NEARLY FOUR[1] DECADES LATER: IS ACCOUNTING STILL USEFUL IN PREDICTING BUSINESS FAILURE?

PROBABILISTIC BUSINESS FAILURE PREDICTION ON NORDIC MANUFACTURING FIRMS

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Master Thesis

Stockholm School of Economics

2021

[1]The Skogsvik (1987) study used financial statements up to 1982, while this thesis uses financial statements up to 2019. Hence nearly four decades later.

Nearly four decades later: Is accounting still useful in predicting business failure?

Abstract:

With the aim of examining whether accounting-based failure prediction models still can be used effectively, this thesis investigates how well prediction models classify a modern sample of firms applying IFRS. In doing so, this thesis anchors on the Skogsvik (1987) study and performs a three-step plan. The first step tests the robustness of the original Skogsvik (1987) model. The second step recalibrates the coefficients in the Skogsvik model to assess how the relative importance of each financial ratio has changed. In step three an entirely new failure prediction model, the Haglund and Olufsen (2021) model, is created to see which financial ratios best predict firm failure in a modern context. The sample of firms used to generate the model consists of Nordic manufacturing firms. Probit analysis was performed from one year before failure up to five years before failure on a sample of 388 survivor firms and 52 failure firms in the time period 2005-2021. The results indicate that the original Skogsvik (1987) model works well in the shorter prediction span, while one must recalibrate or create a new model in order to get a high predictability in the longer prediction span. We conclude that accounting information still can be used effectively in predicting business failure under IFRS, as the error rates in the models generated are similar to those in Skogsvik (1987). However, the compositions of the models are to a large extent different. Therefore, we conclude that business failure prediction models must mirror the business environment of the firms they examine.

Keywords:

Business failure prediction, Probit analysis, Financial ratio analysis, IFRS, Decision relevance of accounting

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Acknowledgement:

We would like to extend our deepest gratitude towards our supervisor Kenth Skogsvik, for his guidance and help through each stage of the process of writing this thesis. His valuable insights and expertise on business failure prediction has been instrumental in the creation of this thesis.

Master Thesis
Master Program in Accounting, Valuation and Financial Management
Stockholm School of Economics

1. Introduction

"It's hard to make predictions - especially about the future."
-Niels Bohr (Ellis, 1970, p. 431)

In the 1960s, the business failure prediction domain emerged with the ground-breaking studies of Beaver (1966) and Altman (1968). The Beaver study was the first to incorporate financial ratios in a business failure setting in his univariate model. While the Altman study was not the first of its kind, the innovative aspect was the incorporation of multiple financial ratios into one model for the predictions. In the Nordics, the Skogsvik (1987) model predicted business failure on a Swedish sample of manufacturing firms. The studies found financial ratios to be useful predictors. However, several studies from the turn of the millennium (c.f. Brown, 1999; Francis & Schipper, 1999; Lev & Zarowin, 1999) pointed towards a declining decision relevance of accounting information since the earlier studies. Different studies cite different reasons, but there seems to be three main themes affecting the decision relevance of accounting. These themes are *changes in business models, changes in accounting regimes* and *macroeconomic factors.*

One big difference in today's business models compared to those of the 1960s-1970s is the high share of intangible assets (intangibles). Intangible assets can be defined as assets that are not physical in nature. Ponemon Institute (2020) calculated that the total tangible assets of all S&P 500 firms in 1975 were 0.59 trillion USD and that the total intangible assets were 0.12 trillion USD. By 2018, intangible assets were 21.03 trillion USD and tangible assets were 4 trillion USD. Studies have shown that the rise of intangible assets has negatively affected the value relevance of accounting (c.f. Brown, 1999; Francis & Schipper, 1999; Lev & Zarowin, 1999). The main reason cited for this effect is that intangibles are harder to value than tangibles.

A major change in the accounting regime since the 1960s-1970s is the implementation of the International Financial Reporting Standards (IFRS). The standards have homogenized financial accounting in European countries. Also, it has put an increased emphasis on fair value accounting compared to for instance the Swedish GAAP (SGAAP), which among other things increases the volatility in the financial statements.

As for the macroeconomic environment, inflation and interest rates in the Nordics have gone from double digits in the 1980s to close to zero in the 2010s. One practical implication of the lower interest rate level is that it has become cheaper to employ high leverage. For the lower inflation, one practical implication is that the amounts generated by historical cost accounting (HCA) are closer to what would be generated by current cost accounting (CCA). However, the effects of the lower interest and inflation levels on failure predictability are less explored.

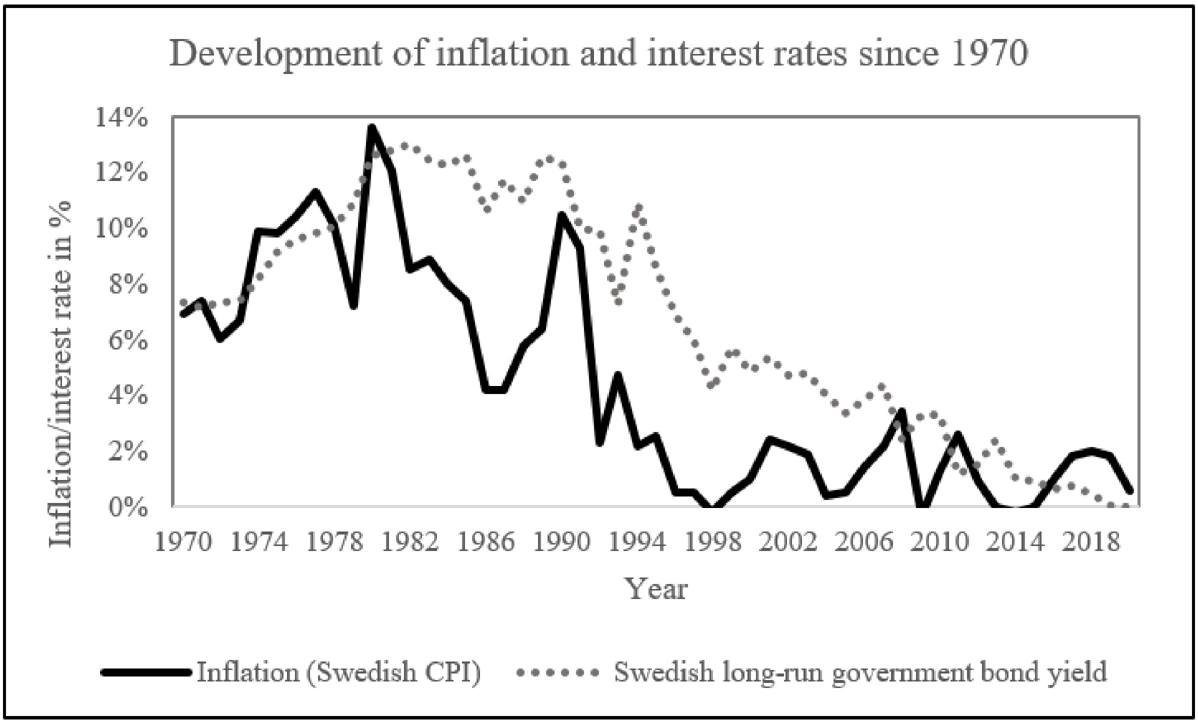


Figure 1: Development of inflation and interest rates from 1970 to date (Based on rates from Statistiska Centralbyrån (2021; n.d.))

This thesis will examine whether accounting-based failure prediction models still can be used effectively on a modern sample of firms applying IFRS. In addition, it will be examined whether the prediction relevance with regard to business failure has improved or deteriorated over the last roughly 40 years. There are several practical advantages of being able to predict business failure. Practitioners that adequately incorporate failure risk in their investment assessments can come closer to the fair value. Researchers can test the robustness of previous business failure/bankruptcy prediction models or assess whether new factors affect failure risk. In terms of sample firms, looking at Nordic manufacturing firms is of interest as the results of the Skogsvik (1987) study could be used as a reference of the ratios' predictive power. In this thesis a three-step plan will be performed. In step one, a test of Skogsvik's (1987) original failure prediction model on the modern sample will be conducted. This is done in order to test the robustness of the Skogsvik model. In step two, a recalibration of the coefficients in Skogsvik's prediction model will be executed. This is done in order to assess whether the financial ratios have gotten less or more weighting and thereof importance in the model. In step three an entirely new failure prediction model will be created to see which financial ratios best predict firm failure in a modern context.

The rest of the thesis will be structured in the following way. In part 2 there will be a review of the literature regarding the decision relevance of accounting and business failure prediction, and the regulatory background. In part 3 the methodological choices of this thesis will be explained. Part 4 describes the firm sampling and sample characteristics. Part 5 shows the results of the analysis. In part 6, the results from part 5 are discussed. Lastly, in part 7, we will draw some concluding remarks.

