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Default in the Nordic High-Yield Bond Market

A Study on Original Issue High-Yield Bonds

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Abstract

In this thesis, we analyze the determining factors of default in the Nordic high-yield bond market. The study is carried out on 627 original issue bonds in the period 2006 to 2014. Binary logit models are used to identify the key determinants of default, and the estimated models can be used to predict default probabilities. Our results suggest that a combination of financial ratios, certain characteristics of the issued bond, an industry variable, the size of the issuer and the firm's distance to default (a volatility-adjusted measure of leverage) are the best estimates for predicting default.

Further, we use the determining factors of default to answer the open question of how the probability of default changes over the lifetime of the bonds. By applying a flexible econometric method, the Cox proportional hazard model, we study the bonds' default behavior from the moment of issuance. Unique to our study is that we allow for the underlying risk of default to differ depending on the type of bond. We find that callable and convertible bonds do not age well compared to bonds without these embedded options. Default rates for callable and convertible bonds are found to increase with time after issuance, and a significant increase in default risk is observed after three years.

Keywords: High-yield bond; Default; Nordic market; Logit model; Cox proportional hazard model; Aging effect

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1. Introduction

In little over a decade, the Nordic corporate bond market has evolved from a small regional market into a global market characterized by large issue volumes of high-yield bonds. While Norwegian offshore and energy deals have dominated the high-yield bond market for many years, the other Nordic countries have now burst on to the scene, offering a wide range of sectors and issuers. Instead of looking to London or New York, issuers and investors worldwide are now also turning their attention to the Nordic high-yield bond market in search of capital and returns. As of 2009, only a small percentage of the listed corporate bonds were issued by non-Nordic companies. Today, international issuers comprise more than half of the Nordic market, making it the world's third largest market place for high-yield corporate bonds.

So what exactly has triggered this remarkable growth? One of the main attractions for issuers is the light documentation requirements and standardized loan agreements. Another appeal is the fact that there are no official credit rating requirements. Consequently, investors are often left with insufficient information on the creditworthiness of an issuer. Under these circumstances, additional information on the determinants of financial distress could be particularly valuable for investors. Therefore, we are interested in discovering what factors are important in explaining why issuers default on their debt obligations in the Nordic high-yield bond market. Is it sufficient to evaluate financial ratios from the firms' annual reports? Could certain characteristics of the issued bond provide additional information on the default risk? Or, is financial distress largely related to cyclical conditions in the industry?

We address these questions by estimating models that can forecast default probabilities for high-yield bonds in the Nordic market. Financial ratios of various categories are found to be important predictors of default. Of liquidity measures, the issuer's working capital and cash holdings in relation to total assets are found to be key ratios. A gearing ratio measuring the financial leverage of the firm, and the amount raised in the bond issue in relation to the size of the firm, can also provide valuable information regarding the probability of default. Furthermore, the turnover ratio of sales to current assets, and the debt service ratio of EBIT to current liabilities are important predictors of default.

When it comes to characteristics of the issued bonds, default rates are found to be higher if the bonds are callable or convertible. Bonds paying higher coupons relative to current short-term interest rate levels are also shown to have an increased risk of default. In addition, we find longer maturity bonds to be less likely to default than shorter ones. Moreover, we find that default rates have an inverse relationship with the size of the issuing firms. Lower default probabilities are associated with bonds issued by larger firms.

We also create an industry variable capturing the market conditions in the industry in which each issuer is operating. This variable measures the economic conditions in the industry compared to the immediate past, and is found to be an important predictor of default. When market conditions in the respective industries have recently improved, the bonds are less likely to default. Lastly, for public firms, we find that including the firm's *distance to default* can contribute significantly to default prediction of high-yield bonds. The distance to default is a volatility-adjusted measure of leverage, and is measured using equity market information of the issuers. Firms with a greater distance between the expected value of assets and the value of debt are less likely to default on their bonds.

Having identified the determining factors of default, we then study the relationship between the age of the bonds and the default risk. Since the late 1980's, researchers have studied how default probabilities change over time in the U.S. high-yield bond market. Results have varied, yet a number of studies suggest a distinct relationship between the age of a bond and its default risk. We are particularly interested in exploring this relationship for the Nordic high-yield bond market. Do the bonds tend to default at an early or late stage in their life-cycle? Are most bonds safe investments for the first few years? Or, are bonds that have been outstanding for several years, safe bets?

To answer these questions, we apply a hazard model that allows us to study the bonds' continuous probability of default. Default rates are estimated from the moment of issuance and until the bonds either default, mature, are called or converted, or reach the end of our observation period. Our model specification enables the underlying risk of default to vary depending on the type of bond issued. We distinguish between bonds that have an embedded option to call or convert the bond, and those that do not. Using a model based purely on information available at the issuance time of the bonds, evidence is provided of an increasing risk of default for callable and convertible bonds. A significant increase in default risk is found after approximately three years. In contrast, bonds without such embedded options are found to exhibit fairly constant default rates across the whole lifespan.

We also estimate a hazard model with time-varying covariates. Here, we account for changes in the general economy and market conditions in the relevant industries. The default risk in this model is studied over a three-year period, starting from the bonds issuance date. Financial ratios of the issuers are updated at yearly intervals, while changes in the general economy and industries are accounted for on a monthly basis. Macroeconomic changes are captured partially through the trailing one-year return on the benchmark index corresponding to the country in which the bonds are issued. Further, changes in interest rate levels are accounted for by including the time-varying spread between the bonds' coupon and current short-term interest rates. Even though we explicitly account for these changes, we still obtain similar results to the ones mentioned above. This suggests that our results would still hold in a period of stable interest rate levels, and regardless of changes in the general economy or industry.

Our findings are primarily of interest because we believe we are the first to carry out such a study for this particular market. The vast majority of research on high-yield bonds is carried out on the U.S. corporate bond market, leaving the Nordic market relatively unexplored. Furthermore, our results are important because, to the best of our knowledge, we are the first to explicitly distinguish between bonds with and without embedded options to either call or convert the bond in this kind of study. Previous research on the relationship between default risk and bond age does not appear to differentiate between bond types in the same way as we do. Some studies have separate analyses for convertible and non-convertible bonds, however, call provisions are hardly given any consideration.

This thesis is structured as follows. In the following section, we review previous research on default prediction and the relationship between default risk and bond age. Section 3 presents the two main research questions of this paper, as well as a brief explanation of the methodology applied to each area of research. In section 4, we describe our sample and the data gathering process. Our variable selection is presented and discussed in section 5. Section 6 presents our results from the empirical analysis. In section 7, we discuss the intended use of our models in relation to bond portfolio management. Section 8 covers potential limitations of our study, before the final section concludes.

2. Literature Review

Research on the prediction of financial distress can be traced back to the early 1930's. However, the studies of Beaver (1966) and Altman (1968) are widely recognized as the pioneering work on the subject. Altman's "Z-score" is one of the most well-known bankruptcy prediction models and is still used to this date. Since its publication, the number and complexity of financial distress models have increased drastically. New methods such as logit analysis, probit analysis and neural networks have since been introduced.

In the literature on high-yield bonds, Huffman and Ward (1996) estimated a logit model for predicting default at the time of issuance. Variables used in previous studies were employed based on accounting information from the last available financial report prior to the issuance year. Our study can relate to theirs in that we partly focus on the time around issuance, and we also use accounting information in the same way. One of their main findings is that defaulted high-yield issuers have a higher share of collateralizable assets. In a comparison with Altman's Z-score, they find that their model has a higher predictive ability.

Similarly, Marchesini, Perdue and Bryan (2004) applied four of the most renowned bankruptcy prediction models to high-yield bond issues. Altman's Z-score and Ohlson's (1980) logit model, along with two other cash flow based models by Gentry et al. (1985) and Aziz et al. (1988) were tested. Mixed but unimpressive results were obtained for all four models when applied on their sample of bonds. The cash flow approach by Gentry et al. produced the highest predictive ability with an accuracy rate of 61.5% one year before default. Hence, they conclude that all four models must be rejected as predictors of high-yield bond defaults. Instead, they propose a model with other variables including the log of total assets and EBIT to interest expense.

Studies on high-yield bonds generally suggest that better results are obtained through the use of a variety of variables rather than a model that relies exclusively on financial ratios. For instance, Cotter and Peck (1995) find that shorter maturity debt is associated with higher default probabilities, likely due to the increased debt burden in early periods. Lehman and Fridson (1995) show that high-yield bonds with high coupon payments are more likely to default than equally rated low coupon bonds. In a study on shipping high-yield bond issues, Grammenos et al. (2008) find an industry specific variable capturing the shipping market conditions prevailing at the time of issuance to be a key factor. In view of the offshore sector's dominant position in the Nordic high-yield bond market, we adopt their approach and create a similar industry variable for the Nordic market.

In the Nordic region, Skogsvik (1990) developed a probit model for Swedish mining and manufacturing firms with a predictive ability of more than 70% six years prior to failure. More prominently, Bernhardsen (2001) provided a logit model for corporate bankruptcy prediction in Norway. His work is employed by the Central Bank of Norway in order to estimate bankruptcy probabilities for Norwegian limited liability firms. The SEBRA-model, as it is referred to, has been developed further over the years and is now offered in a basic and an extended version (Bernhardsen and Larsen, 2007).

Grøstad (2013) incorporates the SEBRA-model variables as a starting point for predicting default in the Norwegian high-yield bond market. Issue specific and other variables are also included in his logit analysis. His findings suggest that a model with the SEBRA variables is not suitable for classifying defaulted high-yield firms. Our study is similar in some ways, but also quite different. First, our sample is considerably larger since we include issues in other Nordic countries and also do not restrict our sample to only one issue per firm. Second, instead of applying a specific bankruptcy prediction model to high-yield bonds, we take a different approach. In our study, a wider range of variables are employed in order to estimate models that can predict default for high-yield bonds, regardless of the variables' foundation in any particular model.

Besides predicting default, we are also interested in studying the relationship between default risk and bond age in the Nordic high-yield bond market. Previous studies on the U.S. market have provided mixed results on this research area. Asquith, Mullins and Wolff (1989) first suggested that the longer a high-yield bond is outstanding, the higher the probability of default. This phenomenon is commonly referred to as an "aging effect". Their study provided evidence that cumulative default rates increase more rapidly with time after issuance. However, Altman (1992) expressed skepticism over the findings of Asquith et al. (1989). Results from his mortality analysis shed doubt on the proposed effect.

Moreover, Blume et al. (1991) questioned the presence of an aging effect after observing a larger number of defaults in certain years. They suspected that a large portion of the defaults previously attributed to bond aging, might in fact be a result of general economic conditions. Their analysis confirmed that the previously observed tendency of an aging effect was partially due to cyclical conditions in the credit markets. In addition, Moody's and S&P, whose livelihoods depend on assigning bonds to their appropriate risk categories, strongly disputed the aging effect. They argued that the age of a bond had no systematic effect on its creditworthiness provided the initial rating remained unchanged (Altman, 1992).

Extending the research of Blume et al. (1991), McDonald and Van de Gucht (1996) apply a hazard model to estimate the impact of aging. A significant and positive aging effect is found even though their hazard model explicitly accounts for changing economic conditions. Monthly default rates are found to increase significantly after the first two years, and the default rates continue to increase until the end of year twelve, whereby they seem to level off. Moeller and Molina (2003) adopt a similar approach with comparable results. Using a more comprehensive sample where the bonds have had sufficient time to default, they find that the bonds face a constantly increasing default risk over time. The most significant increase is found beyond four years after issuance, and their results are similar for both convertible and non-convertible bonds.

Regarding the study of an aging effect, this paper relates mostly to the research of McDonald and Van de Gucht (1996) and Moeller and Molina (2003), particularly when it comes to methodology. This thesis does however differ to theirs in that we also account for changes in the firms' financial condition as well as in the relevant industries. Unique to our study is also that our model specification allows for the underlying risk of default to differ depending on the bond type.

McDonald and Van de Gucht (1996) restrict their sample to non-convertible bonds. Meanwhile, Moeller and Molina (2003) include convertible bonds in their sample, but carry out separate analyses for convertible and non-convertible bonds. Instead, they allow the underlying risk of default to vary depending on the rating of the issuer. Contrary to these and other studies, we find that the aging effect of high-yield bonds should not be attributed bonds irrespective of the bond type. Our results suggest that one should also distinguish between bonds containing embedded options to either call or convert the bonds, and those without. Any aging effect on the Nordic high-yield bond market is essentially attributed the former group of bonds, according to our findings.

3. Research Questions

The focus area of research in this paper is twofold. In this section, we clarify the two research questions that we seek to answer, and provide a brief description of the methodology applied to each research area.

3.1 Determining Factors of Default

Issuing a bond in the Nordic corporate bond market is beneficial for several reasons. Lean documentation requirements and standardized loan agreements result in an efficient issue process. Compared to an issue on other international bond markets, the overall process is completed in considerably less time. In addition, there are no official credit rating requirements from agencies such as Moody's and S&P. Combined, these factors lead to much lower transactions costs for the issuers, which in turn allows smaller firms to take part in the Nordic corporate bond market.

Nevertheless, the benefits for the issuers also come at a cost, and it is mainly the investors who pay the price. In the absence of official credit ratings, investors often face inadequate or limited information on the creditworthiness of the issuers. As of January 2016, less than ten percent of high-yield issuers in the Nordic market were officially rated by Moody's, S&P or Fitch.[1] Credit agencies usually provide issuers with a shadow rating in order for them to evaluate a potential bond issue.[2] However, the bond issuer may or may not choose to make this information public. In this setting, it is important for investors to understand why certain issuers default on their debt obligations. Our initial objective in this thesis is therefore to provide investors with essential information on the determining factors of default. Thus, our first research question can be summarized as follows:

What are the main determining factors of default in the Nordic high-yield bond market?

Logistic regression models are estimated in order to provide an answer to this question. An important aspect in this regard is that we seek to estimate models that can actually be applied for forecasting purposes. Quantifying the impact of past events, such as the financial crisis, is

[1] Using the "Pareto High-Yield Bond Report, January 2016" as a representation of the market.

[2] A shadow rating is a type of credit rating that helps issuers determine how well a potential bond issue would appeal to investors. The shadow rating is prepared by a credit agency for the issuer and is not necessarily available to potential investors.

beyond the scope of this thesis. Instead, the goal of this study is to present – for the first time on the Nordic market – models that can predict default probabilities for high-yield bonds. Moreover, the aim is not to build models through technical improvements of previous ones. Logit analysis is therefore deemed appropriate for our purpose. Logit models yield output in terms of probabilistic outcomes, and unlike other methods they do not require a certain score to be converted into probabilities. This can be an additional source of error, which is one of the major contributions of using logit analysis (Ohlson, 1980).

