Bankruptcy prediction of Swedish SMEs and the importance of CEO characteristics

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Abstract

This thesis investigates whether an accounting-based bankruptcy prediction model based on the logit analysis developed by Altman and Sabato (2007) can be enhanced by incorporating CEO specific variables. The study concentrates on Swedish non-listed SMEs by reason that the SME sector is an important engine to the growth of the Swedish economy. Furthermore, the applicability of the original model is evaluated in regard to the new setting of Swedish SMEs as well as whether the inclusion of CEO characteristics increases in importance for smaller firms. The data encompasses 15,885 non-listed Swedish limited liability companies, out of which 226 are failed. By validating the models on an out of sample, it is found that the original model using solely financial ratios is applicable to predict bankruptcy among Swedish non-listed SMEs. Moreover, the classification accuracy is improved when adding the CEO specific variables *age* and *gender*, given a predefined cut-off rate. However, the inclusion of CEO specific variables does not gain in importance as firm size decreases.

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1. Introduction

1.1 Background information

Private companies are somewhat of a puzzle. Information asymmetry and uncertainty regarding a company's financial soundness impose passive investors and creditors with risk. Given investors risk appetite and anticipation for luscious returns, the ability to predict the likelihood of whether a company will find itself in the state of financial failure reduces uncertainty and adds value. In the case of private small and medium sized companies, this matter becomes even more evident. Previous research indicates that non-listed firms face the highest risk of corporate failure (Altman et. al., 2008).

Bankruptcies are costly, both for internal and external stakeholders. Internal stakeholders such as employees and managers risk losing their jobs, while shareholders face the risk of losing their equity investment. External stakeholders such as suppliers and creditors risk not being paid, while customers risk not receiving their products and services. Moreover, corporate bankruptcies have a large negative impact on their societies (Branch, 2002). As a company enters the state of bankruptcy, there are few actions available to stakeholders to protect their interests.

During 2017, 5,528 Swedish limited companies filed for bankruptcy, slightly more than during 2016 (5,270 companies) (Nyström, 2018). These statistics indicate that bankruptcy filings increased by approximately five percent. Bankruptcy prediction models are of constant interest for both investors and creditors by the reason that bankruptcies are affected by the business cycles and the macroeconomic stability of the economy (Bhattacharjee et. al., 2009) (Hol, 2006). Past and present literature portrait multiple definitions for bankruptcy and hence, no universal definition can be applied when classifying a firm as *bankrupt* or *failed*. The Swedish Companies Registration Office however defines bankruptcy as *"A procedure where all assets of a limited company are turned into money and used to pay off the company's debts."*. The process of closing a limited liability company can be initiated either by the company or a creditor and starts with an application for bankruptcy at the district court in the area where the company has its registered office (The Swedish Companies Registration Office, 2015).

In recent years, small and medium sized companies (SMEs), usually non-listed, have gained escalating dedication from the European Union and its member states. SMEs contribute significantly to the European economy by being responsible for 57 % of value added in the EU-28 non-financial business sector (European Commission, 2017). The European Union devotes several campaigns and support programs to SMEs in order to enhance the business-friendly and practice sharing environment. An industry report by the European Commission indicates that the role of SMEs in the Swedish non-financial business sectors is gaining in importance, as the SMEs accounts for 60 % of value added and employment over the period 2008-2013 (European Commission, 2017). Moreover, the outlook for Swedish SMEs is positive, underpinned by the fact that the value-added by Swedish SMEs increased by 30 % over the period 2010-2015. Therefore, it appears necessary to concentrate efforts towards ensuring the financial soundness of these companies and invest in SMEs that have the ability to add value in the future. In contrast, identifying SMEs with a greater probability of entering the state of financial failure allows passive investors as well as creditors to undertake more informed and safer investment decisions and loan issues.

The idea that the CEO plays a more important operational role in smaller businesses is widely accepted in business practice (Corporate Finance Institute, 2018). The reasoning follows that he or she is assumed to have a more active role in not only the executive management team, but also in the operations. An active CEO is therefore expected to personally have a disproportionally large impact on the survival of the company.

1.2 Purpose

The purpose of this study is threefold. Firstly, this thesis mimics the study conducted by Altman and Sabato (2007) by applying their logistic bankruptcy prediction model uniquely developed for SMEs. Given the previous mentioned importance of SMEs to the Swedish economy, it is of interest to investigate whether the original model is applicable to Swedish data. Hence, the first objective is to investigate how accurate Altman and Sabato’s original model developed for US SMEs can predict the likelihood of corporate failure for private Swedish companies. In line with Grice and Dugan’s conclusions (2001), the original model is also re-estimated for the dataset of Swedish SMEs.

Secondly, this study has the intent to go one step further and assess whether the predictability of financial failure can be improved by incorporating CEO specific variables. The dimension of CEO characteristics is usually not included in quantitative studies predicting the probability of bankruptcy. Partly because this qualitative information is scarce. The studies by Argenti (1976) and Sheppard and Chowdhury (2005), however, find a direct correlation between bankruptcy-filed companies and the leadership of the company. With these findings in mind, it is valuable to investigate whether the incorporation of CEO specific variables age and gender improve the accuracy of predicting financial failure.

Thirdly, this thesis assesses whether the size of SMEs is a determining factor for the importance of the CEO specific variables in the bankruptcy prediction model. As a firm grows larger in terms of turnover, the role and tasks of the CEO change. Namely, the CEO becomes less involved in the daily operational business. Therefore, it is assumed that the CEO specific variables, when included in the model, change in importance as well. Hence, this report examines whether the bankruptcy prediction model including CEO variables yields disparities in classification power for companies of different sizes.

When analysing the probability of failure for non-listed Swedish SMEs, this thesis connects two dimensions, one financial and one non-financial. The informative value derived by the present study yields a more extensive assessment of the failure-probability when compared to traditional, one-dimensional, bankruptcy prediction models. Moreover, this thesis combines the financial ratio variables commonly used in corporate lending, with personal characteristics assumed to be used in private lending.

The thesis concludes that Altman and Sabato's (2007) original model is indeed applicable to Swedish SME data. The model's predictive power is high in reference to identifying failed companies. Moreover, the study yields the result that the CEO variables *age* and *gender*, when added to the model, improve the percent correctly classified companies. Lastly, it cannot be confirmed that the CEO variables age and gender increase in importance when the SME in terms of turnover is relatively smaller.

Due to these findings, debtholders as well as other external stakeholders such as early stage investors, venture capitalists and passive investors are supposed to find the more extensive information of value as they now are able to make more informed decisions when infusing capital to non-listed SMEs. The study enables stakeholders to discover potential risks and take corrective measures before the state of financial failure is realized.

1.3 Limitation of scope

Bankruptcy prediction models are divided into two categories; accounting-based bankruptcy prediction models and market-based bankruptcy prediction models. The accounting-based prediction models rely solely on accounting data drawn from the company's financial statements, whereas the market-based bankruptcy prediction models also incorporate market variables, such as the share price, interest rate and other macroeconomic variables.

Due to the nature of the companies in this study, being private SMEs, market-based variables such as share price cannot be applied. Instead, this thesis is based upon Altman and Sabato's (2007) accounting-based bankruptcy prediction model specially developed for SMEs. As this model uses input variables from the companies' financial statements, the prediction for future performance is based upon the company's past performance. Later, a new model is derived by incorporating non-financial variables. A motivation for using Altman and Sabato's logit model instead of other accounting-based bankruptcy prediction models is that the ratios are assumed to be the most significant when using a dataset concerning Swedish SMEs (Altman and Sabato, 2007).

It should be noted that the Altman and Sabato model (2007) is solely accounting-based, and therefore does not incorporate any macroeconomic variables. Due to the co-movement of the macroeconomic environment and the number of bankruptcies in a year, variables capturing the macroeconomic conditions are likely to contribute to the model's overall accuracy rate. However, as this study does not seek to find the optimal bankruptcy prediction model, but rather aims to investigate whether an accepted accounting-based bankruptcy prediction model applies to the Swedish market, as well as whether it can be improved by adding CEO specific variables, macroeconomic variables are excluded. Thereto, the lack of data and realistic time-related execution are further reasons for the exclusion. Disregarding these external factors does not imply that they are viewed as non-value adding, but rather creates opportunities for further research within this area.

1.4 Question formulation

With regards to the above stated purposes, this report answers the following questions:

- Does the Altman Sabato (2007) bankruptcy prediction model apply when predicting corporate failure for private Swedish small and medium sized companies?
- Does the incorporation of CEO specific variables improve the classification accuracy of failed private Swedish SMEs?
- Do the CEO specific variables become more important when assessing failure for smaller SMEs compared to larger?

2. Literature review

When prognosticating financial failure, accounting-based bankruptcy prediction models have gained strong approval since the 1960s. The goal of analysing a company's financial statements is to assess its value. Therefore, a financial statement analysis ensures that all facets relevant to the investment decision are identified (Penmann, 1996). The following section outlines previous literature on the subject of accounting-based bankruptcy prediction models.

2.1 Univariate analysis

The pioneering bankruptcy prediction studies from the early 20th century regarding ratio analysis are based upon the univariate approach. The univariate approach implies that various financial ratios are analysed individually and thereafter, comparisons between failed and non-failed firms are made. In a study from 1966, Beaver examines 30 financial ratios to analyse their usefulness when predicting failure, where he defines failure as *"the inability of a firm to pay its financial obligations as they mature"* (Beaver, 1966). For his analysis he uses a matched sample consisting of 158 paired observations. Beaver acknowledges that the probability of failure is smaller for larger asset companies than for smaller asset- and private companies, however, his sample is dominated by the former (Beaver, 1966). A conclusion to be drawn from the study is that there are a number of accounting ratios that can be used to discriminate between failed and non-failed companies. However, the univariate approach is criticized, namely by Altman (1968), for being too simplistic.