2. Literature review and regulatory background

2.1 Decision relevance of accounting

The foundation of exploring the decision relevance of accounting in predicting business failure was laid out in the study by Beaver (1966), which examined financial ratios of surviving and failing firms over a five-year period - in the failing firm case the five years prior to failure. Financial ratios were found to be stable over time for surviving firms while they deteriorated over time for failing firms, creating a gap in the ratios between survivors and failures. The study was able to detect 92% of firms going bankrupt or surviving one year in advance using only the net income to total debt metric. More studies soon followed within bankruptcy prediction using different methods to assess the predictability. Two of the most influential studies, the Altman (1968) multi discriminant analysis-based study and the Ohlson (1980) logit-based study, showed high predictability of bankruptcies using financial ratios. However, more recent literature has been more skeptical towards the decision relevance of accounting in predicting bankruptcies or other variations of business failure. Beaver et al. (2012) looks at financial reporting attributes in order to assess whether financial ratios have the ability to predict bankruptcy. The study finds that there has been a decline in the predictive ability of financial ratios for bankruptcy and that the decline is associated with financial reporting attributes, such as the increased presence of intangible assets in more modern firms.

2.1.1 Changes in business models

The literature suggests that the loss in decision relevance of accounting is not only attributable to the area of business failure. Francis & Schipper (1999) explored the decision relevance of accounting data to explain market values over the period 1952-1994. They found that the predictability of various accounting measures to explain market values had decreased over the time period. However, the results of the study did not provide unambiguous evidence that financial reports have lost their relevance. Moreover, the paper examined whether the decreased predictability is greater for high-technology stocks compared to low-technology stocks. The reason why this was examined is that there is a notion that high-technology firms have certain items that yield future cash flows that are not properly recognized in financial statements, like R&D expenditures. The study showed that the decision relevance had not declined more for high-technology firms compared to low-technology firms. A further analysis of the study was done by Brown et al. (1999), who found that the decision relevance of accounting variables to explain the market value of equity had declined significantly according to the R^2 metric. Another study with similar results was conducted by Lev & Zarowin (1999). The authors studied the usefulness of financial information to investors in comparison to the total information available on the marketplace. The evidence in the study suggested that the usefulness of book values of equity, reported earnings and cash flows had deteriorated over the past 20 years.

The underlying reason for the declining decision relevance of accounting is contested. Srivastava (2014) looked at cohorts of firms being listed on the U.S. stock markets. The study found that each new cohort had more investments into intangibles and that earnings quality decreased with higher intangible investments. Therefore, the author argues that firms have become more knowledge-intensified, which has led to "the widening gap between the intangible intensities for the new- and seasoned-firm segments" (p. 198). With the shift of the U.S. economy from being primarily an industrial economy to being a knowledge-based economy (Thurow 2000), firms have invested more into intangibles. One example is R&D expenses, which in U.S. GAAP are expensed immediately but are expected to generate future cash flows (KPMG, 2017). The level of the future expected cash flows is hard to assess by the businesses, which has increased the volatility of revenues and cash flows. Another example is SG&A (Selling, General and Administrative) intensity, as the study finds a relationship between high SG&A expenses in relation to measures like revenue, other income and low earnings quality. The conclusion of the study is that the increased volatilities combined with increased matched timing of investments and the cash flows they are expecting, has led to a decreased relevance of earnings. Lev & Zarowin (1999) cites the rate of innovative changes of businesses, mainly driven by investments in intangible assets, as the reason for this deterioration. The authors argue that the then prevailing accounting standards failed to properly value intangibles due to mismatching revenues and costs and that there is a positive correlation between decreased decision relevance of accounting and change in R&D expenditures.

In another study of the U.S. market, Fama and French (2004) makes the argument that weaker firms and firms with riskier payoffs were able to be listed between 1970-2000 compared to earlier. As the number of new listings per year increased from about 160 to about 550 in the 1980s and 1990s, there was an increased supply of public companies for investors to invest in. They argue that an increased supply of capital drove the cost of equity down, which allowed for firms with riskier or more distant expected payoff to issue public equity. They saw that there was a shift from profitable firms to growth firms being listed, which was reflected in the increased failure rate of newly listed firms. The study makes the argument that the market was inexperienced at pricing such firms that were listed between 1970-2000, hence the decision relevance of accounting was weakened.

In their working paper regarding the development of earnings quality, Starica and Kang (2020) frames the views of Fama and French (2004) and Srivastava (2014) as the two narratives regarding the decline in earnings quality. The authors argue that the declining development of earnings quality directly reflects the declining business strength of listed firms, regardless of intangible intensity. In contrast to the findings in Srivastava (2014), the study finds that the level of earnings quality measures is roughly independent of the level of SG&A intensity. The study finds that while increased SG&A intensity is associated with decreased business strength, the decline in business strength can as well occur without increasing SG&A intensity.

2.1.2 Changes in accounting regimes

Firms that are listed in the Nordics have to conduct their accounting in accordance with the IFRS. IFRS was implemented in Europe in 2005, when the European Union adopted legislation that required all listed companies within the European Union to prepare their financial statements in accordance with IFRS (FASB, n.d.). Kouki (2018) studied the effect of voluntary IFRS adoption for firms in Germany, Belgium and France for the decision relevance of the book value of equity and earnings. The study found that implementing IFRS increased the decision relevance. A similar study was done by Suadiye (2012), which found that the adoption of IFRS increased the decision relevance of accounting information for Turkish listed firms.

The value effect of IFRS has also been studied in the Nordics. As firms that adopted IFRS in 2005 had to restate their 2004 annual reports from the national GAAP (Generally Accepted Accounting Principles), Gjerde et al. (2008) looked at both the IFRS version and the Norwegian GAAP (NGAAP) version of annual reports of Norwegian listed firms. The findings of the study indicated that the restatements from NGAAP to IFRS increased the decision relevance. A main reason was explained to be due to IFRS' handling of intangible assets. More intangible assets are capitalized in IFRS than in NGAAP, where they more frequently are expensed. The finding makes the increased decision relevance consistent with the view that capitalizing intangible assets is more value-relevant than expensing them as incurred or through amortization.

A contrasting finding was made by Hamberg et al. (2011), who found that the transition to IFRS 3 (Business Combinations) made the handling of goodwill, which is an intangible asset, more dependent on managerial decision-making. As managerial decision-making can differ depending on i.e., economic incentives, the study suggests that the decision relevance regarding goodwill has gotten weaker since the adoption of IFRS 3. Hellman et al. (2016) came to a similar conclusion when examining how 40 business analysts viewed fictional acquisitions made by Ericsson based on whether the price premium (price paid over the fair value of the net of identifiable assets and liabilities) was allocated to goodwill or identifiable intangible assets. The study showed that when the price premium was allocated to goodwill, the acquisition was more likely to be seen as value adding, while the acquisition was more likely to be seen as value reducing when allocated to identifiable intangible assets.

Wu & Lai (2020) found a positive relationship between goodwill intensity and stock price crash due to information asymmetry, as high goodwill intensity increased the probability of goodwill impairment and managers tend to hoard bad news until it is finally released to the public. Intangible intensity contains proxies for factors such as goodwill size and R&D expenses, as its purpose is to capture all intangible elements of a business (Wu & Lai, 2020). Another study regarding analysts' views, in this context the earnings forecast, was conducted by Gu & Wang (2005). The study found that analysts' earnings forecast errors increased when a firm's intangible intensity was higher than the industry norm or when a firm had more complex intangibles (e.g. diverse and innovative technologies). However, the study found that industries with high intangible intensity did not have higher analyst forecast errors than industries with low intangible intensity.

An Australian study by Bodle (2016) analyzed the effect of IFRS adoption on bankruptcy prediction in an Australian setting. In contrast to Norwegian GAAP (NGAAP), Australian GAAP (AGAAP) allows intangibles to be capitalized and revalued upwards to a larger extent than IFRS does. Empirical evidence from Australia had shown that financially distressed firms were more likely to capitalize and revalue intangibles upwards compared to healthy firms. By using Altman's (1968) bankruptcy prediction model, the study found that under IFRS the model was able to predict bankruptcy with higher accuracy than under AGAAP. However, the amount of type 2 errors (see section 3.1 for a definition of type 2 errors) increased under IFRS for non-failure firms. Overall, the results did seem to indicate that the change from AGAAP to IFRS improved the decision relevance of financial information in predicting bankruptcy. Besides the findings, the study touches upon small firms having a higher likelihood of going bankrupt. This phenomenon is also documented in Beaver (1966), where survivor and failure firms were paired by total asset size before the testing of financial ratios. This was done to mitigate the effect asset size had on the failure prediction, so that the effect of financial ratios could be tested as independently as possible.

2.1.3 Changes in macroeconomic factors

When it comes to the macroeconomic environment, a striking difference between the 1970s-1980s and today is the level of the interest rates, which are at a significantly lower level today. Long-term government bond yields were between 5-13% back then, drastically different compared to the current levels of 0.14% per February 2021 (Edvinsson et al. 2014; Sveriges Riksbank 2021a & 2021b). The higher interest rates back then made the high emphasis on interest expense in prior bankruptcy prediction models (c.f. Skogsvik, 1987) reasonable, as profitability declines would result in difficulties to pay interest on loans - especially for highly levered firms. However, as the interest rates are significantly lower today, we hypothesize that the interest expense will be a predictor with less weight in a failure prediction model in the current macroeconomic environment.

