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Risky Business

Modelling Distress on the Swedish Market

by

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Abstract

Financial distress is costly for a company and affects many stakeholders. Although models of distress and default have been constructed and developed by researchers for a long time, a model adapted to the unique characteristics of the Swedish market is still missing. This study has two major purposes: (1) to construct a model of distress on the Swedish market, and (2) to use this model to investigate the existence of a distress risk premium. The sample consisted of companies listed on Nasdaq Stockholm's Large- and Mid Cap lists in 2007. Companies with a credit rating were used for model construction while non-rated companies were used for model application and to investigate the distress risk premium. The model was of the ordered probit type and was constructed using variables and ratios known to explain distress. The model was then applied by estimating credit ratings of the non-rated companies and then constructing portfolios of companies with the highest and lowest credit risk respectively. The stock returns of these portfolios were compared in order to investigate the existence of a distress risk premium. The result of this study is a model with eight significant variables measuring profitability, leverage, short-term liquidity, relative size, excess return, market-to-book value, share price and volatility. The significance of the variables confirms their adequacy in explaining financial distress. Moreover, this study does not find a significant distress risk premium but further research on the area is required.

Keywords: Distress risk, credit ratings, ordered probit model, distress risk premium, Nasdaq Stockholm

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1. Introduction

Enron, Lehman Brothers and, most recently, Toys'R'Us are all examples of infamous and large bankruptcies that have shaken the world. Although default does not necessarily lead to bankruptcy, the risk of bankruptcy and financial distress has a great impact on the company itself as well as on its stakeholders. These stakeholders include primarily shareholders but also taxpayers and the financial market in full. Despite the fact that it is difficult to estimate the cost of distress, the importance and severity of the matter are evident when considering governments' constant efforts to avoid bankruptcy of its largest companies and banks through costly bailouts. One recent example is the US Government's bailout of the automotive company General Motors in 2009, costing more than 50 billion dollars (Beech, 2014). Consequently, the process of investigating, measuring and quantifying financial distress is of great importance.

One of the main issues regarding default risk is which model is implemented to measure it. Finding the most appropriate way to model and predict companies' distress and bankruptcy risk has interested researchers for many years. Beaver (1966), Altman (1968), Merton (1974) and Ohlson (1980) have all presented ideas and models that are considered fundamental in the field. Beaver (1966) began by investigating financial ratios based on accounting data as predictors of default. He found that ratios could be used to predict default, but that some were better at predicting failure than others. For example, cash flow to total debt was a better measure than asset value ratios. The Merton model presented by Merton (1974) is probably the most well-known model used to estimate a company's credit risk. It uses the firm's characteristics to find the probability of default, where default occurs when the value of the company's assets fall below the value of its liabilities. Another popular model used to predict default is Altman's (1968) Z-score, a model based upon five ratios assumed to affect default probability. Apart from variables like the value of assets and liabilities (as in the Merton model), the model also includes variables such as working capital and earnings. Ohlson's (1980) O-score has a similar structure to that of the Z-score and consists of measures of size, financial structure, performance and current liquidity.

Newer research focuses on expanding the number of explanatory factors underlying these basic models in order to more fully capture the drivers of bankruptcy and distress. Shumway (2001) develops a model leaving out some of the so-called accounting-based variables from Altman's

Z-score while adding market-based ratios such as stock return and the standard deviation thereof. The superior performance of Shumway's hybrid model over traditional models such as Altman's Z-score has been confirmed by Chava and Jarrow (2004) who also present their own model with a mix of accounting- and market-based measures. One of the most recent hybrid models introduced is presented by Campbell, Hilscher and Szilagyi (2011) and builds even further on this idea by constructing a model with three accounting-based measures together with five market-based measures in order to estimate the probability of default. They suggest that their model is intuitively better since it includes more variables and they also show that it performs better than previously presented models. An adaptation of this model is used in this essay as it can be considered the newest and most developed model to date.

When it comes to application and use of default risk models, distress risk premium is a common subject of interest to researchers. Although controversial, shareholders are often regarded as the most important stakeholders to a company and maximizing shareholder value is by many considered the ultimate goal of business (Lazonick & O'Sullivan, 2000). Investigating the economic consequences of company distress for its shareholders by looking at the effect on stock return therefore seems relevant. Stock price movements are also transparent signs of a company's financial health available to all stakeholders. In addition, it is an interesting subject to investigate since research tends to show different result. Some reports suggest that there is a distress risk premium, while others state that companies in distress on average yield lower returns than companies that are not distressed.

The basic question regarding whether or not a distress risk premium is existent on the stock market is if the risk of bankruptcy is systematic. Dichev (1998) brings up this issue and finds that there is no premium due to bankruptcy risk but that stocks with high risk of bankruptcy rather earn a lower return. The finding of a negative distress risk premium has been confirmed by several reports, e.g. Campbell, Hilscher and Szilagyi (2008), Garlappi and Yan (2011) and Gao, Parsons and Shen (2018). Bauer (2012) also finds a negative distress risk premium and in addition proves that this result holds irrespective of the type of model used, i.e. if it is based on accounting variables, market variables or a hybrid of these.

Although it seems as if most studies find a negative relationship between distress risk and equity return there are also studies that have found a positive distress risk premium. Vassalou and Xing (2004) use the Merton model to estimate default risk and connects this risk to the size of the firm as well as to book-to-market value. They find that stocks of firms with high risk of default yield a higher return than stocks from firms with low risk of default, when they are small in size and/or has a high book-to-market value. Chava and Purnanandam (2010) also find a positive distress risk premium in the stock market using implied cost of capital to predict stock returns (ex ante) rather than using realized returns (ex post). Anginer and Yildizhan (2018) take the systematic nature of default into account through the use of credit risk premiums, estimated from the sample companies' credit spreads, as a proxy for default risk. The authors argue that this measure captures and isolates the systematic part of default risk. They discover that stocks with a higher credit risk premium, and therefore a higher systematic default risk, earn a higher return indicating that there exists a positive distress risk premium.

On the Swedish market, models of distress and distress risk premiums are yet rather unexplored subjects. Dahlbom and Wahledow (2017) use Ohlson's O-score to analyse possible excess returns on investment in distressed stocks on the Swedish stock market but do not find any significant results. The research on the Swedish market is otherwise scarce and a default risk model adapted to this market is non-existent at the moment.

The costs associated with financial distress and the consequences it implies for different stakeholders make the modelling of distress risk important. A model that is also adapted to the unique characteristics of the Swedish market would be particularly interesting to use when evaluating Swedish companies from this perspective. Therefore, the purpose of this essay is to adapt the distress risk model presented in Campbell, Hilscher and Szilagyi (2011) to the Swedish market using data from credit rated companies listed on Nasdaq Stockholm Large Cap. This model will then be used to investigate if there is a distress risk premium on the Swedish stock market by comparing the performance of stocks from companies with high and low estimated distress risk.

The remainder of the thesis is structured as follows. Chapter 2 describes the theoretical framework outlining the concept of credit risk, Standard & Poor's rating system as well as Campbell, Hilscher and Szilagyi's (2011) model which forms the basis for this essay. Chapter 3 presents the data and methodology used for both model construction and application while chapter 4 presents the results from these procedures. A section discussing the results with a starting point in previous research and the theoretical framework follows in chapter 5. Chapter 6 concludes the main findings and implications of the study.

2. Theoretical Framework

2.1 Credit Risk

When lenders offer loans, they always face a risk of not getting repaid by the borrowers. This risk is called credit risk and since borrowers expect to repay the loan with future cash flows, the credit risk can never be fully avoided. Interest payments received from borrowers are the compensation for credit risk. These payments consist of the risk-free rate and the credit spread, where the latter is the compensation for credit risk. The credit risk of a specific borrower can be assessed by analysing the borrower's general ability to repay a loan which is done by credit rating agencies by order of the borrower. Credit ratings are a way of reducing the information asymmetry between the lender and the borrower (Hull, 2015).

2.2 Standard & Poor's Rating System

The US-based firm Standard and Poor (S&P) is one of the three biggest credit rating agencies in the world, alongside with Moody's credit rating and Fitch credit rating. S&P provides credit ratings in 28 countries around the world with over one million credit ratings outstanding. The agency issues forward-looking ratings on the creditworthiness of an obligor such as a corporation, a state or city government but also on bonds and issues. However, since the financial crisis the ratings of corporates have become more prominent (Hung et al., 2013). The rating an obligor is given reflects S&P's opinion on the obligor's capacity and willingness to meet its financial commitments at the time they are due (Standard & Poor's [S&P], 2014).

