2006	Songa Floating Production ASA	2007
North Atlantic Drilling Limited	2011	North Atlantic Drilling Limited	2011
Northern Offshore Ltd.	2006	Northern Offshore Ltd.	2007
NORTHERN OIL ASA	2004	Norse Energy Corp. ASA	2005
NORWEGIAN AIR SHUTTLE ASA	2006	Norwegian Air Shuttle ASA	2007
NORWEGIAN CAR CARRIERS ASA	2005	Norwegian Car Carriers ASA	2006
Norwegian Energy Company ASA	2006	Norwegian Energy Company ASA	2007
OCEAN RIG ASA	1999	Ocean Rig ASA	2000
Ocean Rig UDW Inc.	2010	Ocean Rig UDW Inc.	2011
Ocean Yield ASA	2011	Ocean Yield ASA	2012
Oceanteam Shipping ASA	2006	Oceanteam Shipping ASA	2007
Odfjell SE	2004	Odfjell SE	2005
OLYMPIC SHIP AS	2010	Olympic Ship AS	2011
OREN OIL ASA	2006	Oren Oil ASA	2006
OSX Brasil S.A.	2011	OSX 3 Leasing B.V	2012
OTIUM AS	2011	Otium AS	2012
PA Resources AB	2004	PA Resources AB	2005
Pacific Drilling S.A.	2011	Pacific Drilling S.A.	2012
PAN FISH ASA	2002	Marine Harvest ASA	2003
Panoro Energy ASA	2009	Panoro Energy ASA	2010
Petrobank Energy and Resources Ltd.	2006	Petrobank Energy and Resources Ltd.	2007
PETROJACK ASA	2005	Petrojack ASA	2006
Petroleum Geo-Services ASA	2006	Petroleum Geo-Services ASA	2007
PETROLIA DRILLING ASA	2004	Petrolia ASA	2005
PETROMENA AS	2005	PetroMena ASA	2006
Petrominerales Ltd.	2006	Petrominerales Ltd.	2007
Polarcus Ltd.	2008	Polarcus Ltd.	2008
PROSAFE ASA	2003	Prosafe SE	2004
REALKAPITAL EUROPEAN OPPORTUNITY AS	2010	Realkapital European Opportunity AS	2011
REM OFFSHORE ASA	2009	Rem Offshore ASA	2010
RENEWABLE ENERGY CORPORATION AS	2004	Renewable Energy Corporation ASA	2005
Reservoir Exploration Technology ASA	2006	Reservoir Exploration Technology ASA	2007
ROCKSOURCE ASA	2006	Rocksource ASA	2007

ROXAR AS	2007	Roxar AS	2008
SAFETEL AS	2003	Safetel AS	2004
SCAN GEOPHYSICAL AS	2005	Scan Geophysical ASA	2006
Scandinavian Airlines System (SAS)	2004	Scandinavian Airlines System (SAS)	2005
SCHIBSTED ASA	2009	Schibsted ASA	2010
Seabird Exploration Plc	2005	Seabird Exploration Plc	2006
Seadrill Ltd.	2006	Seadrill Ltd	2007
SEKTOR GRUPPEN AS	2011	Sektor Gruppen AS	2012
Sevan Marine ASA	2006	Sevan Marine ASA	2007
Ship Finance International Limited	2009	Ship Finance International Limited	2010
SINOCEANIC SHIPPING ASA	2011	SinOceanic II AS	2012
SINVEST ASA	2004	Sinvest AS	2005
SOFTWARE INNOVATION AS	2005	Software Innovation AS	2006
SOLSTAD OFFSHORE ASA	2005	Solstad Offshore ASA	2006
Songa Offshore SE	2006	Songa Offshore SE	2007
SPECTRUM ASA	2010	Spectrum ASA	2011
Stena Metall AB	2010	Stena Metall Finans AB	2011
STEPSTONE ASA	2005	Axel Springer Norway AS	2006
Stolt-Nielsen Limited	2010	Stolt-Nielsen Limited	2011
Svithoid Tankers AB	2005	Svithoid Tankers AB	2006
SYNNØVE FINDEN ASA	1999	Synnøve Finden AS	2000
TANDBERG DATA ASA	2005	Tandberg Data ASA	2006
TANDBERG STORAGE ASA	2007	Tandberg Storage ASA	2008
Teekay Corporation	2011	Teekay Corporation	2012
TELIO AS	2005	Telio Holding ASA	2006
THULE DRILLING ASA	2005	Thule Drilling AS	2006
TiZir Ltd.	2011	TiZir Ltd.	2012
TMG International AB	2005	TMG International AB	2006
TRANSOCEAN NORWAY DRILLING AS	2010	Transocean Norway Drilling AS	2011
TTS GROUP ASA	2006	TTS Group ASA	2007
UMOE INDUSTRI AS	2005	Umoe AS	2006
VIKEN FIBERNETT AS	2006	Viken Fibernett AS	2007
Viking Drilling	2006	Viking Drilling ASA	2006
Viking Supply Ships A/S	2011	Viking Supply Ships A/S	2012
VILLA ORGANIC AS	2007	Villa Organic AS	2008
VISMA ASA	2003	Visma AS	2004
VMETRO ASA	2005	Vmetro ASA	2006
VOLSTAD MARITIME AS	2005	Volstad Maritime AS	2006
WEGA MINING AS	2006	Wega Mining AS	2007
Wentworth Resources Limited	2005	Wentworth Resources Limited	2006
Wilh. Wilhelmsen ASA	2003	Wilh. Wilhelmsen ASA	2004
ZIEBEL AS	2007	Ziebel AS	2008