2.2 The Skogsvik (1987) failure prediction study

One of the main purposes of this thesis is to test the conditions of the Skogsvik (1987) study on a more recent sample. Skogsvik (1987) used probit analysis to predict business failure on a sample of Swedish manufacturing firms in the time period 1966-1982. One of the main purposes of the study was to examine the predictive power of current cost accounting (CCA) compared to historical cost accounting (HCA). The rationale for examining the measures was the high inflation level in Sweden during the 1970s and 1980s, which spanned from 4.2% to 13.6% on an annual basis. The Skogsvik study found little evidence that CCA had different predictive power than HCA, and since the inflation rates have been significantly lower in recent times in the Nordics, with inflation rates ranging from -0.3% to 3.4% per year since 2005, we hypothesize that the differences in CCA compared to HCA would be even lower currently than in the Skogsvik study.

The study contained a sample of 51 firms classed as failures and 328 classified as survivors. To determine whether a firm was manufacturing, Skogsvik looked at firms registered in Sweden with an SNI-code starting with 2 (“Gruvor och mineralbrott”, mining and quarrying industries) or 3 (“Tillverkningsindustri”, manufacturing industries). In order to examine mature, established firms, Skogsvik looked at limited liability firms (Aktiebolag) with 200 or more employees or 20 MSEK or more in total assets (in 1970 price level) for any of the years 1966-1971. The probit analysis generated the following equation as the optimal function one year prior to the failure (t-1):

$$V = -1.5 - 4.3 * R_1 + 22.6 * R_2 + 1.6 * R_3 - 4.5 * R_4 + 0.2 * R_5 - 0.1 * R_6 \qquad (1)$$

Where:
R_1 = EBIT to average total assets
R_2 = Interest expense to average total liabilities
R_3 = Average inventory to revenue
R_4 = Owner's equity to total assets
R_5 = Change in owners’ equity
R_6 = Change in interest cost in relation to average interest cost last 4 years

The same procedure was repeated from year two up to year six prior to failure, and the coefficients and statistically significant ratios varied slightly from year to year. The functions were able to predict business failure with an average error rate in the holdout sample ranging from 16.7% one year before failure to 26.7% six years before failure using the sample proportion of failure firms as a benchmark. Measures that were found to reduce the probability of failure one year prior to failure were return on assets and solidity, while interest expense, inventory size and change in equity were found to increase the probability of failure. Although defined differently from study to study, these measures are recurring in the business failure literature (cf. Beaver, 1966; Altman, 1968; Ohlson, 1980). Other measures that are common in business failure prediction that were not found to be statistically significant enough in Skogsvik (1987) includes working capital and asset turnover, amongst others. The coefficients of the ratios give an indication of their impact on the failure prediction. One can therefore argue that Skogsvik found that interest expense seemed to be a strong indicator of business failure, while relative change in interest cost had the least significant effect of the measurements in equation 1. Please see table 9 in section 5.1 for the probit functions and t-values for year 1 to 5 before failure in the Skogsvik (1987) study. See table 1 on the next page for a summary of a sample of previous studies regarding business failure prediction. Note that the study by Bodle et al. applies Altman’s (1968) MDA model, and the paper focuses more on the type 1 errors achieved as they are perceived as more costly. The type 1 error rate of that study is 5.6% using the IFRS-restated financial statements in (t-1).

Author(s)	Method	Sample	Sample size	Average error rate for t-1	Time period
Beaver	Univariate Discriminant Analysis	US industrial, publicly owned companies with total assets between 0.6-45 mUSD	79 failing firms, 79 surviving firms	13%	1954-1964
Altman	Multiple Discriminant Analysis	US manufacturing firms with total assets between 1-25 mUSD	33 failing firms, 33 surviving firms	5%	1946-1965
Ohlson	Logit Analysis	US industrial, publicly traded firms	105 failing firms, 2058 vectors from surviving firms (one from each survivor)	14.9%	1970-1976
Skogsvik	Probit Analysis	Swedish manufacturing firms with total assets <20 mSEK or <200 employees	51 failing firms, 328 surviving firms	16.7%	1966-1982
Bodle et. al	Multiple Discriminant Analysis	Listed Australian firms, retroapplying IFRS. Excluded firms in financial industry	46 failing firms, 46 surviving firms	31.1%	1996-2004

Table 1: Summary of a sample of previous studies regarding business failure prediction.

2.3 Business failure definition in prior studies

The definition of business failure differs across the literature. Some studies include only bankruptcy in their definition (cf. Altman, 1968; Ohlson, 1980), while others use a broader definition. Beaver (1966) defines business failure as "the inability of a firm to pay its financial obligations as they mature." In practice, this definition includes bankruptcy, bond default, an overdrawn bank account or nonpayment of a preferred stock dividend. Skogsvik's (1987) definition includes bankruptcy and/or composition arrangement, voluntary shut-down of the main operating activity and government support being provided to a substantial extent. The rationale for using this broader definition was that it would capture more cases where the substance of the business failure was the same, but the form of the outcome differed. In theory, this would reduce estimation errors as the indicators from accounting would be similar in failure firms regardless of the eventual failure or survivor outcome. The differences in failure definitions have made it difficult to directly compare models from different studies with another (Bellovary et al. 2017).

2.4 Development of Nordic GAAPs from 1970s up to date

Accounting in Denmark, Norway and Sweden is traditionally based on company law and links financial reporting to tax accounting (Camfferman & Zeff, 2007). This linkage is described by Marton (2017) as: "Accounting regulation affects the calculation of taxable income, and tax regulation affects the measurement of accounting income." One example where taxation historically has influenced financial accounting is that R&D expenditures rarely were disclosed on the financial statements, as the effect of reducing the taxable income was seen as a greater concern than possible rationales for capitalization that were found in other countries (Wilmott et al., 1992). As the primary users of financial statements were the government and banks, the information requirements were suited for these users rather than for other potential users like investors (Jönsson, 1991 & Smith, 2000, p. 64). One example of how this view has expressed itself is that IFRS requires financial statements to include a statement of comprehensive income and a statement of changes in equity, which is not required under Swedish GAAP (Marton, 2017). As time progressed, the need for Nordic accounting standards to converge with international standards increased as it facilitated the participation of Nordic companies on international capital markets. Particularly influences from U.S. accounting was welcomed, as many of the largest firms were quoted on the U.S. securities markets (Wilmott et al., 1992). Hellman (2011) looked at the Swedish voluntary adoption of IFRS from 1991 to 2005. The study found that “Sweden's ambition to voluntarily move toward more capital market-oriented financial reporting was delayed and hindered by forces defending the conservative accounting tradition and, accordingly, a soft IFRS adoption policy was chosen,” where a soft IFRS adoption meant that IFRS was adopted in such a way that traditional national accounting practices could be maintained. Nowadays, listed firms in Sweden need to follow IFRS and non-listed firms need to follow any of the K-regulations, depending on the size of the firm (Bokföringsnämnden, 2020). For example, K3 is based on IFRS for SMEs, although it does not converge completely with IFRS for SMEs (André, 2017).

2.5 Key differences between IFRS and Nordic GAAPs

As previously mentioned, Nordic listed firms have since 2005 been required to make the consolidated financial statements applying IFRS. IFRS was introduced with the intention of standardizing the annual and consolidated financial statements for companies. While IFRS and the Nordic GAAPs have many similarities, they also differ in certain aspects. In this section a few of these aspects will be looked into.

Principally there is a key difference between IFRS and the Nordic GAAPs. The GAAPs are so-called result-oriented, meaning the overall goal is to get as good as possible of a measurement of the period's result. Implicitly this means that the balance sheet gets a more subordinated role. On the other hand, IFRS is balance-oriented and has a starting point in the definitions of assets and liabilities. An asset is defined as "a resource controlled by an entity as a result of past events from which future economic benefits are expected to flow to the entity" ref. IAS 38 §8, while a liability is defined as "a present obligation of the entity to transfer an economic resource as a result of past events" ref. IFRS conceptual framework 4.26. These definitions are then used to define results, revenues and costs - which are defined as changes in assets and liabilities. This then means that under IFRS, the income statement has the subordinated role. Another key difference is that IFRS to a larger extent is detail oriented. While the Norwegian standards in total amount to ±450 pages and the Swedish K3-regulations amount to ±300 pages for instance, the IFRS consists of approximately 2 000 pages. The GAAPs are typically more principle-based, while IFRS to a larger extent has detailed regulations for issues firms come across.

One of the more striking differences between IFRS and the Nordic GAAPs is that IFRS to a larger extent uses the concept of "fair value". The Nordic GAAPs build on a transaction-based historical cost model which requires there to be a transaction, such as a purchase or a sale, before one is allowed to account for it in the financial statements. Typically, this means that assets are valued at the acquisition cost less any depreciation or impairment, with write-ups not being allowed. There are however certain exceptions to this, for instance that marketable stock is to be valued at fair value as well. So, what is fair value? IFRS 2 appendix A defines fair value as "the amount for which an asset could be exchanged, a liability settled, or an equity instrument granted could be exchanged, between knowledgeable, willing parties in an arm's length transaction."

The assets or liabilities are measured using business criteria, meaning by calculating the present value of expected future inflows and outflows - so called capital values. In a well-functioning efficient market, capital values should be approximately equivalent to market values. IFRS permits, and sometimes requires, that certain assets and liabilities are recorded at their fair value. And unlike the GAAPs, these are recorded at fair value regardless of if a transaction has happened or not. A consequence of this is that unrealized gains occur on the income statement under IFRS to a larger extent than under the GAAPs, with the implicit result that the fair value introduces more volatility to the financial statements. Assets such as biological assets, financial instruments, investment property and stock-based compensation are all accounted for using fair value. Biological assets are defined as "a living animal or plant," and the GAAPs typically require firms to account for these at the lowest of fair value and cost price. As the cost price is typically always lower than the fair value, this means the book value of a biological asset is typically significantly lower in GAAP compared to under IFRS. For Norwegian listed salmon-producing firms this meant that the IFRS-implementation blew up the book value of the assets and reduced the leverage, but it also raised other issues like determining when a salmon is big enough to be placed on the balance sheet (Fardal, 2007 & Bernhoft, n.d.).