S&P is widely recognized for having an impact on credit markets. In fact, there is evidence of credit rating agencies' ratings affecting borrowing costs for firms with credit ratings, implying that ratings bring information to the market which is considered valuable (Micu et al., 2004). While credit ratings may be used as a tool for making decisions about investments the credit ratings do not provide an investment worthiness recommendation of the firms rated. This means that a rating does not represent a buy, hold or sell recommendation but rather a credit quality of a firm and the rate of recovery that can be expected in the case of default. Neither does the credit rating give a probability of default but act as a relative measure of the likelihood of default. This implies that a firm with a high credit rating has less likelihood of defaulting in relation to a firm with a lower credit rating but still with no guarantee of not defaulting (S&P, 2018a).

S&P's credit ratings can be either short-term or long-term. Short-term ratings are generally assigned to entities with obligations due in less than a year. Long-term ratings are more of an assessment of default risk and the chance of recovery in the case of default. The long-term credit ratings are based on S&P's analysis of the type of obligations of the entity, the capacity of payment and readiness of the entity to meet its financial commitments as well as the protection against default the entity can afford and implement (S&P, 2011).

To provide an entity with a credit rating, S&P evaluates the entity's capacity and willingness to meet its obligations, based on the terms of the obligations. The process of the credit rating begins with a request of a rating by an entity, e.g. a firm. S&P collects a team of analysts to evaluate the firm, which is done by obtaining public information from published reports as well as from internal interviews and discussions with the firm in question. The rating is then pre-published for the issuer of the rating to check facts and accuracy which is then followed by an official publication by S&P. The rating accounts for internal factors such as the entity's financial state, performance, policies, risk management and currency risk exposure besides external factors such as industry, country and business cycle. These are factors that would affect the firm permanently and are therefore relevant to include in the credit risk analysis for a long-term credit rating. Events and factors that are considered to only affect entities in the short-term do not typically influence the credit rating (S&P, 2014).

S&P gives ratings in a letter scale from AAA being the highest credit rating to D being the lowest. Plus (+) and minus (-) signs can be added to the rating categories which indicate relative position inside that category. The rating scale can be divided into two parts: investment grade and speculative grade. Ratings from BBB and higher are considered to be an investment grade while ratings from BB to C is considered to be a speculative grade. This distinction between the ratings is used in order to be able to make a broad classification of a firm's rating. The investment grade refers to firms with high creditworthiness and credit quality while the speculative grade refers to firms with the ability to meet its financial commitments but that face uncertainties if the financial circumstances would change (S&P, 2018b; S&P, 2018c). Table 1 illustrates the different S&P's ratings and their broad definitions.

Table 1. Credit Rating Definitions

	S&P	Definition
Investment Grade	**AAA**	Minimal credit risk, highest quality
	AA+ **AA** **AA-**	Very low credit risk, high quality
	A+ **A** **A-**	Low credit risk, upper medium quality
	BBB+ **BBB** **BBB-**	Moderate credit risk, medium grade
Speculative Grade	**BB+** **BB** **BB-**	Substantial credit risk, somewhat speculative
	B+ **B** **B-**	High credit risk, low grade, speculative
	CCC+ **CCC** **CCC-**	Very high credit risk, low grade, default possible
	CC **C**	In or near default, with partial possibility of recovery
	D	In default, with little chance of recovery

Note. Adapted from "S&P Global Ratings Definition" (Standard & Poor's, 2018c) and "Econometric Analysis" (Greene, 2018).

Even though the credit market generally trusts credit ratings, the accuracy of credit ratings can be discussed. For example, when Lehman Brothers declared bankruptcy in 2008 they had an S&P credit rating of A, indicating that they would have strong capacity to meet its financial commitments and hold an adaptability to changes in the economic environment. This shows that credit ratings do not freely function as predictors of default but should be observed as measures of default likelihood. As a measure of default risk, credit ratings have the highest accuracy since ratings are based on firms' financial ratios which in turn affect default (Hung et al., 2013).

2.3 Campbell, Hilscher & Szilagyi (2011) model

Campbell, Hilscher and Szilagyi's (2011), hereinafter referred to as CHS, approach is an expansion of Altman's Z-score model and the Merton model, using variables from Shumway (2001) as well as adding new ones. The traditional models (Altman's Z-score, Merton model and Ohlson's O-score) and the Shumway (2001) model, which are considered fundamental to modelling distress in general and also impact the choice of variables used by CHS (2011) are described in Appendix 1.

CHS (2011) construct a model consisting of three accounting-based and five market-based measures to forecast distress which is measured as probability of default. The model is implemented on a data sample including more than two million monthly observations of American firms during the period 1963-2008. They use the following variables in their model, where *i* is the firm and *t* is the month:

$$NIMTA_{it} = \frac{Net\ Income_{it}}{Market\ Equity_{it} + Total\ Liabilities_{it}} \quad (1)$$

$$TLMTA_{it} = \frac{Total\ Liabilities_{it}}{Market\ Equity_{it} + Total\ Liabilities_{it}} \quad (2)$$

$$CASHMTA_{it} = \frac{Cash\ \&\ Short\ Term\ Investments_{it}}{Market\ Equity_{it} + Total\ Liabilities_{it}} \quad (3)$$

$$EXRET_{it} = \log(1 + R_{it}) - \log(1 + R_{Index,t}) \quad (4)$$

$$RSIZE_{it} = \log\left(\frac{Market\ Equity_{it}}{Total\ S\&P500\ Market\ Value_t}\right) \quad (5)$$

$$MB_{it} = \frac{Market\ Equity_{it}}{BE_{adjusted,i,t}} \quad (6)$$

$$\text{where } BE_{adjusted,i,t} = BE_{it} + 0.1(Market\ Equity_{it} - BE_{it}) \quad (7)$$

$$SIGMA_{i,t-1,t-3} = \left(252 * \frac{1}{N-1} \sum_{k \in \{t-1,t-2,t-3\}} r_{i,k}^2\right)^{\frac{1}{2}} \quad (8)$$

$$PRICE_{it} = \log(P_{it}) \quad (9)$$

R indicates the return, BE the book value of equity and P the stock price. The book value of equity (BE) is adjusted to avoid unreasonably small values of BE which would then lead to improperly large values of MB. The probability of default within the next month for a firm is calculated according to the logit model presented by Equation 10 below.

$$P_{t-1}(Y_{it} = 1) = \frac{1}{1+exp(-\alpha-\beta x_{i,t-1})} \qquad (10)$$

where $Y_{it} = 1$ is the case of default and $Y_{it} = 0$ is the case of survival. $\beta x_{i,t-1}$ is the linear combination of the eight variables above. The α- and β-coefficients for a particular firm, estimated by the model with the abovementioned ratios, can in this way be used to predict the probability of default for that firm at a chosen point in time (CHS, 2011).

The explanatory variables CHS (2011) use for their model are selected based on what is believed to affect default and what is used in previous models. The eight variables the authors use affect default in different ways but are all significant at the 1% significance level. The authors describe the impact of the variables as intuitive and in line with previous research. Their findings are that distressed firms have low and volatile returns, a high ratio of leverage and high levels of market-to-book value. These aspects are represented by the variables TLMTA, EXRET, SIGMA, MB and PRICE which are measures of leverage, return, volatility, market-to-book value and price respectively. If the leverage measure is high it would mean that the firm is closer to distress. The measure is scaled by market value of assets, as opposed to book value of assets that is commonly used, since the authors find that the market value is more accurate to use when forecasting distress. As for returns, which are measured in relation to the index return, a firm close to distress shows low or negative values in addition to high volatility. Market-to-book measures the market value of the firm scaled by the book value and may in that way capture overvaluation which may be a consequence of recent heavy losses. Price is often low for distressed firms as the equity value declines, something that is reflected in the price (CHS, 2011).

The remaining variables NIMTA, CASHMTA and RSIZE are measures of profitability, liquidity, and size, respectively. High values of these are usually connected to non-distress. Intuitively, high profitability is connected to a non-distressed firm seen to that variable alone.

Liquidity is measured and used as a variable since a firm's cash holding is important in the sense of being able to secure financing. This applies even if the value of assets would be larger than the value of liabilities. The size of the firm is a common variable when modelling distress as larger firms tend to have a higher ability to avoid distress by temporary financing than smaller firms (CHS, 2011).

By using a higher number of explanatory variables in their model than in previous models of distress, the authors argue that the forecast accuracy and the explanatory power of their model is higher than for the Merton model as well as the model presented by Shumway (2001). In addition, the authors implement the distance-to-default variable from the Merton model into their model but find that this only increases the explanatory power marginally. They also assess the predictive power of their model through comparing the realized failure rate with the predicted and find a correlation of 84%. The R-squared of the model is 31.6%. Following these results, the authors reach the conclusion that their model has higher accuracy when predicting defaults than other commonly used models (CHS, 2011).

Further, the authors measure the returns of stocks in distress by sorting them in different portfolios based on the probability of default. They compare the returns of the portfolios and conclude that stocks of distressed firms underperform stocks from safe firms. Even though the authors reach this conclusion, their results also show a large variation in the percentage firm failure rate over the years observed, which would indicate that default risk can not be diversified away and thus is systematic. According to the study, investors should therefore require a premium for holding distressed stocks (CHS, 2011).