3.1.1 Methodology

The Logit Model

Using the logit model, we generate a value for each bond by weighting the independent variables. Following Grammenos et al. (2008), we assume the variable $y_t \in \{0,1\}$ is related to an index y_t^* by a linear function of the independent variables $x_{i1}, x_{i2}, \dots, x_{ik}$ and the random term u_i so that:

$$y_i^* = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + u_i = x_i' \beta + u_i. \tag{1}$$

We assign y_i^* the value of 1 if the bond has defaulted, and 0 otherwise. The conditional probability of default for bond *i* can then be calculated as:

$$\Pr(y_i = 1 \mid x_i' \beta) = F_u(-x_i' \beta) = \frac{1}{1 + \exp(x_i' \beta)}. \tag{2}$$

F_u is the cumulative distribution function of u, which is assumed logistically distributed. The independent variables are given by $X_i (i = 1, \dots, k)$ and $\beta_i (i = 0, \dots, k)$ are the estimated parameters.

Testing for Functional Misspecification

Logistic regression models build on the underlying assumption that the logit of the outcome variable is a linear combination of the independent variables. However, Lennox (1999) finds both leverage and cash flow ratios to have non-linear effects on bankruptcy probability. Hence, we must test whether the linear combination is sufficient, and that we have not omitted any relevant variables due to functional misspecification. To test for specification errors, we apply the framework suggested by Pregibon (1979). For each estimated model, the linear predicted value ($\hat{p}$) and the linear predicted value squared ($\hat{p}^2$), are regressed on the outcome variable as independent variables, as shown below.

$$\hat{p} = \hat{\beta}X \tag{3}$$

$$y = \beta_0 + \beta_1\hat{p} + \beta_2\hat{p}^2. \tag{4}$$

Since $\hat{p}$ is the predicted value from the fitted model, it should be a statistically significant variable. On the other hand, $\hat{p}^2$ should not be statistically significant if our model is correctly specified.

Hosmer-Lemeshow Goodness-of-Fit Test

The Hosmer-Lemeshow (H-L) goodness-of-fit test is used to evaluate whether the number of predicted outcomes reflect the number of observed outcomes in the data. Here, we rank and group each bond based on the value of the estimated probability from the respective models. We use a group number of 10 as suggested by Lemeshow and Hosmer (1982). With the number of bonds equal to *n*, this results in the first group containing the n'_1 = *n/10* bonds with the lowest estimated probabilities, and the last group containing the n'_{10} = *n/10* bonds with the highest estimated probabilities. The H-L test statistic is used to determine if there is a statistically significant difference between at least one group in the number of predicted outcomes, compared to the observed number of outcomes. A model is considered a poor fit for the data if the test statistic is statistically significant.

3.2 Default Risk and Bond Age

After identifying the determining factors of default, we are interested in studying the relationship between default risk and bond age for the Nordic high-yield bond market. To our knowledge, such a study has not been carried out for this particular market, making this an intriguing area to explore. This leads us to our second research question:

How do default probabilities change over time for bonds issued in the Nordic high-yield bond market?

To answer this question, we look to an entirely different branch of statistics, namely survival analysis. Hazard models are commonly used in survival analysis to study the duration of time until an event occurs. Although these models are primarily used in medicine (survival time of patients under treatment) and engineering (failure time of materials), they are to a lesser extent used in finance as well. For instance, Hensler et al. (1997) employ a hazard model to investigate the indicators of firm survival for initial public offerings (IPO's). In bankruptcy prediction, a hazard model was first applied by Lane, Looney and Wansley (1986) to predict bank failures.

In this thesis, we center our interest on the survival time of a bond without defaulting. Building on the findings from our first research question, we apply the Cox (1972) proportional hazard model. In contrast to the logit model, which estimates default probabilities for a single moment in time, the hazard model estimates the probability that a bond will survive longer than some specific length of time. Thus, the major contribution of using a hazard model over other econometric models is that the probability of default can be studied through time. Based on the estimated Cox models, we can recover the bonds' underlying risk of default as a function of time.

Measuring the default risk of bonds has been a controversial topic over the years, and many different approaches have been taken. As stipulated by Moeller and Molina (2003), estimated default rates on high-yield bonds can vary from insignificant to substantial depending on the methodology. Both Altman (1992) and Asquith et al. (1989) find ten-year cumulative default rates for non-convertible high-yield bonds to be over 30%. Hessol (1991), on the other hand, finds ten-year cumulative default rates to lie between 18.5% and 23%. The methodology choice is therefore not trivial. A large amount of the inconsistency in the literature can be attributed to the constant change in bond population due to bonds that are either called, mature or default. One of the main benefits of hazard models is that they can explicitly account for changing bond populations through censoring of observations.[3] The constantly changing bond population in our observation period is therefore not an issue with this particular model specification.

Among the wide range of hazard models, we have chosen to apply the Cox proportional hazard model due to the fact that it is a flexible semi-parametric model. The major advantage

[3] In this study, bonds that are either called, converted, mature or still outstanding at the end of our observation period, are censored observations. Defaulted bonds are considered completed observations.

of the semi-parametric approach is that we are not required to impose any distributional assumptions on the data. In a parametric hazard model, we would have to model the time dependence on a specific distribution such as exponential, Weibull, gamma or log-logistic.

Based on empirical research on the U.S. high-yield bond market, one could argue that default probabilities are either constant or increasing with time. Therefore, an exponential or Weibull distribution could be justified. However, in the absence of a strong theoretical reasoning for a specific distribution, the semi-parametric approach is preferred. In this way, we allow for the explanatory variables themselves to affect the distribution. More importantly, since we – to our knowledge – are the first to carry out such a study on this particular market, we would like to accommodate for the possibility that the Nordic high-yield bond market may differ from that of the United States.

3.2.1 Methodology

The Cox Proportional Hazard Model

Let *T* indicate the time to default of an individual bond, and *t* denote the survived time. The Cox proportional hazard model describes the distribution of time to failure in terms of the hazard function:

$$\lambda(t) = \lim_{h \to 0} \frac{P(t \leq T < t + h \mid T \geq t)}{h}, \qquad t > 0. \tag{5}$$

The hazard rate, $\lambda(t)$, is the probability of failure in the next instant *h*, given the survived time *t*. In other words, it is the continuous probability of a bond defaulting. We aim to quantify the effect of explanatory variables in the hazard model, so we multiply the hazard function by a scale vector. The hazard function can then be expressed as

$$\lambda(t) = \lambda_0(t) \exp[\mathrm{Z(t)}'\beta], \tag{6}$$

where $\lambda_0(t)$ is the baseline hazard function (Kalbfleisch and Prentice, 2002). $Z(t) = [Z_1(t), \ldots, Z_p(t)]'$ is a vector of derived covariates. These covariates are obtained as functions of *t* and the basic covariates *x*, and they can either be fixed or time-dependent.
$\beta = (\beta_1, \ldots, \beta_p)'$ is a vector of parameters.

Recovering the baseline hazard function

To evaluate how the bonds' probability of default changes over time, we need to recover the baseline hazard function $\lambda_0(t)$. In our case, the baseline hazard function is interpreted as the underlying risk of default over time, which is common to all bonds. The function itself is not estimated within the Cox model. However, it can be obtained by setting all the covariates equal to zero in the hazard function, i.e. $Z(t) = [0, \dots, 0]'$ for all t. Kalbfleisch and Prentice (2002) provide a detailed explanation of this procedure.

Showing the significance of the observed pattern in the estimated baseline hazard function is a challenge in the semi-parametric approach (Moeller and Molina, 2003). As a qualitative comparison to the Cox model, we also specify the hazard function parametrically. Therefore, we repeat our analysis and estimate the baseline hazard functions assuming a Weibull distribution. Kalbfleisch and Prentice (2002) explain the similar methodology of estimating a parametric hazard model with a Weibull distribution.

Testing for Non-Proportional Hazards

A key assumption in the Cox model is that of proportional hazards. Observations have to be proportional to one another and the proportionality must be maintained over time. It is critical to correct for non-proportional hazards because it can lead to biased parameter estimates and the power of the statistical tests can decline (Keele, 2010). To account for this, we adopt the framework of Grambsch and Therneau (1994), which produces a global test statistic (χ^2) based on the scaled Schoenfeld residuals.[4] The global test statistic is used to determine whether the model as a whole violates the proportional hazard assumption. It is also possible to obtain test statistics for specific covariates in order to examine which variables are causing the violation. Test statistics that exceed the critical value of 5% are considered to violate the proportional hazard assumption. Keele (2010) provides a detailed explanation of the test statistic used for our models.

[4] Schoenfeld residuals are the observed minus the expected values of the covariates at each failure time.

4. Data

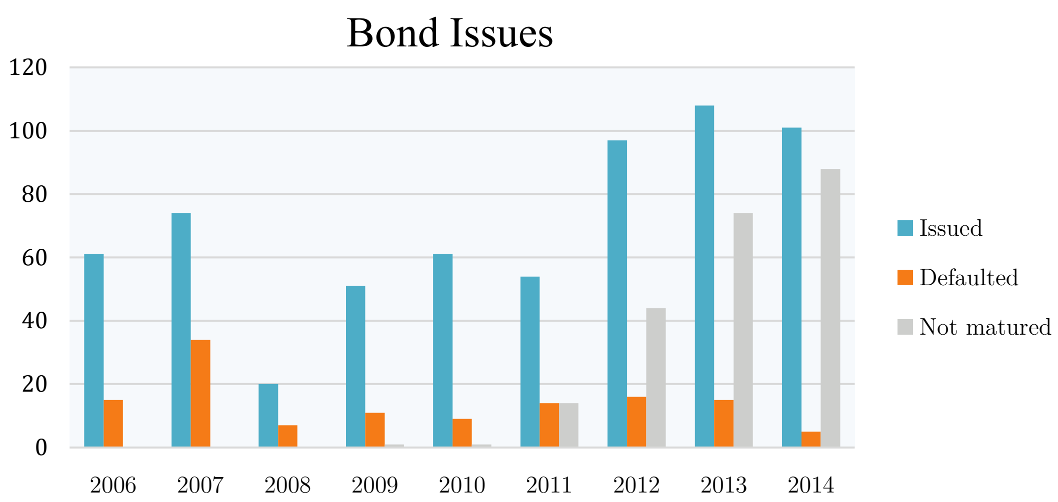
In this section, we present our sample of bonds and explain the data collection process. We also describe the datasets that are used for the analysis.

4.1 Sample Selection

The final sample for this study consists of 627 original issue high-yield bonds in the Nordic market. The bonds are issued by a total of 301 issuing firms, implying an average of approximately two issues per firm. The sample is quite evenly distributed between private and public firms, as 369 bonds (146 issuers) are issued by public firms. All bonds are issued in the time period of 2006 to 2014.[5] Figure 1 provides an overview of our sample by issuance year.

As of April 2016, a total of 126 bonds had defaulted (66 by public firms), equivalent to 20% of our sample. Despite our sample not being a complete representation of the market, this gives a rough indication of the turbulent observation period of our study. Table I explains in further detail how our final sample was reached and how it compares to the actual high-yield bond market, depending on the definition of high-yield.

Figure 1 - Sample by Issue Year



Note: The figure shows the number of bonds that were issued for each year in our sample. For each group of issues, the corresponding numbers of defaulted and still outstanding bonds are also displayed.

[5] Prior to 2006, the Nordic high-yield bond market was relatively small and dominated by a small number of issuers. The decision to exclude bond issues after 2014 was made because the lifespan of these bonds were considered too short to provide a qualitative contribution to the sample.

To arrive at our final sample, it is necessary to go through several steps. The first step is to identify all high-yield bond issues in the Nordic region. Stamdata, a database operated by the Nordic Trustee[6], was used as the main source in this process. Stamdata provides information and statistics on bonds issued in the Nordic region. Detailed information on each bond issue is available in their database. Loan agreements, documents and letters from the trustee are all published. In addition, updated information regarding coupon payments, extended maturity and other changes in covenants are accessible. An exhaustive list of bonds classified as high-yield was extracted from the Stamdata database for the period 2006 to 2014.

Table I - Filtering Process

	Bonds	Issuers	Defaults
High-yield issues in Stamdata (2006-2014)	1540	665	218
Removal of financial institutions and government guarantees etc.	1058	505	215
Removal of comm. papers, warrants and perpetual bonds	924	464	184
Final sample due to unavailable data	**627**	**301**	**126**

Note: The table provides an overview of the filtering process before ending up with our final sample of bonds. The final filtering process, due to unavailable data, includes both missing loan documents in Stamdata and unavailable accounting information for the issuers.

Many of the bonds classified by Stamdata as high-yield are not generally considered a part of the "actual" high-yield bond market. Issues belonging to firms that are not widely recognized as high-yield are therefore removed from the sample. This includes companies classified to be in the financial or public sector, companies with substantial government ownership (and issues with government guarantees), energy companies[7] and unlimited liability companies. In addition, further filtering was needed due to the inclusion of bond types other than regular bonds. Commercial papers, warrants and perpetual bonds are excluded.

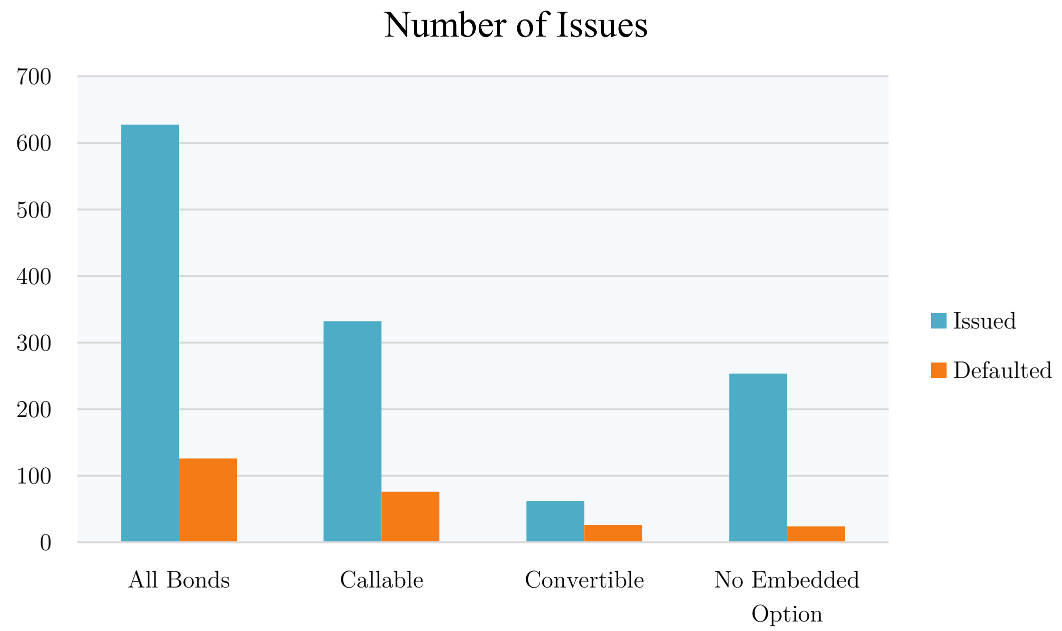
On the other hand, a substantial amount of convertible bonds were found to be issued by firms that are in fact widely recognized as part of the high-yield bond market. Some previous studies exclude convertible bonds from their samples because of the equity component. However, Altman (1992) states that high-yield bond returns have equity-like features, due to the significant risk carried. Since this is the case for both convertible and non-convertible bonds,

[6] The Nordic Trustee (operating in Norway, Sweden, Denmark and Finland) is the leading supplier of trustee services in the Nordic region for bond investors.