Another key difference between the GAAPs and IFRS are the requirements for the notes. The GAAPs typically have relatively liberal note requirements, while IFRS has detailed requirements as to which information that has to be given in notes. This partially comes from the increased use of fair value under IFRS, but also since it has more discretionary assessments. Information about assumptions, methods etc. are useful for understanding the assessments that have been made. Certain items can under IFRS either be dealt with under a historical cost model or at fair value, but even if the firm decides to use the historical cost model the notes require that the firm discloses the fair value of the item too. One of these items are investment properties, which ref. IAS 40 §30 either can be accounted for under the fair value model or the cost model. However, since listed property firms have to declare the fair value in the note requirements anyways, most firms also choose to account for it in their financial statements using the fair value model. Obviously, the fact that the fair value typically is higher than the value under the historical cost model reinforces this development as well, as this among other things affects the leverage positively.

Arguably the area with the greatest difference between IFRS and GAAP is financial instruments, which are regulated under IFRS 9. As a key rule under IFRS 9, most financial instruments are required to be dealt with using fair value, and the standard provides detailed regulation as to how this should be done. Under the GAAPs, financial instruments are typically dealt with using historical cost with impairment tests. IAS 32 §11 defines financial instruments as "any contract that gives rise to a financial asset of one entity and a financial liability or equity instrument of another entity." Financial assets are typically divided into three larger groups: debt instruments, derivatives and equity. Debt instruments are to be dealt with either by using amortized cost, fair value through other comprehensive income (FVOCI) without recycling or fair value through profit and loss (FVTPL) dependent on whether certain criteria are met. Derivatives are always to be dealt with using FVTPL, while equity can either be dealt with under FVTPL or FVOCI without recycling dependent on whether certain criteria are met. IFRS 9 typically has the biggest impact on banks and other financial institutions, but it also affects manufacturing firms. If a manufacturing firm has hedged the purchasing price of a raw material or the exchange rate for exporting the produced goods, these derivatives have to be dealt with using FVTPL under IFRS and changes in fair value will hence affect both the balance sheet and income statement.

As referred to under section 2.1.2, the treatment of intangible assets varies. IFRS has requirements as to how one should identify and properly recognize intangible assets after mergers and acquisitions. The GAAPs have historically to a larger extent than IFRS allocated any excess amount paid to goodwill, while IFRS attempts to divide it more onto other items such as brand, intellectual property, customer lists, customer and supplier relationships etc., with the residual amount then being allocated to goodwill. As prior studies have pointed to however, this leaves room for managerial influence and judgment. Another key difference is that under many GAAPs goodwill is to be amortized using a reasonable amortization plan, and it should be tested for impairments if there are indications of such. Under IFRS, however, goodwill is not to be amortized, but it has to be checked for impairment annually plus whenever there are indications of impairments. Under both alternatives reversing previous impairments is not allowed. In practice this means that IFRS-applying firms will have more irregular changes to goodwill than GAAP-applying firms - such as the firms in Skogsvik's (1987) sample. This could imply that reductions in goodwill for IFRS-applying firms could be a signal for failure and that the firms in our sample in general will have higher proportions of goodwill in relation to the total assets.

Another area where Nordic GAAPs differ from IFRS is leases. In Nordic GAAPs, there is a distinction between financial leases and operating leases. Financial leases are accounted for as assets and liabilities on the balance sheet, while operating leases are expensed linearly throughout the leasing period. This treatment is in line with IAS 17, which was the accounting standard to be followed before IFRS 16 was implemented January 1st, 2019 (IFRS, n.d.). If a lease is classified as operating, it has the practical implication that the lease will not be accounted for on the balance sheet. Under IFRS 16 all leases are accounted for on the balance sheet. Therefore, contrasting firms that apply IFRS 16 with firms that apply IAS 17 could be of interest from a value relevance of accounting perspective. However, the effect of IFRS 16 will be captured very briefly in this thesis since it includes information from 2005-2019. As IFRS 16 was implemented January 1st, 2019, only the financial statements from 2019 will be affected by the implementation. All else equal, the implementation of IFRS 16 will tend to increase the leverage on the balance sheet and increase the interest expenses compared to the prior practice laid out in IAS 17 (Bokföringsnämnden, 2020).

3. Methodology

3.1 Basics of failure prediction models

Predicting business failure, often referred to as bankruptcy in prior literature, has been an area of extensive research since the 1960s. As it is an area highly relevant for creditors, investors and other stakeholders, it is of high importance. Various models have historically had different approaches, some models build on accounting numbers whereas others rely on market data. Models using accounting numbers as input typically convert these into financial ratios, which are put into a prediction model that uses some statistical analysis or technique. From these prediction models, one typically gets two possible outcomes, hence a binary variable - either the firm is deemed to be failing/bankrupt, or it is deemed to be surviving based on the model input. Different models can have different forecast horizons and use different financial ratios. Some models are univariate like Beaver's model from 1966, while others are multivariate like Altman's model from 1968. Common for most models are that the output from the model is compared to some threshold - and depending on whether the value is higher or lower than this threshold, a firm is classified as a survivor or failure. In this classification there are two types of errors that can be made. Either one can classify a failing firm as a surviving one which is an error type 1, or one can classify a surviving firm as a failure which is an error type 2 as illustrated in table 2.

		Actual outcome	
	State	Survive	Fail
Predicted outcome	Survive	Correct	**Error type 1**
	Fail	**Error type 2**	Correct

Table 2: Overview of errors type 1 and 2

In determining how well a prediction model works, one often calculates an average prediction error for the forecast horizon(s). Generally speaking, the lower the average prediction error, the better the model works. In terms of errors type 1 and 2, the average error rate can be calculated as following:

$$\text{Average error rate} = \frac{\text{Type 1 error rate} + \text{Type 2 error rate}}{2} \tag{2}$$

Where:

$$\text{Type 1 error rate} = \frac{\text{Number of failure firms classified as survivors}}{\text{Total number of failure firms}} \tag{3}$$

$$\text{Type 2 error rate} = \frac{\text{Number of survivor firms classified as failures}}{\text{Total number of survivor firms}} \tag{4}$$

The average failure rate gives an indication on the robustness of the model and how accurate it is in terms of predicting failure.

3.2 Modelling approach and choices

This thesis will conduct three separate tests on the same sample of Nordic listed firms. The first test is one using the same ratios and coefficients as the Skogsvik (1987) study. In a sense, this part will test the robustness of Skogsvik's model. The second test is one using the same ratios as in Skogsvik (1987), but with newly calibrated coefficients based on our sample. The third test is one where there will be created a new, robust prediction model with new ratios and coefficients optimized based on our sample. The ratios used in Skogsvik's (1987) probit functions are shown in figure 2 under:

$$R_1 = R_A = \frac{EBIT}{Average\ assets}$$

$$R_2 = R_L = \frac{Interest\ expense}{Average\ liabilities}$$

$$R_3 = t(1) = \frac{Income\ taxes}{EBT}$$

$$R_4 = TIV = \frac{Average\ inventory}{Revenues}$$

$$R_5 = LI_1 = \frac{Cash}{Current\ liabilities}$$

$$R_6 = E_R = \frac{Equity}{Assets}$$

$$R_7 = E' = \frac{Change\ in\ equity}{OB\ equity}$$

$$diff(R_L) = \frac{R_{L,t} - \overline{R_{L,t-1}}}{[\sum_{T=t-4}^{t-1}(R_{L,T} - \overline{R_{L,t-1}})^2/3]^{0.5}}$$

Where:

$$\overline{R_{L,t-1}} = \sum_{T=t-4}^{t-1} R_{L,T}\ /\ 4$$

Figure 2: Ratios used in Skogsvik's (1987) probit functions. Please note that R_1, R_2, …, R_7 refer specifically to the allocation in this thesis, and not Skogsvik's (1987) study.

In this thesis, 7 out of the 8 ratios from Skogsvik (1987) have been used in step 1 and 2. The last ratio is a bit cumbersome to calculate and was found to be not very influential in the original study and has hence been left out. The reason why the same ratios are tested as those used in Skogsvik (1987) is to see whether the Skogsvik model could predict failure in our sample, and if it is still viable for failure prediction many decades after it was created. In order to conduct our tests, some choices have been made which will be elaborated upon in the following sections.

3.2.1 Definition of failure

In this thesis failure has been defined as any of the following: bankruptcy, restructuring, liquidation or turnaround. By bankrupt firms one means bankrupt in the formal sense, which is a criterion many prior studies have used for failure. In this thesis however, the scope is slightly wider than just bankruptcy, and includes among others restructuring. Firms undergoing restructuring are typically characterized by high debt and severe liquidity issues, which eventually makes it inevitable to survive without undergoing drastic measures. This typically includes converting debt to equity, often leaving prior equity holders with a tiny stake of the new total equity holding. Since many restructurings are very tiny, for instance tiny changes to a firm's capital structure, only the more severe restructurings have been included as failures in this thesis. In a sense this can be said to be conservative.

