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The Value of Non-Financial Factors in Business Failure Prediction

- A Study of Swedish Small and Medium-Sized Enterprises

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Abstract

Access to financing is frequently listed as a top concern among Europe's small and medium-sized companies. Accounting for two-thirds of Europe's aggregated gross domestic product, their ability to finance new initiatives is going to have a large impact on the overall economic development within the region. Improved business failure prediction models could help mitigate frictions in the capital provision process. Up to this point, most researchers have primarily focused on developing prediction models based on accounting data or market prices. As a result, little is known about the impact non-financial information may have on classification results. Using financial information for a sample of 27 527 unlisted Swedish small and medium-sized firms, of which 3.3% failed during the period 2009-2010, we develop a conventional business failure prediction model. Adding qualitative factors to the prediction model is found to improve the classification results by up to 5.4 percentage points. In addition to already established non-financial measures, we find that qualified audit opinions and information regarding auditor changes can be quantified and used as metrics to improve the overall classification results.

Tutor: Katerina Hellström

Keywords: Business Failure Prediction, SMEs, Non-Financial Variables, Auditor

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1. Introduction

Small and medium-sized enterprises (SMEs) are of great importance for the economic development in most industrialized countries. Accounting for more than two-thirds of Europe's aggregated gross domestic product, their ability to finance growth and new innovations is likely to play a vital role in providing new employment opportunities in the region (EU Commission, 2011). Nevertheless, access to financing is frequently listed as a top concern among SMEs, a problem that seems to have been exacerbated by the recent financial crisis (ECB, 2011).

Improved business failure prediction models could potentially help mitigate some of these frictions, by enabling capital providers to make more informed investment decisions. Generally, bankruptcy prediction models have been developed using accounting information (Altman, 1968; Ohlson, 1980) or market prices (Merton, 1974). Because of characteristics specific for SMEs, it is not clear if these approaches are directly applicable for this segment (Keasey & Watson, 1987). Market prices are often not directly available and the accounting information may not be as reliable as for larger firms. Specifically, it has been argued that less extensive reporting requirements, as well as larger opportunities for manipulation, may impair the predictive ability of models based solely on accounting information (Keasey & Watson, 1987). As a result, the financial reporting might have to be complemented by other sources of information, capturing important elements that accounting-based financial ratios are missing (Peel et al., 1986; Keasey & Watson, 1987). Indeed, information regarding the timeliness of corporate reporting, company age, defaulted payments and industry riskiness has been found to improve the overall classification results of models developed specifically for SMEs (Altman et al., 2010). In the pursuit of reducing frictions in the lending to SMEs, further investigation of the usefulness of non-financial variables is warranted.

One dimension that has not been thoroughly investigated in previous research is the incremental explanatory value of information related to the auditor, as the results from empirical studies are inconclusive (Hopwood et al., 1989; Lennox, 1999). However, it has been suggested that the auditor's report and auditor changes could provide additional information on top of the financial reporting (Schwartz & Menon, 1985; Senteney et al., 2006). Specifically, companies experiencing financial difficulties may be inclined to apply aggressive accounting principles in order to hide the severity of the situation from external parties, giving rise to conflicts of interest with the auditors (Schwartz & Menon, 1985). Consequently, including information regarding auditor changes and qualified audit opinions, could potentially result in more accurate assessments of the credit risk; thereby reducing frictions in the lending process to SMEs.

Most prior researchers looking at qualitative factors have used British or American data (Lennox, 1999; Senteney et al., 2006). It is plausible that regulatory differences in different jurisdictions could affect the informational content of financial as well as the impact of non-financial factors. Consequently, it may be interesting to assess the incremental explanatory power of non-financial factors in predicting business failure for Swedish SMEs. Hence, using accounting data and non-financial information from 27 527 unlisted Swedish small and medium-sized firms, we provide empirical evidence on the following research questions:

> *Do non-financial measures add incremental explanatory power to a conventional bankruptcy model in the prediction of business failure for Swedish small and medium-sized companies?*

This is explored by adding non-financial variables to a conventional bankruptcy model primarily based on information from the companies' financial statements. In addition to already established non-financial factors, we include information regarding qualified audit opinions and auditor changes. The inclusion of non-financial factors is found to improve the average prediction results by up to 5.4 percentage points. Importantly, qualified audit opinions as well as auditor changes are found to improve the model's classification results.

Our contribution to the existing literature is twofold. First, we conduct a comprehensive evaluation of the incremental explanatory power of non-financial variables in business failure prediction for a geographically different sample than previous studies, including most Swedish SMEs. Secondly, the incremental signal value of qualified audit opinions and auditor changes are investigated, two variables that currently is not used by Swedish credit rating institutions (Patrik Schéele, 2011).

2. Review of Relevant Research Literature

In order to provide an overview of the development within the bankruptcy prediction literature, we have included a description of the two major streams of research: models based on accounting information and model using market prices. However, the primary focus is on research utilizing both financial and non-financial information.

2.1 Default Prediction Studies Utilizing Accounting Information

The first studies that used financial information to analyse bankruptcies were published in the 1930s and include FitzPatrick (1932) and Merwin (1942). The studies compared financial ratios for samples of failing and surviving companies, but did not use ratios to predict business failure. Instead, it was Beaver (1966) who was first to assess individual ratios' predictive abilities in classifying companies as failing or surviving. Using an univariate approach[1] and 30 financial ratios from six standard categories, he found that financial ratios could discriminate between failing and surviving firms for as much as five years before the event. Amongst the financial ratios studied, cash flow to total debt was identified as most important (Beaver, 1966).

Cognizant of the limitations of univiariate analysis, Altman (1968) employed multivariate discriminant analysis (MDA)[2], which makes it possible to analyse several financial ratios simultaneously. In his study, Altman (1968) identified 33 manufacturing firms that failed during 1946-1965 and matched them with surviving companies on a stratified random basis by using industry and asset size as selection variables. He compiled a list of 22 potentially helpful financial ratios based on popularity and relevance in prior research; of which 5 was selected to be included in the resulting Z-score model.[3] The model was able to classify 94% of the firms in the original sample accurately using a one year forecast horizon. However, the predictive ability decreased with the length of the forecast horizon and 36 percent of the firms were correctly classified five years prior to bankruptcy. Nevertheless, the Z-score

[1] Each individual ratio is evaluated in terms how well it alone can classify firms

[2] Multivariate Discriminant Analysis (MDA) had previously primarily been employed in behavioural and biological sciences. In its simplest form, MDA tries to derive a linear a combination of independent variables that best discriminates between a priori defined groups (Altman, 1968)

[3] The factors were: working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of equity to book value of liabilities and sales to total assets.

model's classification accuracy constituted a major improvement compared to Beaver (1966) and multivariate discriminant analysis became the dominant standard statistical technique for bankruptcy prediction.

Most of the studies conducted until this point had focused on large, publicly traded companies (Beaver, 1966; Altman, 1968). Edmister (1972), on the other hand, noted that bankruptcies were much more frequently occurring among small firms, and estimated a bankruptcy prediction model for that segment. In addition to using traditional one year ratios, he also included ratios reflecting developments over previous years and found that they could be helpful in predicting business failure in the sample. However, his largest contribution was that he illustrated that accounting information could be used to predict business failure for small firms.

Following Edmister (1972), the research field focused on developing more accurate prediction models using the MDA approach. Altman et al. (1977) provided a refined version of his original Z-score model. In contrast to its predecessor, the new ZETA model did not solely rely on reported accounting information. Rather, adjustments were made for off-balance-sheet debt and for intangible assets.[4] The design of the ZETA model remains proprietary, but the authors demonstrate that it generates significantly more accurate classifications than previous models. For example, the type I errors (classifying a failing firm as surviving) declined to 30 percent 5 years prior to bankruptcy compared to 64 percent for the Z-score model (Altman et al., 1977).

As noted by Altman & Loris (1976) and Foster (1986), MDA requires strict assumptions about the independent variables being multivariate normal and the covariance-variance matrices of the two samples being equivalent; conditions that are unlikely to be fulfilled. Hence, in the 1980s MDA began to be replaced by logit/probit techniques which do not require a normal distribution. Ohlson (1980) pioneered the use of logit analysis, whereas Zmijewski (1984) was first to apply a probit model.

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[4] Off-balance-sheet is primarily referring to operational leases. Intangible assets were adjusted by expensing capitalized items such as goodwill and interest costs.

Ohlson (1980) used a data set consisting of 105 bankrupt firms and 2 058 surviving firms, and based the analysis on 9 predictors used in previous research. In contrast to most preceding papers, he explicitly considered the fact that a company may file for bankruptcy after the fiscal year end, but before issuing the financial statements. Ignoring this fact will cause the predictors to be derived from data that was not available at the time of bankruptcy. Ohlson (1980) did not achieve the same high prediction accuracy as previous papers in the field, e.g. Altman (1968) and Altman et al. (1977). However, from a statistical perspective, logit analysis seemed to be preferable; and subsequent studies have found the prediction accuracy to be fairly similar between the two approaches (Lo, 1985).

Recently, models have been developed for privately held firms as well as for non-manufacturing companies. Altman (2000) made refinements to his Z-score and ZETA models in order to make them directly applicable for unlisted firms as well as for service companies. Specifically, market value of equity was replaced by book value of owners' equity, and the sales turnover ratio was omitted since the ratio was considered to vary too much between different industries. Moreover, rather than just changing the solvency and the sales turnover ratio, the entire models were re-estimated. With these changes, he was able to obtain classification results comparable to those of models designed for publicly traded companies.

The use of accounting information to predict business failure has received extensive criticism within the corporate finance literature. It has been argued that the models are reflecting past performance, and consequently, that they are unsuitable for predicting future developments (Foster, 1986; Agarwal & Taffler, 2007). Their usefulness could also be impaired by accounting principles such as historical cost accounting (Pinches, 1996) or due to manipulation (Agarwal & Taffler, 2007). Furthermore, financial statements are prepared on a going-concern basis, which may weaken their ability to predict business failure (Hillegeist et al., 2004).

2.2 Market Based Prediction Models

Models utilizing market information are able to overcome many of the drawbacks associated with financial ratios since they are based on investors' expectations about the future. Since the model's predictive abilities hinges upon efficient market prices, the assumption of rational investors becomes substantially more important. Market-based models are derived from Merton's (1974) and Black & Scholes' (1973) option/corporate bond valuation technique. The credit risk of a firm is assessed by viewing the firm's equity as a call option on its assets with a strike price equal to the face value of the company's debt. Default is assumed to occur when the value of the firm's liabilities have reached a predetermined level relative to the company's assets. Using expected returns and standard deviations it is possible to estimate the probability of default. The results from empiric evaluations of accounting and market-based models have been mixed. Hillegeist et al. (2004) found that market-based models marginally outperformed accounting-based ones, whereas Reisz & Perlich (2004) reached the opposite conclusion. Taking misclassification costs and loan pricing aspects into account, Agarwal & Taffler (2007) showed that accounting based models generated higher risk-adjusted profits.

Using the option/corporate bond valuation technique is associated with a number of complications. Importantly, the models are based on the assumptions that the firm only holds zero-coupon bonds and that the company's true asset values and their volatility can be measured (Agarwal & Taffler, 2008). Hence, despite the strong theoretical underpinnings, market based models do not appear to be superior to accounting-based ones.

2.3 Models Using Non-Financial Variables

For small firms, models based solely on market prices or accounting information may not be appropriate (Keasey & Watson, 1987). Market prices are naturally not readily available and the accounting information may not always be reliable (ibid.). A growing body of research have demonstrated that non-financial factors may prove useful in business failure prediction for SMEs (Keasey & Watson, 1987; Blanco et al., 2010; Altman et al., 2010). Keasey & Watson (1987) investigated if non-financial information could be used to predict business failure, either on a stand-alone basis or in conjuncture with financial information. Using a sample consisting of 73 failed and 73 surviving British firms during 1970 to 1983, they found that including non-financial measures provides a marginal improvement in the overall classification results. However, the signs of some coefficients were surprising. For example, companies were seen as less risky the longer they delayed filing their accounts after they had been signed by the auditor.

More recently, Blanco et al. (2010) developed a business failure prediction model specifically designed for SMEs in the U.K. Using a data set consisting of 39 000 unlisted companies of which 19 500 failed during 1999 to 2008, they found that including non-financial information improved their model's predictive abilities by up to 4.5 percentage points. Variables reflecting legal actions by creditors to recover unpaid debts, the timeliness of corporate filing and company age were all contributing to better prediction results. Altman et al. (2010) conducted a similar study, using a sample of six million British SMEs during the period 2000 to 2007. They included a wide range of non-financial variables reflecting various company characteristics and operational risks. Examples of variables included are: financial reporting compliance, industry riskiness, delayed payments and company age. As were the case in Blanco et al. (2010), introducing non-financial variables improved the conventional model's prediction accuracy.

Furthermore, a number of studies have also been undertaken to evaluate the importance of specific non-financial factors (Peel et al., 1986; Chen & Church, 1992; Whittred & Zimmer, 1984). Whittred & Zimmer (1984) investigated if the timeliness of financial reporting could be used as an explanatory variable in a bankruptcy prediction model, but did not observe any improvements. Peel et al. (1986), on the other hand, conducted a similar study and found that a variable reflecting time lags in financial reporting contributed significantly to the classification accuracy.

The signal value of qualified audit opinions has also been examined. Sundgren (1998) used a sample of 188 bankrupt and 304 non-bankrupt Finnish small and medium-sized firms and demonstrated that qualified audit reports were more common among companies that were unprofitable, highly leverage and failing. Similarly, Gaeremynck & Willekens (2003) studied the relationship between qualified audit opinions and business termination for a sample of 114 surviving and 114 liquidated Belgian companies. According to the study, liquidated companies were more than 7 times as likely to have received a qualified audit report as surviving firms. Thus, they conclude that qualified audit reports are likely to be issued for companies in financial distress.

In an empirical investigation of the usefulness of qualified audit opinions, Hopwood et al. (1989) estimated a prediction model including 6 accounting ratios reflecting profitability, cash flows and leverage. Adding dummy variables for consistency exceptions and going-concern qualifications improved the model's classification accuracy. However, important explanatory variables such as company size and industry belonging were omitted for the original model, possibly invalidating their results. Similarly, Chen & Church (1992) found that including going-concern qualifications for sample of 127 companies during 1983 to 1986 improved the explanatory power of a prediction model exclusively based on accounting information. In a comparable study, Lennox (1999) chose to control for size, industry sector and the economic cycle. In contrast to Hopwood et al. (1998) and Chen & Church (1992), he found that including audit opinions in a prediction model did not add any incremental explanatory value. Lennox (1999) argued that the auditor's report was not reflecting all publicly available information. Importantly, the fact that the probability of bankruptcy varied between industries and over the business cycle was not taken into account. Moreover, auditors were found to be reluctant to provide first-time qualifications or change the status for companies once they had received a qualified report.

Having reviewed the major research streams within the field, we see that there are drawbacks with using accounting-based as well as market-based models. For privately owned SMEs, using market-based models is not a viable option since no such prices exist. Consequently, accounting information has commonly been used in studies of small, unlisted firms. The prediction results have not been as good as for larger companies and it has been suggested that less demanding financial reporting requirements and potential manipulation may be contributing factors (Keasey & Watson, 1987). As a result of the supposedly less useful financial reporting information, qualitative factors are likely to become more important.

3. Framework for The Study

In order to design a business failure prediction model using accounting as well as non-financial information three major issues have to be decided upon: (1) the definition of business failure, (2) choice of explanatory variables and (3) which statistical method to use.

3.1 The Definition of Business Failure

In previous research, failure has often been defined as filing for bankruptcy, or alternatively, as entering into liquidation, receivership or administration (Altman et al., 2010). The availability of data, rather than economic theory, seems to have been the decisive factor. Few researchers have provided an extensive discussion of how business failure ought to be defined. One exception is Altman & Hotchkiss (2006) who states that:

> *"Failure, by economic criteria, represents the situation where the realized rate of return on invested capital, with allowances for risk considerations is significantly and continually lower than prevailing rates on similar investments."*

Failure is referring to a situation when a company consistently generates a return lower than its cost of capital. In principle, a firm could survive for years while realizing returns significantly below the prevailing rates on similar investments and it may not necessarily result in losses for creditors. Predicting such situations is likely to be of limited use to lenders and investors. The timing of failures would be arbitrary and the actual implications somewhat unclear since it would be hard to make a meaningful distinction between surviving and failing entities. For practical reasons, and to meet the users' needs, business failure should refer to events where the firm is unable to meet its maturing obligations. Altman (1971) discusses this in terms of "*technical insolvency"* and *"insolvency in a bankruptcy sense"*. Companies that are experiencing technical insolvency are suffering from temporary cash flow problems, but have promising long-term prospects. Insolvency in a bankruptcy sense, on the other hand, is referring to a situation where future profits are unlikely. Assuming efficient capital markets, technical insolvency should not be very interesting to forecast (Skogsvik, 1987). Business failure should instead be referring to a situation where the company's survival is in jeopardy. Companies with high future profitability will have no problems receiving additional financing in a market with reasonably rational investors and low or no transaction costs. Consequently, under efficient capital markets, business failure could be limited to situations reflecting insolvency in a bankruptcy sense. If, on the other hand, information is very costly to obtain, making it hard to receive new financing, technical insolvency should also be included.

Arguably, all companies that are insolvent in a bankruptcy sense should be classified as failures, regardless of whether or not the markets can be assumed to be efficient. This includes firms that have reached voluntary composition agreements or filed for bankruptcy/business reorganization since they have been unable to receive additional financing through equity issues or by taking on new loans. Voluntary composition agreements are private settlements and are therefore not registered in legal records of failing firms. Hence, we have not been able to include them in the study. Since composition agreements usually are reached after a bankruptcy process has been initiated, their omission should not pose any major problem.

Companies that are insolvent in a technical sense are harder to classify. There are two forms of potential insolvencies that could be included: companies that have received shareholders contributions and firms that have consumed more than half of their share capital without being liquidated as the mandatory liquidation regulation usually would require.[5] In the latter form, the firms are able to continue their operations through personal guarantees from the owners/managers. The fact that the owners have to take over the firm's liabilities could be seen as a business failure per se, since the firm is unable to meet its obligations as they mature. On the other hand, the creditors may not necessarily make any credit losses and the firm could potentially survive. We decided to include companies that have consumed their share capital since the firm by itself is unable to meet its maturing obligations.