[7] The energy companies were non-petroleum and gas companies, primarily related to the electricity industry.

we are not restricting our sample to non-convertible bonds only. Figure 2 shows our sample according to the bond type.

Figure 2 - Sample by Bond Type



Note: The figure displays an overview of our sample depending on the bond type. We distinguish between bonds with embedded options to either call or convert the bond, and those without.

In order to verify the final sample of high-yield bond issues, a Nordic high-yield bond report from Pareto Securities was provided. The report includes most of the high-yield bond issues starting from 2006, but does not include all. For example, convertible bonds and many of the multiple issues by one company in the same year are left out. Thus, the report is primarily used as a starting point in identifying high-yield firms. It is worth noting that a few of the bonds in the report are stated to possibly be in the lowest investment grade category. Nevertheless, all bonds in the report (given available data) are included in our sample.[8]

Finally, Stamdata provided a comprehensive list of bonds that have defaulted since 2006, according to the Nordic Trustee's definition of default. The list is used to identify the defaulted bonds in our sample. It also includes the dates for which the defaults occurred, which is a crucial piece of information in order to carry out a survival analysis. Information for the non-defaulted bonds on the survival time was collected manually from the Stamdata database.

[8] Arne Eidshagen, high-yield bond portfolio manager at Forte Fondsforvaltning AS, verified the remaining bonds from our filtering process (outside of the high-yield firms in the Pareto report) as being high-yield.

Defaulted bonds in the list are separated into three categories, namely bankruptcy, non-payments and distressed exchanges. The first category involves both bankruptcy proceedings and voluntary liquidations. Non-payments include a standstill of coupon payments, installments or principal. Deferred payments are also defined as default. Distressed exchanges occur when a distressed company offers creditors new or restructured debt. Securities, assets or cash that amount to a diminished portion of the original obligation are occasionally offered instead.

4.2 Accounting Information

After identifying the high-yield bond issues in the Nordic market, we collect accounting information for the issuers. For each bond issue, accounting information is collected for three years on the respective issuers. An important aspect to this thesis is the timing of the data collection. Due to relatively low liquidity in the Nordic high-yield bond market, the decision has been made to focus on the time around issuance. Our observation period starts when the bonds are issued, and we trace the bonds going forward. For an original bond issue, the most recent annual report prior to the year of issuance is used. In other words, when a bond is issued in year *t*, the corresponding accounting information is from year *t-1*. Three years (annual reports) of accounting information is collected by this method going forward.

The first challenge in this process is to identify the appropriate entity to collect accounting information from. To determine this, it is necessary to search through each loan document in Stamdata in order to identify potential guarantors. When a parent or another company is explicitly stated as the guarantor of the bond, this entity is considered the real borrower. Some bonds have multiple companies guaranteeing the issue. In these cases, the issuer itself is considered the debtor. Moreover, many of the issuers are parent or holding companies. For instance, drilling and shipping companies will typically establish an oilrig or a vessel as a wholly owned subsidiary. Using financial statements purely from the parent company can then be quite misleading regarding the actual state of the business. Consolidated financial statements of the group are used instead, as they are considered more representative of the company as a whole.

Initially, accounting information was extracted from the SNF[9] database for Norwegian firms, whereas accounting information for foreign firms was gathered manually through annual reports. However, the accounting information from SNF turned out to be accompanied by quite

[9] SNF is operated by the Centre for Applied Research at NHH. The database provides accounting information for most companies registered in the Brønnøysund Business Register Centre.

a few errors. Further examination revealed an inconsistency between SNF and the annual reports (which were cross-checked with the databases of Proff and Orbis).[10] Therefore, we decided to go with the more time consuming approach and collect the accounting information for the Norwegian companies manually from annual reports as well. As a result, the number of years we were able to collect accounting information for was limited to three years. On the other hand, we are now confident in the quality of our data. Most of the annual reports are found in the PI-Navigator database.[11] For the remaining companies, annual reports and accounting information are found in Proff, Orbis and other websites providing such information.

With a large part of our sample consisting of Norwegian companies, a majority of the annual reports are reported in NOK. Daily exchange rates were extracted from DataStream[12] in order to convert the financial figures from the other reports to the same currency (NOK). Average yearly exchange rates are used to convert the figures from the income statement. An average rate is generally appropriate only when the exchange rate does not fluctuate significantly. Since the majority of the figures in this thesis are used on a ratio basis, exchange rate volatility is not taken into account. Closing exchange rates for the year-end are used to convert figures from the balance sheet.[13]

4.3 The Datasets

Having collected accounting data for the first three years of each bond issue, there are different ways to carry out the analysis. One is to estimate separate models on cross-sectional datasets for different time periods of the bonds life-cycle. By doing so, one can observe whether some factors are more important at certain stages of the bonds' life. The main issue with this approach is that the bond population shrinks significantly for each year, mainly due to calls and defaults. With an already small obtainable sample size, we take a different approach.

Instead, we estimate "static" models based purely on the available information at the issuance time of the bonds. The static models are estimated on cross-sectional data with one observation per bond. All bonds are included in the static models and we have 627 observations. Additionally, we construct datasets consisting of panel data where we include the observations for the second and third years of the bonds' lives, one for each year. We refer to these models as "dynamic". Since these datasets are of a discrete nature, we define yearly grouping intervals.

[10] Proff and Orbis provide accounting information for Scandinavian and international companies, respectively.
[11] PI-Navigator is a database providing information for company analysis and modelling.
[12] DataStream is an economic research database.
[13] This method is similar to the foreign currency translation method currently proposed by the IFRS.

For a bond that defaults during the third year, the default is recorded in the third and final observation. Bonds that are outstanding for more than three years will only have three observations in these datasets, while a bond that defaults in the first year will only have one observation. As such, the study period in these models is restricted to three years post issuance, and the total number of observations depends on the time period each bond is outstanding.

The datasets can be summarized as follows. In our logit analysis, we carry out a separate analysis for a subsample of bonds issued by public firms. Therefore, we have a total of four datasets for this area of research. Two static models are estimated based on cross-sectional data for the issuance time, one for all bonds in our sample and another for bonds issued by public firms. Similarly, two dynamic models are estimated based on panel data using all information collected from the first three years of the bonds' lives. In the survival analysis, we do not carry out a separate analysis for bonds issued by public firms. Here, we only have two datasets, one for a static and a dynamic model. The dataset for the static model is similar to that of the static model for all bonds in our logit analysis, only the survival time is now the dependent variable. Likewise, the dataset for the dynamic model is similar to that of the dynamic model for all bonds in our logit analysis. The main difference in datasets for the dynamic model is that we have monthly observations instead of yearly in order to account for changes in the general economy and the various industries. Monthly grouping intervals also allows us to study default rates more frequently.

In terms of estimating default probabilities in our logit analysis, the construction of the datasets has some implications. Due to the discrete nature of the datasets in the dynamic models, the estimations are based on year-to-year observations. Probability estimates can therefore be interpreted as yearly default rates. On the other hand, the static models are not time-dependent in the same way. The longest outstanding bond in our sample is over seven years and the shortest is only a few months, the average being just below three years. The static models do not capture the discrepancies in the different time periods the bonds are outstanding, but merely quantify the impact of available information at the issuance moment. Hence, one could argue that the dynamic models are more suitable for application purposes.

Nevertheless, the static models can help investors determine which new issues have a high likelihood of default. Issuers can also benefit by identifying the factors they need to focus on in order to offer an issue with a low probability of default. Due to low liquidity in the market, it is not uncommon for investors to hold a bond from the issuance time and until the bond either matures, is called or defaults. Therefore, it makes sense to include static models based on information at the issuance time.

5. Variable Selection

For the purpose of identifying determining factors of default, we start by introducing our variable selection. In addition, we discuss the anticipated effects of the selected variables on default probabilities from a univariate perspective. The explanatory variables are largely related to bond characteristics and financial ratios. However, we also include other variables that may have an impact on default probabilities. Credit ratings are not included in our variable selection due to the scarcity of official ratings.

5.1 Bond Characteristics

From the original loan agreements at the issuance time, we identify several characteristics of the issued bonds. First we record whether the bond is callable (CALL), convertible (CONV) and if the coupon is floating or fixed (FIXED). These variables are accounted for by the use of indicator variables. The indicator variables are assigned the value of one if the bond is callable, convertible or if it pays a fixed coupon. Otherwise, they are equal to zero. Further, we note the declared coupon rate (COUP), the issue size (ISSIZE) and the time to maturity (MAT).

For callable bonds, one would assume that strong companies (i.e. those with low perceived default risk) are able to negotiate better loan agreements than weaker companies (i.e. those with higher perceived default risk). Hence, it is possible that the stronger companies have the option to call the bond, whereas the weaker ones may not. On the other hand, strong companies may not have the same need for a call option if they are able to negotiate a low coupon. By this logic, it could be mainly the weaker firms that have the option to call the bond. Another possibility is that weak companies can negotiate the inclusion of a call option, but the call option comes at a relatively higher redemption price compared to stronger companies. In lack of a clear intuitive argument for this variable, we will let our findings determine the relationship between this variable and the probability of default.

Table II - Variables Tested in Default Prediction

Notation	Exp. Sign	Variable Definition	Origin
		Bond Characteristics	
CALL	+/-	Callable bond	Own
CONV	+/-	Convertible bond	Rosengren, 1993
FIXED	+	Fixed coupon bond	Own
COUP	+	Coupon spread	Lehman & Fridson, 1995
ISSIZE	-	Issue size (in NOK)	Huffman & Ward, 1996
MAT	+/-	Time to maturity (in months)	Cotter & Peck, 1995
		Leverage & Debt Service	
TDTE	+	Market (Book) Value of Debt/Total Equity	Altman, 1968
ARTA	+	Amount Raised/Total assets	Grammenos et al., 2008
GEAR	+	Long Term Debt/(Long Term Debt+Equity)	Grammenos et al., 2008
EBITIE	-	EBIT/Interest Expense	Altman et al., 1977
EBITCL	-	EBIT/Current Liabilities	Own
		Profitability	
NISALES	-	Net Income/Sales	Park & Han, 2002
NITE	-	Net Income/Total Equity	Park & Han, 2002
EBITTA	-	EBIT/Total Assets	Altman, 1968
RETA	-	Retained Earnings/Total Assets	Altman, 1968
		Liquidity	
WCTA	-	Working Capital/Total Assets	Altman, 1968
CACL	-	Current Assets/Current Liabilities	Zmijewski, 1984
CASHTA	+/-	Cash/Total Assets	Nam et al., 2008
		Turnover	
SALESCA	-	Sales/Current Assets	Beaver, 1966
SALESTA	-	Sales/Total Assets	Beaver, 1966
SALESFA	-	Sales/Fixed Assets (PP&E)	Grammenos et al., 2008
		Other	
LNTA	-	Natural log of total assets	Ohlson, 1980
PPETA	+	Property, Plant & Equipment/Total Assets	Huffman & Ward, 1996
INDUS	-	Industry index return	Own
MACRO	-	Stock market return	Duffie et al., 2007
DTD	-	Distance to default	Duffie et al., 2007
AGE	-	Firm age (in years)	Altman, 1993

Note: The table presents the variables used in default prediction. The notations are used to identify the variables in our model estimations in section 6.

For convertible bonds, the option to convert the bond provides added value to the investor, which in turn usually results in lower coupon payments than a comparable non-convertible bond. Rosengren (1993) shows that convertible bonds have lower default rates than non-convertible bonds. Considering the market has accepted the convertible bond despite lower coupon payments, it could suggest that investors are optimistic about the issuer's prospects.

Moreover, if the company shows temporarily good results after issuance, investors will likely convert the bond into common stock. Even if the firm experiences financial distress at a later stage, the bond will not default since it is no longer outstanding. Nevertheless, there is an argument to be made for convertible bonds to carry higher risk than non-convertible bonds. Weak companies may issue convertible bonds because it is the only way they can persuade creditors to lend them money. Thus, there could be a higher risk of default, but the convertible provision is included as compensation. We let our findings determine the relationship with default rates for this variable as well.

Close to 40 percent of our bond sample consists of bonds with fixed coupon payments, while the remaining bonds are Floating Rate Notes (FRNs). FRNs pay a variable coupon equal to a benchmark reference rate, such as the three-month LIBOR, plus a quoted margin that remains constant. Therefore, FRNs are almost immune to interest rate risk. The main risk component in an FRN is credit risk. Since fixed coupon bonds are exposed to both interest rate risk and credit risk, we expect these bonds to be subject to a greater risk of default.

In regard to the declared coupon of the bond, a high coupon rate obviously implies high cash requirements for interest payments. Consequently, high coupon bonds should default more frequently than lower ones. However, since the bonds in our sample are issued over a nine-year period with highly varying interest rate levels, we normalize the coupon rate by subtracting the three-month reference rate that corresponds to the denominated currency of the bond. That is, if the bond is denominated in euros, we subtract the three-month EURIBOR rate. Similarly, for a bond denominated in Norwegian krone, we subtract the three-month NIBOR rate.[14] The COUP variable can thus be interpreted as a coupon spread over the risk-free rate. For bonds issued at par value, the coupon spread should reflect the perceived credit risk of the issue. In our dynamic models we include this variable as a time-varying covariate with updated spreads, and we expect a positive coefficient sign.

For the issue size, the amount raised in each bond issue is adjusted for inflation and converted into NOK for all bonds at the prevailing exchange rates at the issuance time. An issuer that is able to raise a large amount has evidently either attracted a large group of investors, or an investor that is willing to commit a significant amount of money. This would not be possible unless investors have a positive outlook on the firm. Besides, this variable is clearly positively correlated with the size of the firm, so it also serves as a measure of the size effect

[14] Short-term interest rates are collected from Datastream.

of a firm. With large firms also believed to default less often, ISSIZE should have a negative effect on default probabilities.

The final variable in the category of bond characteristics is the time to maturity (MAT). The time is measured as the number of months from the issuance date until the stated maturity date. As mentioned earlier, a short maturity often leaves insufficient time for companies to realize return on their investment and generate the required cash to repay principal. However, a long maturity clearly allows more time for unforeseen events and consequently failure. As a result, we let our findings in the analysis determine the relationship between this variable and the probability of default. The variable is also included as a time-varying covariate in our dynamic models.

5.2 Financial Ratios

Leverage and Debt Service

In order to assess the financial risk of the companies, we employ ratios that measure the degree of financial leverage and the firms' abilities to service their debt. First, we measure the debt-to-equity ratio by market (book) value of debt over total equity (TDTE). The market value of equity is used for our subsample of public firms, while the book value is used for the full bond sample. We also have another gearing measure (GEAR), calculated as long-term debt over long-term debt plus total equity. In the issuance year of the bond, we do not include the issue amount in the long-term debt. Only if the firm issues new bonds later in the same year will the previous issue amounts from the other bonds be included. Hence, this variable is a pre-issue measure. Further, we have the amount raised over total assets (ARTA). The probability of default should have a positive relationship with these leverage measures.