2.2 Multi-discriminant-analysis

In 1968, Altman advances Beaver's findings, by introducing the Z-score to predict the probability of corporate bankruptcy (Altman, 1968). The Z-score is based on a multi-discriminant-analysis (MDA) and is used to classify an observation into one or another pre-established group based upon the observation's individual characteristics. The benefit of the MDA over the univariate approach is that it allows prediction and classification in situations where the dependent variable exhibits a qualitative character such as *bankrupt* and *non-bankrupt*. In particular, the multivariate framework's primary advantage over the one-dimensional ratio analysis when dealing with classification contentions is that this statistical approach enables the simultaneous analysis of the entire variable profile (Altman, 1968). Furthermore, the Z-score overcomes some of the limitations of the traditional ratio analysis by reason that it assesses corporate stability as well as predicts potential corporate failures (Elliot & Elliot, 2006).

For his research, Altman uses a sample of 66 listed manufacturing firms that are divided into two equally large groups of 33 corporations, which either are classified as bankrupt or non-bankrupt. His linear model includes five variables consisting of financial ratios that are based on balance sheet and income statement data.

The outcome, known as the Z-score, is compared to a predefined discriminant cut-off value in order to classify the observations as bankrupt or non-bankrupt. Corporations with a Z-score above the cut-off point of 2.99 are classified as non-bankrupt and firms with a Z-score below the cut-off point are classified as bankrupt. Altman concludes that his bankruptcy prediction model makes accurate predictions two years prior to the event of bankruptcy, however, the accuracy of the model's predictability declines significantly as the lead time exceeds two years.

Although the MDA approach gained traction among scholars, it also became a victim for serious criticism. The main issues with the methodology is that the MDA demands certain statistical requirements such as normal the distribution among predictors, and an objective matching process. Furthermore, the output from the MDA is considered by some scholars to lack intuitive interpretation (Ohlson, 1980).

2.3 The logistic model

Ohlson is regarded as one of the main critics of the multi-discriminant analysis when used in bankruptcy prediction models. As a substitute, he developed a conditional logit model that is based upon fewer assumptions and hence is considered superior to the MDA approach (Ohlson, 1980). Furthermore, the outcome of a logistic regression is a value between 0 and 1, yielding a more intuitive interpretation for a dependent variable with a binary outcome.

In his study from 1980, Ohlson develops the O-score using a sample of 105 bankrupt and 2,058 non-bankrupt U.S. industrial firms over the study-period 1970-1976. He establishes three different estimates for predicting bankruptcy within one year, two years and one or two years, respectively. The derived model is a nine-factor linear combination of coefficient-weighted ratios measuring size, current liquidity and financial structure of the company. The main difference between Ohlson's and Altman's variables is the number of variables included, where Altman uses five, while Ohlson includes seven ratios and two dummy independent variables.

2.4 The probit model

In a report from 1984, Zmijewski enhances the logistic bankruptcy prediction model by introducing the probit model. Similar to the logistic regression, the probit model's dependent variables can only take values between 0 and 1. The two methods differ in their assumption of the distribution of the error term. In the logit model, error terms are assumed to follow the standard logistic distribution, whereas they are assumed to follow a normal distribution in the probit model (Wooldridge, 2013).

Zmijewski's (1984) probit function is based on the ratios $net\ income\ /\ total\ assets$, $total\ liabilities\ /\ total\ assets$ and $current\ assets\ /\ current\ liabilities$. Regardless of the model yielding high accuracy rates in the original paper, as well as in the follow-up papers (Zmijewski, 1984) (Grice and Dugan, 2001), it has received criticism for the correlation between the variables (Shumway, 2001). Moreover, critics comment that ratios are not based on theory, but rather on results from prior studies (Grice and Dugan, 2003). However, the latter criticism can also be directed to models developed by both Altman (1968) and Ohlson (1980).

Similar to Zmijewski, Skogsvik develops two probit models. His models, however, regard Swedish data from the period 1966-1979 and uses a sample consisting of 51 failed and 328 non-failed companies. His observations are classified as large cap industrial companies with a head count of more than 200 employees or assets of at least 200 million SEK. He defines failed or financially failed companies as companies that have gone bankrupt or reached a composition agreement, voluntary shut down their primarily production activity or received a substantial subsidy by the state (Skogsvik, 1990). Skogsvik's probit analysis is based upon an extensive set of financial ratios that can be categorized into one of the following groups of accounting ratios; profitability, cost structure, capital turnover, liquidity, asset structure, financial structure and growth (Skogsvik, 1990). The probit analysis results in an outcome value, known as the V-score and by using a normal distribution, the V-score is converted into the probability of failure. A higher V-score indicates a greater risk of financial failure. The two probit models are developed independently, where one of them is based on current costs accounting (CCA) and the other on historical cost accounting (HCA). The reasoning behind developing two models is to evaluate the models' respective prediction accuracy and where the latter model is used as a reference model. Skogsvik's findings state that both models yield similar Type I and Type II errors, as well as overall performance (Skogsvik, 1990). The HCA model, relying on historical information, is therefore considered to be suitable for predicting bankruptcies.

2.5 Bankruptcy prediction models for SMEs

In 1972, Edmister applies an MDA approach to a sample of SMEs over the period of 1954-1969 and analyses a set of 19 financial ratios to predict default (Edmister, 1972). Although he recognizes that only a set of financial ratios should be used when predicting financial default for SMEs, he lacks to explain why small firms distinguish themselves from larger, and why models for SMEs need adjustments.

Altman and Sabato (2007) capitalize on the lack of quantitative studies of SME defaults, and bring Edmister's work one step further by developing a logistic default prediction model for SMEs. They use the Basel 2 definition of SMEs, gathering a sample consisting of 2,010 U.S. firms, including 120 default firms, over a sampling period stretching from 1994-2002. Despite several scholars recognizing that qualitative information, when added to quantitative financial information, can improve the accuracy of bankruptcy prediction models (Lehmann, 2003) (Grunet et al, 2004), Altman and Sabato are constrained to solely rely on financial information. To construct their logistic model, Altman and Sabato examine a set of financial ratios within five accounting ratio categories; leverage, liquidity, profitability, coverage and activity. Five financial ratios are selected, predicting SME default in the best manner (Altman and Sabato, 2007):

$Leverage = Short\ Term\ Debt /\ Book\ Value\ of\ Equity,$
$Liquidity = Cash /\ Total\ Assets,$
$Profitability\ 1 = EBITDA /\ Total\ Assets,$
$Profitability\ 2 = Retained\ Earnings /\ Total\ Assets$
$Coverage = EBITDA /\ Interest\ Expenses$

Altman and Sabato (2007) run two logistic regressions, where the difference lies in whether the value of the variables to predict the probability of non-defaulting (KPG) are logged or not. The unlogged variable regression, which is the one used in this report, has the following form:

$$KPG = +4.28 + 0.18 * Profitability\ 1 - 0.01 * Leverage + 0.08 * Profitability\ 2 + 0.02 * Liquidity + 0.19 * Coverage$$

Altman and Sabato compare the accuracy ratio (AR) between the two logit models, as well as the original Z-score model previously developed by Altman (1968). The cut-off rate is arbitrarily set to 30 %. The accuracy ratio, as described by Altman and Sabato (2007), expresses the area of the cumulative accuracy profile (CAP) of the model in question versus the CAP of a perfect rating model. Altman and Sabato find that the accuracy ratio is the highest for the logit model with logged variables (AR = 87 %), in contrast to the logit model with non-logged variables (AR = 75 %) and Altman's Z-score (AR = 68 %). Furthermore, error Type I is reduced from 21 % to 12 % when applying the logarithmic transformed variables to the logistic model.

Their study concludes that the performance, in terms of prediction accuracy, is improved when applying the logit model with logarithmic variables to the SME sector in contrary to bankruptcy prediction models relying upon the statistical technique MDA, such as Altman's Z-score (Altman and Sabato, 2007).

2.6 Non-financial key ratios used for the prediction of financial distress

Research regarding management behaviour and processes related to business failure and bankruptcy is extensive. Managerial incompetence is acknowledged as the most pervasive reason for distress and business failures, and deficiencies among management is commonly the basis for corporate failure (Altman and Hotchkiss, 2005).

Argenti's qualitative research (1976) identifies reasons for bankruptcies by studying weaknesses among the management and board of directors in financially distressed and bankrupt companies. He acknowledges the usefulness of bankruptcy prediction models, such as Altman's Z-score, but argues that these models only analyse the symptoms of failure, and not the causes. Argenti's A-score model suggests that the process of failure follows a predictable sequence, beginning with defects, continuing with mistakes and lastly ending with the symptoms of failure. In the A-score model, management weaknesses as well as some accounting deficiencies such as having no budgetary controls increase the score, and if the total score exceeds a certain limit, the result in unsatisfactory. Koponen's (2003) findings are in line with Argenti's (1976) and conclude that bankruptcy often follows inefficient leadership along with uncontrolled growth conflicts and unprofitable investments.

Despite the quantity of qualitative research analysing the relationship between management and financial distress, non-financial ratios are seldomly included in the quantitative bankruptcy prediction models (Pervan and Kuvek, 2013). However, Grunert et. al. (2005) shows that when using data from German banks, the combination of financial and non-financial data results in the highest accuracy of predicted bankruptcies. The non-financial variables used by Grunert et. al. are factors regarding market position and management quality, as judged by the German banks.