Firms entering liquidation tend to have a business model which has not worked out, and instead of continuing with the non-functioning business the assets are liquidated and any eventual surplus are paid out to shareholders. Liquidation is here defined as a failure since if the business model was successful, the firm would not consider liquidating. Liquidation and voluntary shutdowns are perceived to be within the same category. Company turnarounds can occur when the original business model failed, and the firm is now operated in another form - i.e., as a holding company for the purpose of utilizing deferred tax assets. In Skogsvik's (1987) study, the criteria for business failure were bankruptcy and/or composition agreement, voluntary shutdown and various forms of governmental funding. In our thesis the latest failure requirement has been left out, primarily for two reasons. One being that it would be difficult to identify governmental funding with the data material the thesis is built on, and second because governmental funding seems to be less common nowadays.

3.2.2 Geographical limitation

In this thesis the geographic scope has been set a bit wider than the one used in Skogsvik's (1987) study, by not only looking at Swedish firms but also including listed firms from Denmark, Finland and Norway. In general, firms in Scandinavia tend to have quite similar business models, with similar institutional settings, similar historical accounting rules and similar legal framing (Nordea, 2021a). Including these additional countries should hence not affect the sought homogeneity drastically. In order to achieve a sufficient number of failures which is needed to get reasonably reliable estimated models, the scope had to be set wider than just looking at listed Swedish firms as the number of identified Swedish failure firms was insufficient.

3.2.3 Choice of time period and type of firms

As IFRS is the framework that will be used for listed firms in Scandinavia in the foreseeable future, it would be valuable to have updated prediction models based on post-IFRS data. In Denmark, Finland, Norway and Sweden IFRS became mandatory from the financial year 2005 for listed firms, which is the underlying reason for why this thesis looks at failures in the time period from 2005 up until February 2021 (EUR-Lex, n.d. & Deloitte IAS Plus, 2021). As non-listed firms in Scandinavia generally are not required to apply IFRS in their financial reporting, a choice was made to only look at listed firms to ensure they were applying IFRS.

3.2.4 Choice of industry

As this thesis in some ways can be viewed as a continuation on Skogsvik's (1987) prior work, a decision was made to include similar types of firms in our sample. Skogsvik's study included manufacturing firms from SNI category 2 (mining and quarrying) and SNI 3 (manufacturing) (Skogsvik, 1987, p. 150). The SNI classification has been changed and updated slightly since the 1980s, but today's category B (mineral extraction) and category C (manufacturing) have been deemed to be comparable. As the data from the other countries does not include a SNI-code, as it only exists for Swedish firms, the Standard Industrial Classification (SIC) has been used in this thesis. In order to get a similar categorization as in the SNI-code, all SIC-codes from 1000 up to 4000 have been deemed to be relatively comparable to the classification in Skogsvik's original study (U.S. Securities and Exchange Commission, 2020). The range includes industries like metal mining, crude petroleum & natural gas, tobacco products, household furniture, paper mills, engines & turbines, aircraft and much more.

3.2.5 Criterion for firm size

In order to remove some of the smaller firms, a choice had to be made in terms of how this would be done. In Skogsvik (1987), firms with total assets over 20 million SEK and/or an employee count over 200 were included (Skogsvik, 1987, p. 150). Firms that did not meet any of the criteria were excluded. As there have been some difficulties in gathering information about the number of employees for the firms in our sample, this thesis will solely use the size of total assets as a criterion. As there has been some inflation since the 1980s, we have inflation-adjusted the total asset threshold using a Swedish consumer price index calculator (Statistiska Centralbyrån, n.d.). Skogsvik began his study in 1982, and 20 million SEK in 1982 was equivalent to approximately 46.1 million SEK in 2005. For simplicity this number has been rounded down to 45 million SEK, and is a benchmark used on both survivors and failures. On the survivor firms the total assets benchmark has been used against the firms' total assets reported for the most recent financial year, which is 2019. For the failures, the total assets benchmark has been used against the failures for year (t-3), the third last financial report before failure. This was done since many of the failure firms were observed to have quite drastic reductions in total assets in the years prior to failure. Also, total assets have support in prior literature on being a good benchmark for size, c.f. Beaver (1966) and Ohlson (1980).

3.2.6 Type of financial reports

For the firms included in the sample, a decision had to be made whether to use the consolidated or non-consolidated financial statements as a basis. In this thesis all the data has been extracted from the consolidated financial statements. This was done to be aligned with the unit view of accounting, where you view everything under one unit. In theory this should increase the comparability between the firms, as one may remove some group organizations that potentially could distort the picture of a firm. It could be special purpose vehicles (SPVs) that are subsidiaries specifically designed for a narrow purpose, such as isolating financial risk. The basis used is the annual reports, and not the interim reports. As the annual reports of listed firms are audited, whereas the interim reports are usually not, it is viewed as more likely that the information provided in the annual reports is reliable and accurate.

3.2.7 Determining the point of failure and defining the prediction horizon

For failure firms, financial information from the last annual report before failure has been classified as one year before failure (t-1). The second to last annual report before failure has been classified as two years before failure (t-2), and the same goes for (t-3) to (t-5). While this means that the information taken is not necessarily from one year before failure (for example, if a firm goes bankrupt in June, we classify the numbers as of 31st December as one year before failure), it is deemed to be the most practical approach to tackle the problem of timeliness and is in line with what has been done in prior studies. As some firms did not have financial statements up to year 6 prior to failure, the number of failure firms varies slightly from year to year, as table 3 below illustrates.

Prediction horizon	Number of failure firms	Number of survivor firms	Total
t-1	52	388	440
t-2	52	388	440
t-3	52	388	440
t-4	48	388	436
t-5	47	388	435

Table 3: Overview of firms in the prediction horizons

In order to allocate financial statements from various years into the various prediction horizons, one must be able to determine the point of failure. There has been an attempt to identify failure signals as early as possible. This proved to be a challenge, especially for the older failures. In the instances where it was not possible to identify any early signs of failure through news stories, press releases from the firm etc., the failure date has been set to the formal failure date, typically the formal announcement of bankruptcy. See table 4 under for an overview of the time to failure for the failure firms.

Days from last report to failure	Number of firms
0-90	5
91-180	24
181-270	5
271-360	11
361-720	4
720+	3
	52

Average time to failure	
In days	237
In months	7.9

Table 4: Overview of time to failure. See appendix A for a detailed overview

3.2.8 Choice of prediction horizon

As a consequence of many failures only having data access for years (t-1) to (t-6), the prediction horizon in this thesis will be limited to years (t-1) to (t-5). As line items for (t-6) are needed to calculate average metrics for year (t-5), one needs six years of data for prediction horizons of up to five years. Various studies have different prediction horizons, and in Skogsvik (1987) the prediction horizons ranged from (t-1) to (t-6) for instance. As observed in prior studies however, the longer the prediction horizon, the worse the predictive ability of the models. Thus, the choice of having a prediction horizon of up to five years prior to failure is judged to be sufficient.

3.2.9 Setting upper and lower bounds for financial ratios

In the analysis of the data, a decision had to be made in terms of what to do with extreme values. While truncating data adds a layer of subjectivity, the decision to do so was made in order to remove the risk of extreme values destroying the predictive ability of the models. This thesis has an approach where truncation of all values more than ± 5 standard deviations away from the mean has been undertaken. This means that for all financial ratios, one gets an upper bound and a lower bound that the values get limited to. Out of the 54 775 observations across the 26 ratios, 0.27% were truncated due to being higher or lower than the bounds, whereas 4.99% had DIV 0-errors - meaning the denominator was zero. 90% of the DIV 0-errors were set to 0 due to the numerator being close or equal to zero, whereas 10% of the DIV 0-errors were set to upper or lower bound depending on the sign of the numerator - since as a denominator approaches zero, the value theoretically goes to ± infinity. Please see appendix B for an overview on truncation, bounds and more for all 26 ratios.

3.2.10 Assigning survivor firms to failure firms

To partially remove part of the time bias there has been an attempt at making the proportions of years included equal for both the sample of survivors and failures. In practice this means that for each failure firm, 7 or 8 survivors were assigned. So, if the failure firm went bankrupt in 2013, then (t-1) is 2012, (t-2) is 2011 etc. - and then the 7 or 8 survivors assigned will also have (t-1) as 2012, (t-2) as 2011 etc. to match the time periods. As not all of the firms had data going back to 2000, this allocation was only possible to do in a partially randomized way. For the more recent failures, more newly listed firms were allocated. When all survivor firms listed after 2001 were assigned to the more recent failures, the rest of the survivors were randomly assigned among the remaining failure firms by using a random select function. Hence, among the firms with data going back to 2000, the allocation was completely randomized. The data for the failure firms and the survivor firms should be for the same year, so a comparison based on the same time period is possible. See section 4.2.3 for the outcome of the pairing procedure.

3.2.11 Determining a threshold for survivor/failure-classification

In order to decide whether a firm will be classified as surviving or failing, a benchmark/threshold needs to be set. In an article by Skogsvik & Skogsvik (2013), it is argued that one can choose between three different thresholds, where none of them necessarily are better than the other.