As for debt service measures, we include two ratios; earnings before interest and taxes over interest expense (EBITIE) and current liabilities (EBITCL), respectively. The former is an interest coverage ratio, while the latter is a debt-service coverage ratio. Low debt service ratios correspond to a high debt burden for the company. Therefore, we expect negative signs for these two ratios.

Profitability

Four measures are used to capture the profitability of the firms. Firstly, we have the profit margin, calculated as net income over sales (NISALES). Low profit margins could indicate that a company is underpricing its goods or struggling to keep the costs low. Secondly, we have a return on equity measure, calculated as net income to total equity (NITE). This ratio is important for shareholders as it reveals how much profit the company is generating with the invested capital. Thirdly, EBIT over total assets (EBITTA) provides an indication of how effectively a company is using its assets to generate earnings before contractual obligations need to be met. Lastly, retained earnings over total assets (RETA) is used to measure the companies' cumulative profitability over time. A high retained earnings ratio suggests a history of profitability and the ability to withstand a period of bad losses. We expect higher values of all four ratios to be associated with a lower probability of default.

Liquidity

Three liquidity measures are used to predict default. The working capital over total assets (WCTA) expresses a firm's net liquid assets relative to the total assets. The current ratio, calculated as current assets over current liabilities (CACL), is commonly used to measure a company's ability to pay back its short-term obligations. As a measure of the company's most liquid assets, we employ the ratio of cash and cash equivalents over total assets (CASHTA).

Naturally, a company with insufficient funds to cover its debt obligations is highly vulnerable to failure. By intuition, one would assume that the more liquid assets a firm holds, the lower the probability of default. However, excess amounts of cash could also prove to be inefficient use of resources and indicate a lack of investment opportunities. These ratios could therefore have different impacts on default probabilities.

Turnover

Certain sectors, such as energy and shipping, are highly asset intensive, requiring large and expensive machinery, equipment and vessels to operate and generate sales. In light of the Norwegian offshore sector's dominant position in the Nordic high-yield bond market, we engage turnover ratios to quantify the companies' efficiency in using its assets. Sales to current assets (SALESCA), total assets (SALESTA) and fixed assets (SALESFA) are included in our analysis. Generally speaking, well performing companies will have higher asset turnover ratios. Higher values of these ratios are therefore predicted to lower the likelihood of default.

5.3 Other Variables

Size and Collateralizable Assets

In their study on high-yield bonds, Huffman and Ward (1996) find that firms with large amounts of assets that can be used as collateral relative to the book value of the firm have a greater probability of default. This is because companies with large amounts of collateralizable assets can be higher leveraged without investors demanding higher premiums or restrictive covenants. In the event of the collateralizable assets being greater than the book value of the firm, the company is likely worth more liquidated than as a going concern. Moreover, Gilson, John and Lang (1990) find that firms with large amounts of intangible assets are more likely to restructure privately. To account for this aspect, we employ the variable of property, plant and equipment over total assets (PPETA), and expect a positive relationship with default probabilities.

Large firms are typically less risky and have more financial flexibility than smaller firms (Duffie et al., 2007). Derived from the renowned study of Ohlson (1980), size is often accounted for by the natural logarithm of a firm's total assets in the bankruptcy prediction literature. We adopt this approach when capturing the size effect (LNTA) of the firms, which should have a negative relation to default rates.

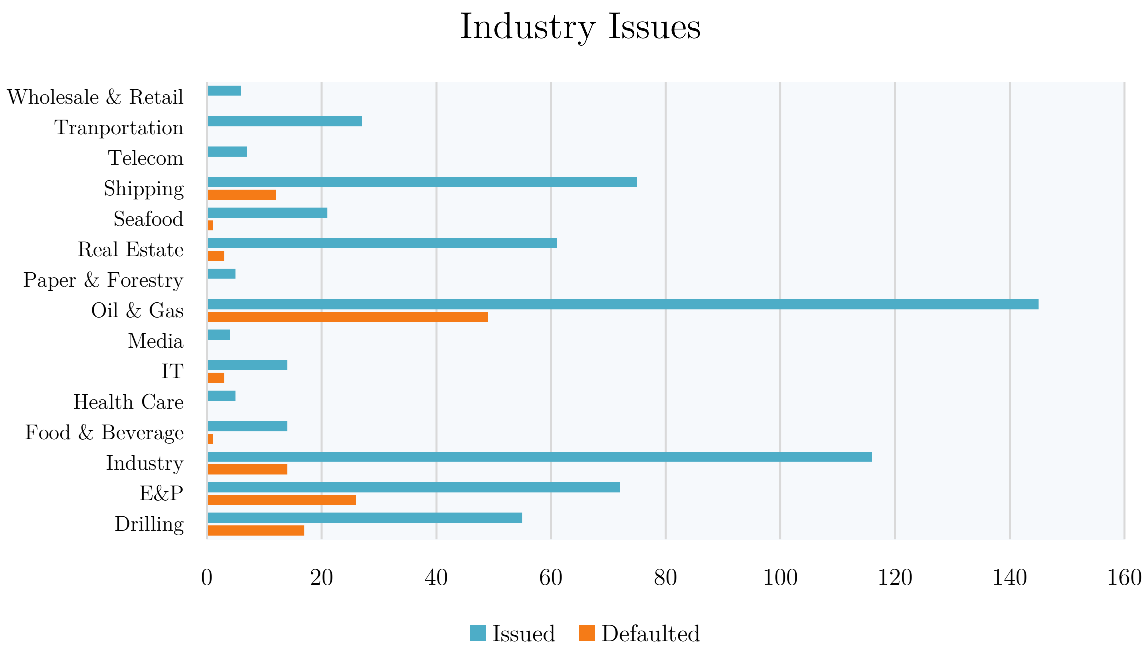
Industry Variable

Inspired by the findings of Grammenos et al. (2008), we create a similar industry specific variable capturing the market conditions prevailing at the time of issuance. Based on the industry classifications in Stamdata and Pareto's high-yield bond report, we divide the companies into separate industries. Figure 3 displays an overview of our sample in terms of the assigned industries.

The UCI function in DataStream allows us to construct stock indices for the respective industries. [15] Nordic traded companies are identified in their database and added to the corresponding industry indices. With our first bond issued in 2006, the starting point of the indices is set to 2005, and the companies are weighted according to their market value. In order to avoid a bias toward persisting companies, we also include companies that are delisted for various reasons, including bankruptcy.

[15] UCI stands for User Created Indices.

Figure 3 - Sample by Industry



Note: The figure presents an overview of our sample of bonds grouped by industry. The Norwegian energy sector dominates the Nordic high-yield bond market, and this is also where the most defaults occur. E&P is related to the oil sector, and stands for "Exploration & Production".

After constructing the industry indices, we compare the returns of the indices at the issuance time with the moving average of the last twelve months. This allows us to evaluate the market conditions at the moment of issuance in each industry relative to the preceding year. If the returns are above the previous year's moving average, the bond is issued at a favorable time because market conditions have improved compared to the immediate past. As a result, we anticipate a negative relationship between this variable (INDUS) and the probability of default.

In contrast to the study of Grammenos et al. (2008), we use a twelve-month moving average instead of a three-year moving average. This is due to the highly volatile period of our study.[16] In our dynamic models we include this variable as a time-varying covariate.

Macroeconomic Variable

Among a wide range of macroeconomic variables tested, Duffie, Saita and Wang (2007) find two variables to be highly important in predicting corporate default. One is the three-month Treasury bill rate, and the other is the trailing one-year return on the S&P 500 index. Having already somewhat accounted for short-term interest rates in the coupon spread variable, we

[16] We also tried a three-year moving average, however, this did not improve our results.

decided to use a proxy for the trailing one-year return on the S&P 500 index for the bonds in our sample. To do so, depending on which country the bond is issued in, we use the benchmark (main) index of the respective country in place of the S&P 500 index (i.e. the OSEBX index for a bond issued in Norway).[17] A higher trailing return on the benchmark index should imply that market conditions have improved. Hence, we expect this variable (MACRO) to be inversely related to default probabilities. In our dynamic models we include this variable as a time-varying covariate.

Distance to Default

For our subsample of bonds issued by publicly traded companies, it makes sense to incorporate a structural approach to default prediction. With that in mind, we include the firms' distance to default as an explanatory variable, based on the original Merton (1974) model.

The Structural Approach to Default Prediction

The general idea behind structural models is that default occurs when a firm's asset value falls below a critical value related to its liabilities. Following the concept proposed by Merton (1974), we assume that the firm's liabilities are comprised of a single zero-coupon bond with notional value *L* maturing at time *T*. No payments are made until T, at which equity holders will decide whether to default or not. Further, the probability distribution of the asset value at maturity is expected to follow a log-normal distribution, where the yearly variance of the log asset value is denoted σ^2 (Löffler and Posch, 2007). From here we expect the yearly change in log asset value to be $\mu - \sigma^2/2$, where μ is the drift parameter. Lastly, we let *t* denote today. The distance to default can then be computed as:

$$DTD = \frac{lnA_t + \left(\mu - \frac{\sigma^2}{2}\right)(T-t) - lnL}{\sigma\sqrt{T-t}}. \tag{7}$$

The distance to default measures how many standard deviations the expected asset value A_t is away from the default point (value of debt). In practice, the only problem with the

[17] The OMX Copenhagen 20 is used for Danish issues, OMX Stockholm 30 for Swedish, and OMX Helsinki 25 for Finnish.

abovementioned formula is that we cannot observe the market value of assets and the asset volatility. Therefore, we look to option pricing theory to help us derive these parameters. We know that the equity value of a firm can be described as the pay-off of a European call option on the firm's assets with strike price equal to L. Assuming the firm does not pay any dividends, we can determine the equity value by applying the standard Black-Scholes call option formula. By using this formula, we have an equation that links the observable equity value to the unobservable market value of assets and asset volatility.

Implementation

In order to compute the distance to default in practice, we follow a similar approach to Löffler and Posch (2007). First, share prices and numbers of outstanding shares were extracted from Datastream for all public companies in our subsample of issues by public firms. The market values of equity E_T are then obtained by multiplying these figures for the various dates. Secondly, we set the horizon $T - t$ equal to one year. In other words, all the firm's liabilities are assumed to mature in one year. Further, we set the firm's liabilities L equal to book value[18] and use the one-year treasury yield as the risk-free rate.[19]

Although we have successfully linked the equity value to the unobservable parameters through the Black-Scholes formula, we still have only one equation and two unknowns. Another equation containing the two unknowns must be introduced. Since equity is considered a call option on the firm's assets, its riskiness depends on the risk of the underlying asset. Equity volatility σ_E is therefore assumed to have the following relationship with asset value A_t and asset volatility σ:

$$\sigma_E = \sigma \, \Phi(d_1) \, A_t / E_T, \tag{8}$$

where Φ is the cumulative standard normal distribution. We compute annualized estimates of equity volatility based on historical volatility measured over the preceding 260 days.[20] Accordingly, an equation system of two equations with two unknowns is reached. The Black-

[18] The book value of debt is obtained from the most recent annual report.
[19] Treasury yields are collected from Datastream, and depend on which country the bond is issued in.
[20] Specifically, we convert daily stock prices to daily log returns. Using Excel's standard deviation command on the range of returns, we obtain the standard deviation of daily returns. Then we multiply this figure by the square root of 260 to get the annualized equity volatility.

Scholes equation system can then be solved in order to obtain estimates of the market value of assets and asset volatility for a given date.[21]

Before computing the distance to default using our newly obtained values for A_t and σ, we need the expected change in asset values. The abovementioned calculations are applied to the past 260 days, providing a series of asset values. Regressing the asset value returns on the benchmark index returns gives us an estimate of the asset's beta. The return on asset i is then determined by applying the Capital Asset Pricing Model (CAPM) formula;

$$E[R_i] - R = \beta_i\big(E[R_m] - R_f\big), \tag{9}$$

where R is the simple risk-free rate of return.[22] As previously explained, depending on the country in which the bond is issued, we use the respective benchmark indices as a proxy for the return on the market portfolio R_m. Further, we assume a standard value of 4 % for the market risk premium $E[R_m] - R_f$. Finally, the expected asset returns from the CAPM formula are converted to logarithmic returns in order to obtain the drift rate μ.

Having determined the market value of assets, asset volatility and the drift rate, the firm's distance to default is calculated by simply inserting the parameter values into equation (7). Higher values of the distance to default measure should correspond to a lower probability of default. The distance to default is updated yearly in our dynamic logit model for public firms.

Firm Age

The relationship between the age of a firm and the likelihood of failure is well documented (e.g. Altman, 1993). For young firms, it is critical to establish valuable resources and capabilities that generate positive cash flows before initial asset are depleted. Failure among older firms is usually attributable to an inability to adapt to environmental changes. In general, firms are at greater risk of failure when they are young and small. Therefore, we include the age of the issuing firms as an explanatory variable. The age is recorded in years starting from when the bond is issued, and we expect a negative sign.

[21] Applying Excel's solver function, we minimize the sum of squared differences between model values and observed values, as described in Löffler and Posch (2007).

[22] We calculate the simple risk-free rate of return as $R = \exp(r) - 1$.

6. Empirical Results

In this section, we present and discuss the results from our empirical analysis. Section 6.1 is related to our first research question, while section 6.2 addresses the second research question.

6.1 Determining Factors of Default

This subsection covers the determining factors of default and our logistic regression analysis. We start by presenting descriptive statistics for our variable selection. Next, the model building strategy is explained before the models are presented and discussed. Finally, we evaluate the estimated models.

6.1.1 Descriptive Statistics

Descriptive statistics for the selection of variables tested in our analysis are presented in Table III. The statistics are based on data from the time of issuance. In the last column, we present the t-statistics of testing the null hypothesis that the mean values of the defaulted and non-defaulted bonds are equal. The test gives us a general idea of the potential explanatory variables for our model estimations. Most variables have significantly different means at the 5% level, suggesting the variable selection is appropriate.

Specifically, at the issuance time, issuers of bonds that defaulted are characterized as being smaller firms with lower profitability and turnover compared to non-defaulted issuers. Bonds that defaulted are more likely to be callable or convertible, and pay fixed coupons and higher spreads. Rather surprisingly, issuers of defaulted bonds are also characterized as having significantly better liquidity (CACL and CASHTA) and lower gearing (GEAR) than non-defaulted issuers. Moreover, issues that defaulted on average raised a considerably higher amount in relation to the size of the firm, equal to 77% of total assets, while the same number for non-defaulted issues is 31%.

Since this particular data is based on the time around issuance, this could indicate that many defaulted issuers are actually companies in a start-up phase with large cash holdings and low debt levels. The highly significant difference in means of firm age can confirm this theory. The average defaulted bond is issued by a firm close to eight years old. Meanwhile, the average firm age of non-defaulted issues is almost 25 years.