3. Methodology

3.1 Data

3.1.1 Stock Market Data

The sample of firms in this thesis consisted of public firms listed on Nasdaq Stockholm Mid Cap and Large Cap as of 2007. This means that all firms listed on Mid Cap and Large Cap in 2007 were included in the sample, regardless of re-listing or de-listing after 2007. The firms were observed during the period 01-01-2007 to 01-01-2017. This time period was chosen as it captured both the effects of the financial crisis 2007-2008 but also the more stable situation occurring at the end of the sample period. The basic idea behind this was to construct a model based on data from different business cycles, making it more general.

Large Cap companies with credit ratings were used to construct the model and the total number of firms listed on Large Cap in 2007 was 69. When the same company had two or more stock series listed (e.g. an A- and B-share) the least traded stock, measured by share turnover, was excluded from the sample. This was due to the fact that the value of the accounting variables presented in chapter 2, and further described below, was the same for all stocks from the same firm while only the market variables changed. Since only one credit rating per company was wanted, the most representative stock was chosen for the sample. Not all 69 firms had credit ratings and so there was a reduction of the sample and 32 firms were left. Ultimately, the number of observed firm months for the model construction was 3 562. The 32 firms are listed in table 12 in Appendix B.

Large Cap companies without credit ratings and all Mid Cap companies were used for model application and in the construction of portfolios. These 106 companies are listed in table 13 in Appendix B. The Mid- and Large Cap segments were chosen due to the extensive data availability. However, the following companies were deducted from the sample because of insufficient data availability: D. Carnegie & Co AB, Eniro AB and Vostok Nafta Inv Ltd SDB (all listed on Large Cap 01-01-2007) and Cloetta Fazer AB, Nefab AB, Pergo AB Protect Data AB and ScanMining AB (Mid Cap). The total number of observed firm months for the model application was 10 635.

The index used for Equation 5 (see chapter 2.3) was Stockholm OMX 30, containing the 30 most traded shares on Nasdaq Stockholm, as it is one of the most well-known and commonly used indexes on the examined market.

3.1.2 Accounting and Market Data

The accounting and market data variables for the firms were retrieved from Thomas Reuters Datastream. The variables collected for each firm were: net income, market value of equity, total liabilities, cash and short-term investments (used for Equations 1, 2 and 3) and common equity (Equation 7). For firms that did not have the post cash and short-term investment (mainly banks) the variable cash and cash equivalents was used instead. This post is equivalent to cash and short-term investments for industrial companies but includes cash and dues from banks for banks. The monthly share price for each firm was collected, used directly in Equation 9 and transformed into returns in Equation 4. The daily share price for each company was also collected, transformed into returns and then used when calculating return volatility similarly to Equation 8. Further, the index value and total index market value used for Equation 4 and 5 respectively were obtained. Total index market value, i.e. the total market capitalization from all firms listed on OMX Stockholm 30, was found through the online database Quandl (n.d.). All data was retrieved with monthly frequency which means that the two market variables share price and market value of equity varied monthly. The accounting variables, such as net income and common equity, came from annual reports and were therefore the same for all 12 months within a year.

3.1.3 Credit Ratings

The credit ratings of the firms were collected from the Bloomberg terminal. S&P's long-term issuer credit ratings for the firms were chosen as this rating provides an overall rating of the firm. Credit ratings from S&P were retrieved in the first place as they had the highest availability of credit rating data for our sample of firms. For some firms in our sample that lacked a rating from S&P but had a rating from Moody, the latter was retrieved and translated into a rating according to the S&P's system. This was done in order to increase the sample size as much as possible. Since S&P's and Moody's credit ratings are based on the similar conditions the ratings are considered to be equivalent and therefore the credit ratings from Moody's could easily be translated into S&P's system (Bank of International Settlements [BIS], n.d.). Table 2 later in this chapter shows how the translation was conducted.

3.2 Construction of the Model

3.2.1 Variables

Firstly, a model of financial distress on the Swedish stock market was constructed. As previously stated, the theory behind the model presented by CHS (2011) was used. The authors prove that the model outperforms the Merton model as well as several other recent models, which in addition to the intuition that the model takes into account more relevant factors, made the model suitable as a basis for this study. By using data from Swedish companies to obtain the coefficients values, the model was adapted to the specific characteristics of the Swedish market.

The eight different ratios based on accounting and market data were calculated and used as explanatory variables in the model. These eight measures were net income over market value of total assets (NIMTA), total liabilities over market value of total assets (TLMTA), cash and short-term investment over market value of total assets (CASHMTA), market value of equity over the total market value of OMX Stockholm 30 index (RSIZE), excess return relative to the index (EXRET), market-to-book value (MB), the logarithm of the stock price (PRICE) and the standard deviation of the stock returns (SIGMA). The equations for the eight measures were similar to Equation 1-9 in the previous section, with one difference being the use of OMX Stockholm 30 as index instead of S&P 500 in Equation 4 and 5. Additionally, the returns in Equation 4 were in our thesis calculated through Equation 11, using stock and index prices respectively.

$$R = \frac{P_1 - P_0}{P_0} \qquad (11)$$

The SIGMA equation was also somewhat simplified compared to CHS's (2011) and was in this study calculated based on daily stock return standard deviation that was then transformed into a yearly volatility measure through multiplying it by the square root of the average number of trading days during one year, 252. This calculation is illustrated below.

$$SIGMA_{it} = \sqrt{252} * STDEV(R_{it}) \qquad (12)$$

CHS (2011), as well as most other studies on the area, use bankruptcy as the dependent variable in order to estimate default risk. Since the number of bankruptcies on the Swedish market was considered too low during the period of this study credit ratings were instead used as a proxy for the level of financial distress. As mentioned, a credit rating is not an exact measure of the probability of default. It is however based on factors that affect default (Hung et al., 2013). Because of this, credit ratings were regarded as sufficiently good indicators of financial distress for this study, even though the characteristics of a credit rating need to be taken into account when interpreting the result. To be able to use credit rating as a dependent variable, they were transformed into numbers according to table 2.

Table 2. Credit Rating Transformations

S&P	Moody's	Number
AAA	Aaa	1
AA+ **AA** **AA-**	Aa1 Aa2 Aa3	2
A+ **A** **A-**	A1 A2 A3	3
BBB+ **BBB** **BBB-**	Baa1 Baa2 Baa3	4
BB+ **BB** **BB-**	Ba1 Ba2 Ba3	5
B+ **B** **B-**	B1 B2 B3	6
CCC+ **CCC** **CCC-**	Caa1 Caa2 Caa3	7
CC **C**	Ca	8 9
D	C	10

Note. Adapted from "Long-Term Rating Scales Comparison" (Bank of International Settlements [BIS], n.d.).

Table 2 shows 10 different rating categories from 1 to 10. However, none of the sample companies used to construct the model had a rating number higher than 7 which meant that the non-rated firms on which the model was applied only got estimated rating numbers between 1 and 7. Furthermore, as described in the previous section, the plus and minus signs added to some ratings only indicate the relative position within each category and was therefore not considered in the transformation. For example, BB+, BB and BB- all yield a number of 5 in this study, independent of the sign accompanying the rating. As the number of credit rating categories was already large, and the output from the model consequently would be specific to a high degree, this was not considered to affect the model negatively but rather the opposite.

After calculating the above measures as well as transforming the credit rating for each of the companies on a monthly basis, a regression was performed with the eight ratios as independent variables and the credit rating values as dependent variables. The result from the regression was a model with which the default risk for a company on the Swedish market could be estimated.

3.2.2 Regression

The credit ratings used as dependent variables when constructing the model are ordinal category variables, i.e. are categorical with a natural order (credit rating AAA is better than category AA and so on) but the distance between the different categories are unknown (for example, the distance between AAA and AA is not necessarily equal to the distance between C and D) (Agresti, 2002). Due to the fact that regular OLS treats the variables as cardinal it would have been inappropriate to use for this purpose (Mora, n.d.). Instead an ordered probit model was used with the assumption of normally distributed errors. The estimation was done in Eviews where we received coefficient values, their respective p-values as well as limits points that could be used to classify output values into credit rating categories.

In order to test the model, Eviews allowed for a prediction evaluation where the observed values were compared to the model's predicted values. The percentages of correct and incorrect estimations were presented and compared to a constant probability specification (a simple model without regressor) in order to evaluate the ordered probit model (Eviews, 2017).

3.2.3 Interpretation of the Model

Since our model is an ordered probit model, the interpretation of the coefficients is different from a regular OLS. The signs of the beta-coefficients in the ordered probit model indicate in what direction the probability of falling in the smallest or largest ranking changes when the x-values change. The probability of falling in the smallest ranking changes in the opposite direction of the coefficient value while the probability of falling in the largest ranking changes in the same direction (Eviews, 2017). In our case, with rankings between one and seven, this means that the probability of $y = 1$ changes in the opposite direction and the probability of $y = 7$ changes in the same direction as the coefficient sign.