The first of these is the sample proportion of failure firms (SPOFF) threshold, which is based on the number of failure and survivor firms in the sample for the specific prediction horizon. In (t-1) in this thesis, there are 52 failure firms and 388 survivor firms included ref. table 3. Hence out of 440 firms in total, 11.82% were failures. This would then be the threshold that the estimated probabilities of failure would be benchmarked against. An estimated probability higher than 11.82% would classify the firm as a failure, and vice versa.

The second alternative to decide whether a firm is surviving or failing turns things around. Rather than comparing the cutoff to the calculated probabilities based on sample proportions, one adapts the cutoff to the probabilities in order to minimize the average error rate. It can hence be said to be a procedure based on trial and error, where one changes the cutoff-value ever so slightly until the cutoff which minimizes the average error rate is found. This procedure is then performed on all the prediction horizons from (t-1) up until (t-5), meaning one will have different thresholds for each prediction horizon.

The third alternative way to set a benchmark is by using the failure rate in the population. As in Skogsvik (1987), the proportion of failure firms in relation to surviving firms in the estimation sample in this thesis is higher than the proportion of failure firms in the population. In a paper by Bărbuță-Mișu, N., & Madaleno (2020) assessing the bankruptcy risk of large companies, the frequency of company insolvency in Denmark, Finland, Norway and Sweden is respectively reported to be 3.76%, 1.47%, 2.44% and 3.33%. As our sample mixes firms from these countries, one could argue for a probability of failure in the population of listed, Nordic firms of around 3%. What this ultimately means is that the probabilities calculated in our models will be upwards-biased, which one can adjust for by applying the formula in equation 5 below (Skogsvik & Skogsvik, 2013). This procedure has to be performed if the calculated probabilities are to be used in exercises such as calculating the value of equity or bonds incorporating a probability of failure. As this is deemed outside the scope of this thesis, it will not be used at any point except for being mentioned here.

$$p(\text{fail})_{POP} = p(\text{fail})_{ES} * \left[\frac{\pi * (1-\text{prop})}{\text{prop} * (1-\pi) + p(\text{fail})_{ES} * (\pi - \text{prop})} \right] \quad (5)$$

where:

$\boldsymbol{\pi}$ = probability of failure in the population of companies

prop = proportion of failure in the estimation sample of companies

$..._{POP}$ = value of variable in the population of companies

$..._{ES}$ = value of variable in the estimation sample of companies

In the analysis of our data material, the cutoff will be tested based on the SPOFF threshold and the threshold that minimizes the error rate, which is in line with the decisions made in Skogsvik (1987). In terms of phrasing, the words threshold and cutoff will be used interchangeably throughout this thesis and will refer to the same thing.

3.3 Choice of statistical method

In making predictions, statistics are of crucial importance. In prior business failure or bankruptcy studies, various statistical methods have been used. While some studies used fairly simple univariate statistics, others have created more advanced multivariate models with techniques like probit analysis, logit analysis, multiple regression analysis, linear multiple discriminant analysis (MDA) etc. These techniques have different assumptions, which may influence what technique that can be deemed to be more suitable in a thesis of this kind. More recent research has also applied option valuation techniques in predicting failure.

3.3.1 Linear MDA

In many previous bankruptcy prediction studies, linear multiple discriminant analysis (MDA) has been used. Linear MDA builds on the idea that the total population of firms can be split into two sub-groups, here of failures and survivors. The result from linear MDA is only informative for ranking firms' bankruptcy probability within the sample. In other words, there is only a possibility to see whether one firm is more likely to fail than another in the sample, not to determine the absolute probability of failure (Linnergren-Fleck & Skarle 2008). Studies by Skogsvik & Skogsvik (2013) and Zavgren (1985) have shown that this approach is less useful for decision contexts and practical applications compared to probabilistic approaches (Gerdin & Rump, 2017). The technique assumes that the independent variables are multivariate normally distributed in each sub-group, and that the variance/covariance - matrices for the independent variables are identical in the sub-groups. One of the main critiques towards MDA is that the assumptions behind the model do not seem to hold in reality. As Zavgren (1985) formulates it, "discriminant analysis requires that the variables are normally distributed, and the populations have equal variance-covariance matrices." Several studies have shown that these assumptions rarely hold in reality (cf. Ohlson, 1980; Skogsvik, 1990; Zavgren, 1985), and one may hence question how relevant linear MDA is for use in predicting business failure.

3.3.2 Option valuation techniques

Several more recent studies have applied an option valuation technique in predicting failure/insolvency. The techniques build on the option pricing theory set out in Black & Scholes (1973) and Merton (1974). In simple terms, many of these techniques assume that the shareholders hold a European call option on the firm, where they may either pay the exercise price or not depending on whether the value of the assets exceed the liabilities or not. The exercise price is the amount of cash needed to pay the liabilities. Using this technique, you get a probability of failure independently assigned to each firm. Compared to the financial-ratio-based bankruptcy prediction models, the performance of option valuation-based bankruptcy prediction models has in general not been inferior (Jackson & Wood, 2013).

3.3.3 Probit and logit analysis

Probit and logit analysis are quite similar statistical methods. Although they do not produce identical results, they produce very similar results. Neither method requires that the independent variables are multivariate normally distributed or that the variance/covariance-matrices are identical like linear MDA does. Probit analysis enables the probability of failure for each firm in the sample to be expressed in percent, as the index variable that is calculated is assumed to be normally distributed. Logit analysis enables the same but assumes that the index variable is logistically distributed. Uğurlu and Aksoy (2006) examined the bankruptcy prediction accuracy of both logit and discriminant models on a sample of Turkish manufacturing firms. The logit model was found to be more accurate over the four years prior to bankruptcy. As a key goal of this thesis is to test the robustness of the Skogsvik (1987) model on a modern sample, using the same method would increase the comparability compared to if another method was used.

As the method that was used in the Skogsvik (1987) study was probit regression, this thesis will use probit as well in order to make the results more comparable. Probit regression is defined as a binary regression where the inverse standard normal distribution of the probability is modeled as a linear combination of the predictors (UCLA Institute for Digital Research & Education Statistical Consulting, 2021). The two outcomes in the binary regression are survive (0) or fail (1). To conclude whether a firm should be classified as a failure or survivor, the value from the cumulative normal distribution function of the index variable generated through the model is compared to a threshold, ref. section 3.2.11. If the value is lower than the threshold, the firm is classified as a survivor firm, and if the value is higher than the threshold it is classified as a failure (UCLA Institute for Digital Research & Education Statistical Consulting, 2021). The index variable typically consists of a constant and multiple independent variables (here: financial ratios) with different weights assigned, like illustrated in equation 6 under:

$$V = constant + weight_1 * financial\ ratio_1 + weight_2 * financial\ ratio_2 + \cdots \quad (6)$$

Failures will have high values for the index variable, and vice versa for survivors. A positive weight/coefficient for a ratio means that high levels of that ratio is associated with a higher probability of failure, all else equal. And vice versa, a negative coefficient for a ratio means that high levels of that ratio are associated with a lower probability of failure.

3.4 Selection of financial ratios

The ratios to be tested in step 3 were selected in two stages. First, the strongest ratios from the components used in the Skogsvik (1987) study were selected to examine their importance in a modern context. However, one of the ratios that were used in the Skogsvik (1987) study, growth in untaxed reserves, is not included. The reason is that these kinds of untaxed reserves are not recorded in IFRS (Nordea, 2021b). Instead, growth in deferred taxes is included. These ratios are named R_1 - R_{15} and R_{26} in our thesis. Second, multiple additional ratios have been carefully and selectively added. Criteria for the selection included perceived relevance in the decision relevance and business failure literature, but also keeping in mind the changes from the 1970s both regulatorily and in the business environment. This approach differs slightly from the approach in Skogsvik (1987), where only ratios that had been found to be successful in previous business failure literature were included.

As for the new ratios tested, interest coverage ratio (R_{16}) has been added as it is a frequently used covenant in loan arrangements. Several ratios including intangible assets and R&D expenses have been added (R_{17} - R_{20} and R_{23} - R_{25}). There are two reasons why they are added. First, as mentioned in section 1 and 2, intangibles are a major part of businesses today. Second, none of the prominent earlier studies within the business failure domain has tested such ratios specifically, so investigating them is adding to the existing literature. This is the reason as to why several iterations of ratios are tested as there is no previous knowledge of what types of measures would be the most relevant to test. As there are subjective judgments that can influence whether to expense or capitalize R&D, ratios regarding R&D expenses are included. A FCF (free cash flow) ratio has been added as we want to examine a cash-based return metric to complement the accounting-based return ratios already included (which are EBITDA, EBIT and EBT-based). Worth noting is that the ratio added is FCF to current liabilities and hence is a liquidity ratio primarily rather than a return ratio. See appendix C for definitions for some of the inputs to the ratios. The final sample of the 26 ratios tested is shown in figure 3 on the next page. The letter next to R_1 - R_7 relates to which component the ratio was assigned to in the Skogsvik (1987) study (p. 201).