Companies that have received additional shareholders' contributions, on the other hand, have not been included. Such firms may receive financing for numerous reasons, not all of them related to poor financial performance. For example, firms may receive additional shareholders' contributions in order to be able to expand. We

[5] 25 Ch. 13-20§§, Swedish Companies Act (2005:551)

have assumed that the capital is provided on commercial terms and that the investors are expecting to obtain a reasonable return on their investments. Moreover, liquidation is not seen as business failure, since a firm may be liquidated for various reasons. Consequently, our definition of business failure includes:

1. *Bankruptcy*
2. *Business reorganization*
3. *Consumption of more than half of a firm's share capital*

3.2 Choice of Explanatory Variables

There are two approaches available for selecting accounting ratios. The first one is to let the numbers speak for themselves, i.e. selecting ratios from previous research and use the ones that maximize the model's predictive abilities within the sample. If such an approach is applied, no conclusions can be drawn about as to why business failures occur and the prediction results are likely to be lower if the model is used out of sample. The second option is to select ratios based on some underlying theory of the bankruptcy process. Naturally, building a model based on theory requires one to make several simplifying assumptions, and it is not obvious that it will generate a more robust predictive model. Since there is no widely accepted comprehensive economic theory and our aim is to assess the additional prediction power of the non-financial information, we have decided to follow the first approach and select financial ratios from prior research, which has proven to influence the likelihood of business failure.

In prior research, financial ratios have usually been selected from a number of standard categories that is expected to represent important aspects of the firm's financial position and competitiveness (Altman & Sabato, 2007). Ratios from different categories will reflect more relevant and potentially unique information, thereby improving classification result and mitigating correlation problems. Ohlson (1980) found that ratios reflecting profitability, leverage, size and liquidity could be used in designing business failure prediction models. Other researchers have included additional dimensions such as activity, coverage and cost structure ratios (Altman & Sabato, 2007; Skogsvik, 1987). In order to capture all relevant aspects and construct a model in line with prior research, one should preferably select at least one ratio from each of the aforementioned categories.

Non-financial Variables

Our selection of non-financial ratios is also based on prior research. Using data of small British companies, Altman et al. (2010) illustrated that variables reflecting company age, defaulted payments, timeliness of reporting and industry weighted risks improved the overall prediction accuracy of a conventional business failure prediction model. To our knowledge, no comparable study has been conducted on SMEs in Sweden. Since, differences in regulatory systems in different countries could affect the informational content of both financial and non-financial variables; we found it interesting to test similar variables also on Swedish data. These differences may be even more important for privately held SMEs than listed companies, since their financial statements are not prepared under any international standard.

As mentioned in the introduction, several researchers have noted that audit related information could be used to prediction business failure (Hopwood et al., 1989; Lennox, 1999; Senteney et al., 2006). As far as auditor changes are concerned, there have been empirical studies indicating that failing firms have a higher propensity to change auditors than financially stable ones (Schwartz & Menon, 1985; Chow & Rice, 1982). Although we cannot be certain as to why this is occurring, a number of potential explanations have been provided in the literature. A frequently raised theory is that auditors favour conservative accounting principles in order to avoid unnecessary legal problems that could arise if revenues or assets are overestimated and the company fails. This is in line with Pierre & Anderson (1984) who showed that litigations are frequently occurring following income overstatements but virtually non-existing after equivalent understatements. A company receiving a qualified opinion could be excluded from credit markets; thereby aggravating an already challenging situation. Realizing that this adverse development potentially could be avoided if a more aggressive application of accounting principles were applied, management is likely to argue for such an approach. These conflicts may not always be easily resolved and could cause the company to change audit firm (Schwartz & Menon, 1985).

Another viable explanation to why distressed companies are more prone to change auditors than other firms could be that the auditor has failed to detect internal control weaknesses and therefore are deemed to be unsuitable (Senteney et al., 2006). Such disputes may not be reflected in the company's financial statements, but could potentially serve as a helpful discriminating device when it comes to classify firms as survivors or potential bankrupts. We are not claiming that all firms that change auditors are facing financial difficulties. Such decisions can be made for various reasons, natural attritions or costs being the obvious examples. It is possible; however, that auditor changes or auditor tenure during the preceding year could add discriminatory power to prediction models.

It is not only the changes of auditors that could prove useful in business failure prediction. Qualified audit opinions could possibly be seen as early warning signs of impending corporate failure (Altman & McGough, 1974; Connor, 1986). Argenti (1976) argues that financial reporting information is likely to become less reliable as a firm's financial problems intensify. Specifically, a firm's management team may utilize creative accounting principles in order to keep external parties uninformed of the severity of the situation (Keasey & Watson, 1987). Ceteris paribus, such firms are more likely to receive qualified audit opinions. In addition, deficiencies in the company's internal control system could also cause the financial accounts to be unreliable, resulting in less useful accounting information.

A number of empirical studies have been conducted to examine the usefulness of qualified audit opinions, beginning with Altman & McGough (1974) who first identified the link. However, most studies have focused on a few audit opinions such at going concern qualifications and consistency exceptions (Hopwood et al., 1989; Chen & Church, 1992). Since the usefulness of various qualified audit opinions have not been thoroughly established (Hopwood et al., 1989; Lenox, 1999), and the regulatory environment is likely to differ between countries, the incremental explanatory power of the auditor's report was considered especially interesting to investigate. The operationalization of all aforementioned financial and non-financial variables will be presented in section 5.

3.3 Statistical Method

In order to be able to estimate the relation between our selected financial/non-financial variables and business failure, a multivariate statistical technique has to be used. There are two dominant approaches in the bankruptcy prediction literature: multiple discriminant analysis and logit/probit models.[6] As mentioned in previous research, multiple discriminant analysis assumes that the independent variables are multivariate normal and the covariance-variance matrices of the two samples are equivalent; assumptions that highly unlikely to be fulfilled (Altman & Loris, 1976; Foster, 1986). [7] Moreover, multiple discriminant analysis does not directly provide for the assessments of failure probabilities (Skogsvik, 2005). Hence, from a statistical perspective logit/probit analysis should be preferred. According to Long et al. (1997), the choice between logit and probit is largely one of convenience.[8] Considering that logit is more commonly used in the literature, we have chosen to use that technique.[9]

In a logit regression, the dependent variable is modelled as the natural logarithm of the odds of business failure.[10] Hence, the "log odds" of business failure is modelled instead of whether or not a company belongs to a specific category.[11] The dependent variable is assumed to be related to a function of independent variables x_{i1}, x_{i2},….,x_{in} and a random variable e_i in the following way:

$$y_i = \mathrm{Log}(\frac{p}{1-p}) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_n x_{in} + e_i$$

where:

y is the log odds of the event

p is the probability of business failure

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[6] Linear regression models are not suitable since the estimated probabilities have to be restricted to a range between 0% and 100%.

[7] In its simplest form, MDA tries to derive a linear a combination that best discriminates between a priori defined groups (Altman, 1968). Thus, the coefficients are estimated in a way such that the obtained values for all surviving firms are fairly homogenous, whereas the difference between the two samples is maximized.

[8] The principal difference between logit and probit is that logit assumes a logistic distribution instead of a cumulative distribution function of the standard distribution. The probit distribution also has slightly fatter-tails, meaning that probability of an observation deviating significantly from the mean value is assumed to be smaller.

[9] Probit models can be found in Zmijewski (1984) and Skogsvik (1987).

[10] Odds = probability of business failure/(1- probability of business failure)

[11] Transforming the dependent variable into the natural logarithm is considered to simplify the modelling, since it allows the dependent variable to take on all values from negative infinity to positive infinity, i.e. making it continuous (Aziz & Dar, 2004).

p/(1-p) is the odds ratio

X_1, X_n are predictors, β_0 a constant*, β_1 coefficients and e_i an error term*

The predictors' coefficients are estimated with the maximum likelihood method. It seeks to maximize the log likelihood function L (β), which represents the probability of observing the particular set of independent variables that occur in the sample according to our model:

$$\max_{\beta} L\,(\beta)$$

where

$$L\,(\beta) \;=\; \sum_{i \in b_1} \log P\,(X_i |\, \beta) + \sum_{i \in S_2} \log[1 - P(X_i|\beta)]$$

and:

b_1 is an index of firms experience business failure

s_2 is an index of surviving firms

β is a vector of unknown variables

The estimation is done by trying to push up the probability of financial distress for bankrupt firms and lower the probability for surviving firms, thereby increasing the likelihood for observing the particular set of independent variables. Each individual company is consequently assigned a probability of business failure calculated as:

$$P = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_{i1} + \,\beta_2 x_{i2} + \cdots + \,\beta_n x_{in})}}$$

By selecting a threshold value, e.g. a probability of failure exceeding 5 percent, companies can be classified into different categories. Firms with a likelihood of failing that exceeds five percent will be predicted as potential failures, whereas companies with lower estimated probabilities are anticipated to survive. If 100 percent would be selected as a threshold value, all firms would be classified as surviving, whereas no firm would be expected to survive if 0 percent was chosen.

An issue that is often overlooked in the literature is the occurrence of a choice-based sample bias. Many researchers have chosen to use non-random samples of companies when estimating their logit models. If a matched-pair design is employed, the proportion of failing companies will amount to 50 percent. Using such a model on a population with different proportions of failed companies will cause the estimated probabilities to be incorrect (Skogsvik, 2005). Thus, if he model is used on a population with a different proportion of failed companies, it is necessary to adjust the estimated probabilities.[12]

A second statistical issue that needs to be addressed is the occurrence of type I and type II errors. In its normal course of business, a bank can lose money by lending to firm that become insolvent and therefore fails to pay its loans back as they mature. However, a bank may also forego profitable business opportunities by being too conservative in its lending. The bank has made a mistake in both situations. However, the costs of these mistakes are likely to be very different. Having lent money to a failed company usually means that a sizeable part of the investment has been lost. Foregoing a business opportunity can, depending on the competitive situation in the market, result in an economic loss that is anything from zero to a substantial amount. Still, under normal business conditions, it should be assumed to be lower than lending money to a firm that ultimately fails. In the research, these mistakes are commonly known as type I and type II errors, defined as:

- Type I errors refers to the misclassification of a failing firm as surviving.
- Type II error refers to the misclassification of a surviving firm as bankrupt.

To classify a bankrupt firm as surviving, a type I error, has been estimated to be 35 times as costly as a type II error (Altman et al., 1977). Naturally, such estimates are fairly uncertain since they are based on the assessment of the value of missed business opportunities. Due to the high uncertainty of the relative cost of type I and type II errors, it is hard to evaluate the efficiency of a prediction model. Some researchers, but by no mean all, aim to minimize the average prediction error.

- Average prediction error = [Type I errors/Number of failed firms + Type II errors/Number of surviving firms]/2

[12] See Skogsvik (2005) for a more thorough discussion of how the adjustments should be done.

If the classifications were to be made randomly, an average prediction error of 50 per cent would be expected. Thus models that generate prediction errors lower than 50 per cent could potentially be helpful for prediction purposes. Still, it is important to recognize that the asymmetric costs between type I and type II errors means that a lower average prediction error is not necessarily better. A rudimentary strategy such as minimizing the total number of classification errors is therefore not likely to be an optimal. Instead, users should take the relative costs of type I and type II errors as well as the proportion of failing companies in the population into consideration. Since a logit approach is applied and a probability of business failure is estimated for each observation, this can be done through selecting different threshold values reflecting the user's specific needs.

Having selected a multivariate regression technique and discussed potential problems with applying the model, a description of the design of the study is provided in the following section.

4. Design of the Study

This section will outline the general description of the tests that are going to be conducted as well as how the results are going to be evaluated. This is followed by a specification of the forecast horizon that is going to be used.

4.1 Measurement of Non-Financial Variables Additional Impact

Using a logit regression technique, two models are developed in order to examine whether non-financial variables may add incremental explanatory power to a conventional business failure prediction model. The *conventional model* is estimated by applying accounting-based variables from prior research. The second model, referred to as the *full model*, is derived using the same accounting-based variables as in the first model, while also including a number of non-financial variables. Both models are estimated using 80% of all observations in the data set, whereas the remaining observations are used as a hold-out sample for evaluation purposes. In addition to constructing the aforementioned two models, we are also going to conduct a sensitivity analysis to examine the incremental explanatory value of qualified audit opinions and auditor changes. This is done by adding the two variables to the conventional model on a stand-alone basis as well as by eliminating them from the full model.

The assessment of the signal value of non-financial information will be based on two criteria. First, the non-financial variables may add incremental explanatory power to conventional business failure prediction models if they are statistically significant at a five percent level and have coefficients that differ from zero. Second, the non-financial variables will be seen as important if including them improves the overall prediction results. This will be assessed by changing the threshold values used to classify firms as failing or surviving since users are likely to have different preferences regarding the trade-off between type I and type II errors.

4.2 Forecast Horizon

The prediction models that are employed by banks and credit rating institutions are usually based on a 12 month forecast horizon (Patrik Schéele, 2011). Since we are interested in establishing whether or not non-financial variables may add explanatory power to existing models, we have decided to make predictions for the following 12 months. A longer forecasting horizon would eliminate the possibility to use financial information from the most recent years, as the prediction outcomes are yet to be realized. As illustrated in Figure 1, we use data for two years. Financial statements for the financial years 2008 and 2009 are used to predict business failure for the financial years 2009 and 2010.

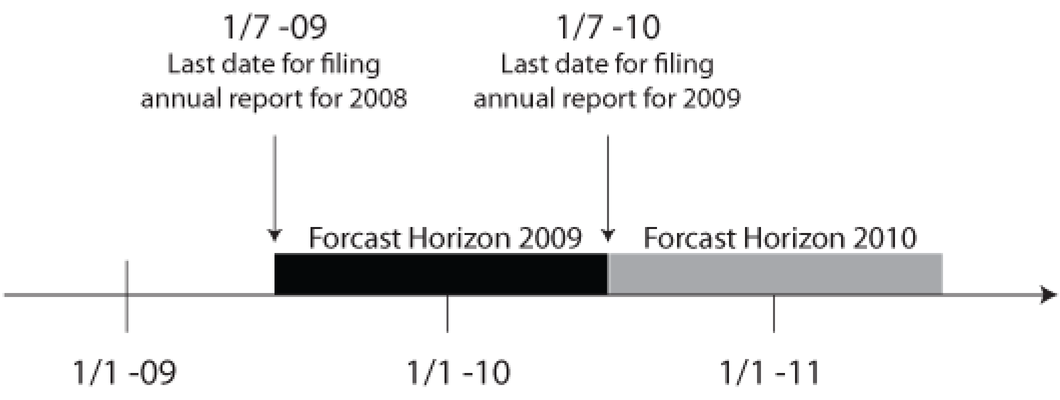

Figure 1: Timeline

We have only utilized financial statements that were available at the prediction point in time. Thus, if a firm failed in 2009, but before publishing their financial statements for the preceding year (2008), we used the annual reports for 2007. As a result, the average lead time for failing firms between publishing their annual reports and failing exceed the forecast horizon and amounts to 21 months. The results are in line with those of Watson & Keasey (1987), who reported an average lead time of 26 months for failed companies in their study of small British firms. The long lead times do not have to constitute any major problem when it comes to assessing the usefulness of prediction models, considering that more recent accounting information would not have been available for external parties dealing with the firm.

As pointed out by Ohlson (1980), financial statements must be publicly available at the prediction point in time if the results are to be dependable. A common practice in the literature has been to assume that they are available in the beginning of the year or after three months (Altman, 1968; Altman et al., 2010). For failing companies this may not always be the case, as the auditing process is likely to be particularly demanding and time-consuming for such firms (Ohlson, 1980). Preferably, one would have liked to use the actual filing days. However, the only annual reports that we have information regarding the filing days for are those that were delayed. Consequently, we have assumed that all reports that were filed in time became available 6 months after the financial year ended.[13] One could perhaps argue that external capital providers such as banks and investors are likely to be able to demand access to financial information before it is revealed to the authorities, considering that private companies do not have to comply with insider information legislation. However, since we also want to include qualified audit opinions and we do not know when the information actually became available, using earlier dates was not seen as appropriate.

5. The Data Set

We have decided to restrict our study to limited liability companies in order to capture entities that are commercial in nature. The data is primarily covering the financial years 2008 and 2009 and was retrieved by using BusinessCheck's database as well as

[13] Six months is the longest time a company can delay their reporting without being late.

by requesting industry classifications from SCB.[14] If the annual report for a failed firm did not exist at the prediction point in time, we have used the report for the previous year. Furthermore, the European Commission's definition of small and medium-sized companies has been used instead of the Swedish one, in order to make the results more comparable to international studies.[15] Companies must have revenues exceeding 20 million SEK as well as more than 10 employees to be included in the sample. Smaller companies are likely to have key ratios that are extremely volatile, making it necessary to develop prediction models specifically for them. Moreover, the credit-worthiness of such firms is probably best assessed by looking at the manager's personal finances rather than on those of the company. The restriction is also ensuring that the companies included are both active and commercial. In addition, firms with more than 250 employees and revenues exceeding 500 million SEK are not included in the sample. Very large companies are fundamentally different from SMEs and should preferable have business failure prediction models designed specifically for them.

In line with Ohlson (1980) we have chosen to exclude firms active in financial services, insurance and real estate. Companies in these industries are likely to have leverage and profitability ratios that deviate substantially from other firms, and may, as evidenced by the recent financial crisis, be subject to different bankruptcy environments. Private companies operating within natural monopolies such as electricity distribution have been excluded for the same reasons. Moreover, municipal and state owned companies are not included in the sample since they are assumed to operate in business environments that are fundamentally different from commercial firms. This incorporates most firms operating within: public administration/defence; electricity, gas and heating and water treatment/waste management; and some of the firms within industries such as education, care, and culture. While it is certainly possible for municipalities to fail, it is deemed to be highly unlikely.[16]

[14] All information used in the study is publicly available, but was retrieved through the credit rating institute BusinessCheck. However, some of the SNI-codes for failing companies were missing from the database and was instead collected from Statistiska Centralbyrån (SCB).
[15] The European Commission defines SMEs as firms with 10 to 250 employees and revenues between 2 to 50 million Euros.
[16] See all included Industry Codes (SNI 2007) in Appendix 2.

We have decided to include both subsidiaries and stand-alone firms in line with previous studies (Altman et al., 2010; Blanco et al., 2010). Since subsidiaries are likely to have access to internal capital markets, and thus be able to raise new funds with low transaction costs, they are not exposed to the same business failure environment as stand-alone firms. Hence, it could perhaps be argued that they should have been excluded. Nonetheless, they have been included for two reasons. First, the parent companies do not have to save their subsidiaries from failure and the group's financial position is therefore not the only aspect that matters. Secondly, credit rating agencies as well as banks have to assess the credit risk of both stand-alone and group companies; considering that not all groups provide guarantees for their subsidiaries.

5.1 Descriptive Statistics

The data consists of Swedish 27 527 privately held companies and 50 546 observations, constituting a vast majority of all Swedish SMEs. We have 1 657 observations that are classified as business failures; representing a failure quota of 3.3%. Business failures associated with the financial years 2009 and 2010 are presented in Table 1.

Business failure	2010	2009	Total number	Of total
Bankruptcy	389	567	956	60.5%
Reorganization	53	47	100	6.3 %
Consumed share capital	292	309	601	33.1%
	734	**923**	**1 657**	**100 %**

Table 1. Portrayal of the number of business failures for each year.