However, in order to interpret the coefficient values for all probabilities we investigated the marginal effects on probabilities. In other words, we wanted to see how the probability for the different rankings changes when the x-values change marginally. We began by calculating the x-values, in other words the different ratios (NIMTA, TLMTA etc.), for an average firm in our sample of rated firms i.e. an average across all years and firms. Then, the probabilities for each of the rankings were calculated using the following formulas (Greene, 2008):

$$\Pr(y = 1) = N(\gamma_1 - \beta_1 * x_1 - \beta_2 * x_2 - \cdots - \beta_8 * x_8)$$

$$\Pr(y = 2) = N(\gamma_2 - \beta_1 * x_1 - \beta_2 * x_2 - \cdots - \beta_8 * x_8) - N(\gamma_1 - \beta_1 * x_1 - \beta_2 * x_2 - \cdots - \beta_8 * x_8)$$

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$$\Pr(y = 7) = 1 - N(\gamma_6 - \beta_1 * x_1 - \beta_2 * x_2 - \cdots - \beta_8 * x_8) \qquad (13)$$

where N is the normal cumulative distribution, γ represents the limit points retrieved from the regression, β the coefficient values for each of the eight explanatory variables and x the x-values. The x-values used were, as mentioned above, averages for all firms over time. The probabilities sum to one (Greene, 2008).

Lastly, we differentiated these probabilities with respect to x. In our case, this meant that we differentiated the seven probabilities with respect to each of the eight x-values respectively, which yielded 56 marginal effects in total. The marginal effects were calculated using Equation 14 below.

$$ME_{ij} = \frac{\delta \Pr(y=i)}{\delta x_j} \qquad (14)$$

where $i = 1,2, \ldots, 7$ represents the rating and $j = 1,2, \ldots, 8$ denotes the explanatory variable. Since the probabilities sum to one, the marginal effects will sum to zero (Greene, 2008).

The marginal effect indicates at what rate the probability of a certain credit rating changes when there is a marginal increase in the related x-variable. For example, if the marginal effect for an x-variable at Pr $(y = 1)$ is 0.1, an increase in that x-variable with 0.2 would mean that the probability of receiving a credit rating of 1 (i.e. Pr $(y = 1)$) increases with $0.1 * 0.2 = 0.02$, or 2% (Williams, 2018).

In order to facilitate the interpretation of the model even further, we investigated the impact of a one standard deviation increase in the explanatory variables, on the probabilities of different ratings. Each variable was increased in isolation, with all other variables held to their average value. This was done in order to evaluate each variable's effect on the probability distribution of the credit rankings and to see which explanatory variables had the largest effect in the model. The variables are sensitive to too large changes in the variable, and also to the value of the other variables, and this is why an increase with a standard deviation is sufficient in order to investigate the impact of the variables (McKelvey & Zavoina, 1975).

3.3 Portfolio Construction

Using the estimated equation from the regression, the companies listed on Nasdaq Stockholm Mid Cap and Large Cap in 2007 (removing the 32 companies with credit rating used to create the model) were further investigated. The credit rating for each of these companies was estimated monthly and by using the credit rating from December each year, the companies were divided into three portfolios: one including companies with high credit rating and low credit risk (LOW), one with medium credit rating and medium credit risk (MID) and one with low credit rating and high credit risk (HIGH). The LOW portfolio consisted of the 25 companies with the highest estimated credit rating which corresponded to approximately 25% of the total sample. The HIGH portfolio contained the 25 companies with the lowest credit ratings. The portfolios were updated each year and equally weighted.

The returns of the LOW and HIGH portfolios were then tracked and compared over the next year, i.e. the portfolios were constructed based upon their credit rating the first of December each year (e.g. 2007) and then the comparable stock return was measured the year after (e.g. 2008). The credit rating of a company in December was assumed to indicate the risk of distress for the company the following year, which was why the returns were observed during that time. As a result, credit ratings from 2007 to 2016 were used while the stock returns instead were observed from 2008 to 2017. The returns were gathered on a daily basis for each company and then averaged yearly and for each portfolio.

This procedure yielded 10 values of yearly average stock returns for the LOW and HIGH portfolio respectively. The comparison of returns between the two portfolios was performed in order to see if stocks from firms with high default risk yielded a higher or lower return than other firms on average.

4. Results

4.1 The Model

4.1.1 Estimation Output

The estimation output from the regression is presented in table 3.

Table 3. Ordered Probit Model Estimation Output

Variable	Coefficient	Std. Error	z-Statistic	Prob.
NIMTA	-0.288	0.144	-2.006	0.045
TLMTA	-1.327	0.102	-12.982	0.000
CASHMTA	8.330	0.340	24.471	0.000
RSIZE	-0.899	0.0210	-42.894	0.000
EXRET	0.675	0.264	2.563	0.010
MB	0.192	0.012	16.549	0.000
PRICE	-0.636	0.028	-23.036	0.000
SIGMA	1.310	0.157	8.331	0.000
Pseudo R-squared	0.332689			

All variables are significant on a 5% significance level and the model has an R-squared value of 0.33. NIMTA and EXRET are not significant on the 1% level with p-values of 0.045 and 0.010 respectively. All other variables have a p-value smaller than 0.001.

The limit points mentioned in the method section above, from which it is possible to classify the output value from the model into credit rating categories, are listed in table 4 below.

Table 4. Model Limit Points

Credit Rating Category	Limits
1/AAA	$y < 2.59$
2/AA	$2.59 < y < 5.57$
3/A	$5.57 < y < 7.39$
4/BBB	$7.39 < y < 9.42$
5/BB	$9.42 < y < 10.73$
6/B	$10.73 < y < 11.82$
7/CCC	$11.82 < y$

For example, using the data for Axfood in December 2007 in the model yields a y-value of 9.03, which corresponds to a credit rating of BBB. As mentioned, the model only classifies the ratings from 1/AAA to 7/CCC since the sample used to construct the model only contains these ratings.

The percentage of correct and incorrect predictions for each dependent variable (credit rating) by the model is presented in table 5 and is based upon the result from the prediction evaluation also described in the method section.

Table 5. Prediction Evaluation for Ordered Probit Model

Dep. Value	Observations	Correct	% Correct	Incorrect	% Incorrect
1	2	0	0	2	100
2	484	239	49	245	51
3	1413	953	67	460	33
4	1261	826	66	435	34
5	274	154	56	120	44
6	78	10	13	68	87
7	50	41	82	9	18
Total	**3562**	**2223**	**62**	**1339**	**38**

The model is most successful in predicting credit ratings of the lowest grade, i.e. 7/CCC and least successful in predicting credit ratings of the highest grade, i.e. 1/AAA. For the credit ratings with the highest number of observations in the sample, 3/A and 4/BBB, the model predicts the correct credit rating with almost 70% accuracy.

More detailed information about the output from the regression as well as the prediction evaluation can be found in Appendix C.

4.1.2 Marginal Effects

Table 6 presents the probability for each rating with the model, both for the rated companies used to construct the model and for the unrated companies on which we apply the model.

Table 6. Credit Rating Probabilities

Probabilities	Rated Companies	Non-Rated Companies
$\boldsymbol{Pr(y=1)}$	<0.001	<0.001
$\boldsymbol{Pr(y=2)}$	0.037	<0.001
$\boldsymbol{Pr(y=3)}$	0.475	0.005
$\boldsymbol{Pr(y=4)}$	0.468	0.274
$\boldsymbol{Pr(y=5)}$	0.019	0.488
$\boldsymbol{Pr(y=6)}$	<0.001	0.199
$\boldsymbol{Pr(y=7)}$	<0.001	0.034

For the rated companies, the probabilities of receiving a credit rating of 3 or 4 with our model are high while the probabilities of receiving the highest (1) and the lowest (7) credit ratings are smallest. For the non-rated companies, the probability of receiving the lowest credit ratings (i.e. the highest numbers) are larger than for the rated companies.

Furthermore, table 7 shows the distribution of the observations over the different credit ratings for the rated and non-rated companies. The observations for the rated companies are actual credit ratings while the observations for the non-rated companies are credit ratings estimated with the model.

Table 7. Amount of Observations (Firm Months) within Each Rating

	Rated Companies (Actual Rating)		Non-Rated Companies (Estimated Rating)	
	No. of Observations	**% of Observations**	**No. of Observations**	**% of Observations**
1/AAA	2	0	51	0
2/AA	484	14	0	0
3/A	1 413	40	538	5
4/BBB	1 261	35	4 021	38
5/BB	274	8	2 808	26
6/B	78	2	1 443	14
7/CCC	50	1	1 774	17
Total	**3 562**	**100**	**10 635**	**100**

These results also show that the number and percentage of observations falling in the lowest credit ranking categories (highest numbers) are higher for the non-rated companies than for the rated companies.