Table III - Descriptive Statistics

	Defaulted Issues (126)		Non-Defaulted Issues (501)		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	t-statistic
Bond Character.					
CALL	0.730	0.446	0.479	0.500	-5.146***
CONV	0.206	0.406	0.071	0.259	-4.589***
FIXED	0.611	0.489	0.327	0.470	-6.010***
COUP	0.075	0.040	0.053	0.028	-7.066***
ISSIZE	5.14e+08	4.73e+08	6.17e+08	6.21e+08	1.734*
MAT	49.519	16.260	51.025	17.000	0.897
Lev. & Debt Serv.					
TDTE	0.423	7.918	2.184	11.655	0.822
ARTA	0.777	1.378	0.312	1.123	-5.843***
GEAR	0.303	0.747	0.514	0.236	5.344***
EBITIE	-4.509	35.432	2.383	30.263	0.507
EBITCL	-0.881	5.128	0.262	1.060	4.621***
Profitability					
NISALES	-7.285	66.915	-0.585	8.768	2.173**
NITE	0.011	0.905	0.013	1.279	0.015
EBITTA	-0.198	0.863	0.020	0.125	5.450***
RETA	-0.233	0.948	0.054	0.402	5.187***
Liquidity					
WCTA	-0.061	0.766	0.051	0.214	2.863**
CACL	6.915	22.263	2.202	7.585	-3.925***
CASHTA	0.1845	0.241	0.100	0.104	-5.954***
Turnover					
SALESCA	1.004	1.167	2.053	1.869	6.013***
SALESTA	0.284	0.485	0.514	0.590	4.040***
SALESFA	5.490	29.506	6.978	37.677	0.413
Other					
LNTA	21.431	1.143	22.433	1.346	7.685***
PPETA	0.515	0.312	0.517	0.302	0.0801
INDUS	0.039	0.184	0.071	0.148	2.025**
MACRO	0.163	0.252	0.162	0.209	-0.0487
DTD	1.329	0.824	2.463	1.213	7.232***
AGE	7.905	7.346	24.697	32.742	5.717***

Note: *** p<0.01, ** p<0.05, * p<0.1. The table presents descriptive statistics for the variables selected in section 5. The data is based on the dataset corresponding to our static model for all firms, i.e. at the issuance time.

6.1.2 Model Building

In search of the best models to predict default, we follow the stepwise model-building strategy proposed by Hosmer and Lemeshow (2000). This strategy is similar to the methods applied by Barniv et al. (2002), Charitou et al. (2004) and Grammenos et al. (2008) in both bankruptcy prediction and default prediction of high-yield bonds. In order to avoid issues associated with over-fitting, we aim to reach the most parsimonious model that still explains the data.

First, in order to identify the possible explanatory variables, we run a univariate analysis consisting of an intercept term and one independent variable for all variables presented in section 5. Following the suggestion of Hosmer and Lemeshow (2000), variables whose p-values are lower than 0.25 are candidates for inclusion in the multivariate models. Thereafter, stepwise regression is used to arrive at a preliminary model.[23] These models are finally altered by either adding or removing a variable in accordance to its p-value and the Wald test.[24]

Multicollinearity is an area of concern with several of the financial ratios partly deriving from the same accounting figures. This could lead to biased results. Lewis-Beck (1980) suggest that correlation coefficients larger than 0.8 could indicate the presence of multicollinearity. None of the employed variables are that highly correlated. Nevertheless, we test for multicollinearity further by employing the variance inflation factor (VIF) for the explanatory variables included in our models.[25]

The tolerance statistic of an independent variable X_i is $1 - R^2_{X_i}$, where $R^2_{X_i}$ is the R^2 resulting from the regression of the other independent variables in the model on the variable X_i (Lewis-Beck, 1980). The corresponding VIF is simply one divided by the tolerance statistic. If all of the variables in a model are completely uncorrelated with each other, both the VIF and tolerance statistic are equal to one. Following Grammenos et al. (2008), we consider a tolerance statistic lower than 0.2, analogous to a VIF higher than 5, as a cause of concern. Tolerance statistics and VIFs for our models are provided in Table A-I in the appendix. We conclude that multicollinearity is not an issue in any of our estimated models.

[23] In stepwise regression the choice of predictors is carried out by an automatic procedure. A combination of forward selection (starting with no variables in the model and testing the addition of each candidate variable) and backward elimination (starting with all candidate variables and testing the deletion of each variable) procedures were applied.

[24] The Wald test approximates the likelihood ratio test, and is used to compare the goodness-of-fit of two models.

[25] The variance inflation factor provides an indication of how much of the inflation of the standard errors might be caused by collinearity.

Another area of concern is that observations are dependent within clusters. More specifically, firms that issue multiple bonds in the same year have identical financial ratios because the data is collected from the same financial report. Heteroscedasticity can produce biased and misleading parameter estimates in logistic regression models (Lennox, 1999). To deal with this issue, we cluster the observations based on bond issues by each company in a single year. Cluster robust standard errors are then used to relax the assumption that error terms are independent of each other.

6.1.3 Logit Models - All Firms

The results of our estimated models for the full sample of bonds are presented below in Table IV. Both the static and dynamic models include several bond characteristics, a set of financial ratios and the industry variable. INDUS is significant at the 5% level in both models (1% in the dynamic), indicating that not only is the impact of changes in industry conditions important after the bond is issued, but it is also beneficial to issue the bond at a time when conditions have recently improved. As expected, this variable has a negative relationship with default probabilities. The dynamic model also includes the variable capturing the size of the firm (LNTA). The sign of the coefficient reveals that smaller firms are more prone to default on their debt obligations.

Of the bond characteristics, the main determinants of default are CALL, CONV, COUP and MAT. All four variables are found highly significant, though MAT is only included in the dynamic model. The positive coefficient estimate of MAT suggests that longer maturity debt decreases the probability of default, implying that short maturity debt leaves firms with insufficient time to generate the necessary cash to pay interest and/or principal. The two indicator variables CALL and CONV are highly significant in both models. As seen from the sign of the coefficients, the probability of default is found to increase if the bonds are callable and convertible. For callable bonds, we had no rigorous theory to assume a particular relationship between this variable and default rates. The positive sign of the coefficient leads us to believe that it is mainly the weaker companies that push for call provisions in their bond issues because they are not able to negotiate a low coupon. Following the same reasoning, strong companies are able to negotiate a lower coupon, and call options are therefore not as essential.

Table IV - Maximum Likelihood Estimates for All Firms

Variable	Coefficients: Static Model	Dynamic Model	Fixed Effects
CALL	0.909***	0.786***	0.851***
	(0.300)	(0.275)	(0.296)
CONV	1.383***	1.575***	1.550***
	(0.364)	(0.341)	(0.347)
COUP	14.842***	18.029**	20.581***
	(4.303)	(4.074)	(4.020)
MAT		-0.023***	-0.021***
		(0.007)	(0.007)
LNTA		-0.206**	-0.131
		(0.096)	(0.107)
WCTA	-1.465**	-0.519*	-0.585**
	(0.659)	(0.025)	(0.234)
SALESCA	-0.365***	-0.359**	-0.271**
	(0.133)	(0.167)	(0.126)
GEAR		0.379***	0.383
		(0.145)	(0.245)
EBITCL	-0.168*	-0.065***	-0.198*
	(0.098)	(0.025)	(0.106)
INDUS	-1.639**	-3.412***	-2.650***
	(0.808)	(0.636)	(0.670)
CASHTA	2.961**		
	(1.282)		
ARTA	0.073***		
	(0.028)		
Constant	-2.845***	1.042	
	(0.464)	(2.169)	
Wald Chi-Square	88.02 [0.00]	138.80 [0.00]	162.42 [0.00]
Pseudo R^2	0.2399	0.2498	0.2529
Observations	627	1564	1497
H-L statistic	8.98 [0.344]	8.13 [0.421]	
Misspecification	Yes	No	
Mean VIF	1.65	1.11	
Heteroscedasticity	Used CRSE	Used CRSE	

Note: *** p<0.01, ** p<0.05, * p<0.1. CRSE (Cluster Robust Standard Errors) in parentheses.
The Wald Chi-Square statistic is used to test the null hypothesis that all slope coefficients are zero.
The H-L statistic is the Hosmer-Lemeshow test statistic. P-values are in [ ].

It is interesting to assess the impact on default rates depending on whether the bond is callable or not. Since relationships are not linear in logistic regression, we cannot simply observe the marginal effects from the coefficient estimates. Instead, we need to use calculus to determine the marginal effects. In a logistic regression model, the marginal effect for a continuous variable is given by $(\delta E[y \mid x])/\delta x = f(\beta' x)\beta$, where f is the corresponding probability density function (Anderson and Newell, 2003). We compute the *average marginal effects* for our employed variables. For the indicator variables, we calculate the discrete effect by taking the difference in the predictive probability with and without the variable equal to one.[26] The calculations are presented in Table A-II in the appendix. From the dynamic model estimations, we observe that on average, a callable bond is 3.7% more likely to default.

The fact that default rates are found to increase if the bonds are convertible is somewhat surprising as it is contrary to previous research on the U.S. high-yield bond market, such as the prevalent study of Rosengren (1993). On the other hand, considering the fact that 42% (26 out of 62) of the convertible bonds in our sample defaulted, this is not really unexpected. Based on our discussion in section 5, our results likely imply that weak companies are more likely to issue convertible bonds because this is the only way they can encourage investors to lend them money. From the marginal effects calculations (dynamic model), we observe that a convertible bond has a 7.4% higher probability of default.

The coupon spread (COUP) is found highly significant in both the static and dynamic model, which is not surprising since the spread should reflect the perceived credit risk at issuance - given the bond is issued at par. At issuance, the average marginal effect of a one-percentage point increase in the coupon spread is equivalent to an increase in the probability of default of more than 3%.

Among the financial ratios, the models include ratios from all categories apart from the profitability measures. Cash holdings appear to be an important predictor at issuance judging by its inclusion in the static model. Larger cash holdings are found to correspond to higher default rates. As discussed, this is likely a result of many start-up companies having large cash holdings. When examining the data for this variable, it became clear that many firms with relatively large cash holdings were in fact younger companies. In addition, the fact that this variable is only included in the static model, strengthens this theory. WCTA, from Altman's (1968) Z-score, seems to be another important liquidity measure and is included in both models. Higher values of this ratio correspond to a lower likelihood of default.

From the leverage and debt service category, we observe that the amount raised in relation to the size of the firm (ARTA) is an important predictor at issuance. The gearing ratio (GEAR)

[26] The ”*average marginal effects”* are preferred over the standard alternative ”*marginal effects at means”* in order to avoid setting indicator variables to their mean values. A detailed explanation of the calculation method applied is provided in Cameron and Trivedi (2010).

is also highly significant in the dynamic model. Further, the debt-service coverage ratio EBITCL is included in both models. Of the turnover ratios, the sales to current assets (SALESCA) seems to be the most important ratio, as it is highly significant and included in both models. Turnover ratios are not the most commonly used measures in the literature, however, this variable could be particularly important due to the dominant position of highly asset intensive industries in the Nordic high-yield bond market. All coefficients for these variables have the expected signs given our discussion in section 5.

To evaluate how effectively the models describe the outcome variable, we use the Hosmer-Lemeshow test statistic described in section 3.1.1. From the model estimation table, we can see that the two insignificant H-L test statistics confirm the overall goodness-of-fit for both model estimations. Furthermore, both models are tested for specification errors by applying the framework explained under the same section. In the static model, we find that the predicted values squared do in fact have explanatory power (output provided in Table A-III in the appendix), suggesting the model is not correctly specified. Closer examination revealed that the amount raised over total assets (ARTA) variable has non-linear effects on default.[27] Following the research of Lennox (1999), an attempt was made to include quadratic interaction terms for this ratio in the model. However, the inclusion of quadratic terms did not result in a correctly specified model. The variable is included in the model regardless of the specification error due to its high significance level and deemed importance as a predictor of default at the moment of issuance.[28]

Taking into account the volatile observation period of our data, covering both the global financial crisis as well as the European debt crisis, defaults could potentially be dependent on the year in which the bond was outstanding. In that case, our estimated models can suffer from omitted variable bias. Therefore, we analyze the impact of year effects on our dynamic model by running a fixed effects logistic regression model.[29] The observations are grouped based on the year in which the bond is outstanding, and the likelihood of default is then calculated relative to each year. This allows us to remove the effect of unobserved heterogeneity associated with the year in which the bond was outstanding. We can then assess the net impact of our explanatory variables on default after eliminating omitted variable bias due to year effects.

[27] We applied the Box-Tidwell regression model in order to identify the variable.

[28] No empirical reasoning was found to include any other interaction terms besides the quadratic ones for leverage ratios.

[29] Panel data is necessary for estimating fixed-effects models. Hence, we cannot analyze the impact of year effects on our static models.

Comparing the coefficients in the fixed effects model with those in the dynamic model, unobserved heterogeneity does not appear to be of great concern. The coefficients remain largely unchanged and they all have the same expected signs. Although the significance levels are similar as well, we do note that the size (LNTA) and gearing (GEAR) variables are no longer statistically significant. Hence, we need to keep in mind that these two variables could potentially be biased toward certain years in our observation period.

6.1.4 Logit Models - Public Firms

For our subsample of bonds issued by public firms, we estimate separate models applying the same model building strategy as before. The only difference in this part of our analysis is that we add a new market dimension to the analysis by including equity market information in the variable selection. Here, Altman's (1968) market value of equity over total debt (TDTE) and the distance to default (DTD) is also tested for. Model estimations for our sample of public firms are presented in Table V. The estimated models do not differ greatly from the ones above using the full sample of bonds. We still have a set of financial ratios, bond characteristics and the industry and size variables. The most notable change is that the CALL variable, which was significant at the 1% level for the full sample of bonds, is not included in the dynamic model anymore.

Of the two additional variables incorporating the issuers' market value of equity, we observe that only the distance to default is included in the models. The distance to default is significant in both the static and dynamic model at the 1% level. This does come as a surprise considering the amount of information that this variable captures. From the marginal effects calculations (static model), we find that a one standard deviation increase in the distance to default on average leads to a decrease in the probability of a bond defaulting by more than 6%.

Again, the fixed effects model does not differ much from the dynamic model. All coefficients remain largely unchanged and with the expected signs. Only the gearing ratio (GEAR) is no longer statistically significant, as before. Therefore, unobserved heterogeneity related to year effects does not seem to have a large impact on our estimated model. Further, the H-L test statistics are insignificant, indicating a good model fit.

Table V - Maximum Likelihood Estimates for Public Firms

	Coefficients		
Variable	Static Model	Dynamic Model	Fixed Effects
CALL	1.081***		
	(0.361)		
CONV	0.881*	1.085***	1.233***
	(0.464)	(0.415)	(0.460)
COUP	17.652***	15.832**	14.797***
	(6.811)	(7.206)	(5.763)
LNTA	-0.339***	-0.333**	-0.350**
	(0.128)	(0.146)	(0.167)
WCTA	-1.988**	-1.663**	-1.626**
	(0.876)	(0.825)	(0.783)
SALESCA	-0.380**		
	(0.174)		
GEAR		0.429**	0.395
		(0.193)	(0.316)
INDUS		-1.713*	-3.081***
		(0.901)	(1.185)
DTD	-0.602***	-1.191***	-1.359***
	(0.178)	(0.315)	(0.250)
Constant	5.940**	4.940	
	(2.984)	(3.278)	
Wald Chi-Square	71.99 [0.00]	86.30 [0.00]	133.36 [0.00]
Pseudo R^2	0.3059	0.3444	0.4039
Observations	364	914	880
H-L statistic	10.79 [0.214]	5.59 [0.693]	
Misspecification	No	No	
Mean VIF	1.21	1.16	
Heteroscedasticity	Used CRSE	Used CRSE	

Note: *** p<0.01, ** p<0.05, * p<0.1. CRSE (Cluster Robust Standard Errors) in parentheses.
The Wald Chi-Square statistic is used to test the null hypothesis that all slope coefficients are zero.
The H-L statistic is the Hosmer-Lemeshow test statistic. P-values are in [ ].