Most of the firms that have been classified as business failures have filed for bankruptcy, representing almost 61% of all observations in the sample. The number of bankruptcies is considerably higher for 2009 compared to 2010; a pattern that can be seen for the entire population of limited liability companies in Sweden, even if it is slightly less distinct.[17] The number of companies that have consumed more than half of their share capital is relatively stable over both years, and represents approximately 33% of all observations. Business reorganizations, on the other hand, are relatively rare and amounts to 6.3% of the total number of failing observations. In addition to the distribution of various types of business failures for individual years, it is also

[17] Approximately 2.7 % of all limited companies filed for bankruptcy during 2010 compared to 3.1 % for 2009 (Tillväxtanalys, 2010).

interesting to review if failed companies have dissimilar characteristics in comparison to surviving firms. Considering that company size has proved to be statistically significant in several previous studies (Altman, 1968; Ohlson, 1980), it may be useful to look at the distribution of failing and surviving companies in terms of number of employees. This is presented in Table 2.

Employees	Survivors	Of total	Failures	Of total
10 < X < 20	22 386	45.8 %	873	52.7 %
20 < X < 50	18 547	37.9 %	582	35.1 %
50 < X < 100	5 259	10.8 %	138	8.3 %
100 < X < 250	2 286	4.7 %	53	3.2 %
250 < X	411	0.8 %	11	0.7 %
	48 889	**100 %**	**1 657**	**100 %**

Table 2. Distribution of failing and surviving companies based on employees.

The failing firms seem to have slightly fewer employees than the surviving ones. Approximately 52.7% of the failing sample falls within the smallest size class compared to 45.8% for the companies that survive. The relation is reversed for firms with 20 to 50 workers as a slightly higher percentage of the surviving observations belong to this group. A second noteworthy observation is that the majority of the firms in both samples employ fewer than 50 people, whereas only 422 observations have more than 250 employees. In conclusion, both samples seem to be fairly evenly distributed, with failing companies being marginally smaller. The tendency of failing firms to be smaller is even more distinct in relation to revenue. As can be seen in Table 3, approximately 81% of the failing firms have revenues below 50 million SEK compared to 64.2% for the surviving companies. Moreover, relatively few failing companies have revenues exceeding 250 million SEK, merely constituting approximately 1.9% of the sample.

Revenue (million SEK)	Survivors	Of total	Failures	Of total
X < 50	31 374	64.2%	1 342	81.0%
50 < X < 100	8 817	18.0%	192	11.6%
100 < X < 250	6 253	12.8%	92	5.6%
250 < X < 500	2 445	5.0%	31	1.9%
	48 889	**100%**	**1 657**	**100%**

Table 3. . Distribution of failing and surviving companies based on revenue

As previously mentioned, we have chosen to include both stand-alone and group companies in the study. The distribution between surviving and failing companies categorized according to group relation is presented in Table 4.

Group Relation	Survivors	Of total	Failures	Of total	For all
Stand-alone firms	16 301	33.3%	1 246	75.2%	34.7%
Parents	5 331	10.9%	69	4.2%	10.7%
Subsidiaries	27 257	65.8%	342	20.6%	54.6%
	48 889	**100%**	**1 657**	**100%**	**100%**

Table 4. Distribution of companies according to group relation.

Almost 55% of the observations are subsidiaries in groups, whereas 35% are stand-alone firms and 11% parent companies. Representing 75% of all business failures, stand-alone firms have a substantially higher failure rate than companies belonging to a group. This is in line with the findings of Becchetti & Sierra (2003) who asserted that group companies have a considerably lower tendency to fail than stand-alone firms. By having access to internal capital markets, they are often able to survive in situations where a stand-alone firm would not. Indeed, some groups may also have policies against allowing a subsidiary to default, thereby significantly lowering the risk of failure. Finally, it may be interesting to view the distribution of surviving and failing firms categorized after industry type. This is presented in Table 5 and as seen there are no discernible differences in failure rates for companies in the service industry compared to firms operating in manufacturing. However, manufacturing firms tends to have slightly higher propensity to fail.

Company Type	Failed Sample	Of total	Survivors	Of total
Service	1 260	76,0%	37 871	77,5%
Manufacturing	397	24,0%	11 018	22,5%
	1 657	**100%**	**48 889**	**100%**

Table 5: *Industry belonging of failed and surviving companies.*

6. Explanatory Variables

In this section we will present the operationalizations of the financial and non-financial variables previously identified. This will be complemented by an empirical description of the variables for surviving as well as for failing firms.

6.1 Operationalization of Ratios for the Conventional Model

As mentioned in section 3.2, we have not tried to formulate any theory as to why business failure occurs. Rather financial ratios have been selected based on popularity and performance in prior empirical research. In order to capture all relevant elements of the business operations, we have decided to classify the financial variables into a number of standard categories. These include profitability, leverage, liquidity, coverage, cost structure and activity ratios (Altman, 1968; Ohlson, 1980; Skogsvik, 1987). Our strategy has been to select one relevant financial ratio from each category in order to capture unique information carried by each dimension. The starting point has been to choose ratios from Skogsvik (1987), who thoroughly investigated a vast number of financial ratios in relation to Swedish companies. In the cases where Skogsvik (1987) did not have any ratios for the specific category, we selected ratios used in Altman & Sabato's (2007) study of American SMEs.[18] In total, we have selected seven financial ratios as the basis for our conventional model. These are presented in Table 6.[19] No attempt has been made to create any "new" financial ratios since so much previous effort has been directed towards this purpose.

Profitability	**Leverage**	**Liquidity**	**Coverage**	**Cost structure**	**Activity**	**Size**
EBIT / Total assets	Total liabilities / Total assets	Cash / Total assets	Interest expense/ EBITDA	Interest expense / Total Liabilities	Inventory/ Revenues	Ln (Total Assets)

Table 6. Financial ratios selected to be included in the conventional model.

- **EBITTA** = *Earnings before taxes and interest expenses divided by closing balance of total assets*. The ratio is a measure of the true productivity of a firm's assets, without being impacted by tax or leverage factors and has previously been used in Skogsvik (1987). A firm's existence is based on the

[18] Skogsvik (1987) used growth in owners' equity to the opening balance of owners' equity as an explanatory variable. We have not included the variable since it would require data for several years.

[19] All balance sheet items are from the closing balance since we did not have access to financial data for prior years. Consequently, the definition of EBIT/Total assets, Interest expense/Total Liabilities and Inventory/Revenues differ somewhat from the ones used in Skogsvik (1987) where the average of opening and closing balanced was used. Deferred taxes have been included in Interest expense/Total Liabilities. The estimation was made by multiplying the tax rate with untaxed reserves. We decided to use Interest expense to EBITDA instead of EBITDA/Interest expense in order to be able to include firms without interest expenses.

earning power of its assets, and likewise, on its ability to generate a profit on the goods sold or services provided. Hence, the measures should be able to discriminate between financially strong and financially weak companies.

- **TLTA** = *Closing balance of total liabilities divided by closing balance of total assets*. Leverage ratio reflecting the financial risk of a firm and was employed in Skogsvik (1987). A company with low leverage can withstand more severe setbacks before it becomes insolvent than a highly leveraged one and is therefore less likely to fail. One potential disadvantage with the measure, particularly if one uses a sample including subsidiaries, is that the holding companies may make active decisions to use high gearing in their subsidiaries. Still, since the ratio proved important in Skogsvik (1987) as well as Ohlson (1980) we have decided to include it.
- **IE/TL** Liabilities = *Interest expense divided by total liabilities.* The ratio reflects how much compensation a company's creditors are demanding in exchange for lending to the firm. A risky firm is expected to be required to pay higher interest rates. The ratio has previously been used in Skogsvik (1987) and has therefore been included.
- **IE/EBITDA** = *Interest expenses divided by earnings before taxes, depreciation and interest expenses.* This measure is reflecting how much a company's earnings can drop before the firm is unable to meet its interest expenses. The ratio has previously been used in Altman & Sabato (2007).
- **InvRev** = *Closing balance of inventory divided by revenues*. The ratio was used in Skogsvik (1987) and has therefore been included. It is possible, however, that it is more useful for firms that are active in manufacturing, since service companies tend to have low or no inventory.
- **CashTA** = *Closing balance of cash divided by closing balance of total assets.* Firms experiencing operating losses are likely to be drained of cash. Hence, it is possible that the variable could be used to discriminate between surviving and failing firms. The ratio was used in Altman & Sabato (2007).
- **LN(TA)** = *The natural logarithm of the closing balance of total assets*. As demonstrated by Ohlson (1980), size is an important variable in estimating the probability of bankruptcy. Thus a factor reflecting the size of the business is likely to be able to discriminate between surviving and failing firms. The

natural logarithm is used instead of the nominal amount since its distribution is more comparable to the financial ratios (Ohlson, 1980).

Most models, but certainly not all, have been developed for either manufacturing or non-manufacturing companies (Altman, 1968; Skogsvik, 1987). Since we have chosen to include both types of firms, the financial ratios have to be complemented by a dummy variable reflecting the industry type. Rather than defining the variable as non-financial, it is included in the conventional model in order to correct for the fact that we have included companies from different industries. This was necessary in order to avoid overestimating the impact of non-financial variables. For the same reason, we have also introduced a dummy variable depicting whether or not the firm is part of a group.

- ***Cat_Services***: Industry belonging dummy variable taking on the value of 1 if the firm is operating within the service sector and 0 otherwise.
- ***Group***: Dummy variable reflecting the fact that a company is part of group. As suggested by Becchetti & Sierra (2003), group companies have a considerably lower tendency to fail than stand-alone firms.

6.2 Profile Analysis of the Financial Variables

A profile analysis can be used to identify differences between the surviving and failing firms. Such information could prove useful when interpreting the final regression results and has therefore been compiled in Table 7. For a variable to be statistically significant on a five percent level, the t-statistic has to take on a value lower than respectively higher than -2 and +2. InvRev and IE/EBITDA are the only variables not meeting the requirement. The variables may still turn out to be statistically significant in the regressions and will therefore be included in the study.

Variable	Surviving firms		Failed firms		t-statistic
	Mean	Std. Dev.	Mean	Std. Dev.	
EBITTA	*0.10*	0.22	*-0.16*	1.86	*-5.69*
TLTA	*0.72*	0.19	*0.97*	0.91	*4.51*
CashTA	*0.16*	0.18	*0.08*	0.14	*-21.79*
IE/EBITDA	*0.10*	4.87	*0.28*	11.77	*0.61*
InvRev	*0.07*	0.12	*0.68*	20.53	*1.20*
Ln(TA)	*9.83*	1.15	*9.16*	1.25	*-21.64*
IE/TL	*0.02*	0.07	*0.03*	0.05	*-11.45*

Table 7. Mean values and standard deviations for financial variables selected to be included in the conventional model.

Surviving firms tend to have higher profitability, liquidity and larger asset values; whereas failing companies have higher leverage, inventory and interest expenses. It is also interesting to note that the standard deviations of most variables are quite large in relation to the means. This could be a result of the fact that both manufacturing and non-manufacturing companies are included, since such firms are likely to have vastly different key ratios. It is also plausible that failing companies could exhibit abnormal key ratio values before filing for bankruptcy or business reorganization, which could contribute to the high standard deviation.

Having reviewed differences in mean values and standard deviations for surviving and failing firms, it is interesting to investigate how the independent variables relate to each other. Importantly, a high correlation reduces the likelihood for a variable to become statistically significant in the regressions. The signs and magnitude of the regression coefficients could also be affected if the independent variables are correlated to a high degree. In order to ensure that no such problems exist, a correlation matrix is presented in Table 8.

	EBIT/TA	TL/TA	Cash/TA	IEEBITDA	Inv/Rev	Ln(TA)	IE/TL	Group	Cat_Services
EBITTA	1	**-.383**	.146	.000	-.005	-.014	-.060	.001	.029
TL/TA		1	-.110	.004	.004	-.075	-.010*	-.029	.024
Cash/TA			1	-.012	-.012	-.193	-.081	-.092	.170
IEEBITDA				1	-.001	.018	.006	-.008	.000
Inv/Rev					1	.012	.000	.006	-.007
Ln(TA)						1	.048	**.326**	-.144
IE/TL							1	-.009*	-.015
Group								1	-.037
Cat_Services									1

*. Correlation is significant at the 0.05 level (2-tailed).

Table 8. Correlation matrix for all variables included in the conventional model.

No pair of variables is strongly correlated, as the highest value amounts to 0.383. Only two pairs of ratios have correlations exceeding 0.30, these are: EBITTA to TL/TA and Group to Ln(TA). Hence, companies that have a high profitability do not tend to be highly leveraged, which is not surprising since highly profitable firms are likely to be able to finance their own expansion. Moreover, companies belonging to groups tend to be larger than stand-alone firms.

Considering the quite low correlation levels, multicollinearity is unlikely to pose any major problems. Furthermore, multicollinearity will primarily affect individual explanatory variables and it is unlikely to impact the model's predictive abilities (Newbold, et al., 2009). Since our aim is to evaluate the usefulness of non-financial factors, it is primarily correlation related to non-financial variables that could influence the potential results.

6.3 Non-financial Variables Introduced for the Full Model

Several studies have investigated the usefulness of non-financial variables for business failure prediction purposes (Keasey & Watson, 1987; Peel et al., 1986; Altman et al., 2010). They have generally confirmed that qualitative variables improve the overall classification results. However, there are reasons to believe that non-financial variables could be more or less important in different countries. For instance, differences in legislation and regulatory environments between countries are likely to affect the quality of the financial reporting, as well as the informational content of non-financial variables such as qualified audit opinions or defaulted payments. These considerations may be even more important for privately held SMEs than listed companies, since their financial statements are not prepared under any international standard. We have included four non-financial variables that proved important in previous research (Altman et al., 2010; Blanco et al., 2010). These are presented below:

- ***Age dummy variables***: Business life-cycle theory stipulates that companies tend to be more vulnerable and thus witness a higher risk of failure during the stages where the operational model is questioned. These events are most likely to occur in a start-up phase where the operational model has not been proven or in a declining stage where the profitability is deteriorating due to intensified competition. Thus, we propose that company age may be an important explanatory variable. Hudson (1987) argues that companies can be classified in three risk categories. Most risky are companies that are up to three years of age. The second category consists of companies that are three to nine years old; they are considered to be slightly more risky than older firms. Finally, companies that are older than 9 years are comparable in terms of their risk level. To capture these differences we have included two dummy variables: One for companies that are 1 to 3 years old (Age_Risk_1 = 1) and one for those that are 4 to 9 years old (Age_Risk_2 = 1).
- ***Late filing of the annual report***: Peel et al. (1986) establish that a variable representing time lags in financial reporting contributes significantly to the classification accuracy of a conventional bankruptcy prediction model. Arguably, the auditing process is likely to be more time-consuming for firms in financial troubles. Hence, we have introduced a dummy variable reflecting this dimension. The variable takes on the value 1 if the annual report has been handed in late and 0 in all other cases.
- **Number of defaulted payments (Y-1):** Altman et al. (2010) and Blanco et al. (2010) found that business failure is more likely to occur among companies that have a prior record of defaulted payments. We have included a variable reflecting this aspect. It is measured as the total number of defaulted payments that has been handed over to district courts or to the Swedish Enforcement Authority (Kronofogden during the five years preceding the filing of the annual report.

- **Industry risk:** Altman et al. (2010) found that a variable representing industry weighted risks improved the overall classification results. The variable is defined as the industry weighted risk for business failure during 2009-2010. It is calculated as the proportion of failing companies within each industry class using SCB's industry codes.

In addition predictors presented above, we have also included variables reflecting auditor changes and qualified audit opinions. These are presented below:

- **Auditor Change (Y-1)**: Senteney et al. (2006) concluded that information regarding auditor changes adds incremental explanatory power of a bankruptcy prediction model solely based on financial ratios. The dummy variable is reflecting auditor changes during the year before the date that the annual report. The variable takes on the value of 1 if a change has occurred and zero otherwise.

The qualified opinions are phrased in a standardised way as required by the regulatory institute FAR.[20] Hence, we have designed a text analysis program to classify the opinions. Rather than only focusing on creating an aggregated variable indicating whether or not the report is qualified, we have divided the qualified opinions into subgroups depending on the nature of the critique. The first subgroup relates to the valuation of the items in the annual report and includes:

- **GeneralAuditor: The auditor cannot verify the financial statements:** A dummy variable representing if the auditor has found substantial shortcomings in the annual reports, i.e. the report would not provide a true and fair view of the firm's financial position. Typical examples would include uncertain valuation of various claims. The dummy variable will take on the value of 1 if this opinion occurs and 0 otherwise.

[20] FAR is the professional institute for authorized public accountants and approved public accountants in Sweden.
The exact text phrases for all qualified audit opinions can be found in Appendix 3

- **IncorrValuation: The auditor highlights incorrect valuation of balance sheet items:** A dummy variable reflecting whether the company has valued or balance sheet items in accordance with applicable law. Thus, this represents situations where the auditor explicitly states that a balance sheet item is incorrectly valued. The dummy variable will take on the value of 1 if the auditor finds such problems and 0 otherwise.

The second subgroup of opinions relates to mismanagement and the fact the company has not paid their taxes. Such qualified audit opinions could provide incremental explanatory power since the information does not necessarily have to be reflected in the accounting numbers. In addition, deficiencies in the company's internal control system could also cause the financial accounts to be unreliable, resulting in less useful accounting information. Hence, these dimensions have also been included:

- **TaxPaymentProbl: Remark that the company has not paid their taxes correctly:** A dummy variable indicating that the company has not fully met its obligation to pay taxes in a correct way during the reporting year. It involves VAT, employee fees and corporate taxes. The dummy variable will take on the value of 1 if the auditor finds such problems and 0 otherwise.

- **InternalControl: Deficiencies in the company's internal control system:** A dummy variable indicating weaknesses in the internal control system. The critique could be directed to insufficient routines in relation to monthly tax-payment and day-to-day accountancy. The dummy variable will take on the value of 1 if the auditor finds such problems and 0 otherwise.

It should be noted that we have not included all categories of qualified audit opinions; rather we have focused on the more severe cases. Furthermore, we have decided to exclude the opinions concerning compulsory liquidation, since consumed share capital has been included in the definition of business failure.

6.4 Profile Analysis of Non-financial Variables

We have compiled frequency tables for the aforementioned non-financial variables. The distribution for variables related to auditor information is presented in Table 9 below. As illustrated by the table, 17.8% of the firms in the failing sample had auditor changes during the preceding year, whereas the proportion in the surviving sample amounts to 12%. Hence, failing firms are more likely to change auditors than surviving ones. Nevertheless, surviving companies account for the majority of all auditor changes. Consequently, conflict of interest due to financial distress is unlikely to be the sole reason for auditor changes.