Table 8 below presents the probabilities for each credit ranking when each x-variable is changed (increased) with a standard deviation, as described in the methodology chapter.

Table 8. Credit Rating Probabilities After Increase in X-variable

	NIMTA	TLMTA	CASHMTA	RSIZE	EXRET	MB	PRICE	SIGMA
$Pr(y = 1)$	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
$Pr(y = 2)$	0.040	0.072	0.010	0.254	0.033	0.015	0.107	0.025
$Pr(y = 3)$	0.487	0.568	0.293	0.622	0.460	0.345	0.611	0.416
$Pr(y = 4)$	0.454	0.351	0.631	0.123	0.485	0.593	0.277	0.529
$Pr(y = 5)$	0.018	0.008	0.063	0.001	0.022	0.046	0.005	0.030
$Pr(y = 6)$	<0.001	<0.001	0.002	<0.001	<0.001	0.001	<0.001	0.001
$Pr(y = 7)$	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

As can be seen when comparing table 6 and table 8, the variables CASHMTA and RSIZE account for the largest absolute changes in the probability distribution while the variables NIMTA and EXRET have the smallest impact.

Table 9 illustrates the marginal effects of each explanatory variable for each probability. The sign of the marginal effect indicates the direction of impact on the probability of different credit ratings by each variable. Primarily, the marginal effects show which variables affect the probability of a credit ranking positively and which ones affect it negatively. Further, the value of the coefficient shows the speed of change.

Table 9. Marginal Effects per Probability and X-variable

	NIMTA	TLMTA	CASHMTA	RSIZE	EXRET	MB	PRICE	SIGMA
$\boldsymbol{Pr(y=1)}$	<0.001	<0.001	>-0.001	<0.001	>-0.001	>-0.001	<0.001	>-0.001
$\boldsymbol{Pr(y=2)}$	0.023	0.107	-0.673	0.073	-0.055	-0.016	0.051	-0.106
$\boldsymbol{Pr(y=3)}$	0.092	0.422	-2.648	0.286	-0.215	-0.061	0.202	-0.417
$\boldsymbol{Pr(y=4)}$	-0.101	-0.465	2.921	-0.315	0.237	0.067	-0.223	0.460
$\boldsymbol{Pr(y=5)}$	-0.013	-0.062	0.389	-0.042	0.032	0.009	-0.030	0.061
$\boldsymbol{Pr(y=6)}$	>-0.001	-0.002	0.011	-0.001	0.001	<0.001	-0.001	0.002
$\boldsymbol{Pr(y=7)}$	>-0.001	>-0.001	<0.001	>-0.001	<0.001	<0.001	>-0.001	<0.001

The variables NIMTA, TLMTA, RSIZE and PRICE affect the probabilities $\Pr(y=1)$, $\Pr(y=2)$ and $\Pr(y=3)$ positively and the probabilities for the remaining credit rankings negatively as they increase marginally. The variables CASHMTA, EXRET, MB and SIGMA affect the probabilities $\Pr(y=1)$, $\Pr(y=2)$ and $\Pr(y=3)$ negatively and the probabilities for the remaining credit rankings positively as the variables increase marginally in value.

4.2 Model Application

Applying the model on the non-rated companies in the sample gives us estimated credit ratings for these companies on a monthly basis between 2007 and 2017. The average estimated credit ratings over this time period for each company in the sample can be found in Appendix D.

The cumulative return of the two different portfolios LOW (including the 25 companies with the lowest credit risk) and HIGH (including the 25 companies with the highest credit risk) as well as their average return over the observed time period are presented in table 10. The right column illustrates the difference in both cumulative return and average return between the HIGH portfolio and the LOW portfolio.

Table 10. Cumulative and Average Return of Portfolios

	LOW	**HIGH**	**Difference (HIGH minus LOW)**
Cumulative	5.53%	4.51%	-0.90%
Average	0.55%	0.47%	-0.09%

Over the 10 years observed (stock returns from 2008 to 2017), a portfolio containing the 25 companies with the lowest credit risk in December the year before, updated each year, yields a yearly return of 0.55% on average, while the portfolio with the 25 companies having the highest credit risk yields a return of 0.47%. The difference in cumulative return is -0.90% between the HIGH and the LOW portfolio while the difference in average return is -0.09%.

A table showing the cumulative and average returns for the portfolios for all years included in the sample can be found in Appendix D.

5. Discussion

The first, and most relevant, part of the analysis is the study and interpretation of the constructed model. As seen in the estimation output in table 3, all of the variables used in the regression are highly significant with p-values of around 1% and lower. This indicates that the variables chosen for the model were relevant for the purpose and that they to some extent explain financial distress. The addition of more explanatory variables by CHS (2011), in contrast to traditional models such as Altman (1968) and Merton (1974) seems to have been a correct course of action according to our model where all variables are highly significant.

The variable with the highest p-value, net income over total assets (NIMTA), is only marginally significant at the 5% level. This is somewhat surprising since this variable is not only used in CHS (2011) but also in Shumway (2001) and Chava and Jarrow (2004). It can therefore be considered one of the most acknowledged ratios used to predict financial distress. What might explain the higher p-value could of course be the sample at hand as well as the use of credit rating as a dependent variable, which is different from the aforementioned authors' approaches. A credit rating can be considered a relevant proxy for financial distress but represents the relative likelihood of default rather than the absolute probability of default (Hung et al., 2013). The absolute value of a single credit rating estimated with this model should therefore not be analysed excessively but rather be put in relation to its relative position among the ratings. This changes the interpretation of the results from models that use bankruptcy/non-bankruptcy as the dependent variable.

The R-squared value of 0.33 from the model can be compared to CHS's (2011) value of 0.316. This rather high R-squared, together with the significance of the explanatory variables, would indicate that our model gives a fairly acceptable estimation of the credit rating of a listed Swedish company. The results from the prediction evaluation, illustrated in table 15 in Appendix C, also indicate that the model can be considered acceptable since it outperforms the simpler model. The characteristic of this model compared to previous models, dividing the companies into seven categories rather than just two (bankrupt vs non-bankrupt), makes the correct prediction rate of 62% rather remarkable. What is also evident from the prediction evaluation, and can be considered an advantage, is that the model is best at predicting ratings between 3/A and 5/BB (with the exception of credit rating 7/CCC that it is the absolute best at predicting), which is the range that contains most of the observations. An even better predictive power could probably be achieved by a larger sample. That our sample is small becomes evident when comparing our 3 562 firm months for model construction to CHS's (2011) two million firm months. It should however be taken into account that the Swedish market, and therefore the data availability, is much smaller than that of for example the American market.

Hopefully, our model can be used in full or as a basis for developing new models to estimate credit ratings for non-rated companies on the Swedish market. It does offer interesting proof of the ability of the chosen variables and ratios to explain financial distress.

When looking at the probabilities of different credit ratings for rated companies (see table 6), one can easily see that the probabilities are the highest for the ratings in the middle range, i.e. 3/A-4/BBB. When considering the unrated companies in the same table, the probabilities are slightly different. Instead, the probabilities are higher for the higher numbers (i.e. the lower credit ratings). This is confirmed by the amount of observations within each rating for the rated and non-rated firms respectively, illustrated in table 7. There are more observations in the credit rating categories with high numbers (indicating low credit rating) for the non-rated companies than for the rated ones. This would indicate that on average, the non-rated firms have a higher credit risk than the sample of rated firms used to construct the model. One possible reason for why the sample differs is the fact that companies that are stable and considered creditworthy might actually be more inclined to buy a credit rating since they are able to get a higher rating. The group of unrated companies is also more diverse, with companies listed on both Mid- and Large Cap and therefore varying in size, which speak against probabilities of better credit ratings. As stated by CHS (2011), among others, smaller companies typically have a higher credit risk than larger companies.

Moreover, when observing the change in the probability distribution of credit ratings when each variable in the model is changed with one standard deviation at a time, as seen in table 8, the effect of a specific variable on the probability of a certain credit rating is shown. As can be seen when comparing table 8 to table 6, the variables that change the probability distribution the most and therefore have the largest effect on the probabilities in absolute terms are CASHMTA and RSIZE. This can be interpreted as if liquidity and relative size have the largest impact on the credit rating a firm is assigned. It can also be interpreted as if these characteristics are especially important when assessing the financial health of a Swedish firm as the model is adjusted to the Swedish market in particular. The variables NIMTA and EXRET, measures of profitability and return, have the lowest effect on the probabilities.

Observing these effects further by looking at the marginal effects in table 9, liquidity affects the credit rating negatively, which is interpreted as if the higher amount of cash a firm has in relation to its total assets, the lower the probability of a high credit rating according to our model. This contradicts the theory and results from CHS's (2011) study, as increased liquidity is generally presumed to earn a firm a higher credit rating. The effect of relative size is the largest out of the two ratios mentioned above and affects the probability of a high credit rating positively. This would mean that a large firm would have a higher probability of a high credit rating than a small firm. Size is a common factor when discussing default risk, as large firms tend to have a smaller probability of defaulting, which is the result of our study as well.