2.7 Non-financial information included in models for SMEs

In a 2008 study, Altman, Sabato and Wilson update the bankruptcy prediction model previously developed by Altman and Sabato (2007) by applying the logit model to the UK market. Furthermore, they add non-financial and compliance information to the original model (Altman et al., 2008). To account for the fact that many SMEs and non-listed companies only provide limited financial information, they develop a separate model for these firms. The study is based on UK data covering of a sample of 5.8 million sets of accounts of non-listed firms during the period 2000-2007, out of which approximately 66,000 companies are classified as failed. Due to the geographical inconsistency of the financial failure definition, they solely regard small business firms that in the time-period 2000-2007 have entered into liquidation, administration or receivership (Altman et al., 2008). By exploiting non-financial information such as accounting, event, audit and firm specific characteristic data, the accuracy of predicting the probability of corporate failure for non-listed firms is improved.

Two models are used in their study; *SME1* model is used when full accounting data is accessed and *SME2* model used when only limited accounting data is accessed. The *SME1* model, based upon Altman and Sabato's (2007) logistic model for U.S. SMEs, uses five financial ratios for profitability, leverage, liquidity, coverage and activity. The *SME2* model, used for companies reporting abridged accounts, analyses the impact of the modified balance sheet information as well as lack of profit and turnover information. As the focus of the study regards the value added of non-financial information, event data such as country court judgements, audited accounts, cash flow statements, subsidiaries, late filing days, audit report judgements, age of firms and sector information are used. The non-financial information, when added to the original model developed by Altman and Sabato (2007), significantly improves the classification accuracy by 10 % (Altman et al., 2008).

The *SME2* model regards a sample of 3,422,042 non-failed firms and 40,577 failed firms. Adding the non-financial information to this model, all the model's variables are statistically significant and remain their signs. Prediction accuracy is improved by 8 % comparing to the same sample when non-financial information is excluded. Overall, including non-financial information to the logistic model originally established by Altman and Sabato (2007) improves the prediction accuracy up to 13 %. In the case of non-listed SMEs, non-financial information is proven to be even more value adding as these firms only provide limited financial information.

2.8 Previous theses

Multiple academic theses find the topic of bankruptcy prediction appealing and hence, both the Z-score and the O-score, or modified versions, are used to test the models' predictive power in various industries and geographical markets.

Dalberg and Thörnqvist (2012) test whether Altman's Z-score is applicable for Swedish companies, by using a dataset of companies filing for bankruptcy in 2011 and a control group based on a random sample of companies not filing for bankruptcy during the same year. Less than one third of all bankrupt companies are correctly classified as failed five or three years in advance. Hence, they conclude that the Altman Z-score is not applicable for classifying bankruptcies among Swedish companies. Rodriguez and Malm (2015), reaches the same conclusion when using the Z-score for a dataset of surviving and bankrupt Swedish firms in 2014.

Alyhr and Holmberg (2012) examine whether the Ohlson's O-score can be applied to Swedish data for listed companies. Their sample includes 533 firms, from which a focus group consisting of 48 firms of financial distress is identified. Thereto, they assess whether the incorporation of data from audit reports improves the predictability of corporate distress (Alyhr and Holmberg, 2012). Alyhr and Holmberg conclude that the model can be used on Swedish firms, and that embodying the audit report information significantly improves the prediction of the probability financial distress.

2.9 Literature summary

The following table summarizes the most relevant previous literature and highlights their main contributions to academic research by commenting on each study's benefits and disadvantages.

TABLE 1

Literature summary

Author	**Statistical technique**	**Period of study**	**Sample Size (Failed/ Non-failed)**	**Comments**
Beaver (1966)	Univariate analysis	1954-1964	79/79	- Simple approach - Ratios analysed individually
Altman (1968)	Multi-discriminant analysis	1946-1965	33/33	- Widely used among scholars - Profile ratio analysis - Classification in one of two groups is possible when the dependent variable is qualitative - Many assumptions
Ohlson (1980)	Logistic model	1970-1976	105/2,058	- Intuitive score between 0 and 1 - Less restrictive assumptions
Zmijewski (1984)	Probit model	1972-1978	40/800	- External factors included - Variables correlated
Skogsvik 1990	Probit model	1966-1979	51/328	- Historical accounting information is suitable when predicting bankruptcy
Altman and Sabato (2007)	Logistic model with unlogged and logged variables	1994-2002	120/2,010	- Specific model developed for SMEs - Model based upon easily obtainable accounting information - Non-financial information not included
Altman et. al. (2008)	Logistic model	2000-2007	66,000/ 5,734,000	- Models account for financial and non-financial availability
Grunet et. al. (2005)	Probit analysis	1992-2003	120 failed firms	- Combines financial and non-financial ratios - Management quality is assessed and incorporated into the model

3. Hypothesis

In this thesis, the applicability of accounting-based bankruptcy prediction models is investigated for Swedish data. Moreover, non-financial variables are added to enhance the original model developed by Altman and Sabato (2007). The original model is expected to perform well when applied to the present data consisting of private Swedish SMEs. This hypothesis is based upon the assumption that Altman and Sabato's model, uniquely developed for SMEs, is universal and incorporates the most relevant financial ratios to analyse SMEs' creditworthiness. Moreover, it is proven that the model can be applied to not only US but also UK SME data.

Hypothesis 1: The original Altman and Sabato (2007) bankruptcy prediction model performs well in terms of classification accuracy when applied to private Swedish SMEs

The variables used in bankruptcy prediction models are almost exclusively financial metrics, as described in the previous literature section. The idea that financial metrics are good proxies for predicting bankruptcy is generally accepted. Metrics measuring performance, liquidity and leverage are widely used, whereas non-financial metrics seldom are included. Despite the existing knowledge on correlation between firm specific characteristics and the probability of bankruptcy, these non-financial metrics often lack presence in quantitative bankruptcy prediction models.

Altman and Hotchkiss (2005) states that one of the most common reasons for corporate failure is managerial incompetence. In this study the issue that bankruptcy prediction models rarely include non-financial variables is addressed by incorporating variables measuring the CEO characteristics gender and age. It can be assumed that the CEO's accumulated industry experience is an important predictor for a company's survival. Due to the non-available data regarding the CEO's industry experience, age will be used as a proxy for experience. Furthermore, the incorporation of the variable CEO age is in line with research conducted by Platt and Platt (2012), where they find that the CEO of non-bankrupt boards are older, as well as the age of the average director on the board.

The debate about the relationship between gender and financial failure is widespread across the society. Research yields contrasting results, ranging from that a higher proportion of women in top management jobs tends to have positive effects on firm performance (Smith et. al, 2006), to the result that there is no relationship between women's presence on boards and company performance (Haslam et. al., 2009). Furthermore, Barber and Odean (2001) show that men trade more excessively than women and hence are more confident that their investment will result in a profit.

This study does not aim to determine which characteristics a CEO should possess in order to reduce the probability of bankruptcy. Rather, the aim is to analyse whether the inclusion of the *CEO age* and *gender* variables contribute to the model by improving classification accuracy. Moreover, the two variables *CEO age* and *gender* are believed to indicate that creditors view the CEO, rather than solely the corporate structure, as a deciding factor when assessing whether to grant a loan to a private SME. The second hypothesis is stated as:

Hypothesis 2: The incorporation of CEO specific variables improve the bankruptcy prediction for failed companies.

The third hypothesis assumes that the executive management committee, most importantly the CEO, plays a more prominent role in smaller companies. As firms grow larger, the corporate survival becomes dependent on a more diverse range of factors and individuals, such the middle management. Hence, the CEO is expected to become less important for the operational performance and firm survival. Furthermore, the hypothesis is based on the assumption that creditors, when assessing whether to lend to a SME close to financial failure, view these corporate loans similar to a personal loan to the CEO, especially when the company is small.

Hypothesis 3: Including CEO specific variables in the bankruptcy prediction model is more important for the first quartile of SMEs based on turnover

4. Method

The model is derived from Altman and Sabato's theory (2007) concerning SME bankruptcy predictability. However, three main differences are identified. Firstly, a distinctive difference between Altman and Sabato's study (2007) and this thesis regards the underlying data; this thesis is based upon sample data concerning Swedish non-listed companies, more specifically SMEs. Secondly, the present study assesses the probability of default, whereas the study undertaken by Altman and Sabato (2007) assess the probability of non-default. Furthermore, Altman and Sabato use both non-logged and logged predictor variables in their respective models. In this thesis, the variables are solely non-logged. The reasoning behind using non-logged predictors is that the sample otherwise would be reduced by approximately two thirds. From a statistical point of view, there is no requirement that the independent variables in a logistic model need to be normally distributed and therefore, using the model with non-logged variables is considered to be superior in this context. Thirdly, the thesis tests whether the inclusion of the CEO-variables *age* and *gender* improve the classification power for failed companies in the logit model.

4.1 Sample selection

Population data for Swedish non-listed companies is obtained using the database Retriever Business. The population includes both failed and non-failed companies over the study period 2008-2018.

The sampling process counts three rounds, where each round sets up information requirements. The first round determines the outline for the population data, where the following restrictions are made directly on the Retriever database:

I. The company needs to be a Swedish limited company and possess a Swedish organization number.
II. The company is, or has been active, during the past ten years.
III. The company is not listed on a Swedish exchange.
IV. The company needs to have a turnover of between 10 million and 500 million SEK and a staff head count of more than 10 employees.

Requirements I - III are in line with the research questions. Requirement IV is the first step in ensuring that the population solely concerns SMEs. Following Altman and Sabato's theory (2007) and the derived hypothesis concerning non-listed companies, it is natural to limit the data to SMEs. For the following thesis, the determining factors for identifying a SME are a turnover of between 20 million to 500 million SEK and a head staff count of more than ten employees (EU recommendation 2003/361). Due to the Retriever database settings, companies with a turnover of 10 million to 20 million SEK have later been excluded in STATA. Excluding micro companies shelters the sample from being biased towards one-man-companies, as these usually possess different characteristics than SMEs. It should be noted that using turnover as a determining factor, rather than total assets, can result in observations with total assets exceeding the EU SME definition limit being included in the sample. For this report however, this aspect is noted, but not addressed, since the EU definition for SMEs states that either turnover or total assets are sufficient as determining factor (EU recommendation 2003/361).