Auditor Changes	**Failed Sample**	**Surviving Sample**	**Total**
No AC	1 362 (82.2%)	43 005 (88.0%)	44367
AC	295 (17.8%)	5 884 (12.0%)	6179
Qualified audit opinions			
InternalControlProbl	27 (1.8%)	199 (0.4%)	226
No InternalControlProbl	1 501 (98.2%)	48 690 (99.6%)	50191
TaxPaymentProbl	166 (10.9%)	1091 (2.2%)	1257
No TaxPaymentProbl	1362 (89.1%)	47 798 (97.8%)	49160
IncorrValuation	16 (1.0%)	74 (0.2%)	90
No IncorrValuation	1 512 (99.0%)	48 815 (99.8%)	50327
General Opinion	138 (9.0%)	197 (0.4%)	335
No General Opinion	1390 (91.0%)	48 692 (99.6%)	50082
Total	**1657**	**48 889**	**50 546**

Table 9. Profile analysis of auditor changes and qualified audit opinions.

It is worth noting how relatively unusual qualified audit opinions are. Only 90 observations within the both samples have received a qualified audit opinion regarding incorrect valuation of items in the financial statements. Similarly, the total number of opinions concerning deficiencies with the internal control system is only amounting to 226. Most common is tax payment problems with 1257 remarks. Moreover, all types of qualified audit opinions are more frequently occurring for failing firms than for surviving ones. Most striking is the difference for qualified audit opinions of a general kind, as 9% of the failing firms had received such a comment. Conversely, only 0.4% of surviving companies received the same remark. The other three types of qualified audit opinions are approximately 5 times as common for a failing company compared to a surviving one. It is hard to draw any conclusions as to why so few opinions are issued. Arguably, the overwhelming majority of all companies could be following the rules. On the other hand, it is also possible that

Swedish auditors are prudent in issuing qualified opinions or unable to identify misconducts. Despite their relatively infrequent nature, the opinions may still prove valuable as an explanatory variable if they reflect information not captured by the information in the financial statements.

Age Risk Groups	**Failed Sample**	**Surviving Sample**	**Total**
$X \leq 3$	350 (21.1%)	3998 (8.2%)	4348
$3 < X \leq 9$	462 (27.9%)	9721 (19.9%)	10183
$X > 9$	845 (51.0%)	35170 (71.9%)	36015
Late Filing			
Yes	48 (2.9%)	756 (1.5%)	804
No	1609 (97.1%)	48133 (98.5%)	49742
Defaulted Payments			
0	416 (25.1%)	45016 (92.1%)	45432
1	54 (3.3%)	1201 (2.5%)	1255
2	69 (4.2%)	1062 (2.2%)	1131
3	88 (5.3%)	432 (0.9%)	520
4	81 (4.9%)	261 (0.5%)	342
5 ≤	949 (57.3%)	917 (1.9%)	1866
Total	**1657**	**48889**	**50546**

Table 10[21]. Profile analysis of non-financial variables reflecting age risk groups, late filing of the financial reports and defaulted payments.

Frequency tables for company age, late filing and defaulted payments are provided in Table 10. There are noticeable age differences between the two samples: 21.1% of failing companies are less than three years old compared to 8.2% for surviving firms. Moreover, the propensity to fail seems to be declining as the company grows older. Around 49.0% of the failed companies had not reached 10 years of age, whereas the corresponding number for surviving firms amounts to 28.1%. This coincides with previous empirical observations, where young companies have a higher tendency to fail than older ones (Hudson, 1987; Altman et al., 2010). Looking at the timeliness of corporate reporting, companies within the failed sample are almost twice as likely to be late in filing their annual reports. However, the great majority of all firms within both samples seem to be filing their reports in time.

[21] The calculated industry risk weights and their distributions are provided in Appendix 4.

Defaulted payments are much more frequently occurring within the sample of failing companies. Approximately 57.3% of all failed firms have 5 or more defaulted payments during the five last years, whereas only 1.9% of the surviving companies have suffered from the same problems. Considering that almost 74.9% of the failed firms have a record of defaulted payment and only 7.9% of the survivors, it is possible that the variable is going to prove useful for business failure prediction purposes. Intuitively, not being able to pay maturing obligations should be a first sign of impending failure. Consequently, the observed pattern is not surprising.

Multicollinearity could potentially constitute a serious problem if the objective is to assess each qualitative factor's contribution to the overall explanatory power of a model. Their combined incremental explanatory power would probably not be impacted by high correlation, but the variables' coefficients could be affected (Newbold, et al., 2009). Under such circumstances, each individual factor's impact on the risk of business failure would be hard to assess. Having compiled a correlation matrix, we observe that no qualitative variable is highly correlated with any other factor (the correlation matrix is presented in Appendix 7). Consequently, the variables' signs and the coefficients are unlikely to be affected by multicollinearity.

7. Presentation of Models

In this section we will present the conventional model as well as the full model. Additionally, their respective prediction results will be examined in order to assess whether or not adding non-financial variables improves the classification accuracy in the hold-out sample. Having analysed the aggregated impact of non-financial variables, we will also investigate the incremental explanatory power of auditor changes and qualified audit opinions on a stand-alone basis.

7.1 Conventional Model

The first step in assessing the signal value of non-financial variables for business failure prediction purposes is to design a model without such variables. Using the variables previously specified we have estimated a logit regression. The variables entered into the conventional model, their coefficients and p-values are presented in Table 11 below. A positive coefficient should be interpreted as increasing the relative odds of business failure, whereas a negative one reduces the likelihood.[22] The odds ratio represents the change in odds before and after a unit change in the predictor. Thus, if an explanatory variable changes from 0 to 1, the odds will increase with the odds ratio. If the coefficient is zero the impact is going to be 1 and the odds of failing are not affected. Conversely, large positive or negative coefficients are going to have great influence.

Variable	**Coefficient**	**Odds Ratio**	**Significance**
EBITTA	-2.86	0.06	0.000
TLTA	2.51	12.25	0.000
CashTA	-2.83	0.06	0.000
InvRev	0.84	2.31	0.000
Ln(TA)	-0.35	0.70	0.000
IE/TL	1.11	3.04	0.000
Group	-1.82	0.16	0.000
Constant	-5.67		0.000
IEEBITDA			0.41
Cat_Services			0.06

Table 11. The variables included in the conventional model, regression results.

The signs of the coefficients coincide with results obtained in previous studies and with what one intuitively would expect. Higher leverage, interest expenses of liabilities and inventory to revenue increase the probability of business failure, whereas higher profitability, size and liquidity reduce the risk. The variables IE/EBITDA and Cat_services are not statistically significant and have been excluded from the model; whereas all other variables are significant at a 0.5 percent level. The fact that the industry dummy has been excluded is perhaps surprising, considering that companies from a wide range of different industries are represented in the sample. It should be noted, however, that the classifications have been done using SCB's industry classes, which are computed at an aggregated level. As a result, they may not always adequately reflect the kind of business conducted. A second interesting observation is that the group variable turned out to be statistically significant. According to the model, belonging to a group vastly reduces the risk of business failure, evidenced by the impact on the odds ratio of 0.16. This is consistent with the

[22] The odds ratio is calculated as the exponential values of the coefficients, and should be understood as the odds of business failure divided by the odds of surviving.

observations in the data description section, where group companies were substantially less inclined to fail.

The final version of the conventional model is including account-based variables from all standard categories except coverage. Hence, most dimensions seem to carry unique information that potentially could be used to predict business failure for Swedish SMEs. One way to evaluate the overall model's explanatory power is to look at its prediction results. The classification has been done by applying a threshold value of 0.033, corresponding to the average failure rate for the total sample of 50 546 observations. The results are presented in Table 12 below.

	Failure - Model Sample			Failure - Holdout Sample		
Observed Failure	No	Yes	Overall %	No	Yes	Overall %
No	30668	8424	78.5%	7656	2141	78.1%
Yes	283	1011	78.1%	93	270	74.4%
Overall accuracy			**78.4%**			**78.0%**
Average accuracy			**78.3%**			**76.3%**
Nagelkerke R Square			**26.5%**			

Table 12. The prediction results for the conventional model using a threshold value of 0.033.

Approximately 78.1% of the surviving firms within the hold-out sample were accurately classified and 74.4% of the failed companies; corresponding to an average accuracy rate of 76.3%. If the classifications had been random, one would expect an average value of 50%. The classification results are, as expected, lower for the hold-out sample than for the observations used to derive the model. The decline is especially large for failed companies, falling from 78.1% to 74.4%. Nevertheless, the overall results are mostly in line with what has been reported in previous studies of SMEs, e.g. Altman & Sabato (2007) who classified 75.6% of their observations accurately.

Logit models can also be evaluated using a wide number of statistical measurements. They do not have any true R^2 value in the same sense as OLS regressions, but there are a number of pseudo R^2 measures with similar interpretations, e.g. Nagelkerke R

Square.[23] The measure reflects how accurate the model is in its predictions. The impact is commonly referred to as effect size and varies between 0% and 100%. As can be seen in Table 12, the current model has an effect size of 26.5%. Since the classification has been done by estimating a probability of business failure for each observation, it may be interesting to view the distribution of these estimates. The estimates for surviving firms are presented in Figure 2a, whereas the same statistics for failed companies are presented in Figure 2b.

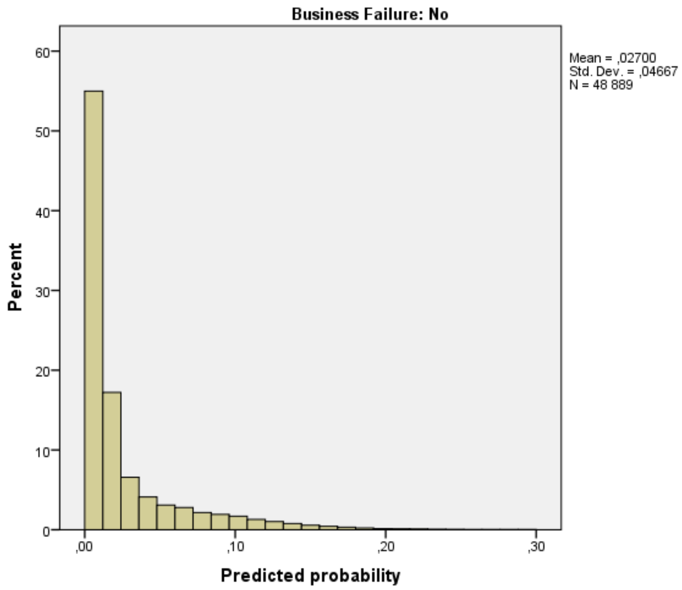

Figure 2a. Distribution of estimates for surviving firms.

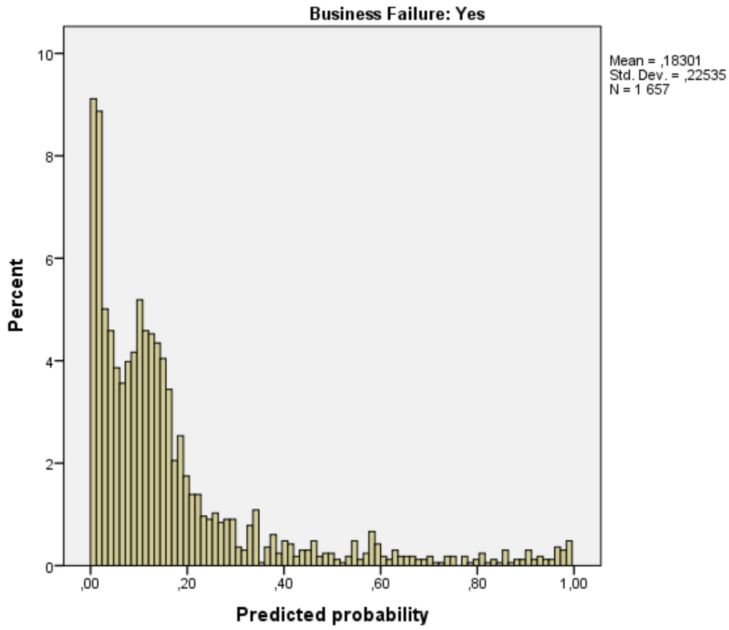

Figure 2b. Distribution of estimates for failing firms.

There are significant differences between the surviving and failing firms. The distribution of the estimates for surviving companies is concentrated the probabilities below 5%, with a mean value of 2.7% and a standard deviation of 0.047. Almost no surviving observations have estimates exceeding 20%, indicating the model is fairly accurate in its assessments of surviving firms. The estimates for failing companies are not evenly distributed; rather they seem to be skewed to low probabilities. Nevertheless, the mean value for failing firms is substantially higher than for surviving ones: 18.3% compared to 2.7%. This should be compared to the expected probability of failing for a randomly chosen firm of 3.3%, i.e. the proportion of failing companies in the whole sample. Clearly, the model has some discriminating ability.

[23] Nagelkerke's R^2 has the same logic as the R^2 in an OLS regression, but is derived from the Wald statistic and therefore not completely equivalent. The Wald statistics, in turn, are given by the values of the coefficients divided by their standard errors.

7.2 Model Including Non-financial Variables (Full Model)

A second model has been developed that includes accounting-based as well as the aforementioned non-financial variables. We are primarily interested in: changes of auditors and qualified audit opinions but have also incorporated established variables such as company age, defaulted payments, industry risk weights and reporting delays. The prediction results are presented in Table 13.

	Failure - Model Sample			Failure - Holdout Sample		
Observed Failure	No	Yes	Overall %	No	Yes	Overall %
No	32 918	6 174	84.2%	8 200	1 597	83.7%
Yes	239	1 055	81.5%	74	289	79.6%
Overall Accuracy			**84.1%**			**83.6%**
Average Accuracy			**82.9%**			**81.7%**
Nagelkerke R Square			**40.6%**			

Table 13. Predicted results for the full model using a threshold value: 0.033.

The full model has an average prediction accuracy of 81.7% of all observation correctly compared to 76.3% for the conventional model. The ability to classify surviving firms has improved, increasing from 78.1% to 83.7% as a result of adding the non-financial variables. A higher percentage of the failing companies were also accurately classified, rising from 74.4% to 79.6%. Importantly, the decline in classification accuracy for failing companies between the samples used to derive the model and the hold-out sample amounted to 1.9 percentage points (from 81.5% to 79.6%). Thus, the results were substantially more robust than for the conventional model where the corresponding decline amounted to 3.7 percentage points. Furthermore, Nagelkerke's R^2 increased from 26.5 % to 40.6%, implying that added the added non-financial variables enhanced the model's explanatory power. The variables entered into the full model, their p-values and coefficients are presented in Table 14 below:

Variable	Coefficient	Odds ratio	Significance
EBITTA	-2.41	0.09	0.000
TLTA	1.90	6.66	0.000
CashTA	-2.31	0.10	0.000
InvRev	0.61	1.84	0.003
Ln(TA)	-0.32	0.73	0.000
IE/TL	0.99	2.69	0.000
Group	-1.58	0.20	0.000
Cat_Services	-0.25	0.78	0.004
LateFiling	0.58	1.78	0.003
InternalControl	1.06	2.90	0.000
TaxPaymentProbl	0.89	2.45	0.000
IncorrValuation	1.78	5.90	0.014
GeneralAuditor	2.05	7.77	0.000
Auditor_Change	0.43	1.54	0.000
DefaultPayment	1.25	3.50	0.000
Age_Risk_1	0.73	2.07	0.000
Age_Risk_2	0.42	1.52	0.041
Constant	-5.68		0.000
IEEBITDA			0.302
Ind_Risk_Weight			0.285

Table 14. Variables included in the full model, regression results.

The coefficients for the variables included in the conventional model have the same signs as previously, but their impact on the odds ratios has declined. Consequently, the introduced non-financial variables appear to complement the accounting-based ones to some extent. The financial variables are all increasing the likelihood of failure, but to varying degrees. EBITTA, TLTA and CashTA have the largest affect on the odds ratio, in line with the results from the conventional model and IEEBITDA was once again excluded from the final model. In contrast to the previous regression, the service industry variable is statistically significant at a five percent level. Companies operating within the service sector are, according to the model, marginally less likely to fail. Belonging to a group tends to reduce the likelihood of failing, coinciding with the results from the conventional model.

All non-financial variables, with the exception of industry riskiness, proved statistically significant at a five percent level. The dummy variable for companies younger than three years had a larger impact on the odds of failure than the variable for companies between 3-10 years of age, in line with the results obtained in Hudson (1987) and Altman et al. (2010). Late filing of the financial statements do also seem to have some discriminatory power, providing support for Ohlson's (1980) suggestion that the auditing process may be particularly troublesome for firms experiencing financial difficulties. As indicated by the distribution in the profile analysis, a record of defaulted payments is also increasing the risk of failure. Similarly, all qualitative variables related to the auditor increase the likelihood of failure. These will be further analysed after we have evaluated the explanatory power of the full model. To obtain a better understanding of the model's predictions, it may be interesting to view the estimated probabilities of failure for both samples. These are presented in Figure 3a and Figure 3b.

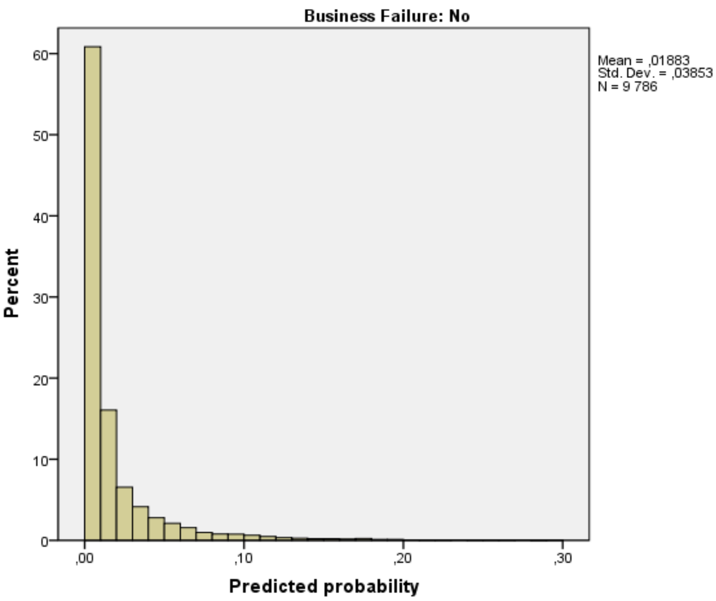

Figure 3a. Distribution of estimates for surviving firms

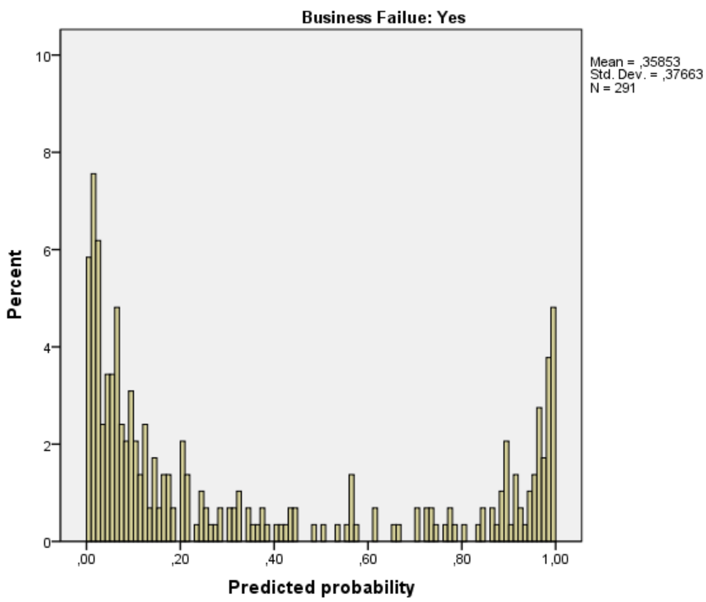

Figure 3b. Distribution of estimates for failing firms.