The variables measuring profitability and price affect probabilities for high credit ratings positively which is in line with the claims of CHS (2011). A firm with high profitability should have lower distress risk and hence the credit rating should increase with profitability in our model. CHS (2011) also argue that price is an indicator of default since distressed firms often have low prices as a result of a low equity value. As for leverage however, our result differs from previous studies. Merton (1974) builds his model on the idea that high leverage in relation to asset value, increases the probability of default. In our study the impact of the leverage variable is positive with the credit rating, which means that the higher leverage of a firm the higher the credit rating. A possible explanation for this might be that firms with high leverage but no credit rating have proven high creditworthiness according to lenders in other ways. Therefore they might have been able to maximize their leverage, resulting in a high leverage ratio in combination with a high estimated credit rating from the model.

The variables affecting the credit rating in the opposite direction, thus increasing the probability of a low credit rating when increasing themselves, are equity return, volatility and market-to-book value. The impact of the variable equity return is not aligned with the results of CHS (2011), as firms in distress usually have low or negative returns. In this study though, the credit rating seems to decrease with higher equity return. In other words, high returns increase the probability of a lower credit rating. The variables market-to-book and volatility affect the credit ratings as expected and in line with CHS's (2011) results. Since firms in distress usually are overvalued, the market-to-book ratio is high and the probability of low credit ratings should therefore increase as this ratio increases. Moreover, high volatility is usually a sign of a distressed firm, which is the outcome of this study as well. Firms with highly volatile stocks have lower credit ratings than those with low volatility.

That some variables differ in direction of impact in our study compared to the study by CHS (2011) may have several reasons. Firstly, since this study is conducted on the Swedish market, variables may differ because of a divergence in regulation and guidelines of what a firm's ratios should amount to. Secondly, as our sample size is smaller than in previous studies, individual firms might bias the results as the weight of each observation is higher. The choice of using data that is partly from the financial crisis 2007-2008 and its aftermaths may also have led to the inclusion of observations that are not representative for companies throughout. Lastly, some variables have lower impact than other variables, as mentioned above, and therefore the direction of which these variables affect the credit rating should not be assigned too much weight as they do not change the outcome substantially.

Regarding the application of the model, where we the existence of a distress risk premium on the Swedish market was examined, the results are vague. As illustrated in table 10, we do find a slightly negative premium of -0.09% (average return) for firms with a low estimated credit rating over all observed years. However, this difference in return between firms with low estimated credit ratings and those with high is neither statistically significant nor consistent over the years. Since previous research on the area of a distress risk premium has shown different results, there was no clear hypothesis regarding the situation on the Swedish market at the beginning of this study. This study does not find a significant distress risk premium, negative or positive, on the Swedish market. It is however important to notice that our definition of high financial distress is a low credit rating. Previous research has rather compared bankrupt firms with non-bankrupt firms, a distinction that can be considered more severe than comparing a firm with a high credit rating to one with a low credit rating, as a low credit rating does not necessarily mean that a firm will go bankrupt. Finally, more research on the area is needed in order to draw any reliable conclusions about a distress premium on the Swedish market.

6. Conclusion

This study aims at constructing a model of distress adapted to the Swedish market using credit rating as a proxy for distress. It is based on the ratios used in CHS's (2011) model which is one of the newest and most developed models of distress available at the moment. The result is an ordered probit model with eight significant variables measuring profitability, leverage, short-term liquidity, relative size, excess return, market-to-book value, share price and volatility. The significance of the variables in our model establishes the conclusions from previous research regarding the ability of these variables to explain distress risk.

By calculating the marginal effects of the variables, the study finds that liquidity and relative size affect the probability of distress the most. It can also be concluded that according to this model a higher value of the measures liquidity, excess return, volatility and market-to-book value increase the probability of a low estimated credit rating while the variables measuring profitability, leverage, relative size and share price increase the probability of a high rating. The effect of the variables measuring liquidity, leverage and equity return differs from previous research while the other variables have the expected effect.

Moreover, the model is applied on a sample of non-rated companies listed on Nasdaq Stockholm Mid- and Large Cap companies to investigate a distress risk premium on the Swedish market. Although a slight negative distress premium is found, the result is not significant. Further research should focus on increasing the sample size in order to find significant results.

One issue in previous literature has been the sample size issue connected to the low number of bankruptcies, an issue that was also apparent in the beginning of this study. Since the model presented in this essay only requires information about companies' credit rating and not on bankruptcies, it would be interesting to investigate the result of a larger sample. It would also be interesting to create an industry specific model and compare distress risk premiums across industries.

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Appendix A. Distress Risk Models

Appendix A describes some of the prominent models used to predict financial distress that have been mentioned in the essay. It begins with the traditional models, Beaver (1966), Altman (1968), Merton (1974) and Ohlson (1980), and ends with the Shumway (2001) model.

Appendix A1. Beaver (1966) model

Beaver's (1966) work is focused on investigating the use of financial ratios, or rather the underlying accounting data, as a predictor of failure. The author uses a profile analysis to compare the mean of ratios for failed firms with non-failed firms. The definition of failure is the inability of the firm to pay its obligation and this is said to be dependent on the amount of liquid funds available including the inflows and outflows of these kinds of assets. Based on this idea, Beaver presents the hypotheses that a large reservoir of liquid assets and a large operational cash flow decreases the probability of default while a large amount of debt and operational costs increases the probability of default. From these ideas, six ratios are formed that according to the author should be able to predict distress risk, two examples of these being cash flow to total debt and net income to total assets. Beaver concludes that the results are consistent and ratios can be used to predict failure. However, some of the ratios are better predictors than others, like for example cash flow to total-debt ratio that predicts failure better than ratios including asset values. The author also notes that non-failed firms are correctly classified more often than failed firms (Beaver, 1966).

Appendix A2. Altman's (1968) Z-score

The Altman's Z-score, developed by Altman (1968) and referred to as the Z-score model, is a way of using accounting ratios to forecast default. The model consists of the following five accounting ratios:

$$x_1 = \frac{Working\ Capital}{Total\ Assets}$$

$$x_2 = \frac{Retained\ earnings}{Total\ Assets}$$

$$x_3 = \frac{Earnings\ Before\ Interest\ and\ Taxes}{Total\ Assets}$$

$$x_4 = \frac{Market\ Value\ of\ Equity}{Book\ Value\ of\ Total\ Liabilities}$$

$$x_5 = \frac{Sales}{Total\ Assets}$$

The Z-score is estimated by a linear combination of the ratios above with a weighted coefficient for each of them. The model is widely used for manufacturing firms traded publicly and the equation looks as follows:

$$Z - score = 1.2x_1 + 1.4x_2 + 3.3x_3 + 0.6x_4 + 0.999x_5 \tag{A1}$$

If the Z-score is greater than 3.0, the company is unlikely to default. If the Z-score is between 2.7 and 3.0 the company may be in the risk zone and should be monitored. If the Z-score is between 1.8 and 2.7 there is a high risk of default. If the Z-score is below 1.8 the risk of default is very high (Hull, 2015).

Altman (1968) estimated this equation from a sample of 66 firms, of which 33 firms defaulted within a year and 33 firms did not. Since the Type I errors (that the firms predicted not to default actually did) and Type II errors (that the firms predicted to default did not) were small, this indicates that the model has high accuracy when predicting defaults.

Appendix A3. Ohlson's (1980) O-score

Ohlson (1980) uses a larger sample than his predecessors consisting of 105 bankrupt firms and 2 058 non bankrupt firms in order to find what factors affects the probability of default for a firm. The author does not use any new ratios but nine intuitively simple ones, for example size and total liabilities to total assets. He also takes into account the timing of the annual reports from which the data is gathered with regards to the time of default of the companies. Ohlson finds that size, financial structure, a measure of performance and current liquidity are all factors that affect the probability of default. His result ended in the Ohlson O-score (Ohlson, 1980):

$$O - score = -1.32 - 0.407\log(Total\ Assets) + 6.03\left(\frac{Total\ Liabilities}{Total\ Assets}\right) - 1.43\left(\frac{Working\ Capital}{Total\ Assets}\right) + 0.076\left(\frac{Current\ Liabilities}{Current\ Assets}\right) - 1.72(1\ if\ Total\ Liabilities > Total\ Assets, 0\ otherwise) - 2.37\left(\frac{Net\ Income}{Total\ Assets}\right) - 1.83\left(\frac{Funds\ from\ Operations}{Total\ Liabilities}\right) + 0.285(1\ if\ a\ Net\ Loss\ for\ the\ last\ two\ years, 0\ otherwise) - 0.521\left(\frac{Net\ Income_t - Net\ Income_{t-1}}{|Net\ Income_t| + |Net\ Income_{t-1}|}\right) \qquad \text{(A2)}$$

The O-score can then be converted into a probability of default using the following equation:

$$PD = \frac{\exp\ (O-score)}{(1+exp(O-score))} \qquad \text{(A3)}$$

A probability of default higher than 0.5 can be interpreted as a high risk of failure (Ohlson, 1980).