The second round in deriving the sample implies that a minimum of financial and non-financial information needs to be obtainable for each observation. Table 2 summarizes the information that is required from the observations in the second stage of sampling process:

TABLE 2

Observation information required

Financial information		Non-financial information	
I.	Turnover	I.	Bankruptcy status
II.	EBITDA	II.	Age of CEO
III.	Interest costs	III.	Gender of CEO
IV.	Cash	IV.	Firm industry
V.	Total assets		
VI.	Retained earnings		
VII.	Book value of equity		
VIII.	Short-term debt		

The financial-information requirements refer to the financial figures that are needed to calculate the ratios used in Altman and Sabato's logit model (Altman and Sabato, 2007). The study period stretches from 2008-2017. The non-financial information-requirements refer to the information needed for the dependent variable, as well as for the CEO-variables added to the logit model.

In the third round of the sampling process, three final requirements are formulated:

I. The firm should not be dissolved through a merger.
II. The firm should not have been involved in a liquidation.
III. The firm should not be operating within the financial sector.

The first requirement is included since the objective of the thesis is to predict the likelihood of financial failure. Firms involved in mergers are excluded from the sample since a merger not necessarily is related to the financial state of the target company. Strategic reasons and economies of scope or scale could provide a solid motivation a merge. Therefore, including companies involved in mergers would add unnecessary uncertainties to the analysis. The second requirement is put in place by reason that it remains unknown whether liquidation refers to the company being compulsory liquidated or not, as well as the reason that a compulsory liquidation might refer to a breach of compliance with regulations rather than financial instability. The third requirement concerns firms operating in the financial sector. These firms are excluded as they might contribute to biased results since financial firms have a different capital structure, face a different bankruptcy environment and has to adjust to a different set of regulations.

After the three rounds described above, 15,885 observations are compiled in the final sample.

TABLE 3

Data summary for derived sample

		N	Mean	Standard deviation	Min	Max	10th percentile	90th percentile
Surviving firms	Turnover	15659	107601	102699	20003	499802	25262	260911
	EBITDA	15659	8458	22099	(755920)	374915	(678)	22694
	Interest costs	15659	860	6317	0	349000	3	992
	Cash	15659	8231	26990	(2659)	1342074	1	18597
	Total assets	15659	110561	645224	342	55479280	9222	174358
	Retained earnings	15659	22948	281217	(2089886)	27699024	14	39009
	Equity	15659	37630	337320	(753639)	28700716	1135	59129
	Short term debt	15659	3628	44592	(3141)	3535406	0	5100
Failed firms	Turnover	226	91214	97623	20021	486442	22668	218823
	EBITDA	226	(2716)	15982	(154896)	33106	(12731)	4492
	Interest costs	226	1441	4081	0	46078	29	3037
	Cash	226	1663	4127	0	25435	1	3500
	Total assets	226	56540	128009	2375	1240915	6741	125706
	Retained earnings	226	(3991)	53120	(468942)	110401	(3825)	10245
	Equity	226	4415	15588	(42997)	130208	(3045)	12610
	Short term debt	226	6192	23707	0	242441	0	12948
All firms	Turnover	15885	107368	102644	20003	499802	25225	260877
	EBITDA	15885	8299	22063	(755920)	374915	(865)	22430
	Interest costs	15885	868	6291	0	349000	3	1024
	Cash	15885	8137	26813	(2659)	1342074	1	18486
	Total assets	15885	109793	640830	342	55479280	9181	173830
	Retained earnings	15885	22565	279299	(2089886)	27699024	12	38294
	Equity	15885	37158	334940	(753639)	28700716	1093	58502
	Short term debt	15885	3664	44365	(3141)	3535406	0	5253

The table shows number of observations, mean, standard deviation, min, max, 10th percentile and 90th percentile for all financial observations included in the in- and out of sample

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4.1.1 Classification of failed firms

The final step in the sampling process regards the classification of failed and non-failed companies. When identifying the failed companies, the classification derives from the company's status and is extracted from the database. The reasoning behind setting up an own definition for failed firms is based on the fact that the paper of Altman and Sabato (2007) does not yield a clear-cut definition for how they define financial distress. Moreover, other bankruptcy prediction models, focus either on solely defaulting companies, failed companies, companies in financial distress or some combination of the different states.

For this thesis, failed companies are subject to at least one of the following status: *bankruptcy initiated*, *bankruptcy terminated*, *bankruptcy filing*, or *bankruptcy terminated with surplus*. The frequency and share of observations within each sub-category are summarized in Table 4.

TABLE 4

Distribution of failed firms

	Freq.	Percentage
Bankruptcy initiated *(Konkurs inledd)*	146	64.60%
Bankruptcy terminated *(Konkurs avslutad)*	78	34.51%
Bankruptcy filing *(Konkursansökan)*	1	0.44%
Bankruptcy terminated with surplus *(Konkurs avslutad med överskott)*	1	0.44%
Total	**226**	**100%**

This table shows the failed firms included in the sample, distributed over the type of classification that has resulted in the firm being considered as failed.

4.1.2 Out of sample

To assess the classification accuracy of the estimated model, an out of sample of 4,000 observations is extracted from the sample. This is made through the "random" selection process *runiform* in STATA. Thereafter the sample is split into two datasets with the out of sample counting 3,725 complete observations, while the remaining 12,160 observations without missing values are used to regress the models.

4.1.3 Data examination

The requirement that all sample observations need to provide both financial- and CEO specific information implies a limitation per se. It is questioned whether the reporting or lack of reporting is a signal for failure itself.

Moreover, restrictions in available data concerning past CEOs lead to a bias in the analysis. For non-failed companies, the latest available financial report, either from 2016 or 2017, is used for the financial ratio calculations. For failed companies, however, the year of the used financial report varies with the year of failure since failed companies stop reporting by the time they enter into the state of being failed. In addition, it is only possible to obtain the CEO specific information for the most recent CEO. Hence, when setting up the model, financial reports for non-failed companies regard the reporting period 2016 or, if available, 2017 and for failed companies, the reporting period varies over the years 2008-2017, depending on when the firm submitted its last report prior to reaching the *failed* state.

An alternative way to handle the restriction of not being able to use past CEO data would be to assume that the CEOs of a company have similar characteristics. This would allow the use of financial reports for surviving firms over the same period as the failed firms, while the characteristics for the current CEO applied to older periods. However, this latter assumption contributes to greater uncertainty in the analysis than the prior of using different reporting periods.

4.2 Statistical methods

In order to fulfil the purpose of this report, a set of statistical regressions and tests need to be performed. Firstly, the full model including all financial variables in the Altman and Sabato's SME model as well as the two CEO-variables *age* and *gender* are analysed through a logistic regression analysis. Thereafter, the percent correctly predicted cases are calculated by using the regressed model on the out of sample.

Secondly, the percent of correctly classified observations given by the full model is compared with the percent correctly classified observations given by using a regressed model solely based on Altman and Sabato's variables, as well as by using the coefficients estimated by Altman and Sabato for the US sample.

Thirdly, some emphasis is put on validating and testing the statistical properties used in the logistic regression analysis. These include the likelihood ratio test, the pseudo R-square measure, correlations as well as the statistical significance of each independent variable.

4.2.1 Logistic regression

In the context of bankruptcy prediction, the logistic regression has several advantages in comparison to the other commonly applied econometric methodology, the Multivariate

Discriminant Analysis (MDA). The disadvantages with the MDA, as described by Ohlson (1980) can be summarized as:

- The MDA demands certain statistical requirements on the distribution of predictors. One of these is the requirement of normal distribution among the predictors. This makes dummy independent variables difficult to use.
- Using the MDA model, the output is a score that lacks intuitive interpretation. It is essentially an ordinal ranking device.
- The matching process typically used in MDA tends to be somewhat subjective. The variables which matching is based upon should be included as predictors rather than solely for the purpose of matching.

Due to the above shortcomings and the advantages of the logistic model, the latter is selected for this thesis. Moreover, the choice of model originates in Altman and Sabato's methodological approach.

In a logistic regression, the outcome of the dependent variable is either 0 or 1, and in contrast to a linear regression, the change in the estimated parameter does not explain a one-unit change in the dependent variable. Instead, the estimates in a logistic regression explain how much the natural logarithm of the odds change when the independent variable changes by one unit. This type of regression works well with the binary outcome of failed or non-failed.

The odds favouring Y=1 can be described as:

$$\varphi(Y=1) = \frac{P(Y=1)}{1-P(Y=1)}$$

To produce a linear function, the logit is calculated by taking the natural logarithm of the odds:

$$L = ln\varphi = ln\frac{P}{1-P}$$

The equation of a logistic model can be written as

$$L_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_{k-1} X_{k-1i}$$

where the logit (L) is a linear function of the X-variables and k is the number of parameters in the model. The logit therefore shows the change in the natural logarithm of the odds for $Y=1$ for a change in the independent variables.

4.2.2 The Wald test and the likelihood ratio test

A commonly used test to determine the goodness-of-fit between two models is the Wald test. The statistic is calculated as:

$$z_i = \frac{\beta_i}{SE(\beta_i)}$$

The Wald test is similar to the t-statistic in a linear regression, but it follows a standard normal distribution, while the square of the statistic follows a chi-squared distribution (Hosmer et. al., 2013). One advantage of using the Wald test is that it approximates the likelihood ratio test, but only requires the full model to perform the test. However, when the coefficients are large, the standard error is inflated, and lead to an increased chance of an error Type II (Mehmetoglu and Jakobsen, 2017).