There is a larger distinction between the two samples than for the conventional model.[24] The mean values of the estimated probabilities for the surviving sample amounts to 1.9% which should be compared to the corresponding value of 2.7% for the conventional model. For failed companies, the mean amounts to 35.9% compared to the mean of 16.6% in the conventional model. The standard deviations have increased, particularly for failing firms, which is a natural consequence of the model's higher discriminating ability as these companies are seen as riskier by the model. The

[24] Tables for both models are presented in Appendix 10.

most striking difference occurred within the sample of failed firms. In contrast to the conventional model, the full model estimated very high probabilities of failure for a substantial proportion of the observations. The improvement within the surviving sample is not as prominent, but still noticeable.

Using the average accuracy rates can be criticized for two reasons: One is the asymmetrical loss functions of type I and type II errors; the second that the population's probability of default may differ from that of the sample. For banks, foregoing a business opportunity by not lending (type II) may, depending on the competitive situation in the market, result in an economic loss amounting to anything from zero to a significant amount. Under normal business conditions, it is reasonable to assume that the loss will be lower than that of lending money to a firm that ultimately fails (type I). A model that makes relatively fewer type I errors may therefore prove more useful than another one, even if it has a higher average prediction error. To adequately assess the incremental explanatory power of a certain model this fact must be taken into consideration. By selecting a great number of different threshold values and calculating both models' misclassification rates for each value it is possible to evaluate their performance.

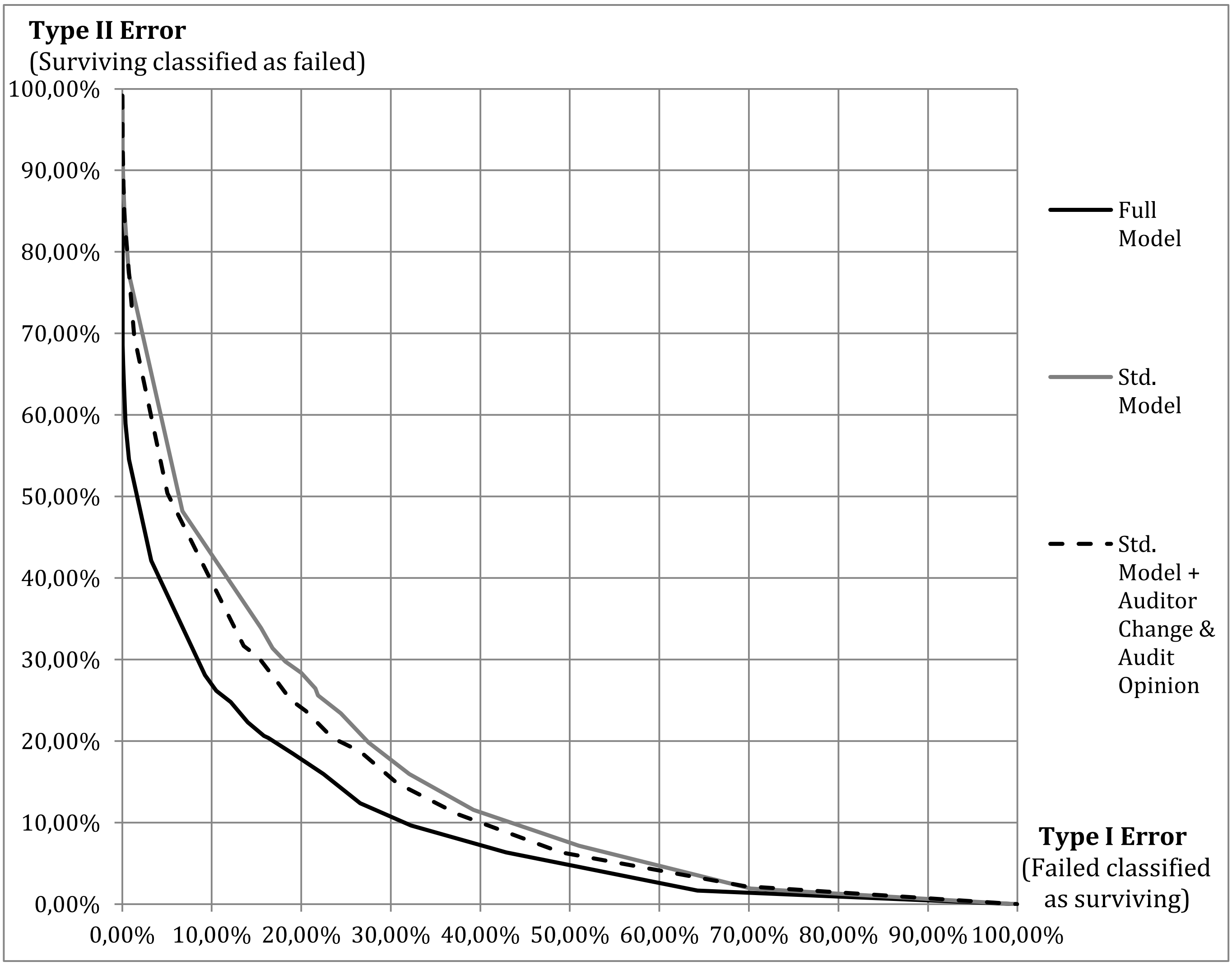

Figure 4. Receiver operator characteristic curve, plotting type I errors versus type II errors.

The receiver operator characteristic curve (ROC) plots type I errors versus type II errors. By looking at the figure we can conclude that adding non-financial variables improves the classification results, evidenced by the fact that it makes fewer type II errors for any given level of type I errors. It is also obvious that adding only qualified audit opinions and auditor changes to the conventional model, improves the overall classification and reduces both type I and type II errors for all threshold values. In other words, for all levels of misclassified failing firms, the full model is going to generate fewer misclassified surviving companies. Hence, all users would benefit from using the full model instead of the conventional one, regardless of their specific preferences for the trade-off between type I and type II errors. Having established that non-financial variables add incremental explanatory power, the next step is to analyse the information related to the auditors specifically.

Auditor Changes

A dummy variable reflecting auditor changes during the preceding year has been chosen based on theoretical considerations and empirical evidence from earlier research (Keasey & Watson, 1987; Senteney et al., 2006). More specifically, it has been suggested that auditors tend to resign or being relieved of their mandate when companies are experiencing financial problems (Schwartz & Menon, 1985). As seen in the full model presented above, auditor changes are indeed statistically significant. However, the impact on the likelihood of failure is small compared to some of the other non-financial variables; and the odds ratio is merely increasing 1.54 times if a company has changed auditor during the preceding year. A sensitivity analysis (presented in Table 15) reveals that adding auditor changes to the conventional model improves the average classification accuracy from 76.3% to 77.1%. Eliminating the variable from the full model, on the other hand, is only lowering the prediction results by 0.3 percentage points. Overall, the variable does not appear to have major impact on the prediction results, especially if other non-financial variables are taken into consideration as well.

Regression	**Nagelkerke R^2**	**AS**	**AF**	**OA**	**AA**
Conventional model	26.5%	78.1%	74.4%	78.0%	76.3%
Conventional model + Auditor changes	26.8%	78.1%	76.0%	78.0 %	77.1%
Full model excl. Auditor changes	40.4%	83.4%	79.3%	83.3%	81.4%
Full model	40.6%	83.7%	79.6%	83.6%	81.7%

Table 15. Prediction results obtained by adding the variable reflecting auditor changes to the full model and excluding the variable from the full model.

AS = percentage of accurately classified surviving companies
AF = percentage correctly classified failing firms.
OA = overall prediction accuracy
AA = average prediction accuracy.

The variable's low explanatory power is also reflected in Nagelkerke's R square, which is only marginally affected when the variable reflecting auditor changes is added to the conventional model. Considering what we wanted to capture was the disruptive changes of auditors for companies suffering from financial problems, it is possible that our definition of the variable in relation to this aim was unsuitable. Companies may change auditors for numerous reasons, not all of them related to poor financial performance. This is supported by the fact that approximately 12% of all surviving observations changed auditors during a year, as illustrated in section 5.4.

Since we include all changes, it is possible that changes occurring due to retirements or cost concerns may impair the variable's discriminating ability. Obviously a more narrow definition, pinpointing the disruptive cases, would have been preferred; however given the information available for the sample, constructing such a variable was not possible. A second aspect that may impair the variable's discriminating ability is that not all financial problems have to result in business failure as we define it. Even if an auditor leaves as a result of disagreements with the management team due to conflicts of interests regarding accounting principles as theory would suggest (Schwart & Menon, 1985), the suggested root of this conflict (poor financial performance) may not threaten the company's survival. Hence, the theory regarding the motives for auditor changes could still be accurate, even if the measures discriminating ability is quite low.

Qualified audit opinions

An auditor's primary mission is to examine companies' external and internal control systems and make sure that the financial statements do not contain any material errors; thereby serving external stakeholders by allowing them to make more informed decisions. Theory stipulates that qualified audit opinions are more likely to occur if the company is experiencing financial difficulties (Keasey & Watson, 1987). Specifically, a company's management team may be inclined to apply aggressive accounting principles in order to hide the severity of the situation from external parties. Another potential explanation to why companies receive qualified audit opinions is that the value of certain assets may be difficult to assess if the going-concern assumption is questionable. As evidenced by Table 14 above, all qualified audit opinions were statistically significant at a one percent level. Moreover, in line with our expectations, the opinions are all increasing the likelihood of business failure. The audit opinion with the largest impact on the likelihood of business failure is GeneralAuditor, which is referring to a situation where the value of certain items in the financial statements is questioned. The relative odds of business failure is more than 7.77 times as large for a company that has received such an opinion than for other firms. IncorrValuation has the second largest impact on the odds ratio, raising it 5.90 times. The variable represents the fact that the auditor believes that specific financial items are incorrectly valued. Hence, the auditor opinions related to valuation issues seem to add information that other predictors are not capturing. The same pattern can be observed for the InternalControl and TaxPaymentProbl variables, as they increase the odds ratio 2.90 and 2.45 times respectively.

The real test of the variables' potential usefulness for business failure prediction purposes is to assess how the prediction results are impacted once the variables are introduced. As illustrated in Table 16, adding qualified audit opinions to the conventional model improves the average prediction accuracy by 1.2 percentage points. Excluding them from the full model, on the other hand, results in a drop in the average prediction accuracy of 1.8 percentage points. This difference is primarily attributable to the classification of failed firms, for which the prediction accuracy declines by 2.2 percentage points. Hence, we are able to conclude that adding qualified audit opinions to the conventional model improve the prediction results, and this improvement do not appear to be captured by the other non-financial variables.

Regression	**Nagelkerke R^2**	**AS**	**AF**	**OA**	**AA**
Conventional model	26.5%	78.1%	74.4%	78.0%	76.3%
Conventional model + Audit opinions	29.0%	79.1%	75.8%	79.0 %	77.5%
Full Model excl. Audit opinions	39.0%	82.3%	77.4%	82.1%	79.9%
Full Model	40.6%	83.7%	79.6%	83.6%	81.7%
Conventional + Defaulted payments	39.0%	82.3%	77.1%	82.1%	79.7%

Table 16. Prediction results obtained by adding qualified audit opinions to the full model and excluding them from the full model.
AS = percentage of accurately classified surviving companies
AF = percentage correctly classified failing firms.
OA = overall prediction accuracy
AA = average prediction accuracy

The improvement in the average prediction accuracy is higher when qualified audit opinions are added to the conventional model than if the variable reflecting auditor changes is introduced. However, neither auditor changes nor qualified audit opinions seem to have a vast impact on the prediction results. For the variable reflecting auditor changes this may not be surprising, considering that changes were frequent for both failing and surviving firms.[25] Qualified audit opinions, on the other hand, exhibited large differences between the two samples. The marked differences were reflected by the variables' big impact on the likelihood of failure, indicating that qualified audit opinions carry important information not captured by other variables.

[25] Frequency tables are presented in the profile analysis section.

One potential explanation to why the prediction results were not substantially improved could be that relatively few companies had received qualified audit opinions. The estimated probability of business failure for companies that have received opinions is going to increase once the variables are added to the model, but since most companies have not, the overall effect does not have to be very large. Instead, defaulted payments proved most important for the classification results by raising the average prediction accuracy from 76.3% to 79.7%; despite not having a very high coefficient value. The major difference compared to qualified audit opinions is that defaulted payments are much more frequently occurring, thereby affecting the estimated risk of failure for more observations.

Conclusively, adding non-financial variables improved the overall classification results for the conventional model in predicting business failure for Swedish SMEs. Specifically, the full model outperformed the conventional one for all possible threshold values. Regardless of the relative cost of type I and type II errors, including qualitative variables were found to increase the classification accuracy. The inclusion of non-financial variables resulted in an improvement of 5.4 percentage point in the average prediction accuracy when the sample's proportion of failed companies is used as a threshold value. It could perhaps be argued that the level of improvement is quite low; making it questionable if non-financial information should be utilized. However, one has to bear in mind that these improvements are from already quite high levels. The conventional model achieved an average prediction accuracy of 76%, implying that the total scope for additional improvements is only amounting to 24 percentage points. In light of these considerations, the increase in prediction accuracy could perhaps even be seen as substantial. Especially considering that it is highly unlikely that any model will be able to classify all companies accurately.

8. Validation of Findings

The aim of this study was to assess if non-financial measures add incremental explanatory power to a conventional bankruptcy model in the prediction of business failure for Swedish SMEs. Thus, we have not set out to understand the key drivers for why business failure occurs or create any theories based on our findings. Rather, we have engaged in analysing several correlative patterns between our independent variables and our defined dependent variable, in order to construct regression models that are able to predict business failure. This conduct implies certain inherent epistemological implications. For instance, there are limitations to what conclusions we are able to draw since it is hard to assess how the model performs outside of our particular sample.

In line with Altman et al. (2010), we found that adding non-financial factors improved the classification accuracy of a conventional prediction model. We attained a 5.4 percentage point improvement in average prediction accuracy for the hold-out sample, whereas Altman et al. (2010) reported an improvement of 10 percentage points. Comparing our results to other similar studies, however, is associated with a number of difficulties, such as varying definitions of business failure, different choices of explanatory variables and different sample selection criteria. Thus, rather than evaluating differences in prediction results between studies, one should try to investigate if these complications could influence the general conclusions of the study at hand. Hence, we will address complicating factors that could invalidate our finding regarding the incremental signal value of non-financial variables.

Choice of Explanatory Financial Variables

Importantly, non-financial variables may turn out to be statistically significant simply because important financial ratios are being omitted from the conventional model. The only way to be certain that omitted variables is not a problem is to try a very large number of financial ratios in an iterative process until the best ones are identified. Still, it could be argued that once a fair number of key ratio categories are represented by measures that have proved important in previous research, any new financial ratios from the same dimension are likely to be strongly correlated with the variables that are already included in the model. For example, adding a different profitability measure would to a large extent capture the same kind of variance as *EBIT to Total Assets*. As a result, they are unlikely to be statistically significant, and even if they are, their impact on the classification results may be relatively small. Moreover, since the non-financial variables are only marginally correlated with the financial ratios in the conventional model, introducing an additional profitability measure is probably not going to have a big impact on the non-financial variables' signal values.

In order to investigate if omitted financial variables could constitute a problem, we have developed a new conventional model using a much larger number of different key ratios.[26] The conventional model's prediction accuracy was only marginally affected once the new financial ratios were introduced, and adding the same non-financial variables to this model improved the average prediction results by approximately 5.8 percentage points. Thus, even though we cannot be certain, it is deemed to be unlikely that omitted financial variables should pose any major problem.

The Definition of Business Failure

It is also plausible that the outcome had been different if another definition of business failure had been utilized. We have defined business failure as bankruptcy, business reorganization and consumption of more than half of a firm's share capital. It could be argued that including consumed share capital may have impacted the results, considering that the leverage ratio is used as an explanatory variable.[27] Evidently, as the leverage ratio approaches one, the share capital will have to be consumed, constituting failure. Conducting tests where companies with consumed share capital had been excluded, we found that the overall conclusions were not impacted.[28] Including non-financial variables still had a noticeable effect on the prediction accuracy, and the qualitative variables' impact on the odds ratios were larger than before. Furthermore, the average classification results improved as a result of using a narrower definition of business failure: Amounting to 85.2% for the full model and 81.0% for the conventional model. Apparently, excluding these observations made it easier for the model to discriminate between the two samples, which potentially could indicate that companies whose share capital has been consumed tend to differ from firms filing for bankruptcy or business reorganization. Conclusively, the choice to include consumption of more than half of a firm's share capital in the definition of business failure does not seem to have exaggerated non-financial variables incremental signal value.

[26] For results see Appendix 8 & 9.
[27] The leverage ratio is defined as *Total Liabilities* to *Total Assets*.
[28] For details see Appendix 5 & 6.

Selection of Sample and Time Period Concerns

When engaging in data-mining, the derived model should preferably be evaluated on a data sample from a different period of time, as there might be time specific effects; owners may be less inclined to file for bankruptcy if they believe that a firm's financial problems are temporary and caused by a recession, rather than if the firm is struggling during booming times. Furthermore, since the models are derived using the actual outcomes in the sample, their predictive abilities should not be tested on the same observations. We have tried to mitigate the impact of the latter problem by using a hold-out sample originating from the same time period. However, it is not implausible to assume that the financial crisis caused 2009 and 2010 to be a unique period in time. Thus, the conclusion that non-financial measures add explanatory power to a business failure prediction models, could perhaps only be valid within our sample. This is also the main problem with only using data from two years to derive the models. On the other hand, financial statements for companies experiencing financial problems are likely to exhibit similar patterns regardless of the business cycle, and the usual problem in prior research have been identifying enough failing firms. Considering that prior papers have reached the same conclusions, it is not deemed to be likely that the non-financial variables improved the classification results purely as a result of time-specific factors. Nevertheless it could not be excluded that the relative importance of the non-financial variables varies over time.

The Chosen Definition of Financial Variables

It is possible that our definition of financial variables may have impacted the outcome. We were required to calculate all accounting ratios based on the closing values of the balance sheet since we only had access to data for the period 2008 to 2010. Using opening balances had forced us to reduce our sample with one year. In light of these practical considerations, we believe that including one additional year was more important. Still, one has to be cognizant of the fact that not using opening or average balance sheet values may have impaired the informational value for some of the accounting-based variables. Arguably, financial ratios for financially distressed companies are likely to provide better indications of the severity of the situation if they are based on the opening or average balance sheet values. Thus, one cannot exclude the possibility that the observed incremental explanatory power of non-financial measures would be less distinct if opening or average values had been used instead of closing balance sheets.