Appendix A4. Merton (1974) model

The Merton model, suggested by Merton (1974), assesses the credit risk of a firm and is built on the implementation of Black and Scholes' (1973) option pricing formula. The model is based on the idea that if the market value of the firm's assets is lower than the value of its debt at the maturity, the firm does not hold enough funds to pay its debtholders and hence the firm will default. If the market value of its assets is higher than the value of its debt, the debt-holders will be payed and the firm will not default.

The model estimates the distance to default, which is a relative distance between asset value and debt, for a time T, at which the debt matures. The distance is expressed in terms of standard deviation by dividing the distance by the standard deviation of the assets. To obtain the probability of default for the firm, the distance to default is set into a cumulative standard normal distribution. Firstly, the equation for calculating the value of the firm's equity looks as follows, and is derived from the Black and Scholes option pricing formula:

$$E_0 = A_0 * N(d_1) - K * \exp(-r * T) * N(d_2) \tag{A4}$$

where E is the market value of equity, A is the market value of assets, K is the face value of debt, r is the risk-free interest rate and N is the cumulative standard normal distribution function of d_1 and d_2. They are given by the following equations:

$$d_1 = \frac{\frac{lnA_0}{K} + \left(r + \frac{\sigma_A^2}{2}\right) * T}{\sigma_A * \sqrt{T}} \tag{A5}$$

$$d_1 = \frac{\frac{lnA_0}{K} + \left(r - \frac{\sigma_A^2}{2}\right) * T}{\sigma_A * \sqrt{T}} \tag{A6}$$

In practice, the market value of the firm's assets and its asset volatility is unobservable. With the assumption of the Merton model that the asset value follows a geometric Brownian motion, Ito's formula can be applied and gives the following equality:

$$\sigma_E E_0 = \sigma_A A_0 * N(d_1) \tag{A7}$$

By observing the value of equity of the firm and the equity volatility, Equation A4 and Equation A7 can be used to obtain the asset value of the firm and the asset volatility. Further, the distance to default, DD, is calculated by:

$$DD = \frac{\frac{lnA_0}{K}+\left(\mu_A-\frac{\sigma_A^2}{2}\right)*T}{\sigma_A*\sqrt{T}} \qquad \text{(A8)}$$

where μ_A is the estimation of the expected asset growth. Lastly, to obtain the probability of default, PD, for the firm, the DD is inserted to the cumulative standard normal distribution:

$$PD = N(-DD) \qquad \text{(A9)}$$

The Merton model is a forward-looking model, which means that the probability of default obtained from the model is an estimate of default for the next period of time. Since the model uses the market value of equity and not the book value, the model captures the effect that the share price is assumed to have on the risk of default. It is intuitive that the share price has a connection to the market's expectation of the firm's performance in the future (Merton, 1974).

Appendix A5. Shumway (2001) model

In contrast to the traditional models, newer models build on market-based variables or a combination of accounting and market variables, so-called hybrid models. Shumway's (2001) hazard model is an example of the last-mentioned. He tests models using Altman's variables as well as one with market-driven variables only and one hybrid model. Shumway finds that the hybrid model, including two accounting variables ($\frac{Net\ Income}{Total\ Assets}$ and $\frac{Total\ Liabilities}{Total\ Assets}$) and three market variables (firm market size, stock return and return volatility), is the best-performing. He argues that the hazard model is preferred over the static models, as it takes into account the fact that firm characteristic change over time. The final model's variables, coefficients and p-values are presented in table 11 (Shumway, 2001).

Table 11. Shumway Model

Variable	Coefficient	*p*-Value
Intercept	-13.303	0.000
$\frac{\text{Net Income}}{\text{Total Assets}}$	-1.982	0.348
$\frac{\text{Total Liabilities}}{\text{Total Assets}}$	3.593	0.009
Relative size	-0.467	0.022
Excess return	-1.809	0.011
Sigma	5.791	0.116

Note. Adapted from "Forecasting Bankruptcy More Accurately: A Simple Hazard Model" (Shumway, 2001).

Appendix B. Sample Companies

Table 12. Sample – Credit Rated Companies (Model Construction)

Company	**Stock Series**	**Average Credit Rating 2007-2017**	**Data availability**
ABB Ltd		A	
Alfa Laval AB		BBB	Not rated 120201-120601
Assa Abloy AB		A	
Astra Zeneca Plc		AA	
Atlas Copco AB	Ser. A	A	
Autoliv Inc. SDB		BBB	
Electrolux AB	Ser. B	BBB	
Ericsson Telefonab. L M	Ser. B	BBB	
Holmen AB	Ser. B	BBB	
Industrivärden AB	Ser. C	A	
Investor AB	Ser. B	AA	
Kaupthing Bank		AA	Until 2007-12-01
Lundbergföretagen AB		A	
Lundin Mining Corporation SDB		BB	Rating from 2014-11-01
Millicom International Cellular S.A. SDB		BB	Rated until 2009-02-01
Nokia Abp, SDB		BBB	From 2007-07-01
Nordea Bank AB		AA	
Old Mutual Plc		BBB	
Sandvik AB		BBB	
SAS AB		B	
SCANIA AB	Ser. B	A	Until 2016-12-01
Securitas AB		BBB	
Skandinaviska Enskilda Banken	Ser. A	A	
SKF AB	Ser. B	A	
SSAB Svenskt Stål AB	Ser. B	BB	
Stora Enso Oyj	Ser. R	BB	
Svenska Cellulosa AB SCA	Ser. B	BBB	
Svenska Handelsbanken	Ser. A	AA	
Swedbank AB		A	
Swedish Match AB		BBB	
TeliaSonera AB		A	
Volvo AB	Ser. B	BBB	

Table 13. Sample – Non-Rated Companies (Model Application)

Company	Stock Series	Average Credit Rating 2007-2017	Data availability
AarhusKarlshamn AB		Mid Cap	
Active Biotech AB		Mid Cap	
Addtech AB		Mid Cap	
Anoto Group AB		Mid Cap	
Avanza AB		Mid Cap	
Axfood AB		Large Cap	
Axis AB		Mid Cap	
Ballingslöv International AB		Mid Cap	Until 2007-12-01
BE Group AB		Mid Cap	
Beijer Alma AB		Mid Cap	
Bergman & Beving AB		Mid Cap	
Bilia AB		Mid Cap	
Billerud AB		Mid Cap	
Biovitrum AB		Mid Cap	
Boliden AB		Large Cap	
Brinova Fastigheter AB		Mid Cap	Until 2011-12-01
Broström AB		Mid Cap	Until 2007-12-01
Bure Equity AB		Mid Cap	
Cardo AB		Mid Cap	Until 2010-12-01
Castellum AB		Large Cap	
Clas Ohlson AB		Mid Cap	
Concordia Maritime AB		Mid Cap	
Fabege AB		Large Cap	
Fagerhult AB		Mid Cap	
Fast Partner AB		Mid Cap	
Gant Company AB		Mid Cap	Until 2007-12-01
Getinge AB		Large Cap	
Gunnebo AB		Mid Cap	
Gunnebo Industrier AB		Mid Cap	Until 2007-12-01
Hakon Invest AB		Large Cap	
Haldex AB		Mid Cap	
Heba Fastighets AB		Mid Cap	
Hemtex AB		Mid Cap	Until 2014-12-01
Hennes & Mauritz AB		Large Cap	
Hexagon AB		Large Cap	
HiQ International AB		Mid Cap	
Home Properties AB		Mid Cap	Until 2008-12-01
HQ AB		Mid Cap	Until 2016-12-01
Hufvudstaden AB	Ser. A	Large Cap	
Husqvarna AB	Ser. B	Large Cap	
Höganäs AB		Mid Cap	Until 2012-12-01
IBS AB		Mid Cap	Until 2010-12-01
Industrial & Financial Systems AB	Ser. B	Mid Cap	Until 2015-12-01
Indutrade AB		Mid Cap	
Intrum Justitia AB		Mid Cap	
JM AB		Large Cap	
KappAhl Holding AB		Mid Cap	
Kinnevik Investment AB	Ser. B	Large Cap	
Klövern AB		Mid Cap	
Kungsleden AB		Large Cap	