The likelihood ratio test is used to test differences between two nested models. It is commonly used when evaluating the difference between two models where one of the models is nested in the other. Hence, the likelihood ratio test evaluates whether constraining one or more of the variables in the full model to zero will lead to a significantly reduced fit of the model (Wooldridge, 2013). The test is therefore used in this report to see whether including the variables for *CEO age* and *gender* significantly improve the model.

When performing the likelihood ratio test, the log likelihoods of the two models are compared, and thereafter it is tested whether the difference received is statistically significant in order to reject the null model. The test statistic is calculated as:

$$LR = -2ln(L(m_1))/L(m_2)) = 2(lnL(m_2) - lnL(m_1)),$$

where $L(m_i)$ is the likelihood for model *i*. The statistic derived is distributed through a chi-square distribution and its degrees of freedom equals the difference of the degrees between the two models.

4.2.3 Psuedo R-square and McFadden R-squared

In a linear regression, R^2 measures the explained sums of squares compared to the total sums of squares and is often used to measure how well the model fits the outcomes. However, when using a nonlinear regression, the R^2 measure cannot be employed. Instead, the goodness-of-fit for logistic models is based on maximum likelihood estimates which is estimated through an iterative process. Several measures are constructed to mimic the R^2 in order to measure the explanatory power of the variables (Wooldridge, 2013).

McFadden's $\tilde{R}^2$ is one of the most commonly used pseudo R^2 measures and is included in the output when performing a logistic regression in STATA. It is computed as;

$$\tilde{R}^2 = 1 - Ln(B)/Ln(y),$$

where $Ln(B)$ denotes the maximized or fitted log-likelihood value, while $Ln(y)$ denotes the log likelihood value given by an intercept-only model. Hence, the ratio of the two likelihoods suggests how much the model including predictors improves over the model only containing the intercept.

4.2.4 Classification measures

In order to validate the models, their respective classification accuracies are examined. These measures display how well a model identifies an observation according to its class, being failed or non-failed. The classification test is a variation to the more commonly known goodness-of-fit measure (Cameron and Trivedi, 2010). It is based on the distribution between four categories and the calculation of percentage correctly classified observations. The analysis quantifies the classification accuracy of the logit model when discriminating between two predefined states; failed and non-failed. The model's classification accuracy is measured by its ability to correctly classify an observation as failed ($y = 1$) or non-failed ($y = 0$) (Cameron and Trivedi, 2010). The following four classification options are possible:

- *True positive:* The company is classified as failed when it actually is failed.
- *False positive:* The company is classified as failed when it is non-failed.
- *True negative:* The company is classified as non-failed when it actually is non-failed.
- *False negative:* The company is classified as non-failed when it is failed.

The true positive rate (TPR) is called sensitivity, and is defined as the fraction of observations that are correctly classified as failed in relation to all observations which are classified as failed:

$$Sensitivity\ (TPR): \frac{True\ positive}{True\ positive\ +\ False\ Negative}$$

The true negative rate (TNR) is called specificity and is defined as the fraction of observations that are correctly classified as non-failed in relation to all observations classified as non-failed.

$$Specificity\ (TNR)\ =\ \frac{True\ Negative}{True\ Negative\ +\ False\ Positive}$$

Both the false positive rate (FPR) and the false negative rate (FNR) are referred to as classification error rates. The false positives are more commonly known as error Type I and the false negatives as error Type II. The better a model's predicted outcomes fit actual outcomes, the lower the classification error rates.

4.2.5 Receiver operating characteristic and area under the curve

The receiver operating characteristic (ROC) analysis builds on the above discussed classification measures. The ROC curve visualizes a model's classification performance (Fawcett, 2006). Moreover, it illustrates the trade-off between sensitivity on the y-axis and 1 – specificity on the x-axis. The greater the area under the curve, meaning that the ROC-curve is flexed towards the upper left corner, the better the average classification accuracy. This yields a situation in which the model achieves high sensitivity and specificity percentages. If all observations are correctly classified, both the sensitivity and specificity measures would correspond to 100 %.

The ROC diagram illustrates, along with the ROC-curve, a diagonal line that corresponds to the outcome of randomly guessing whether the observations belong to one or the other predefined groups. Any point above the diagonal line indicates that the model generates a higher classification ratio than randomly guessing. The greater the difference between the ROC-curve and the diagonal line, the better the classification accuracy and the greater the area under the curve. More precisely, the area under the ROC-curve (AUC) is a measure for the model's ability to correctly classify an observation as failed or non-failed.

The benefit of utilizing AUC rates as a measure for classification accuracy is that the rate is comparable. Hence, it is possible to make statements regarding which model is better suited to make binary classifications. In the context of this thesis, the AUC rate for Model A, being the revised logit model including CEO characteristics, is compared to, among other, the rate for Model B, the Altman and Sabato's original logit model (2007). By comparing the areas under the curves for the logit models with and without CEO-characteristics, area differences have been identified. The results from this analysis are further discussed in section 5.

5. Results and analysis

The variables in the logistic regressions are a linear combination of Altman and Sabato's financial ratios and the CEO-variables *age* and *gender* and are calculated as:

$Failed\ =\ Value\ 1\ if\ firm\ failed\ and\ 0\ if\ surviving$
$Leverage\ =\ Short\ term\ debt\ /\ Equity$
$Liquidity\ =\ Cash\ /\ Total\ assets$
$Profitability\ 1\ =\ EBITDA\ /\ Total\ assets$
$Profitability\ 2\ = Retained\ earnings\ /\ Total\ assets$
$Coverage\ =\ EBITDA\ /\ Interest\ costs$
$CEO\ gender\ =\ Value\ 1\ for\ male\ and\ 0\ for\ female$
$CEO\ age\ 1 = Value\ 1\ if\ CEO\ is\ 40\ years\ old\ or\ younger, 0\ otherwise$
$CEO\ age\ 2 =\ Value\ 1\ if\ CEO\ is\ over\ 40\ but\ less\ than\ or\ equal\ to\ 50\ years\ old, 0\ otherwise$
$CEO\ age\ 3 = Value\ 1\ if\ CEO\ is\ over\ 50\ but\ less\ than\ or\ equal\ to\ 60\ years\ old, 0\ otherwise$
$CEO\ age\ 4 =\ Value\ 1\ if\ CEO\ is\ over\ 60\ \ years\ old, 0\ otherwise$

To answer the hypotheses, four models are developed and discussed in the following section. The models are described as;

$\underline{Model\ A}$:
$$Failed =\ \beta_1 * Leverage + \beta_2 * Liquidity + \beta_3 * Profitability\ 1 + \beta_4 * Profitability\ 2 + \beta_5 * Coverage + \beta_6 * CEO\ gender + \beta_7 * CEO\ age\ 1 + \beta_8 * CEO\ age\ 2 + \beta_9 * CEO\ age\ 3$$

$\underline{Model\ B\ /\ 1}$:
$$Failed =\ \beta_1 * Leverage + \beta_2 * Liquidity + \beta_3 * Profitability\ 1 +\ \beta_4 * Profitability\ 2 + \beta_5 * Coverage$$

$\underline{Model\ C}$:
$$Failed =\ \beta_1 * Liquidity + \beta_2 * Profitability\ 1 + \beta_3 * Profitability\ 2 + \beta_4 * Coverage + \beta_5 * CEO\ gender + \beta_6 * CEO\ age\ 1 + \beta_7 * CEO\ age\ 2 + \beta_8 * CEO\ age\ 3$$

Model A – Model C use coefficients estimated for the sample of Swedish SMEs, while Model 1 uses the coefficients estimated by Altman and Sabato (2007) for US data.

5.1 Descriptive statistics and results from the ratio analysis

By intuition, the coefficient for the variable *Leverage* should be positive to indicate that a higher leverage increases the probability of bankruptcy. The coefficients for the variables *Liquidity*, *Profitability 1*, *Profitability 2* and *Coverage*, are assumed to have a negative sign to indicate that higher liquidity, profitability and interest coverage decrease a company's probability of bankruptcy. As for the gender of the CEO, it is difficult to predict the sign of the coefficient, but in reference to the *CEO age* variable, the coefficient should be of a negative sign, indicating that an older CEOs decrease the risk of corporate failure.

Table 5 shows the summary statistics for all ten independent variables separated by failing and surviving firms, for the remaining 12,160 observations when the out of sample has been extracted.

TABLE 5

Data summary of variables

		N	Mean	Standard deviation	Min	Max	10th percentile	90th percentile
Surviving firms	Leverage	11992	0.49	5.18	(9.04)	221.32	0.00	0.60
	Liquidity	11992	0.15	0.17	(0.19)	0.98	0.00	0.40
	Profitability 1	11992	0.15	0.33	(10.99)	21.98	(0.02)	0.35
	Profitability 2	11992	0.16	0.32	(11.92)	6.55	0.00	0.43
	Coverage	11992	584.27	2794.21	(49678.00)	105788.70	(3.11)	1269.33
	CEO gender	11992	0.89	0.31	n.a.	n.a.	0.00	1.00
	CEO age 1	11992	0.12	0.33	n.a.	n.a.	0.00	1.00
	CEO age 2	11992	0.36	0.48	n.a.	n.a.	0.00	1.00
	CEO age 3	11992	0.38	0.49	n.a.	n.a.	0.00	1.00
	CEO age 4	11992	0.13	0.34	n.a.	n.a.	0.00	1.00
Failed firms	Leverage	168	1.35	4.14	(12.47)	30.40	0.00	4.90
	Liquidity	168	0.04	0.07	0.00	0.52	0.00	0.13
	Profitability 1	168	(0.08)	0.37	(3.33)	0.56	(0.34)	0.15
	Profitability 2	168	0.02	0.49	(5.26)	0.66	(0.09)	0.28
	Coverage	168	(44.83)	466.94	(5959.00)	343.60	(41.60)	15.66
	CEO gender	168	0.98	0.15	n.a.	n.a.	1.00	1.00
	CEO age 1	168	0.11	0.31	n.a.	n.a.	0.00	1.00
	CEO age 2	168	0.24	0.43	n.a.	n.a.	0.00	1.00
	CEO age 3	168	0.42	0.50	n.a.	n.a.	0.00	1.00
	CEO age 4	168	0.23	0.42	n.a.	n.a.	0.00	1.00
All firms	Leverage	12160	0.50	5.17	(12.47)	221.32	0.00	0.63
	Liquidity	12160	0.15	0.17	(0.19)	0.98	0.00	0.40
	Profitability 1	12160	0.14	0.33	(10.99)	21.98	(0.03)	0.35
	Profitability 2	12160	0.16	0.33	(11.92)	6.55	0.00	0.43
	Coverage	12160	575.57	2776.35	(49678.00)	105788.70	(3.71)	1243.71
	CEO gender	12160	0.89	0.31	n.a.	n.a.	0.00	1.00
	CEO age 1	12160	0.12	0.33	n.a.	n.a.	0.00	1.00
	CEO age 2	12160	0.36	0.48	n.a.	n.a.	0.00	1.00
	CEO age 3	12160	0.38	0.49	n.a.	n.a.	0.00	1.00
	CEO age 4	12160	0.13	0.34	n.a.	n.a.	0.00	1.00

This table shows number of firms, mean, standard deviation, min, max, 10th percentile and 90th percentile for all firms included in the in sample.