A Pseudo-R^2 value slightly above 34% can be observed for the dynamic model.[30] Evaluating a Pseudo-R^2 is only meaningful when compared to other models on similar datasets, predicting the same outcome. In the absence of similar models for the Nordic high-yield bond market, we need to look elsewhere. Scoring models for public firms in the US can

[30] For logistic regression, a statistical equivalent to R^2 in OLS does not exist. A Pseudo-R^2 is commonly used instead. Higher values indicate a better model fit, but it is measured on a different scale compared to the R^2 in OLS.

achieve a Pseudo-R^2 of around 35% (Löffler and Posch, 2007; Altman and Rijken, 2004). This leads us to believe that the set-up of the model is quite ideal.

6.1.5 Model Evaluation

Until now, the Hosmer-Lemeshow test statistic and the Pseudo-R^2 measures have provided an indication of the goodness-of-fit of the models. However, we evaluate the models further by use of classification tables and the area under the ROC curve in order to obtain an adequate combination of goodness-of-fit and classification accuracy.

Classification Table

For each model, probability estimates are obtained and used to classify the bonds as either default or non-default, given a predefined cutoff point. The classified outcomes are then compared with the observed ones from the datasets. Table VI summarizes each of our models predictive ability based on the classification tables. Complete classification tables for all four models are presented in Table A-IV in the appendix.

Table VI - Summary of Classification Tables

	All Firms		Public Firms	
	Static	Dynamic	Static	Dynamic
Cutoff Point	**20.20%**	**6.90%**	**19.10%**	**6.90%**
Sensitivity	96/126	78/98	52/66	39/47
Specificity	381/501	1167/1466	233/298	736/867
Type I Error	30/126	20/98	14/66	8/47
Type II Error	120/501	299/1466	65/298	131/867
Correctly classified	**76.08%**	**79.60%**	**78.30%**	**84.79%**

Note: For the given cutoff points, both the accuracy and the inaccuracy of the models are presented. Sensitivity is a measure of the correctly predicted defaults, while specificity is a measure of the correctly predicted non-defaults. A type I error is the misclassification of a defaulted bond as a non-default, and a type II error is the opposite.

In order to classify the bonds, we need to specify a cutoff point. Intuitively, it would make sense to classify the bonds based on a cutoff point of 50%. However, this would implicitly assume that the loss function is symmetric across the two classification errors (Ohlson, 1980). Since a type I error can be regarded as investing in a bond that defaulted, and a type II error is equivalent to rejecting a bond investment that would have resulted in a positive payoff, type I errors are generally considered more costly. A lender may lose principal and interest, in addition to the cost of potential lawsuits. Therefore, to determine the cutoff points, we plot the sensitivity and specificity against all the possible cutoff points. For optimal classification purposes, we select the cutoff point that is determined by the intersection of the two curves, as suggested by (Hosmer Jr. et al, 2013). In reality, the optimal cutoff point depends on the actual cost of a type I versus a type II error. We do not examine this issue further, but for a bond portfolio manager this is a highly relevant matter. A sensitivity analysis for the cutoff points is provided in Figure A-1 in the appendix.

From Table VI, we observe that the model with the highest classification percentage is the dynamic model for public firms with a predictive ability close to 85%. However, a direct comparison between the estimated models is not really suitable. Going back to the description of the datasets in section 4.3, we need to remember at what point in time the models are predicting default. A model that is able to predict default at an earlier stage is obviously more valuable. The static models are predicting default at the moment of issuance. Meanwhile, the dynamic models are predicting default on a year-to-year basis. The dynamic models are also applying more available information. Nevertheless, we do note that the public firm models perform better than their counterparts for the full sample of bonds. This is likely due to the inclusion of the distance to default variable, which captures a lot of information and appears to significantly increase the predictive ability.

Area Under the ROC Curve

Having assessed the predictive ability of our models for a single cutoff point, we now examine the area under the ROC (Receiver Operating Characteristic) curve in order to obtain a more complete picture of the models' predictive ability. Unlike the sensitivity and specificity measures from above, the ROC curve plots the probability of true default (sensitivity) and false default (1 – specificity) for the entire range of possible cutoff points. The curve can then be used to measures the model's ability to discriminate between the bonds that defaulted versus those that did not.

The area under the ROC curve ranges from 0.5 to 1, with a higher value indicating superior discriminative ability. As a general rule of interpretation, Hosmer Jr. et al. (2013) state that an area under the ROC curve above 0.8 and 0.9 demonstrates excellent and outstanding discriminative ability, respectively. Table VII states the area under the ROC curve for all four models. The corresponding graphs are presented in Figure A-2 in the appendix.

Table VII - Area Under the ROC Curve

	All Firms		Public Firms	
	Static	Dynamic	Static	Dynamic
Area under ROC	0.8261	0.8598	0.8748	0.9138

Note: The area under the ROC curve is stated for all four models. An area under the ROC curve closer to 1 indicates superior classification ability. See Figure A-2 in the appendix for the corresponding graphs.

6.2 Default Risk and Bond Age

This subsection aims to answer our second research question. Here, we carry out a survival analysis based on our findings from the previous research area. Our main objective is to study how the bonds' underlying risk of default changes over time. First, we present and discuss the estimated Cox models. Then, we study the baseline hazard functions and evaluate the models.

6.2.1 Cox Proportional Hazard Models

Based on the variables employed in our logit models, we estimate a static and a dynamic (time-varying) Cox proportional hazard model. That is, the variables employed in our static logit models are also used in the static Cox model. Similarly, the variables used in the dynamic Cox model correspond to the variables employed in the dynamic logit models. In that way, we can further validate our logit models to see if they are also suitable using an entirely different approach. Nevertheless, some modifications are necessary to make.

As previously mentioned, it is critical to correct for non-proportional hazards in the Cox model because they can lead to biased parameter estimates. Therefore, we first tested the proportional hazards assumption using the global test statistic described in section 3.2.1. Both the static and the dynamic model initially failed the global test. Upon further examination of the covariate specific test statistics, three variables were found to violate the proportional hazards assumption, specifically CALL, CONV and LNTA. There are certain ways to accommodate for such variables. The most common solution is to add an interaction between the variable and some function of time to the model, typically the natural log of time (Keele, 2010). Another solution is to stratify the model on the respective variables. For the indicator variables defining callable and convertible bonds, a stratified model made more sense. A stratified model allows the (baseline) hazard function to differ across different strata. By doing so, we attain the additional benefit of being able to study the underlying risk of default based on whether the bonds have the embedded option to call or convert the bond.

Stratification does, however, require the strata to be mutually exclusive and also collectively exhaustive. Some of the convertible bonds in our sample are actually callable as well. Considering the relatively small amount of convertible bonds in our sample, we decided to accommodate for this issue by creating a new indicator variable called OPTION. This variable is assigned the value of one if the bond is either callable or convertible, and is equal to zero otherwise. Hence, no discrimination is made between callable and convertible bonds in this part of our analysis. Instead, we only distinguish between bonds that have an embedded option and those that do not. On a separate note, we do not distinguish between private and public firms either in this part of our analysis. The distance to default variable is therefore not included in the Cox models.

For the size variable LNTA, it does not make sense to add this variable as a separate stratum. An attempt was made to add a time interaction, as suggested above, though without success in terms of passing the proportional hazards assumption. In the end, the decision was made to exclude this variable from both models. Although not ideal, we do not believe its inclusion would significantly change our results.

Table VIII presents the results of our stratified Cox models. The dependent variable for these models is the time-to-default, i.e. the hazard. For the static model, the explanatory variables are consistent with the logit models in terms of expected signs of the coefficients. The hazard increases with COUP and CASHTA, and decreases with WCTA, SALESCA, EBITCL, and INDUS. An increase in ARTA also decreases the hazard, but this ratio is no longer statistically significant. Further, we note that the global test statistic is not statistically significant, indicating that the proportional hazard assumption is globally satisfied.

The dynamic model includes four variables that are updated with monthly changes, namely COUP, MACRO, MAT and INDUS. The coupon spread and the time to maturity are both significant at the 1% level, and all four variables have the expected signs given previous reasoning. The industry variable accounts for monthly changes in market conditions for the respective industries, whereas the macroeconomic variable captures the monthly changes in the general economy. Of these two variables, we note that only MACRO is statistically significant. Nevertheless, we have included INDUS in the model in order to account for the industry effects. It is worth noting that the coupon-spread variable implicitly captures macroeconomic changes as well by accounting for changes in interest rate levels for the bonds that pay a fixed coupon. For the rest of the variables in the dynamic model, we observe that the hazard increases with the gearing ratio (GEAR) and decreases with WCTA, SALESCA and EBITCL. This is also consistent with our results from the logit models. And again, the assumption of proportional hazards is globally satisfied.

Table VIII - Stratified Cox Models

	Coefficients	
Variable	Static Model	Dynamic Model
COUP	14.021***	16.047***
	(2.995)	(2.638)
WCTA	-0.464**	-0.579***
	(0.204)	(0.203)
SALESCA	-0.298**	-0.346**
	(0.127)	(0.136)
GEAR		0.193***
		(0.036)
EBITCL	-0.025***	-0.062***
	(0.006)	(0.017)
CASHTA	1.696***	
	(0.614)	
ARTA	-0.002	
	(0.001)	
MAT		-0.030***
		(0.007)
MACRO		-1.149*
		(0.677)
INDUS	-2.042***	-0.103
	(0.773)	(0.918)
Wald Chi-Square	245.69 [0.00]	157.72 [0.00]
Observations	627	17 188
Mean VIF	1.65	1.21
Global Test (χ^2)	6.07 [0.53]	5.69 [0.68]
Heteroscedasticity	Used CRSE	Used CRSE

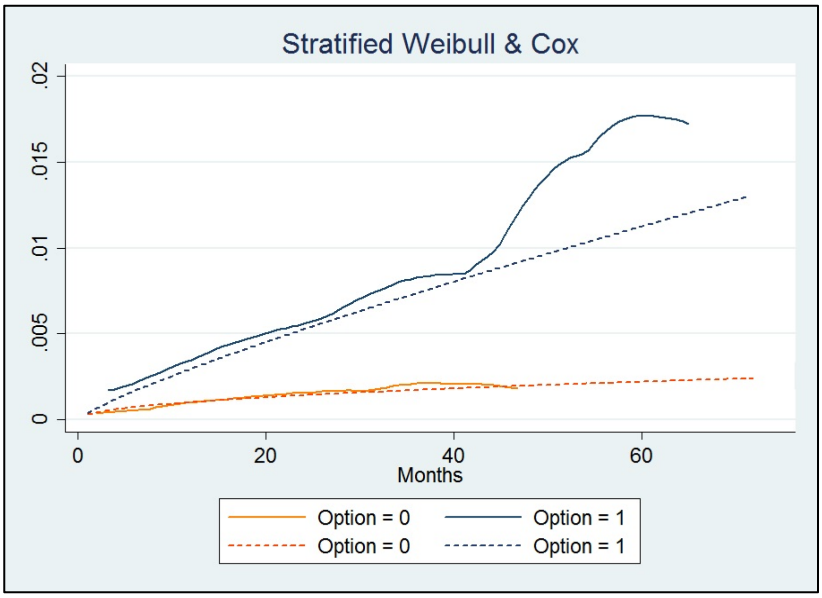
Note: *** p<0.01, ** p<0.05, * p<0.1. CRSE (Cluster Robust Standard Errors) in parentheses.
The Wald Chi-Square statistic is used to test the null hypothesis that all slope coefficients are zero.
The global test statistic (χ^2) is used to test the proportional hazard assumption. P-values are in [ ].

6.2.2 Baseline Hazard Functions

The hazard rate is the bond's continuous probability of default, i.e. the probability of default in the next instant given the already survived time. By setting all the covariates equal to zero in the hazard function, we recover the unspecified baseline hazard function that is common to all bonds, as explained in section 3.2.1.

Figure 4 and Figure 5 display smoothed baseline hazard functions derived from the stratified hazard functions. In order to evaluate the robustness of the baseline hazards from the Cox models, we re-estimated the models parametrically by specifying a Weibull distribution. The dashed lines represent the baseline hazards derived from the Weibull models, while the unbroken lines are recovered from the Cox models. Table A-V in the appendix presents the corresponding model estimations for the Weibull functions. Most coefficient estimates and significance levels are similar to those from the Cox models. This does not surprise us considering the baseline hazard functions match very well for both model specifications. However, it gives us confidence in our semi-parametric estimations.

Figure 4 - Baseline Hazard Functions for the Static Model

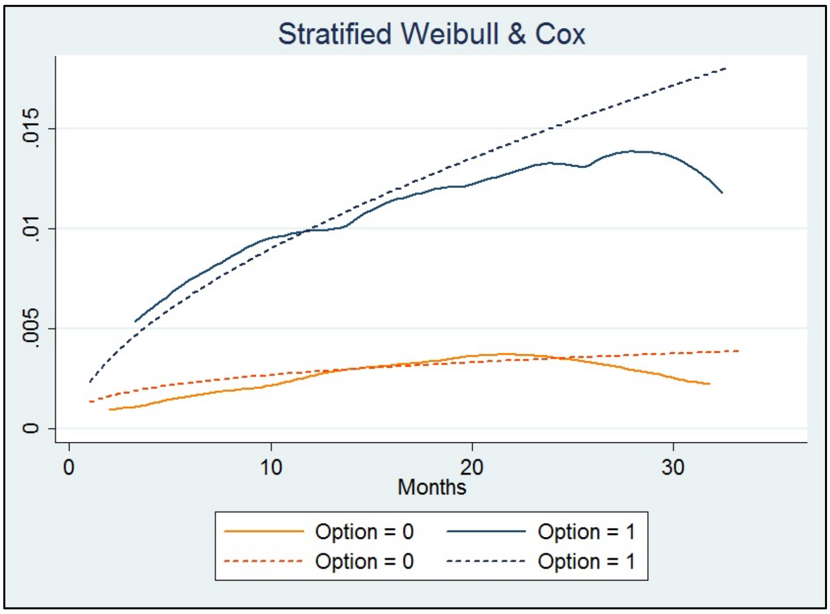


Note: The figure shows how the bonds' continuous default probability evolves over time. Time is measured in months from the issuance date of the bond. The dashed lines are derived from the Weibull model, and the unbroken lines are from the Cox models. The baseline hazard function for the Cox model is a smoothed scatterplot of points corresponding to a default event. Each default event represents the estimate of the baseline hazard at that specific point in time. The blue plots correspond to the stratum of callable and convertible bonds, whereas the orange plots are for the bonds with no embedded option.