Latour Investment AB	Ser. B	Large Cap	
Lawson Software Inc.		Large Cap	Until 2010-05-01
Lindab AB		Mid Cap	
Lindex AB		Mid Cap	Until 2007-08-01
LjungbergGruppen AB		Mid Cap	
Lundin Petroleum AB		Large Cap	
Meda AB		Large Cap	Until 2015-12-01
Mekonomen AB		Mid Cap	
Melker Schörling AB		Large Cap	Until 2016-12-01
Metro International S.A SDB	Ser. A	Mid Cap	Until 2011-12-01
Micronic Laser Systems AB		Mid Cap	
Midway Holding AB	Ser. B	Mid Cap	
Modern Times Group MTG AB	Ser. B	Large Cap	
Munters AB		Mid Cap	Until 2009-12-01
NCC AB	Ser. B	Large Cap	
New Wave Group AB		Mid Cap	
NIBE Industrier AB		Mid Cap	
Nobel Biocare Holding AG		Large Cap	Until 2008-06-01
Nobia AB		Large Cap	
Nolato AB		Mid Cap	
Nordnet AB		Mid Cap	Until 2016-12-01
Observer AB		Mid Cap	Until 2013-12-01
OMX AB		Large Cap	Until 2007-12-01
Orc Software AB		Mid Cap	Until 2011-12-01
Orexo AB		Mid Cap	
Oriflame Costmetics S.A SDB		Large Cap	Until 2014-12-01
PA Resources		Mid Cap	Until 2014-12-01
PartnerTech AB		Mid Cap	Until 2014-12-01
Peab AB		Large Cap	
Q-Med AB		Large Cap	Until 2010-12-01
Ratos AB	Ser. B	Large Cap	
Rezidor Hotel Group AB		Mid Cap	
RNB RETAIL AND BRANDS AB		Mid Cap	
SAAB AB		Large Cap	
Seco Tools AB		Large Cap	Until 2011-12-01
SECTRA AB		Mid Cap	
Securitas Direct AB		Mid Cap	Until 2007-12-01
Securitas Systems AB		Mid Cap	Until 2010-12-01
Skanditek Industriförvaltning AB		Mid Cap	Until 2008-12-01
Skanska AB		Large Cap	
SkiStar AB		Mid Cap	
Studsvik AB		Mid Cap	
SWECO AB	Ser. B	Mid Cap	
Svedbergs i Dalstorp AB		Mid Cap	
Tele2 AB	Ser. B	Large Cap	
Teleca AB		Mid Cap	Until 2007-12-01
Telelogic AB		Mid Cap	Until 2007-12-01
TietoEnator Oyj		Large Cap	
TradeDoubler AB		Mid Cap	
Transcom WorldWide S.A SDB	Ser. A	Mid Cap	Until 2013-12-01
Trelleborg AB		Large Cap	
Unibet Group Plc		Mid Cap	
Wallenstam Byggnads AB		Mid Cap	
Wihlborgs Fastigheter AB		Mid Cap	
Ångpanneföreningen AB		Mid Cap	
Öresund Investment AB		Large Cap	Until 2016-12-01

Appendix C. Eviews Output

Table 14. Eviews Estimation Output

Dependent Variable: DECODED_CREDIT_RATING
Method: ML - Ordered Probit (Newton-Raphson / Marquardt steps)
Date: 04/27/18 Time: 11:47
Sample: 2007M01 2017M01
Included observations: 3562
Number of ordered indicator values: 7
Convergence achieved after 8 iterations
Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
NIMTA	-0.287918	0.143500	-2.006398	0.0448
TLMTA	-1.327070	0.102223	-12.98214	0.0000
CASHMTA	8.329799	0.340401	24.47052	0.0000
RSIZE	-0.899424	0.020968	-42.89408	0.0000
EXRET	0.675633	0.263587	2.563232	0.0104
MB	0.192427	0.011628	16.54878	0.0000
PRICE	-0.635533	0.027589	-23.03587	0.0000
SIGMA	1.310498	0.157309	8.330743	0.0000
		Limit Points		
LIMIT_2:C(9)	2.590757	0.330419	7.840832	0.0000
LIMIT_3:C(10)	5.571900	0.251194	22.18164	0.0000
LIMIT_4:C(11)	7.389782	0.258121	28.62911	0.0000
LIMIT_5:C(12)	9.416043	0.279066	33.74125	0.0000
LIMIT_6:C(13)	10.73082	0.294467	36.44145	0.0000
LIMIT_7:C(14)	11.82283	0.319379	37.01813	0.0000

Pseudo R-squared	0.332689	Akaike info criterion	1.810503
Schwarz criterion	1.834786	Log likelihood	-3210.506
Hannan-Quinn criter.	1.819162	Restr. log likelihood	-4811.110
LR statistic	3201.206	Avg. log likelihood	-0.901321
Prob(LR statistic)	0.000000		

Table 15. Eviews Prediction Evaluation

Prediction Evaluation for Ordered Specification
Equation: EQ02REALORDERED
Date: 05/03/18 Time: 16:24

Estimated Equation

Dep. Value	Obs.	Correct	Incorrect	% Correct	% Incorrect
1	2	0	2	0.000	100.000
2	484	239	245	49.380	50.620
3	1413	953	460	67.445	32.555
4	1261	826	435	65.504	34.496
5	274	154	120	56.204	43.796
6	78	10	68	12.821	87.179
7	50	41	9	82.000	18.000
Total	3562	2223	1339	62.409	37.591

Constant Probability Spec.

Dep. Value	Obs.	Correct	Incorrect	% Correct	% Incorrect
1	2	0	2	0.000	100.000
2	484	0	484	0.000	100.000
3	1413	1413	0	100.000	0.000
4	1261	0	1261	0.000	100.000
5	274	0	274	0.000	100.000
6	78	0	78	0.000	100.000
7	50	0	50	0.000	100.000
Total	3562	1413	2149	39.669	60.331

Gain over Constant Prob. Spec.

Dep. Value	Obs.	Equation % Incorrect	Constant % Incorrect	Total Gain*	Pct. Gain**
1	2	100.000	100.000	0.000	0.000
2	484	50.620	100.000	49.380	49.380
3	1413	32.555	0.000	-32.555	NA
4	1261	34.496	100.000	65.504	65.504
5	274	43.796	100.000	56.204	56.204
6	78	87.179	100.000	12.821	12.821
7	50	18.000	100.000	82.000	82.000
Total	3562	37.591	60.331	22.740	37.692

*Change in "% Correct" from default (constant probability) specification
**Percent of incorrect (default) prediction corrected by equation

Appendix D. Model Application Results

Table 16. Average Estimated Credit Ratings for Non-Rated Companies 2007-2017

A	BBB	BB	B	CCC
Hennes & Mauritz	AarhusKarlshamn	Addtech	Fagerhult	Active Biotech
Hexagon	Avanza	Axis	Gunnebo	Anoto Group
Kinnevik Investment	Axfood	Ballingslöv International	Haldex	Bure Equity
	Boliden	BE Group	Home Properties	Concordia Maritime
	Cardo	Beijer Alma	HQ	Hemtex
	Castellum	Bergman & Beving	Lawson Software Inc.	HiQ International
	Fabege	Bilia	New Wave Group	IBS
	Getinge	Billerud	Nordnet	Metro International
	Hakon Invest	Biovitrum	Observer	Micronic Laser Systems
	Hufvudstaden	Brinova Fastigheter	Orc Software	Midway Holding
	Husqvarna	Broström	Q-Med	Orexo
	Höganäs	Clas Ohlson	RNB Retail and Brands	PartnerTech
	Intrum Justitia	Fast Partner	Securitas Systems	SECTRA
	Kungsleden	Gant Company	Skanditek Industriförvaltning	Svedbergs i Daltorp
	Latour Investment	Gunnebo Industrier	Studsvik	TradeDoubler
	LjungbergGruppen	Heba Fastighets	Teleca	Transcom WW
	Lundin Petroleum	Industrial & Financial Systems	Telelogica	
	Meda	Indutrade	Unibet Group Plc	
	Mekonomen	JM		
	Melker Schörling	Kappahl Holding		
	Modern Times Group MTG	Klövern		
	NCC	Lindab		
	Nobel Biocare Holding AG	Lindex		
	OMX	Munters		
	Oriflame Cosmetics	NIBE Industrier		
	Peab	Nobia		
	Ratos	Nolato		
	SAAB	PA Resources		
	Seco Tools	Rezidor Hotel Group		
	Skanska	Securitas Direct		
	Tele2	SkiStar		
	TietoEnator Oyj	SWECO		
	Trelleborg	Ångpanneföreningen		
	Wallenstam Byggnads	Öresund Investment		
	Wihlborgs Fastigheter			

Table 17. Return per Portfolio and Year

Year	LOW	HIGH	Difference (HIGH minus LOW)
2007	-3.31%	-3.79%	-0.48%
2008	3.05%	4.92%	1.86%
2009	1.49%	0.91%	-0.58%
2010	-0.76%	-2.19%	-1.43%
2011	0.60%	0.90%	0.30%
2012	1.30%	1.56%	0.26%
2013	1.14%	0.77%	-0.38%
2014	0.97%	0.92%	-0.05%
2015	0.66%	0.83%	0.17%
2016	0.38%	-0.18%	-0.56%
Cumulative	5.53%	4.51%	-0.90%
Average	0.55%	0.47%	-0.09%