$$R_1 = A) = R_A = \frac{EBIT}{Average\ assets}$$

$$R_2 = C) = R_L = \frac{Interest\ expense}{Average\ liabilities}$$

$$R_3 = D) = t(1) = \frac{Income\ taxes}{EBT}$$

$$R_4 = G) = TIV = \frac{Average\ inventory}{Revenues}$$

$$R_5 = H) = LI_1 = \frac{Cash}{Current\ liabilities}$$

$$R_6 = M) = E_R = \frac{Equity}{Assets}$$

$$R_7 = O) = E' = \frac{Change\ in\ equity}{OB\ equity}$$

$$R_8 = R_E = \frac{EBITDA}{Average\ equity}$$

$$R_9 = ATO = \frac{Revenues}{Average\ assets}$$

$$R_{10} = LI_2 = \frac{Current\ assets}{Current\ liabilities}$$

$$R_{11} = LTAS = \frac{Long - term\ assets}{Total\ assets}$$

$$R_{12} = FAS = \frac{Inventory + PPE}{Total\ assets}$$

$$R_{13} = AS = ln\ (Total\ Assets)$$

$$R_{14} = \Delta CL = \frac{\Delta Current\ liabilities}{OB\ Current\ liabilities}$$

$$R_{15} = \Delta D = \frac{\Delta Debt}{OB\ Debt}$$

$$R_{16} = ICR = \frac{Interest\ expense}{EBITDA}$$

$$R_{17} = TS = \frac{Tangible\ equity}{Total\ assets}$$

$$R_{18} = R\&DS = \frac{R\&D\ expense}{Sales}$$

$$R_{19} = IAS = \frac{Intangible\ assets}{Total\ assets}$$

$$R_{20} = R\&DR = \frac{R\&D\ expense}{EBIT}$$

$$R_{21} = PM = \frac{Gross\ profit}{Revenues}$$

$$R_{22} = FCFCL = \frac{Free\ cash\ flow}{Current\ liabilities}$$

$$R_{23} = GS = \frac{Goodwill}{Total\ assets}$$

$$R_{24} = \Delta G = \frac{\Delta Goodwill}{OB\ Goodwill}$$

$$R_{25} = \Delta IA = \frac{\Delta Intangible\ assets}{OB\ Intangible\ assets}$$

$$R_{26} = \Delta DT = \frac{\Delta Deferred\ taxes}{OB\ Deferred\ taxes}$$

Figure 3: Financial ratios for step 3.

3.5 Statistical decisions in creating a new prediction model

In order to create the probit functions for (t-1) to (t-5) as displayed in section 5.3, a stepwise probit analysis was performed for all years. For each year, the analysis started by having all 26 ratios as independent variables, and then running the analysis in Stata to see which ratios that seemed to have some predictive ability in our sample. In the first step, the 4-5 ratios with the lowest t-values were removed. Then the analysis was run again and again until there were less and less ratios left. Two guiding principles were applied in terms of deciding which ratios to keep in each step.

1. The ratios should have coefficients with a t-value of about 1.6 or higher (absolute value).
2. The ratios should not have intercorrelations higher than about 0.5.

The first guiding principle is implemented to ensure that one can say with some statistical confidence that the coefficients of the ratios are different from zero. A t-value of about 1.6 will translate to a confidence level of around 90% dependent on the degrees of freedom, which means that one accepts being wrong about one out of every ten times. The probit analysis in essence compares the ratios of the failures and survivors, and if a ratio is very different in the two groups it is likely to have a high t-value and coefficient (in absolute terms). In borderline cases where the t-value is slightly lower than 1.6, it has been included if the ratio was statistically significant for any other bordering prediction horizon. Adding ratios with a t-value lower than 1.6 could possibly give lower error rates, but it could make the model less robust and hence less likely to work well over time. One of the purposes of creating a business failure prediction model is for it to be robust, hopefully over time, and therefore the model has not been built solely for getting low error rates.

The second guiding principle is implemented to get more logical results. Two very highly correlated ratios could be statistically significant when just one of them is included in the probit analysis, but both could be insignificant if they are both included in the probit analysis. In such cases, the ratio with the highest t-value has been included in our models. Another side effect which could occur is that both the highly intercorrelated ratios are statistically significant when included together, but with opposite signs of the coefficients. This was the case with R_6 and R_{17} for instance, meaning equity to assets and tangible equity to assets, which intuitively does not make much sense. Strictly speaking one could argue for having a higher tolerance for intercorrelation if the correlation is typical and can be expected to continue in the future.

Eventually after rerunning the probit analysis over and over and removing insignificant ratios, one gets down to a function with a certain number of statistically significant ratios. To ensure no statistically significant ratios were left out, all removed ratios were then added back one by one to see if they were significant or not. A special case was observed for (t-1), where the constant-term was found to be statistically insignificant. In that case a decision was made to re-estimate the coefficients for the significant ratios based on the constant being set to 0.

The final estimated probit functions including t-values for the Haglund and Olufsen (2021) model are displayed in section 5.3, and the correlation matrices for each prediction horizon are displayed in appendix D. In addition, the chi-square likelihood ratio will be provided. The higher the likelihood ratio is, the higher the association between the dependent and independent variables.

4. Data

4.1 Sample selection

The WRDS Compustat database was used in order to get a sufficient sample of survivor firms that fit the criteria in 3.2.2 - 3.2.5. First, a sample of all firms that had been listed in Denmark, Finland, Norway and Sweden during 2005-2020 was retrieved. Here, the sample contained 1741 firms. Second, identified delistings and failures were removed, which shrunk the sample by 425 firms to 1316. Third, firms that did not fit the size criteria (<45 mSEK in total assets) or operated in the wrong industries were removed. This reduced the sample by 886 firms to 430. In the fourth and last step, a manual review of the remaining sample was conducted in order to remove pre-commercial biotech firms and other non-manufacturing firms with a SIC-code between 1000 - 4000. The firms removed were removed for being service-based, operating in R&D-heavy industries having immaterial or zero revenues, or small inventories and revenues in proportion to total assets. In this last sort out, 42 firms were removed. After these steps were conducted, the final sample of 388 survivor firms was set. For a list of all survivors, see appendix E.

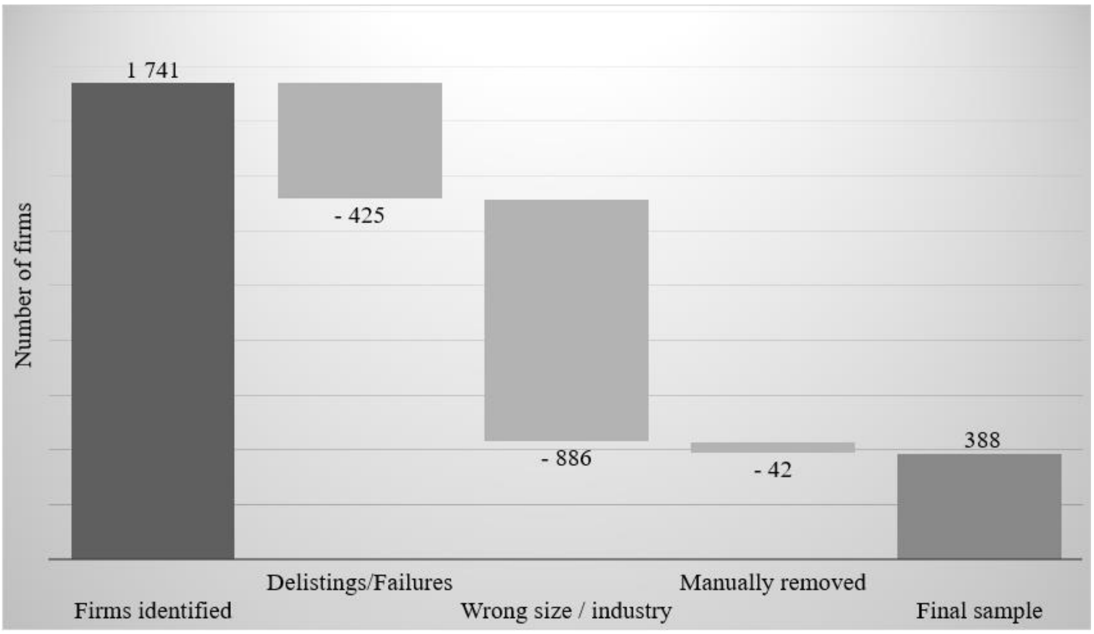


Figure 4: Sample selection of the survivor firms.

For failures, changes in the lists of major stock exchanges in the Nordics were examined. If the reason as to the list change was failure, the firm was selected for the initial sample. The following exchanges and sources were examined: Skatteverket (The Swedish Tax Agency), Nasdaq Copenhagen, Nasdaq Stockholm, Nasdaq First North, the Nasdaq Nordic Surveillance Annual Reports, and Oslo Stock Exchange. The initial sample contained 175 failure firms. This compilation of firms was then filtered using data retrieved from the WRDS Compustat database and Serrano database. The filtering criteria were the size of the total assets and the industry classification (SIC-code). 10 firms that did not fit the size criteria (<45 mSEK in total assets) and 113 firms belonging to the wrong industry were removed. The final sample contained 52 failure firms. For a list of all failures, see appendix F.