Lead-times

There are usually quite long lead-times between when the most recent financial report became publicly available and the occurrence of business failure. The failed firms within our sample had an average lead-time of 21 months. Ohlson (1980) discussed the fact that several researchers had, in a questionable manner, assumed that annual reports were available at the beginning of the year. Without knowing the exact date of filing for each annual report, we have tried to take this valid critique into consideration. Specifically, we have only used annual reports that actually were publicly available at the prediction point in time, resulting in very long lead-times for our sample of failed companies. As seen in earlier research, long forecast horizons reduce the financial information usefulness for business failure predictions purposes (Altman, 1968). Financial measures of liquidity or profitability are based on historical performance and are likely to vary substantially over time. Predictions made over multiple years are therefore going to be less reliable than if they are made for the following 12 months. Thus, the long lead-times may have resulted in an overestimation of the usefulness of non-financial variables. To our defense, more recent financial information would not have been available to external parties dealing with the company. Hence, it may be argued that others have overestimated the impact of financial variables, rather than that we have overstated the impact of non-financials. Another argument implying that our results are robust in relation to this potential critique would be the fact that the non-financial variables not only contributes to better classification of failed companies with long lead times, but also in relation to the classification of surviving companies, where the same long lead-time is not present.[29]

Choice of Non-Financial Variables

Using non-financial measures such as defaulted payments to predict business failure is associated with certain complications, since the firm could file for bankruptcy or business reorganization as a result of the very same claim. Hence, it could be argued

[29] The classification accuracy increases from 78.1% to 83.7% for surviving firms and from 74.4% to 79.6% for failed companies. See tables 11 and 13 in the Presentation of Models section.

that a record of defaulted payments is a sign of insolvency rather than a predictor of business failure. However, even if the variable would be an indication of insolvency, it does not necessary need to imply that the company will fail and be forced into liquidation. The observed patterns within the sample support this notion, as a substantial proportion (25%) of all surviving companies tends to have registered defaulted payments. Furthermore, since these defaulted payments are attributable to the years prior to the filing of the annual report, they could still be used for lenders when they make decisions about whether they should extend their credit facilities to the firm or not.

Moreover, one would also expect that the choice of specific non-financial variables will lead to more or less distinct results. The impact of such effects is hard to assess in the same manner as for accounting variables since non-financial variables are not clearly attributable to a few well-defined dimensions. Our assessment should consequently not be seen as a definite answer to the usefulness of non-financial variables in the prediction of business failure for Swedish SMEs. It is possible that other non-financial variables not related to qualified audit opinions, the changes of auditors or any of the other dimensions we have included would prove to have incremental explanatory power. Potential variables could include ownership structures, the managements' and the owners' histories and information regarding the Board of Directors.

9. Summary & Conclusions

The main purpose of this study was to assess if non-financial measures add incremental explanatory power to a conventional bankruptcy prediction model in predicting business failure for Swedish SMEs. In contrast to previous research conducted on Swedish data, we included variables reflecting qualified audit opinions and auditor changes; measures that currently are not used by Swedish credit rating institutions (Patrik Schéele, 2011). The data set used is also larger than in many prior studies, consisting of 27 527 privately owned companies.[30] In order to evaluate the signal value of the non-financial measures, two models were created using a logit regression technique. One conventional model based on established financial ratios

[30] All Swedish privately held limited liability companies within our size and industry restrictions are included.

from previous research, and one model including both financial and non-financial variables. By applying the two models on a hold-out sample we find that including non-financial measures improves the conventional model's classification accuracy for all threshold values. Consequently, the model including both financial and non-financial variables provides better classifications regardless of the user's preferences. The findings are generally in line with prior research conducted on data from other countries.

Variables reflecting qualified audit opinions as well as auditor changes were statistically significant and increased the likelihood of business failure. Importantly, qualified audit opinions seem to carry important information not captured by other variables and improved the prediction results once they were added. The variable reflecting auditor changes, on the other hand, had a marginal impact on the classification accuracy. However, the biggest improvement in the prediction results were obtained when a variable reflecting prior defaulted payments were included in the model.

We cannot with certainty conclude that the observed effects are not temporary or will deteriorate over time, considering that the time period 2008 to 2010 was unique in many respects. Neither do we claim that our review of audit related information is exhaustive. On the other hand, the low correlation between financial ratios and the auditor related variables could indicate that the qualified audit opinions, and perhaps even changes of auditors, are useful and should be incorporated into business failure prediction models. This study should be seen as a first indication of the usefulness of non-financial information in the prediction of business failure for Swedish SMEs.

10.Suggestions for Future Research

In terms of future research, further analysis of the incremental explanatory power of non-financial information in the prediction of business failure for SMEs is warranted. Using data from a different time periods and selecting different accounting-based ratios would be possible ways of contradicting our results. Moreover, in light of the results obtained in this study, it would be very interesting to examine if the signal value of auditor related information will vary over the business cycle and if less severe qualified audit opinions could add further value. Finally, it is possible that other dimensions of non-financial information could add incremental explanatory power to business failure prediction models. Hence, it would be interesting to conduct similar studies using a wider set of non-financial variables, taking ownership structure and the history of the management team into account.

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12.Appendix

12.1 Swedish Industry Classification

A	**AGRICULTURE, FORESTRY AND FISHING**
01110	Growing of cereals (except rice), leguminous crops and oil seeds
01120	Growing of rice
01131	Growing of potatoes
01132	Growing of sugar beet
01133	Growing of vegetables in the open
01134	Growing of vegetables in greenhouses
01135	Growing of mushrooms etc.
01140	Growing of sugar cane
01150	Growing of tobacco
01160	Growing of fibre crops
01191	Growing of flowers and ornamental plants in greenhouses
01199	Growing of other non-perennial crops n.e.c.
01210	Growing of grapes
01220	Growing of tropical and subtropical fruits
01230	Growing of citrus fruits
01240	Growing of pome fruits and stone fruits
01250	Growing of other tree and bush fruits and nuts
01260	Growing of oleaginous fruits
01270	Growing of beverage crops
01280	Growing of spices, aromatic, drug and pharmaceutical crops
01290	Growing of other perennial crops
01301	Plant propagation in greenhouses
01302	Plant propagation in the open
01410	Milk production and raising of dairy cattle
01420	Raising of other cattle and buffaloes
01430	Raising of horses and other equines
01440	Raising of camels and camelids
01450	Raising of sheep and goats
01461	Raising of piglets
01462	Raising of swine for slaughter
01471	Egg production
01472	Raising of poultry
01491	Reindeer husbandry
01492	Breeding of pet animals
01499	Raising of other animals n.e.c.
01500	Mixed farming
01610	Support activities for crop production
01620	Support activities for animal production
01630	Post-harvest crop activities
01640	Seed processing for propagation
01700	Hunting, trapping and related service activities
02101	Forest management
02102	Silviculture
02109	Other forestry activities
02200	Logging
02300	Gathering of wild growing non-wood products
02401	Wood measurement
02409	Other support services to forestry
03111	Marine trawling
03119	Other marine fishing
03120	Freshwater fishing
03210	Marine aquaculture
03220	Freshwater aquaculture
B	**MINING AND QUARRYING**
05100	Mining of hard coal
05200	Mining of lignite
06100	Extraction of crude petroleum
06200	Extraction of natural gas
07100	Mining of iron ores
07210	Mining of uranium and thorium ores
07290	Mining of other non-ferrous metal ores
08110	Quarrying of ornamental and building stone, limestone, gypsum, chalk and slate
08120	Operation of gravel and sand pits; mining of clays and kaolin
08910	Mining of chemical and fertiliser minerals
08920	Extraction of peat
08930	Extraction of salt
08990	Other mining and quarrying n.e.c.
09100	Support activities for petroleum and natural gas extraction
09900	Support activities for other mining and quarrying
C	**MANUFACTURING**
10111	Livestock slaughtering
10112	Processing and preserving of meat in cuts
10120	Processing and preserving of poultry meat
10130	Production of meat and poultry meat products
10200	Processing and preserving of fish, crustaceans and molluscs
10310	Processing and preserving of potatoes
10320	Manufacture of fruit and vegetable juice
10390	Other processing and preserving of fruit and vegetables
10410	Manufacture of oils and fats
10420	Manufacture of margarine and similar edible fats
10511	Cheese production
10519	Other dairy production
10520	Manufacture of ice cream
10611	Production of flour
10612	Manufacture of breakfast cereals, blended flour mixes and other prepared grain mill products
10620	Manufacture of starches and starch products
10710	Manufacture of bread; manufacture of fresh pastry goods and cakes
10721	Manufacture of crispbread
10722	Manufacture of rusks, biscuits and preserved pastry goods and cakes
10730	Manufacture of macaroni, noodles, couscous and similar farinaceous products
10810	Manufacture of sugar
10821	Manufacture of sugar confectionery
10822	Manufacture of cocoa and chocolate confectionery
10830	Processing of tea and coffee
10840	Manufacture of condiments and seasonings
10850	Manufacture of prepared meals and dishes
10860	Manufacture of homogenised food preparations and dietetic food
10890	Manufacture of other food products n.e.c.
10910	Manufacture of prepared feeds for farm animals
10920	Manufacture of prepared pet foods
11010	Distilling, rectifying and blending of spirits
11020	Manufacture of wine from grape
11030	Manufacture of cider and other fruit wines
11040	Manufacture of other non-distilled fermented beverages
11050	Manufacture of beer
11060	Manufacture of malt
11070	Manufacture of soft drinks; production of mineral waters and other bottled waters
12000	Manufacture of tobacco products
13100	Preparation and spinning of textile fibres
13200	Weaving of textiles
13300	Finishing of textiles
13910	Manufacture of knitted and crocheted fabrics
13921	Manufacture of curtains, bed linen and other linen goods
13922	Manufacture of tarpaulins, tents, sails etc.
13930	Manufacture of carpets and rugs
13940	Manufacture of cordage, rope, twine and netting
13950	Manufacture of non-wovens and articles made from non-wovens, except apparel
13960	Manufacture of other technical and industrial textiles
13990	Manufacture of other textiles n.e.c.
14110	Manufacture of leather clothes
14120	Manufacture of workwear
14130	Manufacture of other outerwear
14140	Manufacture of underwear
14190	Manufacture of other wearing apparel and accessories
14200	Manufacture of articles of fur
14310	Manufacture of knitted and crocheted hosiery
14390	Manufacture of other knitted and crocheted apparel
15110	Tanning and dressing of leather; dressing and dyeing of fur
15120	Manufacture of luggage, handbags and the like, saddlery and harness
15200	Manufacture of footwear
16101	Sawmilling
16102	Planing of wood
16103	Impregnation of wood
16210	Manufacture of veneer sheets and wood-based panels
16220	Manufacture of assembled parquet floors
16231	Manufacture of prefabricated wooden buildings
16232	Manufacture of wooden doors
16233	Manufacture of wooden windows
16239	Manufacture of other builders' carpentry and joinery n.e.c.
16240	Manufacture of wooden containers
16291	Manufacture of wood fuels
16292	Manufacture of other products of wood
16293	Manufacture of articles of cork, straw and plaiting materials
17111	Manufacture of mechanical or semi-chemical pulp
17112	Manufacture of sulphate pulp
17113	Manufacture of sulphite pulp
17121	Manufacture of newsprint
17122	Manufacture of other printing paper
17123	Manufacture of kraft paper and paperboard
17129	Manufacture of other paper and paperboard
17211	Manufacture of corrugated paper and paperboard and corrugated board containers
17219	Manufacture of other containers of paper and paperboard
17220	Manufacture of household and sanitary goods and of toilet requisites

17230	Manufacture of paper stationery
17240	Manufacture of wallpaper
17290	Manufacture of other articles of paper and paperboard
18110	Printing of newspapers
18121	Printing of periodicals
18122	Book printing and other printing
18130	Pre-press and pre-media services
18140	Binding and related services
18200	Reproduction of recorded media
19100	Manufacture of coke oven products
19200	Manufacture of refined petroleum products
20110	Manufacture of industrial gases
20120	Manufacture of dyes and pigments
20130	Manufacture of other inorganic basic chemicals
20140	Manufacture of other organic basic chemicals
20150	Manufacture of fertilisers and nitrogen compounds
20160	Manufacture of plastics in primary forms
20170	Manufacture of synthetic rubber in primary forms
20200	Manufacture of pesticides and other agrochemical products
20300	Manufacture of paints, varnishes and similar coatings, printing ink and mastics
20410	Manufacture of soap and detergents, cleaning and polishing preparations
20420	Manufacture of perfumes and toilet preparations
20510	Manufacture of explosives
20520	Manufacture of glues
20530	Manufacture of essential oils
20590	Manufacture of other chemical products n.e.c.
20600	Manufacture of man-made fibres
21100	Manufacture of basic pharmaceutical products
21200	Manufacture of pharmaceutical preparations
22110	Manufacture of rubber tyres and tubes; retreading and rebuilding of rubber tyres
22190	Manufacture of other rubber products
22210	Manufacture of plastic plates, sheets, tubes and profiles
22220	Manufacture of plastic packing goods
22230	Manufacture of builders' ware of plastic
22290	Manufacture of other plastic products
23110	Manufacture of flat glass
23120	Shaping and processing of flat glass
23130	Manufacture of hollow glass
23140	Manufacture of glass fibres
23190	Manufacture and processing of other glass, including technical glassware
23200	Manufacture of refractory products
23310	Manufacture of ceramic tiles and flags
23320	Manufacture of bricks, tiles and construction products, in baked clay
23410	Manufacture of ceramic household and ornamental articles
23420	Manufacture of ceramic sanitary fixtures
23430	Manufacture of ceramic insulators and insulating fittings
23440	Manufacture of other technical ceramic products
23490	Manufacture of other ceramic products
23510	Manufacture of cement
23520	Manufacture of lime and plaster
23610	Manufacture of concrete products for construction purposes
23620	Manufacture of plaster products for construction purposes
23630	Manufacture of ready-mixed concrete
23640	Manufacture of mortars
23650	Manufacture of fibre cement
23690	Manufacture of other articles of concrete, plaster and cement
23701	Cutting, shaping and finishing of building stone
23709	Cutting, shaping and finishing of ornamental stone
23910	Production of abrasive products
23991	Manufacture of stone and mineral wool products
23999	Manufacture of various other non-metallic mineral products n.e.c.
24100	Manufacture of basic iron and steel and of ferro-alloys
24200	Manufacture of tubes, pipes, hollow profiles and related fittings, of steel
24310	Cold drawing of bars
24320	Cold rolling of narrow strip
24330	Cold forming or folding
24340	Cold drawing of wire
24410	Precious metals production
24420	Aluminium production
24430	Lead, zinc and tin production
24440	Copper production
24450	Other non-ferrous metal production
24460	Processing of nuclear fuel
24510	Casting of iron
24520	Casting of steel
24530	Casting of light metals
24540	Casting of other non-ferrous metals
25110	Manufacture of metal structures and parts of structures
25120	Manufacture of doors and windows of metal
25210	Manufacture of central heating radiators and boilers
25290	Manufacture of other tanks, reservoirs and containers of metal
25300	Manufacture of steam generators, except central heating hot water boilers
25400	Manufacture of weapons and ammunition
25500	Forging, pressing, stamping and roll-forming of metal; powder metallurgy
25610	Treatment and coating of metals
25620	Machining
25710	Manufacture of cutlery
25720	Manufacture of locks and hinges
25730	Manufacture of tools
25910	Manufacture of steel drums and similar containers
25920	Manufacture of light metal packaging
25930	Manufacture of wire products, chain and springs
25940	Manufacture of fasteners and screw machine products
25991	Manufacture of sinks, sanitary ware etc. of metal for construction purposes
25999	Manufacture of various other fabricated metal products n.e.c.
26110	Manufacture of electronic components
26120	Manufacture of loaded electronic boards
26200	Manufacture of computers and peripheral equipment
26300	Manufacture of communication equipment
26400	Manufacture of consumer electronics
26510	Manufacture of instruments and appliances for measuring, testing and navigation
26520	Manufacture of watches and clocks
26600	Manufacture of irradiation, electromedical and electrotherapeutic equipment
26700	Manufacture of optical instruments and photographic equipment
26800	Manufacture of magnetic and optical media
27110	Manufacture of electric motors, generators and transformers
27120	Manufacture of electricity distribution and control apparatus
27200	Manufacture of batteries and accumulators
27310	Manufacture of fibre optic cables
27320	Manufacture of other electronic and electric wires and cables
27330	Manufacture of wiring devices
27400	Manufacture of electric lighting equipment
27510	Manufacture of electric domestic appliances
27520	Manufacture of non-electric domestic appliances
27900	Manufacture of other electrical equipment
28110	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
28120	Manufacture of fluid power equipment
28130	Manufacture of other pumps and compressors
28140	Manufacture of other taps and valves
28150	Manufacture of bearings, gears, gearing and driving elements
28210	Manufacture of ovens, furnaces and furnace burners
28220	Manufacture of lifting and handling equipment
28230	Manufacture of office machinery and equipment (except computers and peripheral equipment)
28240	Manufacture of power-driven hand tools
28250	Manufacture of non-domestic cooling and ventilation equipment
28290	Manufacture of other general-purpose machinery n.e.c.
28300	Manufacture of agricultural and forestry machinery
28410	Manufacture of metal forming machinery
28490	Manufacture of other machine tools
28910	Manufacture of machinery for metallurgy
28920	Manufacture of machinery for mining, quarrying and construction
28930	Manufacture of machinery for food, beverage and tobacco processing
28940	Manufacture of machinery for textile, apparel and leather production
28950	Manufacture of machinery for paper and paperboard production
28960	Manufacture of plastics and rubber machinery
28990	Manufacture of other special-purpose machinery n.e.c.
29101	Manufacture of passenger cars and other light motor vehicles
29102	Manufacture of trucks and other heavy motor vehicles
29200	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers
29310	Manufacture of electrical and electronic equipment for motor vehicles
29320	Manufacture of other parts and accessories for motor vehicles
30110	Building of ships and floating structures
30120	Building of pleasure and sporting boats