The static model is based purely on data from the time of issuance. Hence, we are able to study the baseline hazard for a longer time period. The graph shows the baseline hazard function over a time period of more than five years. The longest outstanding bond in our sample is seven years, yet the latest default occurrs shortly after five years. Thus, there are no plots for the baseline hazard beyond this point. A clearly increasing pattern is observed for the stratum comprising the callable and convertible bonds. This implies an increasing instantaneous probability of default as these bonds age. Moreover, there appears to be a significant increase in risk for these bonds after approximately three years, or around the 40-month mark. Towards the end of year four, the default rates seem to level off.

For the bonds without any embedded options, we observe only a slight increase in default probabilities. The default rates are fairly close to constant, suggesting no real evidence of an aging effect for these bonds. The last default in this stratum occurs at the 47-month mark, so the smoothed baseline hazard is not defined beyond this point for the Cox plot.

Figure 5 - Baseline Hazard Functions for the Dynamic Model



Note: The figure shows how the bonds' continuous default probability evolves over time. Time is measured in months from the issuance date of the bond. The dashed lines are derived from the Weibull model, and the unbroken lines are from the Cox models. The baseline hazard function for the Cox model is a smoothed scatterplot of points corresponding to a default event. Each default event represents the estimate of the baseline hazard at that specific point in time. The blue plots correspond to the stratum of callable and convertible bonds, whereas the orange plots are for the bonds with no embedded option.

In the dynamic model, we follow the bonds over a three-year period with updated time-varying explanatory variables. As previously mentioned, the financial ratios in the dynamic model are updated every twelve months with accounting information from the latest annual report. We also account for monthly changes in the general economy and in the different industries. Monthly changes in interest rate levels are also accounted for by the variable measuring the coupon spread (COUP). Specifying this variable as time-varying eliminates the impact of the general level of interest rates from our hazard estimates. This is crucial given that interest rates differ substantially from the beginning of our observation period to the end.

From the baseline hazard plot we observe consistent results to the static model. This gives us increased confidence in our abovementioned findings, despite the static model being based purely on data from the time of issuance. Since we obtain similar results using this framework, it suggests that our findings would also hold in a period of stable interest rate levels. Again, we see a clear aging effect for the callable and convertible bonds. Nevertheless, we note that the default probabilities now seem to reach a peak during the third year. It would be interesting to explore whether this is actually just a momentary plateau similar to the one found in the static model, or if it is in fact a peak. Unfortunately, with limited time and resources, we could not update the financial ratios beyond three years.[31]

Although the stratum of bonds with no embedded options displays a marginally increasing pattern over the first two years, we find it hard to draw any clear-cut conclusions regarding an aging effect from this plot. The default rates seem to level off or decrease slightly after two years. No significant increase in default rates is observed from the beginning of the observation period compared to the end, particularly in comparison to the bonds containing embedded options. Any observed aging effect for these bonds is at least on a different scale to the callable and convertible bonds.

Previous research on the aging effect of high-yield bonds has produced plausible theories that could underpin our results. Altman and Kishore (1996) find that low rated bonds are least likely to default during the first year after issuance and most likely to default three years after issuance. Their findings are very similar to the stratum of callable and convertible bonds in our dynamic model. Jónsson and Fridson (1996) provide a logical explanation for this occurrence. Bond markets are able to gauge default risk with reasonable accuracy and generally do not lend to firms in immediate danger of default. Companies are also most likely to approach investors when their financial ratios are particularly strong, meaning the risk of default is comparatively low.

[31] However, we did in fact conduct the same analysis only assuming the financial ratios were left unchanged after year three. The results showed a temporary plateau similar to the static model.

Helwege and Kleiman (1996) provide a possible reasoning for the lagged increase in default risk that we find after three years in the static model. They highlight the impact of the economic conditions in explaining default rates. More firms issue high-yield bonds when capital markets are rising in anticipation of a strong economy, because the markets are more receptive to riskier bonds. Judging by our sample, this could be the case. Very few issues are made in the period around the financial crisis, and we see a clear increase in issues as the economy strengthened. Surges in issuance like this could lead to a larger amount of defaults in later years. More than three years subsequent to such a period, the economic environment is likely weaker and more defaults could occur. In addition, a company that newly raised money in the bond markets is likely to have available cash to pay its creditors for a certain period. Even if the envisioned business plan did not materialize initially, liquidity problems would still emerge with a delay. This could be another reason for the lag in default rates that we observe after three years.

The only issue with the reasonings mentioned above is that they do not explain the absence of an aging effect for our bonds without embedded options. This leads us to believe that the rationale proposed by Altman (1992) is the most consistent with our results. Well-performing companies are able to repurchase or call their bonds in order to refinance at lower rates. Firms that have not improved their creditworthiness will not have the same opportunity. For convertible bonds, investors in strong companies are likely to convert their bonds to equity. Therefore, callable and convertible bonds that are outstanding for a long time will naturally belong to weaker firms and therefore exhibit higher default rates.

Our findings are important because, as far as we are aware, previous research on the aging effect of high-yield bonds does not explicitly distinguish between bonds with and without an embedded option to either call or convert the bond. Particularly call provisions are given little emphasis. Moeller and Molina (2003) do in fact conduct a separate analysis for convertible and non-convertible bonds. They find the risk of default to increase for both bond types. However, they report that virtually all of the bonds in their sample are callable, meaning the non-convertible bonds are most likely callable as well.

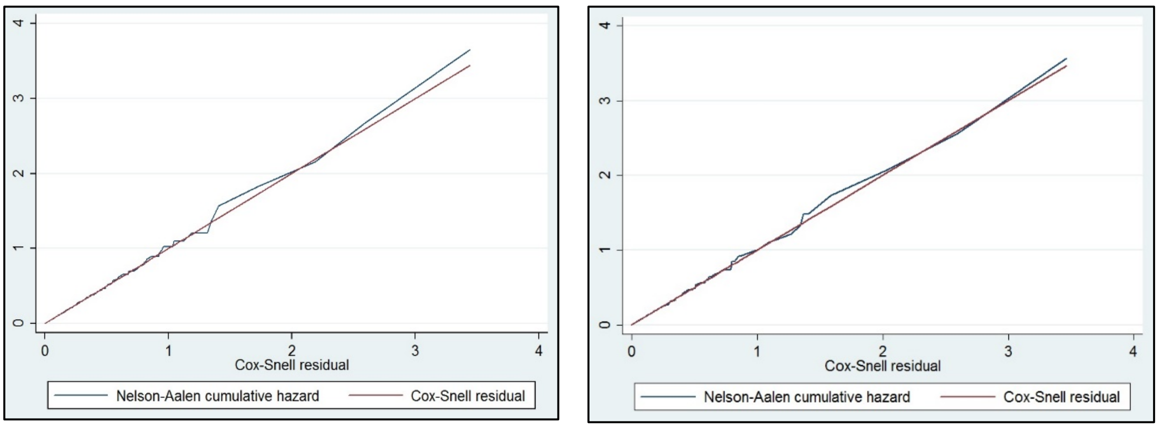
Similarly, McDonald and Van de Gucht (1996) find a clear aging effect in their sample of non-convertible bonds. Still, they neither report whether their bonds are callable nor conduct a separate analysis for non-callable bonds. Let's assume for both studies that the bonds with no embedded options exhibit fairly constant default rates as we find in our analysis, and that there is in fact an aging effect for the bonds with embedded options. Without distinguishing between the two bond types, the baseline hazard function will show an increasing pattern anyway because the aging effect of the callable bonds will always dominate.[32]

6.2.3 Model Evaluation

In order to evaluate the overall model fit, we use the Cox-Snell residuals as proposed by Cleves et al (2008).[33] If the Cox model is a good fit for the data, then the true cumulative hazard function conditional on the covariate vector has an exponential distribution with a hazard rate equal to one. In other words, it implies that the cumulative hazard of the Cox-Snell residuals should be a straight 45-degree line. Therefore, we can assess the model fit visually. The model fit is verified further by estimating the empirical Nelson-Aalen cumulative hazard function.[34] Here, the Cox-Snell residuals are specified as the time variable while the censoring variable is the same as in the original models. Finally, we graph the Nelson-Aalen cumulative hazard function against the Cox-Snell residuals. The results are shown in Figure 6.

Figure 6 - Visual Assessment of the Model Fit

Static Cox Model | Dynamic Cox Model



Note: The figure shows the plot of the Nelson-Aalen cumulative hazard function against the Cox-Snell residuals. The cumulative hazard function should follow the 45-degree line if the model is a good fit for the data.

We observe that the hazard function follows the 45-degree line for both models, implying that it approximately has an exponential distribution with a hazard rate equal to one. Some

[32] We confirmed this theory by estimating the baseline hazard function without distinguishing between bonds with and without embedded options. The results showed a clear aging effect for the whole bond sample with a pattern similar to the stratum of bonds with embedded options.
[33] Cox-Snell residuals are standardized residuals derived from the survival probability of each observation.
[34] The Nelson-Aalen estimator is a non-parametric estimator of the cumulative hazard function.

variability is expected around the 45-degree line, even for a well-fitting Cox model, particularly in the right-hand tail (Cleves et al, 2008). Thus, we conclude that both models fit the data well.

7. Application to Bond Portfolio Management

Having estimated models that we have shown can successfully contribute to default prediction in the Nordic high-yield bond market; default probabilities can subsequently be computed for a given bond. An important quantitative measure of credit risk can thereby be obtained for the bonds, namely expected credit loss. With that in mind, we would like to briefly explain the intended use of our models in relation to bond portfolio management.

Observing the price of a bond, rational investors will also take into account the credit spread before investing. Evaluating the credit spread of a bond in relation to its expected credit loss allows us to rank investment alternatives based on their attractiveness adjusted for credit risk. Taking this concept one step further, Moody's Analytics have in recent years developed a model-based approach to exploiting such relative value in the corporate bond market. The strategy is based on an outperformance measure described as the Alpha Factor (Li, Zhang and Crossen, 2012):

$$Alpha\ Factor = \frac{OAS - FVS}{CEDF * LGD} \tag{10}$$

The Alpha Factor's nominator forms the basis of a relative value measure, calculated as the difference between the issue's *Option-Adjusted Spread* (OAS) and its *Fair-value Spread* (FVS). The option-adjusted spread is an adjusted credit spread derived from the market price of the bond. It accounts for embedded options such as calls and convertibles. Fair value spreads, however, are modeled bond spreads determined by factors that are traditionally considered to be key drivers of a bond's spread (Munves and Choi, 2014).[35] Consequently, the nominator of the Alpha Factor captures an issue's potential mispricing by the market. The denominator of the Alpha Factor provides an estimate of the expected credit loss by multiplying the Cumulative EDF[36] with the loss given default (*LGD).*

[35] The Fair Value Spread is a framework developed by Moody's Analytics. Default probability, loss-given default, issuer size and the issuers' level of market risk are all examples of key drivers.

[36] EDF (Expected Default Frequency) is measured on an annualized basis. The cumulative EDF should match the term of the bond issue in order to account for duration risk to some extent.

The Alpha Factor can be compared to a Sharpe ratio that allows us to select bonds whose market spreads (OAS) offer compensation above their intrinsic risk levels, after controlling for risk in the form of expected credit loss. Once Alpha Factors have been calculated for a set of bonds, a potential investment strategy for a bond portfolio is straightforward. First, divide the bonds into different duration groups in order to avoid concentration in a specific duration range. Then, rank the bonds based on Alpha Factors for each duration group. Finally, buy all the bonds in the top 40% (for example) from each duration group and rebalance the portfolio at regular time intervals. Li, Zhang and Crossen (2012) show that bond portfolios based on such an investment strategy outperform prevalent fixed-income benchmark indices like the Merrill Lynch Index and the MarkIt iBoxx Index.

Of course this exact investment strategy is only possible with the necessary input measures from Moody's Analytics. Still, the basic intuition behind the investment strategy is certainly adaptable to a different setting. The Nordic high-yield bond market consists of many firms that are not officially rated. Updated credit risk measures are therefore not readily available. With the estimation of our logit models, we provide a simple method of quantifying the expected credit loss of an issue. For instance, our dynamic logit models yield output that can serve as a proxy for a one-year EDF. This enables investors to compare the credit spread of an issue with the associated risk. Our models are intended to be applied in such a fashion, and we hope that our findings enable more investors to partake in the Nordic high-yield bond market, perhaps in a similar way.

8. Limitations

When it comes to limitations of our study, we should mention the potential timing issue of our data collection. For a bond issued in 2010 (for instance), regardless of the issue being in January or December, we have used accounting information from the annual report of the previous year, i.e. 2009. By doing so, we implicitly assume that the report is available at the fiscal year-end date. However, it is possible that a company defaulted on a bond some time after the fiscal year date, but prior to the public release of the annual report. If the purpose of our logit models is to investigate forecasting relationships, which is the case here, this is actually an inadequate choice. Ohlson (1980) states that neglecting this possibility is not a trivial problem because it may lead to "back-casting" for many of the defaulted issuers.

In section 6.1.5, we validated our logit models by assessing their predictive ability. The predictive ability of a model is however impacted by whether the model is tested on the estimation sample or a holdout sample. Jones (1987) suggests that a holdout sample provides a better indication of validity. Ideally, we would have been able to reserve a specific time period of historical data for testing purposes. However, the beginning and middle of our observation period is characterized by extraordinary volatility due to the financial crisis and European debt crisis. Meanwhile, many bonds issued in the later years of our sample period have not had sufficient time to default. Therefore, a reserved period for out of sample testing did not make sense as it would likely lead to biased results. In addition, due to the small obtainable sample size, we were not confident that we had sufficient data for out of sample testing.

On top of the abovementioned recessions, the recent downturn in the oil industry has certainly affected the Nordic high-yield bond market given the Norwegian energy sector's dominant position. With such a volatile period covered, one could raise the question whether conclusions drawn from such a sample period are representative for the future. Either way, one should keep in mind that relations determined based on historical data are not necessarily good predictors of default going forward, possibly for a different set of issuers.

9. Conclusion

Through our logistic regression models, we have attempted to provide an answer to the first research question regarding the determining factors of default in the Nordic high-yield bond market. While bankruptcy prediction models tend to be skewed towards accounting figures, we find that incorporating a wider range of variables is more appropriate when predicting default on high-yield bonds. Our findings suggest that investors should take into account several bond characteristics, financial ratios in addition to market information before partaking in a bond issue. Embedded options, such as call and convertible provisions, can provide valuable information regarding the issuer of a bond. Furthermore, the timing of a bond issue in relation to the prevailing market conditions in the relevant industry is also of importance. For public firms, combining market information - for instance in a structural approach - with other determining factors of default, can be particularly beneficial.

To answer our second research question, we studied the relationship between default risk and bond age for our sample of bonds. We provide evidence of a distinct aging effect for bonds containing embedded options to either call or convert the bond. The underlying risk of default is found to increase the longer these bonds are outstanding, implying that these bonds do not age well. This occurrence is likely a result of either an unchanged or deteriorated creditworthiness on the issuers' part. We find a significant increase in default risk for these bonds after three years. Investors should consequently require additional compensation for taking part in these issues. Hence, option-adjusted spreads are highly relevant credit spread measures for investors in the Nordic high-yield bond market.