As predicted, there are notable differences in the values for the failing and surviving firms. Comparing mean values between the two groups, *Leverage* is almost three times larger the for failing firms, while *Liquidity, Profitability* and *Coverage* are higher for surviving firms. Failing firms have negative, or close to zero mean values for both profitability measures as well as for

Coverage, while surviving firms have positive. Regarding the CEO-variables, failed firms have a higher mean value for gender, which indicates that the failed firms have a higher portion of male CEOs than the surviving firms. However, both groups are biased towards male CEOs. Furthermore, failed firms have a higher mean for the dummy variables measuring the CEO age referring to the two older groups than the surviving firms. These findings are the opposite to the initial intuition that age and experience decrease the risk of financial failure. The result, however, is in line with research conducted by Child (1974), who finds that age tends to be associated with less economic growth. Furthermore, Hambrick and Mason (1984) argue that older CEOs are more conservative than younger, and hence less likely to present new ideas.

5.2 Model prediction results

Table 6 presents results for coefficients as well as z-statistics and significance for the four models. Model 1 corresponds to the original model developed by Altman and Sabato (2007) using US coefficients, Model A is the estimated full model based on Swedish SMEs and with CEO specific variables included, and Model B is the model based on Swedish SMEs solely using the five variables described by Altman and Sabato (2007). Lastly, Model C is similar to Model A, but it excludes the variable *Leverage*.

TABLE 6

Prediction results

	Variable									
	Leverage	Liquidity	Profitability 1	Profitability 2	Coverage	CEO gender	CEO age 1	CEO age 2	CEO age 3	Constant
Model 1 (Using Altman and Sabato's coefficients)										
Estimate	0.01	(0.02)	(0.18)	(0.08)	(0.19)					(4.28)
Model A (Using estimated coefficients, including CEO-characteristic variables)										
Estimate	0.00885	(7.838)***	(0.828)***	(0.406)***	(0.000136)***	1.405***	(0.695)**	(0.989)***	(0.431)**	(4.311)***
z-statistic	1.211	(6.918)	(4.435)	(4.533)	(2.723)	2.763	(2.355)	(4.261)	(2.099)	(8.124)
McFadden R-squared	0.1038									
Model B (Using estimated coefficients, Altman and Sabato's model)										
Estimate	0.00813	(7.833)***	(0.839)***	(0.398)***	(0.000128)***					(3.532)***
z-statistic	1.121	(6.970)	(4.516)	(4.418)	(2.583)					(38.13)
McFadden R-squared	0.0852									
Model C (Using estimated coefficients, including CEO-characteristic variables and excluding leverage)										
Estimate		(7.877)***	(0.828)***	(0.407)***	(0.000136)***	1.411***	(0.685)**	(0.982)***	(0.428)**	(4.310)***
z-statistic		(6.948)	(4.428)	(4.541)	(2.726)	2.775	(2.326)	(4.238)	(2.087)	(8.122)
McFadden R-squared	0.1033									

Observations: 12,160

*** p<0.01, ** p<0.05, * p<0.1

This table shows the estimated coefficients and their significance for the four different models examined in this report. Note that Model 1, based on Altman and Sabato's original model and coefficients lacks information regarding z-statistics, significance levels and r-square, since Altman and Sabato (2007) does not give any information regarding these metrics. Furthermore, the coefficients shown for model 1 are the opposite signs of those shown in the Altman and Sabato report (2007) due to this report's focus on determining the probability of failure instead to probability of survival.

To test the null hypothesis and prove that there is no relationship between the dependent and independent variables, the z-statistic for the individual coefficients is used. The Wald statistic is provided for each individual coefficient as well as stars indicating the p-value. For Model A, all coefficients except for *Leverage* are significant at a level of 0.05 or below, indicating that there is little chance of a true null hypothesis of coefficients equalling zero. *Leverage* has a Wald statistic of 1.211, corresponding to a p-value of 0.23, which indicates that the variable is not significant. As for Model B, all estimates are significant at a 0.01 level except for *Leverage*.

Another method to test the null hypothesis in a logistic regression is to use the likelihood ratio test. The test is similar to an F-test for a linear regression and is considered to be the best when evaluating the significance of an individual variable (Menard, 2002). To test whether the model is significantly improved by adding the variables for *CEO age* and *gender*, the full model is compared to the nested model only including the financial variables as in Altman and Sabato's original model (2007). The test statistic gives a value of 33.07, resulting in a p-value close to zero. This implies that the model fit is significantly improved by adding the CEO-specific variables. Furthermore, it is tested whether adding each of the CEO variables alone improves the model, with the result that adding the *CEO age* dummies and *CEO gender* on a standalone basis does improve the model fit.

Since *Leverage* is not significant for neither Model A nor Model B when examining the Wald statistic, it is tested whether the models are improved by including the variable *Leverage*, compared to a model containing all other variables except for *Leverage*. The test for both Model A and Model B shows that including the variable *Leverage* in the respective models does not lead to a significantly improved fit. To investigate whether the variable for leverage could be adjusted to the Swedish SME data, other definitions of the variable are tested. These include using total debt instead of only short-term debt and using total assets as a denominator instead of equity as well as different combinations of these metrics. However, the significance does not improve, indicating that leverage is less important when predicting bankruptcy among Swedish SMEs. Therefore, Model C, which includes the variables measuring CEO-characteristics but excludes *Leverage* is constructed. All variables in this model are significant at a 0.05 level or below.

In regard to the pseudo R-squared metric, Model A seems to have an overall higher fit than Model B, meaning that the bankruptcy prediction is improved by incorporating the CEO specific variables for age and gender. The pseudo R-squared values are low overall, which could indicate that the model does a poor job fitting the values. However, as described above, the pseudo R-squared is not the same measure as the R-squared in a linear regression and can therefore not be interpreted in the same way. The R-squared shown above is the McFadden R-squared, one of many proposed pseudo R-squared for logistic regressions. There is no general agreement of which pseudo R-squared that works best for logistic regressions, and R-squared is not recommended for comparing non-nested models. Therefore, even though both Model A and Model B have a low pseudo R-square overall, the improvement of the fit from Model B to Model A indicates that the inclusion of CEO specific variables increases prediction accuracy. Comparing Model A to Model C, the results show that Model C has a slightly lower R-squared than Model A, which could indicate that Model A, including the variable *Leverage*, fits the data better. However, the improvement is marginal and too much emphasis should not be put on this result.

5.3 Correlation analysis

To further investigate whether all variables independently contribute to the models, a correlation analysis is performed and presented in Table 7. The table is based on Pearson's product-moment correlation and is calculated as the covariance between two variables, divided by the product of the standard deviation of the two variables, holding all other variables constant. Hinkle et al. (1988) state that correlations below the absolute value of 0.3 suggest that there is little or no association between the two variables. Table 7 shows that no variables except the *CEO age* variables have a correlation above an absolute value of 0.3, suggesting that all variables contribute independently to the models. The correlation between the *CEO age* variables is expected since all four variables are dummies based on the age of the CEO. Furthermore, the correlations between the gender of the CEO and the different age variables are all low, indicating that both CEO specific variables contribute to the models independently.

TABLE 7

Matrix of correlations

Variables	Leverage	Liquidity	Profit-ability 1	Profit-ability 2	Coverage	CEO gender	CEO age 1	CEO age 2	CEO age 3	CEO age 4
Leverage	1.000									
Liquidity	(0.055)*	1.000								
Profitability 1	(0.018)*	0.170*	1.000							
Profitability 2	(0.030)*	0.030*	0.018*	1.000						
Coverage	(0.015)*	0.067*	0.211*	0.033*	1.000					
CEO gender	0.016*	(0.063)*	0.002	(0.007)	(0.010)	1.000				
CEO age 1	0.007	0.031*	0.012	(0.051)*	(0.015)*	(0.002)	1.000			
CEO age 2	0.005	(0.002)	0.012	(0.012)	0.004	(0.032)*	(0.284)*	1.000		
CEO age 3	(0.003)	(0.023)*	(0.002)	0.025*	0.009	(0.008)	(0.294)*	(0.589)*	1.000	
CEO age 4	(0.009)	0.001	(0.026)*	0.030*	(0.003)	0.059*	(0.148)*	(0.297)*	(0.307)*	1.000

* shows significance at the 0.1 level

This table shows pairwise correlations and the correlation significance between the variables used in the different models.