30200	Manufacture of railway locomotives and rolling stock
30300	Manufacture of air and spacecraft and related machinery
30400	Manufacture of military fighting vehicles
30910	Manufacture of motorcycles
30920	Manufacture of bicycles and invalid carriages
30990	Manufacture of other transport equipment n.e.c.
31011	Manufacture of office and shop furniture
31012	Manufacture of office and shop fittings
31021	Manufacture of kitchen furniture
31022	Manufacture of kitchen fittings
31030	Manufacture of mattresses
31090	Manufacture of other furniture
32110	Striking of coins
32120	Manufacture of jewellery and related articles
32130	Manufacture of imitation jewellery and related articles
32200	Manufacture of musical instruments
32300	Manufacture of sports goods
32400	Manufacture of games and toys
32501	Manufacture of medical and dental instruments and supplies
32502	Manufacture of artificial teeth, dentures, dental plates etc.
32910	Manufacture of brooms and brushes
32990	Other manufacturing n.e.c.
33110	Repair of fabricated metal products
33120	Repair of machinery
33130	Repair of electronic and optical equipment
33140	Repair of electrical equipment
33150	Repair and maintenance of ships and boats
33160	Repair and maintenance of aircraft and spacecraft
33170	Repair and maintenance of other transport equipment
33190	Repair of other equipment
33200	Installation of industrial machinery and equipment
D	**ELECTRICITY, GAS, STEAM AND AIR CONDITIONING SUPPLY**
35110	Production of electricity
35120	Transmission of electricity
35130	Distribution of electricity
35140	Trade of electricity
35210	Manufacture of gas
35220	Distribution of gaseous fuels through mains
35230	Trade of gas through mains
35300	Steam and air conditioning supply
E	**WATER SUPPLY; SEWERAGE, WASTE MANAGEMENT AND REMEDIATION ACTIVITIES**
36001	Collection, treatment and supply of groundwater
36002	Collection, treatment and supply of surface water
37000	Sewerage
38110	Collection of non-hazardous waste
38120	Collection of hazardous waste
38210	Treatment and disposal of non-hazardous waste
38220	Treatment and disposal of hazardous waste
38311	Dismantling of car wrecks
38312	Dismantling of electric and electronic equipment
38319	Dismantling of other wrecks
38320	Recovery of sorted materials
39000	Remediation activities and other waste management services
F	**CONSTRUCTION**
41100	Development of building projects
41200	Construction of residential and non-residential buildings
42110	Construction of roads and motorways
42120	Construction of railways and underground railways
42130	Construction of bridges and tunnels
42210	Construction of utility projects for fluids
42220	Construction of utility projects for electricity and telecommunications
42910	Construction of water projects
42990	Construction of other civil engineering projects n.e.c.
43110	Demolition
43120	Site preparation
43130	Test drilling and boring
43210	Electrical installation
43221	Installation of heating and sanitary equipment
43222	Installation of ventilation equipment
43223	Installation of refrigeration and freezing equipment
43229	Other plumbing
43290	Other construction installation
43310	Plastering
43320	Joinery installation
43330	Floor and wall covering
43341	Painting
43342	Glazing
43390	Other building completion and finishing
43911	Erection of sheet-metal roof covering
43912	Erection of other roof covering and frames
43991	Renting of construction or demolition equipment with operator
43999	Various other specialised construction activities n.e.c.
G	**WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES**
45110	Sale of cars and light motor vehicles
45191	Sale of lorries, buses and specialised motor vehicles
45192	Sale of caravans, motor homes, trailers and semi-trailers
45201	Non-specialised maintenance and repair of motor vehicles
45202	Bodywork repair and painting of motor vehicles
45203	Installation and repair and painting of electrical and electronic motor vehicle equipment
45204	Tyre service
45310	Wholesale trade of motor vehicle parts and accessories
45320	Retail trade of motor vehicle parts and accessories
45400	Sale, maintenance and repair of motorcycles and related parts and accessories
46110	Agents involved in the sale of agricultural raw materials, live animals, textile raw materials and semi-finished goods
46120	Agents involved in the sale of fuels, ores, metals and industrial chemicals
46130	Agents involved in the sale of timber and building materials
46141	Agents involved in the sale of machinery, industrial equipment, ships and aircraft except office machinery and computer equipment
46142	Agents involved in the sale of office machinery and computer equipment
46150	Agents involved in the sale of furniture, household goods, hardware and ironmongery
46160	Agents involved in the sale of textiles, clothing, fur, footwear and leather goods
46170	Agents involved in the sale of food, beverages and tobacco
46180	Agents specialised in the sale of other particular products
46190	Agents involved in the sale of a variety of goods
46210	Wholesale of grain, unmanufactured tobacco, seeds and animal feeds
46220	Wholesale of flowers and plants
46230	Wholesale of live animals
46240	Wholesale of hides, skins and leather
46310	Wholesale of fruit and vegetables
46320	Wholesale of meat and meat products
46330	Wholesale of dairy products, eggs and edible oils and fats
46340	Wholesale of beverages
46350	Wholesale of tobacco products
46360	Wholesale of sugar and chocolate and sugar confectionery
46370	Wholesale of coffee, tea, cocoa and spices
46380	Wholesale of other food, including fish, crustaceans and molluscs
46390	Non-specialised wholesale of food, beverages and tobacco
46410	Wholesale of textiles
46420	Wholesale of clothing and footwear
46431	Wholesale of electrical household appliances
46432	Wholesale of radio, television and video equipment
46433	Wholesale of recorded audio and video tapes, CDs and DVDs
46434	Wholesale of electrical equipment
46435	Wholesale of photographic and optical goods
46440	Wholesale of china and glassware and cleaning materials
46450	Wholesale of perfume and cosmetics
46460	Wholesale of pharmaceutical goods
46470	Wholesale of furniture, carpets and lighting equipment
46480	Wholesale of watches and jewellery
46491	Wholesale of sporting equipment
46492	Wholesale of stationary and other office goods
46499	Wholesale of other household goods n.e.c.
46510	Wholesale of computers, computer peripheral equipment and software
46521	Wholesale of electronic components
46522	Wholesale of telecommunications equipment and parts
46610	Wholesale of agricultural machinery, equipment and supplies
46620	Wholesale of machine tools
46630	Wholesale of mining, construction and civil engineering machinery
46640	Wholesale of machinery for the textile industry and of sewing and knitting machines
46650	Wholesale of office furniture
46660	Wholesale of other office machinery and equipment

46691 Wholesale of measuring and precision instruments
46692 Wholesale of computerized materials handling equipment
46699 Wholesale of other machinery and equipment n.e.c.
46710 Wholesale of solid, liquid and gaseous fuels and related products
46720 Wholesale of metals and metal ores
46731 Wholesale of wood and other construction materials
46732 Wholesale of sanitary equipment
46741 Wholesale of hardware
46742 Wholesale of plumbing and heating equipment
46750 Wholesale of chemical products
46761 Wholesale of industry supplies
46762 Wholesale of packaging materials
46769 Wholesale of other intermediate products n.e.c.
46771 Wholesale in car wrecks
46772 Wholesale of metal waste and scrap
46773 Wholesale of non-metal waste and scrap
46900 Non-specialised wholesale trade
47111 Retail sale in department stores and the like with food, beverages or tobacco predominating
47112 Retail sale in other non-specialised stores with food, beverages or tobacco predominating
47191 Other retail sale in department stores and the like
47199 Other retail sale in non-specialised stores n.e.c.
47210 Retail sale of fruit and vegetables in specialised stores
47220 Retail sale of meat and meat products in specialised stores
47230 Retail sale of fish, crustaceans and molluscs in specialised stores
47241 Retail sale of bread, cakes and flour confectionery in specialised stores
47242 Retail sale of sugar confectionery in specialised stores
47250 Retail sale of beverages in specialised stores
47260 Retail sale of tobacco products in specialised stores
47291 Retail sale of health foods in specialised stores
47299 Other retail sale of food in specialised stores n.e.c.
47300 Retail sale of automotive fuel in specialised stores
47410 Retail sale of computers, peripheral units and software in specialised stores
47420 Retail sale of telecommunications equipment in specialised stores
47430 Retail sale of audio and video equipment in specialised stores
47510 Retail sale of textiles in specialised stores
47521 Retail sale of wood and other building materials in specialised stores
47522 Retail sale of plumbing and heating equipment in specialised stores
47523 Retail sale of paints in specialised stores
47531 Retail sale of carpets, rugs, wall and floor coverings in specialised stores
47532 Retail sale of home furnishing textiles in specialised stores
47540 Retail sale of electrical household appliances in specialised stores
47591 Retail sale of home furniture in specialised stores
47592 Retail sale of office furniture in specialised stores
47593 Retail sale of glassware, china and kitchenware in specialised stores
47594 Retail sale of electrical fittings in specialised stores
47595 Retail sale of musical instruments and music scores in specialised stores
47610 Retail sale of books in specialised stores
47621 Retail sale of newspapers in specialised stores
47622 Retail sale of stationery in specialised stores
47630 Retail sale of music and video recordings in specialised stores
47641 Retail sale of sporting equipment except bicycles in specialised stores
47642 Retail sale of bicycles in specialised stores
47643 Retail sale of boats and boating accessories in specialised stores
47650 Retail sale of games and toys in specialised stores
47711 Retail sale of men's, women's and children's clothing in specialised stores
47712 Retail sale of men's clothing in specialised stores
47713 Retail sale of women's clothing in specialised stores
47714 Retail sale of children's clothing in specialised stores
47715 Retail sale of furs in specialised stores
47721 Retail sale of footwear in specialised stores
47722 Retail sale of leather goods in specialised stores
47730 Dispensing chemist
47740 Retail sale of medical and orthopaedic goods in specialised stores
47750 Retail sale of cosmetic and toilet articles in specialised stores
47761 Retail sale of flowers, plants, seedsand fertilisers in specialised stores
47762 Retail sale of pet animals and pet food in specialised stores
47771 Retail sale of watches and clocks in specialised stores
47772 Retail sale of jewellery in specialised stores
47781 Retail sale of spectacles and other optical goods except photographic equipment in specialised stores
47782 Retail sale of photographic equipment in specialised stores
47783 Retail sale of art in specialised stores; art gallery activities
47784 Retail sale of coins and stamps in specialised stores
47789 Other retail sale in specialised stores n.e.c.
47791 Retail sale of antiques and second-hand books in stores
47792 Retail sale of other second-hand goods in stores
47793 Activities of auctioning houses
47810 Retail sale via stalls and markets of food, beverages and tobacco products
47820 Retail sale via stalls and markets of textiles, clothing and footwear
47890 Retail sale via stalls and markets of other goods
47911 Non-specialised retail sale via mail order houses or via Internet
47912 Retail sale of clothing via mail order houses or via Internet
47913 Retail sale of books and other media goods via mail order houses or via Internet
47914 Retail sale of computers and other electronic equipment via mail order houses or via Internet
47915 Retail sale of sports and leisure goods via mail order houses or via Internet
47916 Retail sale of household goods via mail order houses or via Internet
47917 Internet retail auctions
47919 Other retail sale via mail order houses or via Internet
47991 Retail sale on commission
47992 Ambulatory and occasional retail sale of food
47993 Ambulatory and occasional retail sale of other goods
47994 Auctions not in stores or Internet
47999 Retail sale not in stores, stalls or markets n.e.c.

H TRANSPORTATION AND STORAGE

49100 Passenger rail transport, interurban
49200 Freight rail transport
49311 Urban and suburban road passenger transport
49319 Other urban and suburban passenger land transport
49320 Taxi operation
49390 Other passenger land transport n.e.c.
49410 Freight transport by road
49420 Removal services
49500 Transport via pipeline
50101 Scheduled sea and coastal passenger water transport
50102 Non-scheduled sea and coastal passenger water transport
50201 Scheduled sea and coastal freight water transport
50202 Non-scheduled sea and coastal freight water transport
50301 Scheduled inland passenger water transport
50302 Non-scheduled inland passenger water transport
50401 Scheduled inland freight water transport
50402 Non-scheduled inland freight water transport
51101 Scheduled passenger air transport
51102 Non-scheduled passenger air transport
51211 Scheduled freight air transport
51212 Non-scheduled freight air transport
51220 Space transport
52100 Warehousing and storage
52211 Towing incidental to land transportation
52219 Other service activities incidental to land transportation
52220 Service activities incidental to water transportation
52230 Service activities incidental to air transportation
52241 Harbour cargo handling
52249 Other cargo handling
52290 Other transportation support activities
53100 Postal activities under universal service obligation
53201 Other postal activities
53202 Courier activities
53203 Newspaper distribution

I ACCOMMODATION AND FOOD SERVICE ACTIVITIES

55101	Hotels with restaurant except conference centres
55102	Lodging activities of conference centres
55103	Hotels without restaurant
55201	Youth hostels
55202	Other short-stay accommodation
55300	Camping grounds, recreational vehicle parks and trailer parks
55900	Other accommodation
56100	Restaurants and mobile food service activities
56210	Event catering activities
56291	Canteens
56292	Catering for hospitals
56293	Catering for schools, welfare and other institutions
56294	Catering for the transport sector
56299	Other catering
56300	Beverage serving activities
J	**INFORMATION AND COMMUNICATION**
58110	Book publishing
58120	Publishing of directories and mailing lists
58131	Publishing of daily newspapers
58132	Publishing of advertising newspapers
58140	Publishing of journals and periodicals
58190	Other publishing activities
58210	Publishing of computer games
58290	Other software publishing
59110	Motion picture, video and television programme production activities
59120	Motion picture, video and television programme post-production activities
59130	Motion picture, video and television programme distribution activities
59140	Motion picture projection activities
59200	Sound recording and music publishing activities
60100	Radio broadcasting
60200	Television programming and broadcasting activities
61100	Wired telecommunications activities
61200	Wireless telecommunications activities
61300	Satellite telecommunications activities
61900	Other telecommunications activities
62010	Computer programming activities
62020	Computer consultancy activities
62030	Computer facilities management activities
62090	Other information technology and computer service activities
63110	Data processing, hosting and related activities
63120	Web portals
63910	News agency activities
63990	Other information service activities n.e.c.
K	**FINANCIAL AND INSURANCE ACTIVITIES**
64110	Central banking
64190	Other monetary intermediation
64201	Activities of financial holding companies
64202	Activities of non-financial holding companies
64301	Investment funds
64309	Other trusts, funds and similar financial entities
64910	Financial leasing
64920	Other credit granting
64991	Activities of investment companies and venture capital companies
64992	Trading in securities on own account
64993	Trading in securities for a limited and closed group of owners
64999	Various other financial service activities, except insurance and pension funding n.e.c.
65111	Unit link insurance
65119	Other life insurance
65120	Non-life insurance
65200	Reinsurance
65300	Pension funding
66110	Administration of financial markets
66120	Security and commodity contracts brokerage
66190	Other activities auxiliary to financial services, except insurance and pension funding
66210	Risk and damage evaluation
66220	Activities of insurance agents and brokers
66290	Other activities auxiliary to insurance and pension funding
66301	Investment fund management activities
66309	Other fund management activities
L	**REAL ESTATE ACTIVITIES**
68100	Buying and selling of own real estate
68201	Renting and operating of own or leased dwelllings
68202	Renting and operating of own or leased industrial premises
68203	Renting and operating of own or leased other premises
68204	Property management of tenant-owners' associations
68209	Other renting and operating of own or leased real estate
68310	Real estate agencies
68320	Management of real estate on a fee or contract basis
M	**PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITIES**
69101	Legal advisory and representation activities of solicitor's firms
69102	Other legal advisory activities
69103	Advisory activities concerning patents and copyrights
69201	Accounting and bookkeeping activities
69202	Auditing activities
69203	Tax consultancy
70100	Activities of head offices
70210	Public relations and communication activities
70220	Business and other management consultancy activities
71110	Architectural activities
71121	Construction and civil engineering activities and related technical consultancy
71122	Industrial engineering activities and related technical consultancy
71123	Electric engineering activities and related technical consultancy
71124	Engineering activities and related technical consultancy in energy, environment, plumbing, heat and air-conditioning
71129	Other engineering activities and related technical consultancy
71200	Technical testing and analysis
72110	Research and experimental development on biotechnology
72190	Other research and experimental development on natural sciences and engineering
72200	Research and experimental development on social sciences and humanities
73111	Advertising agency activities
73112	Delivery of advertising material
73119	Other advertising activities
73120	Media representation
73200	Market research and public opinion polling
74101	Industrial and fashion design
74102	Graphic design
74103	Activities of interior decorators
74201	Portrait photography
74202	Advertising photography
74203	Press and other photography
74204	Photographic laboratory activities
74300	Translation and interpretation activities
74900	Other professional, scientific and technical activities n.e.c.
75000	Veterinary activities
N	**ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES**
77110	Renting and leasing of cars and light motor vehicles
77120	Renting and leasing of trucks
77210	Renting and leasing of recreational and sports goods
77220	Renting of video tapes and disks
77290	Renting and leasing of other personal and household goods
77310	Renting and leasing of agricultural machinery and equipment
77320	Renting and leasing of construction and civil engineering machinery and equipment
77330	Renting and leasing of office machinery and equipment (including computers)
77340	Renting and leasing of water transport equipment
77350	Renting and leasing of air transport equipment
77390	Renting and leasing of other machinery, equipment and tangible goods n.e.c.
77400	Leasing of intellectual property and similar products, except copyrighted works
78100	Activities of employment placement agencies
78200	Temporary employment agency activities
78300	Other human resources provision
79110	Travel agency activities
79120	Tour operator activities
79900	Other reservation service and related activities
80100	Private security activities
80200	Security systems service activities
80300	Investigation activities
81100	Combined facilities support activities
81210	General cleaning of buildings
81221	Other building cleaning activities
81222	Chimney cleaning
81290	Other cleaning activities
81300	Landscape service activities
82110	Combined office administrative service activities
82190	Photocopying, document preparation and other specialised office support activities
82200	Activities of call centres
82300	Organisation of conventions and trade shows
82910	Activities of collection agencies and credit bureaus
82920	Packaging activities

82990 Other business support service activities n.e.c.

O PUBLIC ADMINISTRATION AND DEFENCE; COMPULSORY SOCIAL SECURITY

84111 Executive and legislative administration of central and local government
84112 Inspection, control, permit and licensing activities of central and local government
84113 Fiscal activities
84114 Public dissemination of information
84115 Supporting service activities for the government as a whole
84121 Administration of primary and secondary education
84122 Administration of higher education and research
84123 Administration of health care
84124 Administration of social welfare
84125 Administration of culture, environment, housing etc. programmes
84131 Administration of infrastructure programmes
84132 Administration of programmes relating to agriculture, forestry and fishing
84133 Administration of labour market programmes
84139 Administration of other business, industry and trade programmes
84210 Foreign affairs
84221 Military defence activities
84222 Defence support activities
84223 Civil defence activities
84231 Public prosecutor activities
84232 Law court activities
84233 Detention and rehabilitation of criminals
84240 Public order and safety activities
84250 Fire service activities
84300 Compulsory social security activities

P EDUCATION

85100 Pre-primary education
85201 Compulsory comprehensive school education and pre-school class
85202 Special school primary education
85311 General secondary education
85312 Municipal adult education
85321 Technical and vocational secondary education
85322 Special school secondary education
85323 Other secondary education
85324 School activities for occupational drivers
85410 Post-secondary non-tertiary education
85420 Tertiary education
85510 Sports and recreation education
85521 Activities of municipal culture schools
85522 Other cultural education
85530 Driving school activities
85591 Labour market training
85592 Folk high school education
85593 Activities of adult education associations
85594 Staff training
85599 Various other education n.e.c.
85600 Educational support activities