The establishment of Nordic Bond Pricing has made daily bond prices in the Nordic market more accessible. With sufficient pricing data, credit spreads, and thus an outperformance measure such as the abovementioned Alpha Factor, could be obtained for a collection of bonds. It would then be interesting to see if a portfolio consisting of bonds with historically high outperformance measures yields consistently higher returns than a portfolio of lower ones. Ideally, we would have had available time and resources to study this as well. We hope that future research will look further into this area.

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Appendix

Table A-I - Multicollinearity

Table A-I - VIF and Tolerance Statistics

	All Firms		Public Firms	
Variables	Static	Dynamic	Static	Dynamic
CALL	1.15 (0.871)	1.23 (0.816)	1.10 (0.909)	
CONV	1.07 (0.933)	1.08 (0.929)	1.12 (0.891)	1.09 (0.921)
COUP	1.22 (0.818)	1.24 (0.808)	1.32 (0.757)	1.27 (0.785)
MAT		1.07 (0.936)		
LNTA		1.22 (0.822)	1.22 (0.820)	1.22 (0.821)
WCTA	2.94 (0.340)	1.04 (0.957)	1.15 (0.873)	1.07 (0.938)
SALESCA	1.19 (0.843)	1.11 (0.899)	1.14 (0.876)	
GEAR		1.02 (0.978)		1.03 (0.973)
EBITCL	1.05 (0.951)	1.04 (0.960)		
CASHTA	1.71 (0.586)			
ARTA	3.47 (0.288)			
INDUS	1.07 (0.931)	1.03 (0.969)		1.05 (0.953)
DTD			1.42 (0.706)	1.38 (0.724)
Mean VIF	1.65	1.11	1.21	1.16

Note: The table presents the variance inflation factors (VIFs) and tolerance statistics for all four models. Tolerance statistics are in parentheses. A tolerance statistic lower than 0.2, analogous to a VIF above 5, is considered a potential concern in this study.

Table A-II - Average Marginal Effects

Table A-II - Average Marginal effects

	All Firms		Public Firms	
Variables	Static	Dynamic	Static	Dynamic
CALL	0.108***	0.037**	0.111***	
	(0.036)	(0.014)	(0.038)	
CONV	0.165***	0.074***	0.090**	0.039**
	(0.041)	(0.017)	(0.046)	(0.016)
COUP	3.147***	0.852***	1.807***	0.572**
	(0.481)	(0.203)	(0.656)	(0.273)
MAT		-0.001***		
		(0.000)		
LNTA		-0.010**	-0.035***	-0.012**
		(0.004)	(0.013)	(0.005)
WCTA	-0.174**	-0.025*	-0.203**	-0.060*
	(0.078)	(0.015)	(0.087)	(0.033)
SALESCA	-0.043**	-0.017**	-0.039**	
	(0.015)	(0.008)	(0.018)	
GEAR		0.018***		0.016**
		(0.007)		(0.007)
EBITCL	-0.020*	-0.003**		
	(0.012)	(0.001)		
CASHTA	0.353**			
	(0.151)			
ARTA	0.009***			
	(0.003)			
INDUS	-0.195**	-0.161***		-0.062*
	(0.096)	(0.030)		(0.032)
DTD			-0.062***	-0.043***
			(0.018)	(0.012)

Note: The table presents the average marginal effects calculations for all four models. A detailed explanation of the calculation method applied is provided in Cameron and Trivedi (2010).

Table A-III - Misspecification Tests

Table A-IV - Functional misspecification test

	All Firms		Public Firms	
Variables	Static	Dynamic	Static	Dynamic
Predicted	0.997***	0794**	0.704***	0.747***
	(0.102)	(0.180)	(0.154)	(0.184)
Predictedsq	-0.0004***	-0.055	-0.179	-0.069
	(0.0003)	(0.044)	(0.072)	(0.046)
Constant	0.001	-0.100	0.146	-0.089
	(0.163)	(0.219)	(0.213)	(0.274)

Note: The test is used to test for functional form misspecification. For all models, we observe that the predicted values are stastically significant. In the static model for all firms, the predicted values squared are statistically significant, indicating that this model is not correctly specified.

Table A-IV - Classification Tables

Static Model - All Firms

		Observed		
		Default	Non-default	Total
Classified	Default	96	120	216
	Non-default	30	381	411
	Total	126	501	627
Correctly classified default if predicted		Pr(D) >= .202		76.08%
Sensitivity		Pr(+| D)		76.19%
Specificity		Pr(-|~D)		76.05%
False - rate for true D (Type I error)		Pr(-| D)		23.81%
False + rate for true ~D (Type II error)		Pr(+|~D)		23.95%

Dynamic Model - All Firms

		Observed		
		Default	Non-default	Total
Classified	Default	78	299	377
	Non-default	20	1167	1187
	Total	98	1466	1564
Correctly classified default if predicted		Pr(D) >= .069		79.60%
Sensitivity		Pr(+| D)		79.59%
Specificity		Pr(-|~D)		79.60%
False - rate for true D (Type I error)		Pr(-| D)		20.41%
False + rate for true ~D (Type II error)		Pr(+|~D)		20.40%

Static model - Public Firms

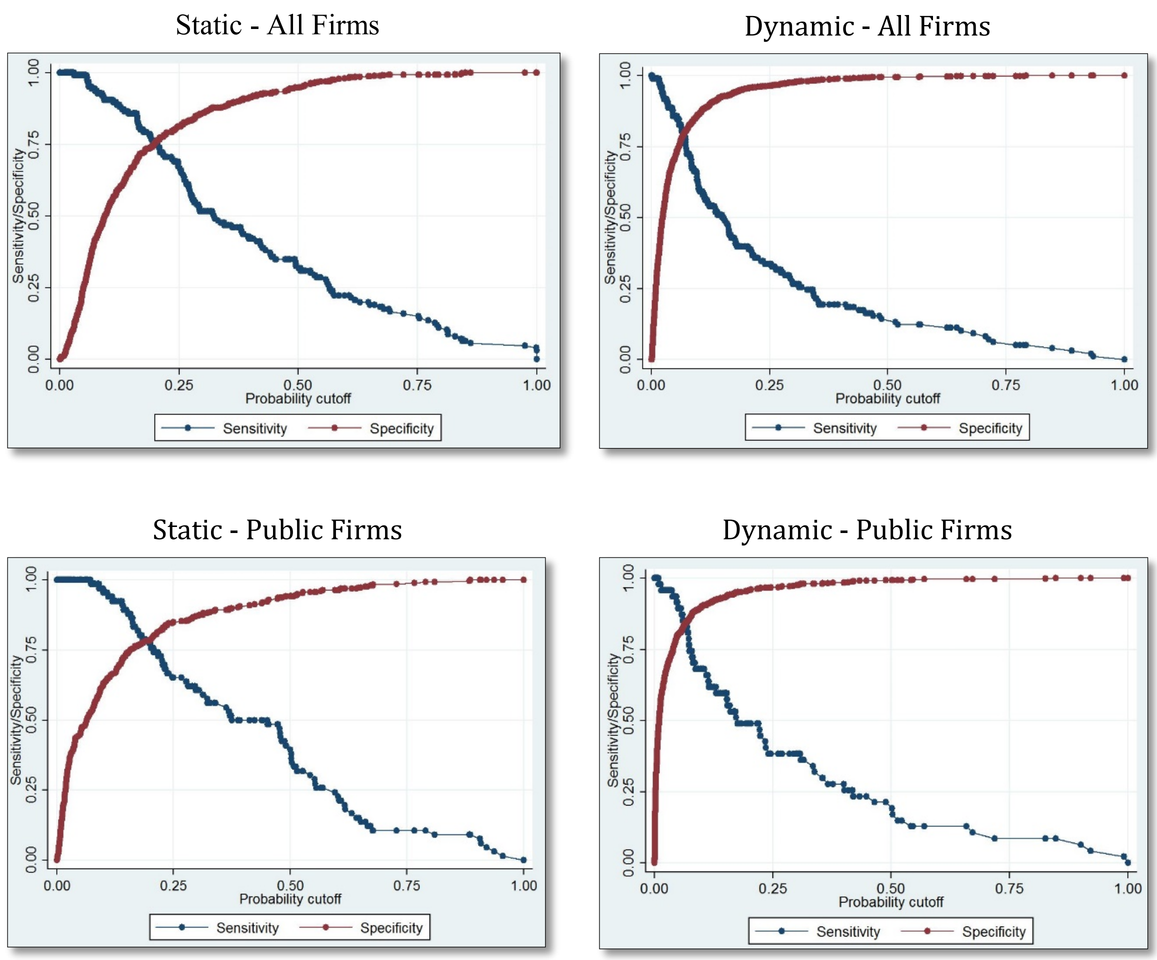
		Observed		
		Default	Non-default	Total
Classified	Default	52	65	117
	Non-default	14	233	247
	Total	66	298	364
Correctly classified default if predicted		Pr(D) >= .191		78.30%
Sensitivity		Pr(+| D)		78.79%
Specificity		Pr(-|~D)		78.19%
False - rate for true D (Type I error)		Pr(-| D)		21.21%
False + rate for true ~D (Type II error)		Pr(+|~D)		21.81%

Dynamic model - Public Firms

		Observed		
		Default	Non-default	Total
Classified	Default	39	131	170
	Non-default	8	736	744
	Total	47	867	914
Correctly classified default if predicted		Pr(D) >= .069		84.79%
Sensitivity		Pr(+| D)		82.98%
Specificity		Pr(-|~D)		84.89%
False - rate for true D (Type I error)		Pr(-| D)		17.02%
False + rate for true ~D (Type II error)		Pr(+|~D)		15.11%

Note: Table A-IV presents the complete classification tables for all four model estimations. For the given cutoff points, both the accuracy and the inaccuracy of the models are presented. Sensitivity is a measure of the correctly predicted defaults, while specificity is a measure of the correctly predicted non-defaults. A type I error is the misclassification of a defaulted bond as a non-default, and a type II error is the opposite.

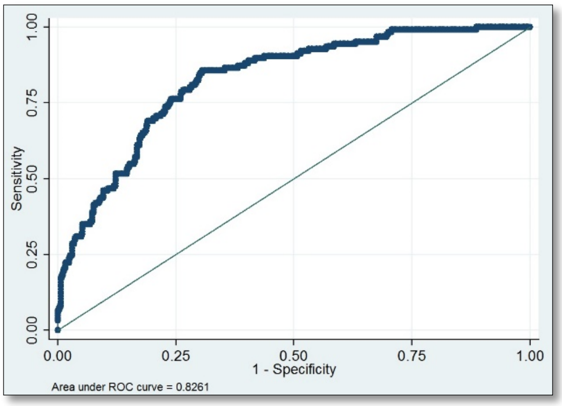
Figure A-1 - Sensitivity Analysis of the Cutoff Points



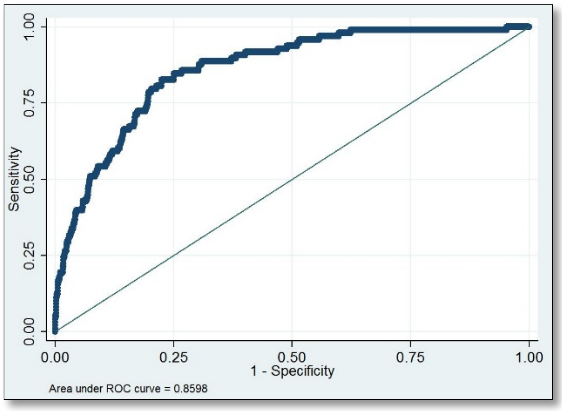
Note: Figure A-1 displays the sensitivity analysis for the cutoff points. The relationship between sensitivity and specificity is plotted for all possible cutoff points. Sensitivity is a measure of the correctly predicted defaults, while specificity is a measure of the correctly predicted non-defaults.

Figure A-2 - Area Under the ROC Curve

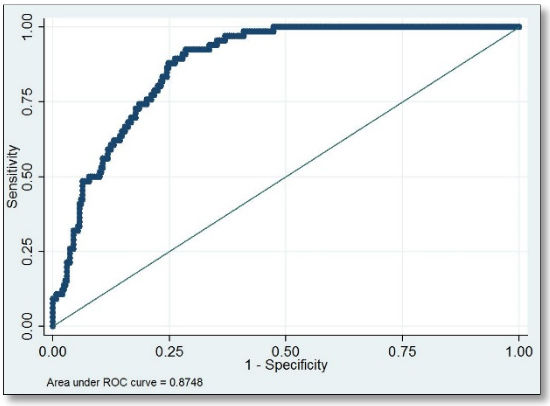
Static - All Firms



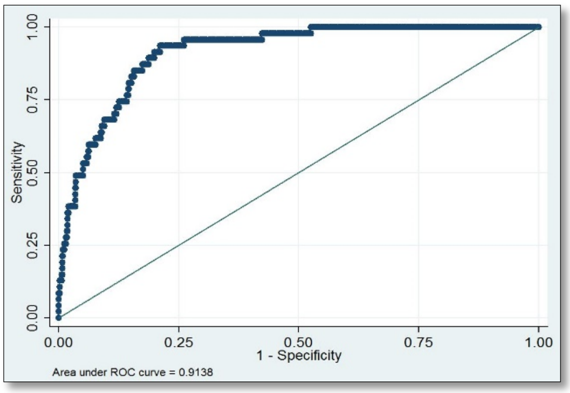
Dynamic - All Firms



Static - Public Firms



Dynamic - Public Firms



Note: The ROC curve plots the probability of true default (sensitivity) and false default (1 – specificity) for the entire range of possible cutoff points. The area under the ROC curve ranges from 0.5 to 1, with a higher value indicating superior discriminative ability.

Table A-V - Weibull Model Estimation

Table A-V - Weibull Hazard Estimation (Stratified by OPTION)

	Coefficients	
Variable	Static Model	Dynamic Model
COUP	14.487***	16.701***
	(3.079)	(2.654)
WCTA	-0.495**	-0.603***
	(0.203)	(0.169)
SALESCA	-0.307**	-0.385***
	(0.131)	(0.141)
GEAR		0.151***
		(0.029)
EBITCL	-0.024***	-0.062***
	(0.006)	(0.013)
CASHTA	1.727***	
	(0.621)	
ARTA	-0.002	
	(0.001)	
MAT		-0.029***
		(0.007)
MACRO		-1.265**
		(0.641)
INDUS	-2.086***	-0.417
	(0.800)	(0.887)
OPTION	0.178	0.482
	(1.368)	(1.543)
Wald Chi-Square	328.64 [0.00]	189.68 [0.00]
Observations	627	17 188
Mean VIF	1.71	1.21
Heteroscedasticity	Used CRSE	Used CRSE

Note: The table presents the output for the estimated parametric Weibull models.
*** p<0.01, ** p<0.05, * p<0.1. CRSE (Cluster Robust Standard Errors) in parentheses.
The Wald Chi-Square statistic is used to test the null hypothesis that all slope coefficients are zero.