Note: Names appearing under name annual report with only capital letters are annual reports retrieved from the SNF database.

Issuers excluded due to unavailable financial data:

Issuer	**Issuer**
Aberdeen Bergerveien 12 AS	Middle East Jackup I Company
Aberdeen Eiendom Holding Norden/ Baltikum AS	Mosvold Drilling Ltd.
Atlantic Oilfield Services Ltd.	Mosvold Supply Plc
Bassdrill Alpha Ltd.	MPU Offshore Lift ASA
Bergen Group ASA	Navigator Holdings Ltd.
Bluestone Offshore Pte Ltd.	Neptune Marine Invest AS
Bluewater Holding B.V.	NOR Energy AS
Chloe Marine Corporation Ltd.	Nordic Heavy Lift ASA
Club Cruise Entertainment & Travelling Services Eu	Oceanlink Ltd NUF
COSL Drilling Europe AS	Offshore Heavy Transport AS
COSL Drilling Semi AS	Onetwocom AB (publ)
Crew Gold Corp	Oro Negro Drilling Pte. Ltd.
Davie Holding AS	PetroProd Ltd.
DDI Holding AS	Primorsk International Shipping Ltd.
Deep Drilling 1 Pte. Ltd.	Remedial (Cyprus) Company Limited
Deep Drilling 7 Pte. Ltd. and Deep Drilling 8 Pte.	Rowan Drilling Norway AS
Deep Sea Bergen Invest AS	Rubicon Offshore Holdings
Delphin Kreuzfahrten	Sea Production Ltd.
Didon Tunisia Ltd.	SeaDragon Offshore Ltd.
Eastern Drilling ASA	Seametric International AS
Eastern Echo Holding Plc	Selvaag Bolig ASA
Enovation Resources Ltd.	Sevan Drilling Invest AS
EOAL Cyprus Holdings Limited	Siem Industries Inc
Equinox Offshore Accomodation Limited	Skdp 1 Ltd.
Estatia Resort Property AS	Skøyen Næringsbygg AS
Floatel Superior Ltd.	Solstad Rederi II AS
Fram Eiendom AS	Solør Bioenergi Infrastruktur AS
Frigstad Discoverer Invest Ltd. (BVI)	Standard Drilling ASA
Geopard A/S	Sølvtrans Rederi AS
Golden Close Maritime Corp Ltd.	Teekay LNG Partners LP
Hambo Ab Oy	Teekay Offshore Partners LP
Heritage Oil Corp	Teodin Acquico AS
IBB Byg AS	Transeuro Energy Corp
Indekshuset Holding AS	TrollDrilling & Services Ltd.
KCA DEUTAG Offshore AS	Valhalla Oil and Gas AS
Krillsea Group AS	Valiant Petroleum Holdings AS
LK Holding I AS	Vann AS
Malka Oil AB	Venture Drilling AS
Master Marine AS	

Annual reports

Link to annual reports, reporting year, and access date.

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<http://www.akerbiomarine.com/section.cfm?path=142,161> (16.10.2013)

B+H Ocean Carrier Ltd. (2005):
http://www.bhocean.com/files/BHO032206.pdf (11.10.2013)

Belships ASA (2005):
http://hugin.info/17/R/1045535/171335.pdf (11.10.2013)

BW Offshore Limited (2011):
http://hugin.info/136844/R/1598893/504326.pdf (16.10.2013)

Codfarmers ASA (2007):
http://www.codfarmers.com/content/fin_rep_annual_docs/docs/00016_1153588835_Annual_report_2007_english.pdf (16.10.2013)

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