Q HUMAN HEALTH AND SOCIAL WORK ACTIVITIES

86101 Hospital primary health activities
86102 Specialised hospital somatic activities
86103 Specialised hospital psychiatric activities
86211 General primary medical practice activities
86212 Other general medical practice activities
86221 Specialist medical practice activities, at hospitals
86222 Specialist medical practice activities, not at hospitals
86230 Dental practice activities
86901 Activities of medical laboratories etc.
86902 Ambulance transports and ambulance health care activities
86903 Primary health activities, not physicians
86904 Activities of dental hygienists
86905 Activities of physiotherapists etc.
86909 Other human health activities n.e.c.
87100 Residential nursing care activities
87201 Care in special forms of accommodation for persons with mental retardation and mental disability
87202 Care in special forms of accommodation for children and young people with substance abuse problems
87203 Care in special forms of accommodation for adults with substance abuse problems
87301 Care in special forms of accommodation for the elderly
87302 Care in special forms of accommodation for disabled persons
87901 Twenty-four hours care with accommodation for children and young people with social problems
87902 Care with accommodation for adults n.e.c.
88101 Social work activities without accommodation for the elderly
88102 Social work activities without accommodation for disabled persons
88910 Child day-care activities
88991 Social work activities for children and young people with social problems
88992 Day-care activities for adults with substance abuse problems
88993 Social work activities without accommodation for adults n.e.c.
88994 Humanitarian relief activities
88995 Operation of refugee camps

R ARTS, ENTERTAINMENT AND RECREATION

90010 Performing arts
90020 Support activities to performing arts
90030 Artistic creation
90040 Operation of arts facilities
91011 Library activities
91012 Archives activities
91020 Museums activities
91030 Operation of historical sites and buildings and similar visitor attractions
91040 Botanical and zoological gardens and nature reserves activities
92000 Gambling and betting activities
93111 Operation of ski facilities
93112 Operation of golf courses
93113 Operation of motor racing tracks
93114 Operation of horse race tracks
93119 Operation of arenas, stadiums and other sports facilities
93120 Activities of sport clubs
93130 Fitness facilities
93191 Horse racing activities
93199 Other sports activities n.e.c.
93210 Activities of amusement parks and theme parks
93290 Other amusement and recreation activities

S OTHER SERVICE ACTIVITIES

94111 Activities of business membership organisations
94112 Activities of employers membership organisations
94120 Activities of professional membership organisations
94200 Activities of trade unions
94910 Activities of religious organisations
94920 Activities of political organisations
94990 Activities of other membership organisations n.e.c.
95110 Repair of computers and peripheral equipment
95120 Repair of communication equipment
95210 Repair of consumer electronics
95220 Repair of household appliances and home and garden equipment
95230 Repair of footwear and leather goods
95240 Repair of furniture and home furnishings
95250 Repair of watches, clocks and jewellery
95290 Repair of other personal and household goods
96011 Washing and (dry-)cleaning for businesses and institutions
96012 Washing and (dry-)cleaning for households
96021 Hairdressing
96022 Beauty treatment
96030 Funeral and related activities
96040 Physical well-being activities
96090 Other personal service activities n.e.c.

T ACTIVITIES OF HOUSEHOLDS AS EMPLOYERS; UNDIFFERENTIATED GOODS- AND SEVICES-PRODUCING ACTIVITIES OF HOUSEHOLDS FOR OWN USE

97000 Activities of households as employers of domestic personnel
98100 Undifferentiated goods-producing activities of private households for own use
98200 Undifferentiated service-producing activities of private households for own use

U ACTIVITIES OF EXTRATERRITORIAL ORGANISATIONS AND BODIES

99000 Activities of extraterritorial organisations and bodies

12.2 Chosen Industries - SNI Codes

Choosen SNI Codes	Short code for Ind.	Industry
All (01110-03220)	A	AGRICULTURE, FORESTRY AND FISHING
All (05100-0990)	B	MINING AND QUARRYING
All (10111-33200)	C	MANUFACTURING
35140	D	ELECTRICITY, GAS, STEAM AND AIR CONDITIONING SUPPLY
-	E	WATER SUPPLY; SEWERAGE WASTE MANAGEMENT AND REMEDIATION ACTIVITIES
All (41100-43999)	F	CONSTRUCTION
All (45110-47999)	G	WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES
All (49100-53203)	H	TRANSPORTATION AND STORAGE
All (55101-56300)	I	ACCOMMODATION AND FOOD SERVICE ACTIVITIES
All (58110-63999)	J	INFORMATION AND COMMUNICATION
-	K	FINANCIAL AND INSURANCE ACTIVITIES
-	L	REAL ESTATE ACTIVITIES
All (69101-75000)	M	PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITIES
All (77110-82990)	N	ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES
-	O	PUBLIC ADMINISTRATION AND DEFENCE; COMPULSORY SOCIAL SECURITY
All (85100-85600)	P	EDUCATION
All (86101-88995)	Q	HUMAN HEALTH AND SOCIAL WORK ACTIVITIES
All (90010-93290) Except 91011-91020	R	ARTS, ENTERTAINMENT AND RECREATION
95110-96090	S	OTHER SERVICE ACTIVITIES
-	T	ACTIVITIES OF HOUSEHOLDS AS EMPLOYERS
-	U	ACTIVITIES OF EXTRATERRITORIAL ORGANISATIONS AND BODIES

12.3 Classification Criteria for Qualified Audit Opinions

All Auditor Related Classifications Retrived From Annual Reports

Swedish	English	Short Code	Occurence in Total Sample	Incl. In Study
Revisorn har ej tillstyrkt.	The auditor has not recommended	***GeneralAuditor***	447	**X**
Revisorn har ej tillstyrkt ansvarsfrihet för en eller flera styrelseledamöter, alt VD.	The auditor has not granted freedom of liability for the Board of Directors and or the CEO	***InternalControl***	11	**X**
Kontrollbalansräkning visar att likvidationsplikt föreligger.	Control Balance Sheet implies liquidation responsibility in accordance to Swedish law		61	
Likvidationsplikt föreligger. Kontrollbalansräkning är ej upprättad.	Liquidation responsibility exists. No control balance sheet has been established		258	
Kontrollbalansräkning visar att likvidationsplikt ej föreligger	Control balance sheet shows that no responsibility to liquidate is needed		25	
Balans- och/eller resultaträkningen innehåller osäkra eller felaktigt värderade poster.	Annual report includes faulty valuation of certain items	***IncorrValuation***	121	**X**
Påtalad brist i företagets interna kontroll.	Comment on the firms internal control	***InternalControl***	249	**X**
Betalning av skatter och/eller avgifter har ej skötts korrekt.	Tax payment has not been conducted correctly	***TaxPaymentProbl***	1590	**X**
Olaga lån har givits till aktieägare eller närstående	Unlawful loan has been given to a shareholder or other person close to the company		103	
Revisorskommentar av övrig allvarlig art	Audit opinion of other serious kind	***GeneralAuditor***	204	**X**
Allmän upplysning/kommentar från revisorn	General information from the auditor		130	
Koncernuppgift saknas	Information regarding group relation is missing		0	
Bolaget har erhållit kapitaltäckningsgaranti.	The company has received capital cover guarantee		4	
Svårbedömd reservation	Imponderable reservation		3	

12.4 Industry Risk Weight Distribution

Industry Risk Weights	Frequency	Short code for Ind.	Industry
2,54%	1,09%	A	AGRICULTURE, FORESTRY AND FISHING
2,88%	0,21%	B	MINING AND QUARRYING
3,53%	21,29%	C	MANUFACTURING
-	0,00%	D	ELECTRICITY, GAS, STEAM AND AIR CONDITIONING SUPPLY
-	0,00%	E	WATER SUPPLY; SEWERAGE WASTE MANAGEMENT AND REMEDIATION ACTIVITIES
3,59%	15,20%	F	CONSTRUCTION
2,41%	23,72%	G	WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES
3,97%	7,72%	H	TRANSPORTATION AND STORAGE
4,88%	4,87%	I	ACCOMMODATION AND FOOD SERVICE ACTIVITIES
2,98%	5,64%	J	INFORMATION AND COMMUNICATION
-	0,00%	K	FINANCIAL AND INSURANCE ACTIVITIES
-	0,00%	L	REAL ESTATE ACTIVITIES
3,00%	10,34%	M	PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITIES
4,76%	4,53%	N	ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES
-	0,00%	O	PUBLIC ADMINISTRATION AND DEFENCE; COMPULSORY SOCIAL SECURITY
1,85%	1,60%	P	EDUCATION
2,51%	2,60%	Q	HUMAN HEALTH AND SOCIAL WORK ACTIVITIES
3,22%	0,74%	R	ARTS, ENTERTAINMENT AND RECREATION
3,95%	0,45%	S	OTHER SERVICE ACTIVITIES
-	0,00%	T	ACTIVITIES OF HOUSEHOLDS AS EMPLOYERS
-	0,00%	U	ACTIVITIES OF EXTRATERRITORIAL ORGANISATIONS AND BODIES
	100% (50546)		

12.5 Conventional Model excl. companies with consumed share capital

	Failure - Model Sample			Failure - Holdout Sample		
Observed Failure	No	Yes	Overall %	No	Yes	Overall %
No	32002	7090	81.9%	7986	1811	81.5%
Yes	165	772	81.4%	48	197	80.4%
Overall accuracy			**81.9%**			**81.5%**
Average accuracy			**81.7%**			**81.0%**
Nagelkerke R Square			**32.2%**			

* *Cutoff-value 0,024 (Sample's failure ratio)*

Variables in equation

	Coefficient	Odds Ratio	Sig.
EBITTA	-1,605	,201	,000
TLTA	6,281	534,442	,000
CashTA	-2,298	,100	,000
RevenueTA	,070	1,073	,000
InvRev	,726	2,066	,003
IETL	1,597	4,936	,000
Group	-2,774	,062	,000
Cat_Services	-,337	,714	,000
Constant	-7,721	,000	,000

IEEBITDA and LnTA proved insignificant on a 5% level

12.6 Full Model excl. companies with consumed share capital

	Failure - Model Sample			Failure - Holdout Sample		
Observed Failure	No	Yes	Overall %	No	Yes	Overall %
No	33106	5986	84,7%	8286	1511	84,6%
Yes	117	772	86,8%	35	210	85,7%
Overall accuracy			**84,7%**			**84.6%**
Average accuracy			**85.8%**			**85.6%**
Nagelkerke R Square			**45.6%**			

* *Cutoff-value 0,024 (Sample's failure ratio)*

Variables in equation

	Coefficient	Odds Ratio	Sig.
EBITTA	-1,357	,257	,000
TLTA	4,719	112,021	,000
CashTA	1,945	,143	,000
RevenueTA	,063	1,065	,000
IETL	1,278	3,589	,006
Group	-2,598	,074	,000
Cat_Services	-,495	,610	,000
InternalControl	1,197	3,310	,000
LateFiling	,661	1,936	,005
TaxPaymentProbl	,844	2,327	,000
IncorrValuation	2,016	7,512	,000
GeneralAuditor	2,313	10,107	,000
Auditor_Change	,503	1,654	,000
DefaultPayment	1,151	3,160	,000
Age_Risk_1	,517	1,677	,000
Age_Risk_2	0,379	1,461	,000
Constant	,001	,001	,000

IEEBITDA, LnTA, IEEBITDA and Ind_Risk_W proved insignificant on a 5% level

12.7 Correlation Matrix for all used variables

	EBIT/TA	TL/TA	Cash/TA	Inv/Rev	Ln(TA)	IE/TL*	IEEBITDA	Group	Cat_ Services
EBIT/TA	1	-,383**	,146**	-,005	-,014**	-,060**	,000	,001	,029**
TL/TA	-,383**	1	-,110**	,004	-,075**	-,010*	,004	-,029**	,024**
Cash/TA	,146**	-,110**	1	-,012**	-,193**	-,081**	-,012**	-,092**	,170**
Inv/Rev	-,005	,004	-,012**	1	,012**	,000	-,001	,006	-,007
Ln(TA)	-,014**	-,075**	-,193**	,012**	1	,048**	,018**	,326**	-,144**
IE/TL*	-,060**	-,010*	-,081**	,000	,048**	1	,006	-,009*	-,015**
IEEBITDA	,000	,004	-,012**	-,001	,018**	,006	1	-,008	,000
Group	,001	-,029**	-,092**	,006	,326**	-,009*	-,008	1	-,037**
Cat_Services	,029**	,024**	,170**	-,007	-,144**	-,015**	,000	-,037**	1
InternalControl	-,004	,010*	-,009*	-,001	-,026**	,007	,000	-,029**	,017**
LateFiling	-,018**	,008	-,015**	-,001	-,009*	,017**	-,005	-,030**	,019**
TaxPaymProbl	-,022**	,045**	-,082**	-,001	-,068**	,035**	,000	-,066**	,010*
IncorrValuation	-,009*	,006	-,021**	,000	,000	,010*	,000	-,014**	,008
GeneralAuditor	-,040**	,046**	-,037**	,000	-,045**	,033**	,001	-,044**	,016**
DefaultPayment	-,041**	,052**	-,040**	,000	-,039**	,015**	,000	-,073**	-,003
Auditor_Change	-,009*	,018**	-,025**	,001	,051**	,010*	,008	,066**	,002
Age_Risk_1	,010*	,078**	,051**	,015**	-,145**	-,012**	-,002	-,069**	,068**
Age_Risk_2	,007	,029**	,086**	-,006	-,139**	,001	,004	-,069**	,092**
Ind_Risk_W	-,023**	,004	-,107**	,004	-,036**	,000	-,006	-,025**	,015**

	Internal Control	Late Filing	TaxPaym Probl	Incorr Valuation	General Auditor	Default Payment	Auditor Change	Age_ Risk_1	Age_ Risk_2	Ind_Risk_W
EBIT/TA	-,004	-,018**	-,022**	-,009*	-,040**	-,041**	-,009*	,010*	,007	-,023**
TL/TA	,010*	,008	,045**	,006	,046**	,052**	,018**	,078**	,029**	,004
Cash/TA	-,009*	-,015**	-,082**	-,021**	-,037**	-,040**	-,025**	,051**	,086**	-,107**
Inv/Rev	-,001	-,001	-,001	,000	,000	,000	,001	,015**	-,006	,004
Ln(TA)	-,026**	-,009*	-,068**	,000	-,045**	-,039**	,051**	-,145**	-,139**	-,036**
IE/TL*	,007	,017**	,035**	,010*	,033**	,015**	,010*	-,012**	,001	,000
IEEBITDA	,000	-,005	,000	,000	,001	,000	,008	-,002	,004	-,006
Group	-,029**	-,030**	-,066**	-,014**	-,044**	-,073**	,066**	-,069**	-,069**	-,025**
Cat_Services	,017**	,019**	,010*	,008	,016**	-,003	,002	,068**	,092**	,015**
InternalControl	1	-,009	-,011*	-,003	-,006	,012**	,013**	,012**	,008	,011*
LateFiling	-,009	1	-,020**	-,005	-,010*	,005	,001	,010*	,004	,007
TaxPaymProbl	-,011*	-,020**	1	-,007	-,013**	,042**	,009*	,037**	,030**	,007
IncorrValuation	-,003	-,005	-,007	1	-,003	,014**	-,004	,002	-,001	,001
GeneralAuditor	-,006	-,010*	-,013**	-,003	1	,085**	,017**	,042**	,012**	,008
DefaultPayment	,012**	,005	,042**	,014**	,085**	1	,013**	,029**	,007	,007
Auditor_Change	,013**	,001	,009*	-,004	,017**	,013**	1	,093**	-,008	-,032**
Age_Risk_1	,012**	,010*	,037**	,002	,042**	,029**	,093**	1	-,154**	-,029**
Age_Risk_2	,008	,004	,030**	-,001	,012**	,007	-,008	-,154**	1	-,079**
Ind_Risk_W	,011*	,007	,007	,001	,008	,007	-,032**	-,029**	-,079**	1

12.8 Conventional Model with vast number of financial variables

	Failure - Model Sample			Failure - Holdout Sample		
Observed Failure	No	Yes	Overall %	No	Yes	Overall %
No	30956	8132	79.2%	7703	2094	78.8%
Yes	271	1023	79.1%	94	269	74.1%
Overall accuracy			**79.2%**			**78.7%**
Average accuracy			**79.2%**			**76.5%**
Nagelkerke R Square			**28.2%**			

* *Cutoff-value 0,033 (Sample's failure ratio)*

Variables in the Equation

	Coefficient	Odds Ratio	Sig.
RETA	-0,928	0,395	0
EBITTA	-2,72	0,066	0
TLTA	2,175	8,805	0
CashTA	-2,809	0,06	0
APRev	2,27	9,677	0
InvRev	0,484	1,622	0,027
LnTA	-0,38	0,684	0
IETL	1,26	3,526	0
Koncern	-1,832	0,16	0
Cat_Services	-0,201	0,818	0,008
Constant	-0,47	0,625	0,242

EBITRevenue, ShortTermDebttoEquity, CashCurrLiab, RevenueTA, TA, IEEBITDA and Ind_Risk_W proved insignificant on a 5% level

12.9 Full Model with vast number of financial variables

	Failure - Model Sample			Failure - Holdout Sample		
Observed Failure	No	Yes	Overall %	No	Yes	Overall %
No	33046	6042	84.5%	8255	1542	84.3%
Yes	230	1064	82.2%	72	291	80.2%
Overall accuracy			**84.5%**			**84.1%**
Average accuracy			**83.4%**			**82.3%**
Nagelkerke R Square			**41.6%**			

* *Cutoff-value 0.033 (Sample's failure ratio)*

Variables in the Equation

	Coefficient	Odds Ratio	Sig.
RETA	-,693	,500	,000
EBITTA	-2,232	,107	,000
TLTA	1,770	5,874	,000
CashTA	-2,390	,092	,000
APRev	1,647	5,190	,000
InvRev	,445	1,560	,039
LnTA	-,332	,718	,000
IETL	,951	2,588	,002
Group	-1,590	,204	,000
Cat_Services	-,283	,754	,001
InternalControl	1,070	2,915	,000
LateFiling	,585	1,795	,003
TaxPaymentProbl	,857	2,355	,000
IncorrValuation	1,763	5,831	,000
GeneralAuditor	2,008	7,451	,000
PaymentDefault	1,236	3,442	,000
Auditor_Change	,423	1,526	,000
Age_Risk_1	,652	1,919	,000
Age_Risk_2	,380	1,462	,000
Constant	-1,138	,320	,013

EBITRevenue, ShortTermDebttoEquity, CashCurrLiab, RevenueTA, TA, IEEBITDA and Ind_Risk_W proved insignificant on a 5% level

12.10 Tables depicting the estimated probabilities for the both models

Tables depicting the estimated probabilities for the conventional and the full model.

Conventional model	Full model