5.4 Analysis of classification performance

5.4.1 Classification analysis given a fixed cut-off

Predictive power in terms of classification accuracy is analysed for each individual model as well as compared across the four models. A model's predictive power relates to the percent of correctly classified observations given a predefined cut-off value. Classification is based upon model prediction and not actual outcome. It is common to apply a cut-off value of 0.5, however, this rate assumes a symmetric relationship between the two classification error rates. Hypothetically, the use of a cut-off value of 0.5 implies that a company with a predicted probability of 0.5 or higher is classified as failed whereas a company with a predicted probability of less than 0.5 is classified as non-failed. For the present data, the widely used cut-off value of 0.5 is rejected due to the dataset's unbalanced character. In line with recent literature (Skogsvik, 2006) the predefined cut-off value of 0.5 would result in an over-classification bias for failed companies and an under-classification bias for non-failed companies. Therefore, the cut-off rate is set equal to the ratio of failed companies to the total numbers of companies in the in-sample and equals approximately 1.38 % $(= 168/12160)$. The cut-off rate reflects that the sample is biased towards non-failed companies and not matched as in many previous studies.

Table 8 summarizes the classification results for all four models when applied on an out of sample. For Model A, the percent correctly classified observations equals 58.95 %, which seems to be moderately low. However, to understand this value, it is crucial to analyse the trade-off between sensitivity and specificity. Model A scores high on sensitivity, indicating that 77.59 % of the failed companies are correctly classified as failed. In regard to specificity, the model correctly identifies 58.66 % of the non-failed companies. This lower rate is explained by the low cut-off value and the model's emphasis on sensitivity. In the context of bankruptcy prediction and the enormous costs that a failed company places on its stakeholders, the model follows a prudential approach and places a higher focus on sensitivity rather than specificity.

TABLE 8

Classification accuracy and error rates (cut-off 1.38%)

	Accuracy rates			**Error rates**		
	Sensitivity	Specificity	% Correctly Classified	False Positive (Type I)	False Negative (Type II)	% Misclassification
Model A	77.59%	58.66%	58.95%	41.34%	22.41%	41.05%
Model B	86.21%	54.16%	54.66%	45.84%	13.79%	45.34%
Model C	77.59%	58.36%	58.66%	41.64%	22.41%	41.34%
Model 1	63.79%	87.65%	87.28%	12.35%	36.20%	12.72%

This table shows the accuracy rates and error rates for the respective models, given a cut-off rate of 1.38%. Sensitivity refers to correctly classifying a failed firm and specificity refers to correctly identifying a non-failed firm.

In contrast to Model A, the percent correctly classified observations are slightly lower at 54.66 % for Model B. The higher sensitivity rate of 86.21 % reduces the specificity rate, which equals 54.16 % given the cut-off rate of 1.38 %. The classification performance profile for Model C is similar to that of Model A, indicating that the variable *Leverage* does not contribute the model's predictive power. All three models, Model A – C, score high on sensitivity, indicating that the respective models embody a prudential approach. In regard to total percent correctly classified, Model A and C are superior to Model B.

Model 1 is used as a reference model, as it is based on US coefficients and Altman and Sabato's original financial variables. At first sight, it seems rather surprising that the overall classification accuracy is the highest for Model 1. The high rate is explained by the model's emphasis on specificity, placing greater importance on correctly identifying non-failed companies. As the sample is strongly biased towards non-failed companies, the higher specificity contributes to the higher percent correctly classified firms. However, this comes at a cost of the model missing to identify failed firms. From the perspective of passive investors and creditors, the cost of missing to identity failed companies is higher, and hence, Model 1 should be used with caution.

All models have a total error rate that average around 40 %, except for Model 1. The high error rates are partially explained by the fact that the sample is biased towards non-failed companies and uses a low cut-off value, resulting in a higher false positive rate. It should be acknowledged that the chosen cut-off value might not be the optimal value since the different misclassification costs regarding the false positives and false negatives are not taken into account (Altman, 1977).

In accordance with Altman and Sabato's observations, the cut-off value is applied to make statements about and compare the classification accuracy for the different models, not to identify the optimal cut-off strategy (Altman and Sabato, 2007).

Regarding the first hypothesis, Model 1 scores high on percent correctly classified observations. This indicates that the model is well applicable to the present data of Swedish non-listed SMEs. The percent correctly classified observations lie above 80 % and continues to increase as the cut-off rate become higher as shown in Table 9. Moreover, the sensitivity rate of 63.79 % given the cut-off rate of 1.38 % signals that the model does a modest job classifying the failed observations as failed. In contrast, Model B using the Swedish coefficients, scores higher on sensitivity, but yields a low percent of correctly classified observations. Due to the high rate of correctly classified firms for Model 1, the first hypothesis is accepted.

5.4.2 Classification analysis given various cut-offs

Table 9 summarizes the respective models' sensitivity, specificity and percentage correctly classified for a set of different cut-off values when applied to the out of sample. The table displays that as the cut-off value increases, sensitivity and specificity move in opposite directions. Sensitivity decreases, whereas specificity co-moves with the cut-off values. Simultaneously, the percent correctly classified firms increase. For Model A and C, the figures for sensitivity, specificity and percent correctly classified are almost identical. This is explained by the fact that *Leverage* is insignificant and does not contribute to the model. Therefore, the thesis' main focus lies on comparing Model B and Model C.

Comparing Model B and C when applying a cut-off rate of 1.00 %, Model B is worse than randomly guessing and Model C is slightly better. Up until the cut-off rate of 2.50 %, the sensitivity rate falls more drastically for Model C than for Model B. Thereafter, the case is the reverse. In line with these findings, the percent correctly classified observations develop accordingly. More specifically, Model C yields higher total classification rates for cut-off rates below 2.50 %. The table demonstrates the trade-off between either maximizing sensitivity or specificity. However, the table alone cannot be used for making conclusions regarding which model is preferred. Rather, the cut-off values and resulting classification rates need to be analysed in their specific industry context.

TABLE 9

Finding the optimal classification cut-off value

	Model A			**Model B**			**Model C**			**Model 1**		
Cut-off value	Sensitivity	Specificity	% Correctly Classified	Sensitivity	Specificity	% Correctly Classified	Sensitivity	Specificity	% Correctly Classified	Sensitivity	Specificity	% Correctly Classified
0.01	**89.66%**	50.53%	51.14%	**89.66%**	45.35%	46.04%	**89.66%**	50.31%	50.93%	**75.86%**	84.87%	84.72%
0.0138158	*77.59%*	*58.66%*	*58.95%*	*86.21%*	*54.16%*	*54.66%*	*77.59%*	*58.36%*	*58.66%*	*63.79%*	*87.65%*	*87.65%*
0.015	75.86%	61.79%	62.01%	86.21%	56.99%	57.45%	75.86%	61.55%	61.77%	62.07%	88.00%	87.60%
0.02	63.79%	75.02%	74.85%	75.86%	68.23%	68.35%	62.07%	74.75%	74.55%	51.72%	89.12%	88.54%
0.025	53.45%	82.33%	81.88%	60.34%	86.58%	86.17%	53.45%	82.25%	81.80%	48.28%	89.94%	89.29%
0.03	46.55%	89.15%	88.48%	25.86%	96.73%	95.62%	46.55%	89.01%	88.35%	43.10%	90.35%	88.27%
0.035	27.59%	93.56%	92.54%	6.90%	98.31%	96.89%	27.59%	93.59%	92.56%	41.38%	90.67%	88.62%
0.04	13.79%	95.23%	93.96%	6.90%	98.96%	97.53%	13.79%	95.17%	93.91%	41.38%	90.81%	90.04%
0.05	10.34%	98.75%	97.37%	1.72%	99.29%	97.77%	10.34%	98.80%	97.42%	41.38%	91.27%	90.50%
0.1	0.00%	**99.75%**	**98.20%**	0.00%	**99.73%**	**98.17%**	0.00%	**99.78%**	**98.23%**	27.59%	**92.45%**	**91.44%**

The table displays sensitivity, specificity and the percentage of correctly classified observations using 10 different cut-off rates for the respective models. Model A consists of all financial- and CEO specific variables, Model B consists of solely financial variables and Model C consists of both financial and CEO specific variables, excluding leverage. Model 1 consists of the financial variables and uses US coefficients. Optimal cut-off value depends on whether the aim is to maximize sensitivity or specificity.

In reference to the second hypothesis, the models including CEO specific variables score higher in terms of overall classification accuracy, given the fixed cut-off of 1.38 %. Model C, including the CEO-variables but excluding *Leverage*, is superior to Model B in terms of percent correctly classified firms and hence, the findings are in line with the hypothesis. Model C is not directly comparable to Model 1 as the latter uses US coefficients. The overall prediction accuracy, however, comes at a cost of sensitivity. To make statements about which model is preferred given the various cut-off rates, a floor for the lowest acceptable sensitivity rate needs to be set. The cut-off rate of 2.50 % is considered to correspond to a sensitivity-floor, as this cut-off rate corresponds to sensitivity rates of 60.34 % and 53.45% for Model B and Model C, respectively. As sensitivity decreases with a higher cut-off rate for all models, a cut-off rate of less than 2.50 % is preferred. In line with this finding, it can be concluded that Model C is the preferred model for cut-off rates below 2.50 %. Hence, the second hypothesis is accepted.

5.5 Results from the ROC analysis

The ROC analysis is another tool to assess the models' classification power when making comparisons between models. The ROC-curve visualizes the trade-off between sensitivity and 1 minus specificity, and the benefit of the ROC analysis lies in the ease of its interpretation. The ROC-curve's performance is measured by the area under the curve. Another benefit embodied by the curve is, that it is insensitive to changes in the distribution of failed to non-failed companies in the data (Fawcett, 2006). The insensitivity enables analysis over time when the ratio of failed to non-failed companies is subject to changes. This is assumed to be the case in the present dataset.

Table 10 summarizes the AUC values for the different models in regard to the out of sample. All AUC rates are slightly below 80 %, indicating a high average classification accuracy. The ROC-curve for Model C lies well above the random diagonal line, covering an AUC of 76.35 %. This indicates that Model C, estimated for Swedish private SMEs, performs well in predicting failed companies. However, the overall performance is affected by misclassification of mainly non-failed companies. Model B, including solely the financial variables originally found in Altman and Sabato's model (2007) and coefficients estimated for Swedish data, yields an AUC of 79.55 %. It follows that measuring for varying cut-off rates, the CEO specific variables do not improve the overall classification accuracy for failed companies.

TABLE 10

AUC summary

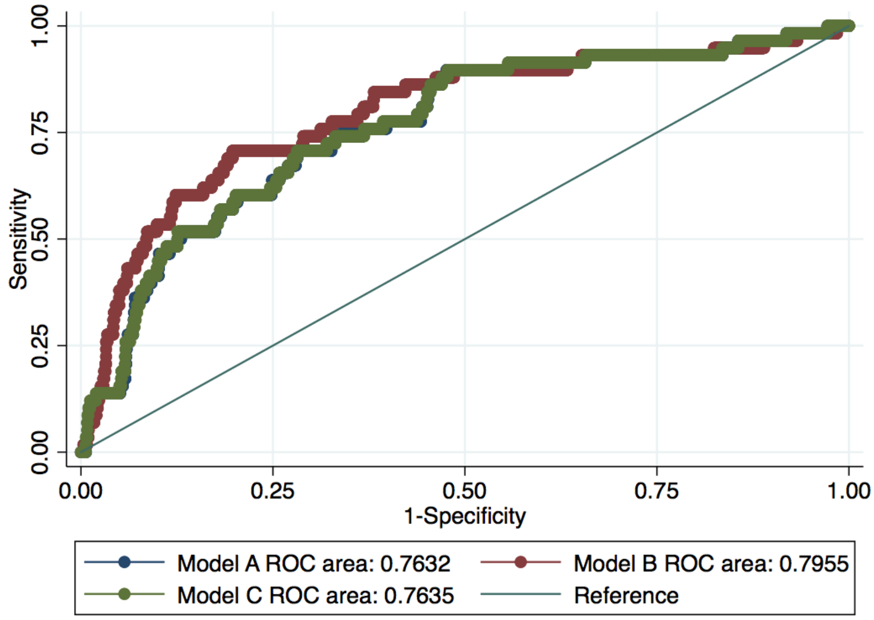
Variables	Model	AUC
Financial and CEO specific variables	Model A	76.32%
Financial variables	Model B	79.55%
Financial and CEO specific variables, excluding leverage	Model C	76.35%
Financial variables, US coefficients	Model 1	n.a.

The table summarizes the AUC for the respective Model A-C.

The closeness in the models' classification power is visualized in Diagram 1, as the ROC-curves track each other very well. Model A and Model C have almost identical AUC rates, with Model C having the highest, further indicating that the variable *Leverage* should not be included in the model. The ROC-analysis does not regard a specific or optimal cut-off value, but rather analyses the models' respective classification power against varying thresholds. Hence, the curve does not take into account that the models have different optimal cut-off values, nor does it take into account whether the aim is to increase specificity or sensitivity. The sensitivity-specificity trade-off is often industry or circumstance-specific and therefore it can be misleading to solely compare the models' AUC to draw final conclusions about the most fit model.

DIAGRAM 1

ROC-curve for Model A, B and C



The diagram shows the ROC-curve and AUC for the respective models for the out of sample. Model A and C share approximately the same AUC. Overall model performance is the highest for Model B.

Further examining hypothesis two, the ROC-analysis states that Model B is superior over Model C when all possible cut-off rates are examined. Therefore, the conclusion to be drawn regarding this hypothesis is less robust and needs to be interpreted with caution.

In order to analyse Model B in terms of average classification accuracy from a more holistic perspective, it is set in relation to Model SME1, which is developed by Altman, Sabato and Wilson (2008). Both models are built upon the same financial ratios, originally included in Altman and Sabato's logistic regression (2007). The main difference between the thesis' estimated Model B and Model SME1 is the coefficients used. The former model uses coefficients for Swedish non-listed SME data, while the latter uses coefficients for UK data. A comparison of the ROC-analysis is conducted on the model's respective out of sample. Model B yields an AUC of 76 % while Model SME1 yields a lower AUC of 67 %. Hence, the original logistic model (Altman and Sabato, 2007) with Swedish coefficients is better in terms of classification performance.

5.5.1 Discussion of classification measures

The results from the model validation tests are not necessarily contradicting. The classification test assesses a model's predictive power regarding a specific and predefined cut-off value, whereas the ROC and AUC analysis yield a classification performance using all possible cut-off rates. It is therefore concluded that the overall classification performance is not enhanced by the incorporation of the CEO specific variables when the performance is tested for all possible cut-off values. However, when applying low cut-off rates to at least reach the minimum acceptable sensitivity rate, Model C performs best in terms of percent correctly classified.

5.6 Examining the relative importance of including CEO characteristics

To address the third hypothesis, stating that including CEO specific variables in the accounting-based logit model is more important for smaller SMEs than larger, the dataset is split into two sets, based on firm size. The first dataset consists of the 25th percentile of smallest firms based on turnover, corresponding to a turnover up to maximum 35,918 KSEK. The second dataset consists of all firms with turnover greater than 35,918 KSEK. However, both groups lie within the definition of SME. Table 11 shows the results when using Model C for the two respective datasets.

TABLE 11

Results based on firm size, using Model C

	Bottom 25th percentile based on turnover	Top 75th percentile based on turnover
Likelihood ratio test	Significant model improvement when including CEO-variables	Significant model improvement when including CEO-variables
Sensitivity	68.42%	84.62%
Specificity	52.16%	62.08%
Correctly classified	52.50%	62.39%
AUC	72.54%	79.06%

This table shows the results of using Model C to firms of different sizes. The results are obtained after dividing the dataset in two parts. The first uses data regarding the bottom 25th percentile of firms based on turnover, while the second includes all firms above the 25th percentile.

In line with the second hypothesis, Model C is significantly improved by adding CEO-specific variables, both for smaller and larger SMEs. However, the results in Table 11 do not support the third hypothesis of CEO-specific variables being more important for smaller SMEs than for those relatively larger. On the contrary, the results show that the measures for sensitivity, specificity, percent correctly classified and area under the ROC-curve are all higher for the relatively larger firms than for the bottom 25th percentile of firms based on turnover. This indicates a higher overall model fit for firms that lie above the 25th percentile. However, these results should be viewed with caution, since splitting the out of sample results in few bankruptcies within each dataset, which could make the predictions distorted. Given the superior results for relatively larger SMEs, the third hypothesis is rejected.

6. Conclusions

This thesis yields answers to the applicability of the bankruptcy prediction model developed by Altman and Sabato (2007) and the importance of CEO characteristics. In regard to question one, this thesis examines how well the logistic bankruptcy prediction model performs when applied to the dataset of non-listed Swedish SMEs. Model 1, based on the same variables and coefficients as Altman and Sabato's original model, results in a 63.79 % sensitivity and 87.28 % correctly classified firms when using with a cut-off rate of 1.38 %. Given the high classification accuracy, the results are in line with the first hypothesis.

In regard to question two, this report examines whether the inclusion of CEO specific variables improve the classification accuracy for Swedish SMEs. The results show that including variables for *CEO age* and *gender*, when added both simultaneously and independently, improve the bankruptcy prediction model significantly. Model C including variables for *CEO age* and *gender*, but excluding the insignificant variable *Leverage*, yields 58.66 % correctly classified firms and a sensitivity of 77.59 % when using the cut-off rate of 1.38 %. Comparing this outcome to Model B, using solely financial variables, Model C experiences a lower sensitivity but a higher percent of correctly classified firms. When comparing the two models' area under the ROC-curve, Model B covers an area of 79.55 %, while Model C covers a slightly smaller area of 76.35 %. To draw a conclusion regarding which model performs the best, a decision of whether applying a predefined cut-off rate or varying cut-off rates needs to be made. Hence, the results are not contradicting. Rather, Model B is superior when measuring the classification accuracy against no specific threshold. However, in the context of this thesis, cut-off values above 2.5% are not considered relevant due to their low sensitivity rates. As Model C achieves a higher rate of correctly classified firms for all cut-off rates below 2.5%, the second hypothesis is accepted.

In regard to question three, the thesis test whether the inclusion of CEO specific variables is more important for smaller firms than larger. The third hypothesis, suggesting that this would be the case is rejected, as Model C performs better on all classification measures as well as the area under the ROC-curve on the dataset with larger SMEs.

6.1 Outlook for further research

The present thesis is of interest for passive investors and creditors when assessing the financial soundness of a non-listed company. However, the thesis is subject to a number of limitations, creating opportunities for follow-up studies. The two strongest limitations are discussed below.

Firstly, this thesis solely analyses firm-specific variables. It is important to acknowledge that firms do not operate in a vacuum and hence, are affected by external conditions related to the market and macroeconomic environment. Due to limitations in the data, such factors have not been incorporated in Model A – C. Variables controlling for political and economic uncertainty, such as booms and recessions as well as inflation, among others, would improve the models' respective accuracy rates.

Secondly, an extended analysis of CEO characteristics such as leadership style, industry experience and education would yield a more holistic picture of how the CEO contributes to firm survival. Due to lack of CEO data, these factors have not been included this report. However, a more holistic profile regarding the CEO behaviour is believed to contribute significantly to the models. This assumption is in line with findings from qualitative bankruptcy prediction studies. If data were available, financial statement data for failed and non-failed firms would also be analysed for the same years in order to avoid time-bias. However, this requires that past-CEO information is obtainable.

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