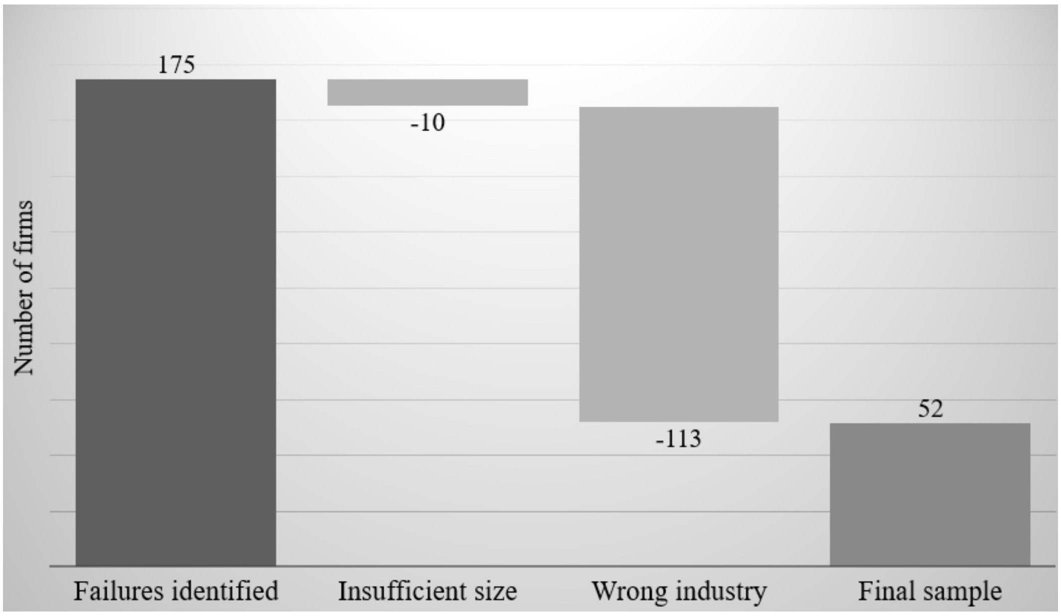


Figure 5: Sample selection of the failure firms.

4.2 Descriptive statistics of the sample

The descriptive statistics in this section are shown to describe the sample of failure and survivor firms in terms of key characteristics. The key characteristics selected are industry, geography, year and size for all firms in the sample, as well as type of failure for the failure firms.

4.2.1 Industrial distribution of firms

There is a wide range of industries represented in the sample of survivor firms. In figure 6 with survivor firms on the next page, industries that contribute with 5% or more of the sample are presented separately. The industries accounting for less than 5% of the sample are presented within the “Other” category. Despite this broad presentation, the four largest categories represent more than half of the sample. In figure 7 with failure firms on the next page, industries accounting for 10% or more of the sample are presented separately. Like the survivors, the failure firms also come from a wide range of industries. The industry with the most failure firms is “Oil and Gas Extraction”, followed by “Metal Mining”. These two industries combined make up more than a half of the failure firms. “Industrial and Commercial Machinery and Computer Equipment” is the only industry that makes up a substantial share of both survivors (13%) and failures (11%).

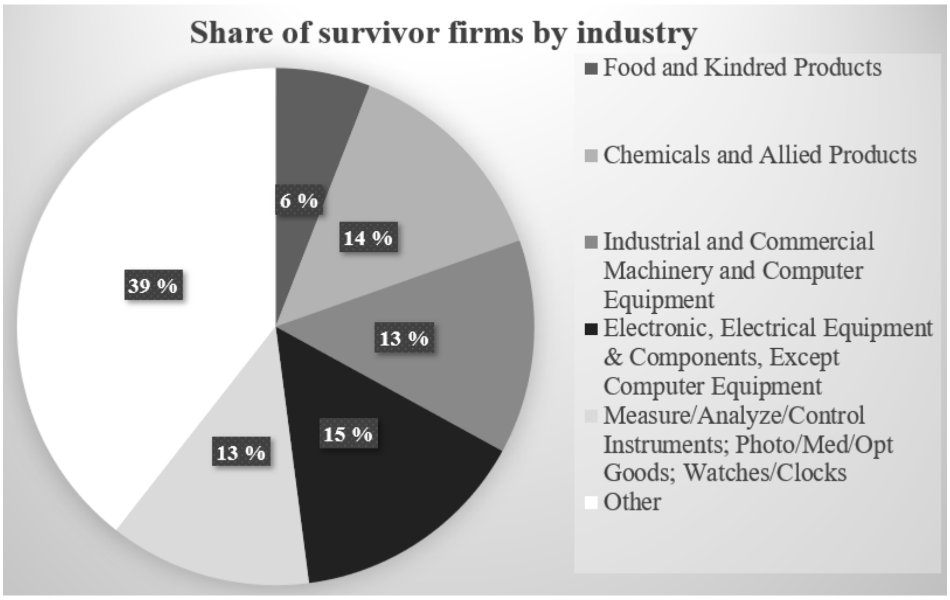


Figure 6: Share of survivor firms by industry

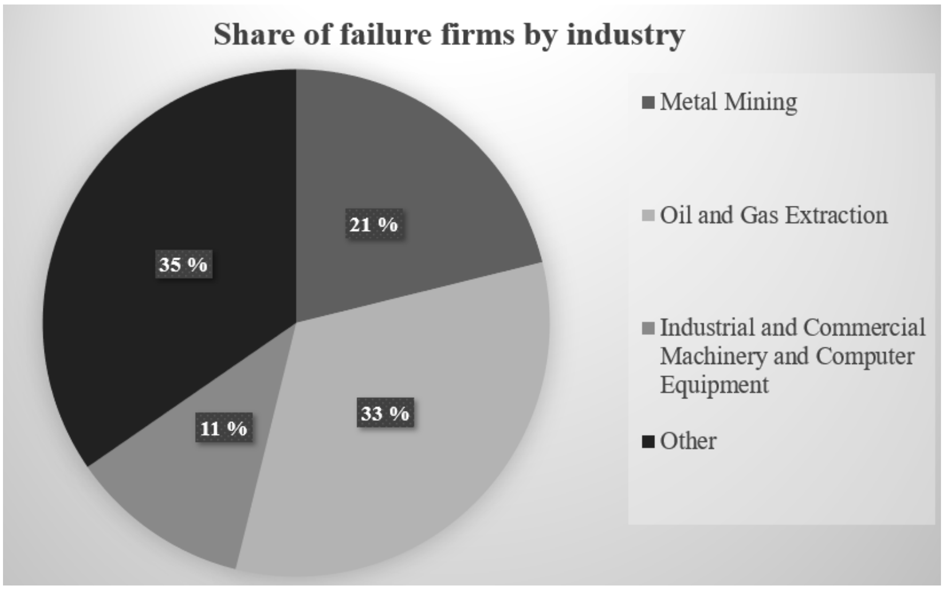


Figure 7: Share of failure firms by industry

4.2.2 Geographical distribution of firms

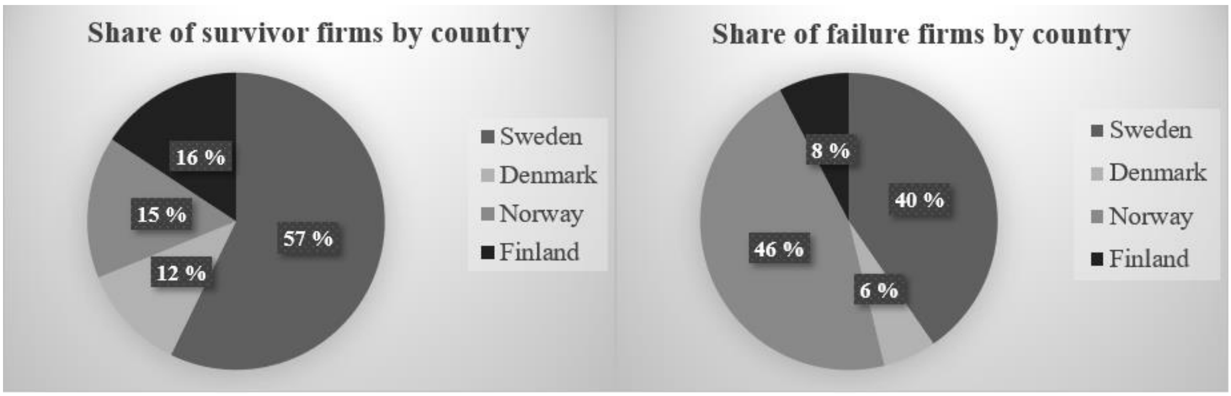


Figure 8 and 9: Share of failure and survivor firms by country

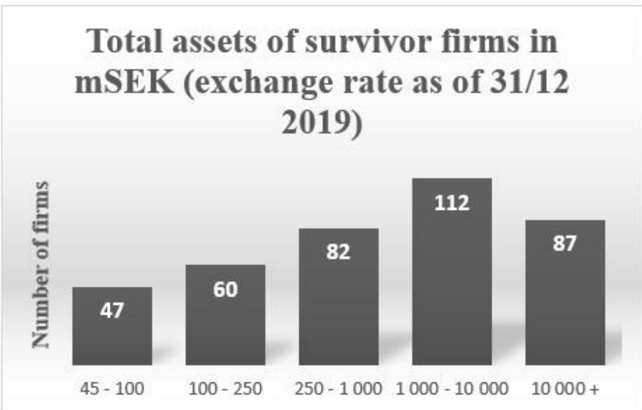
The country where the highest share of survivor firms originate from is Sweden with 57% of the sample. Denmark (12%), Norway (15%) and Finland (16%) all contribute with about equal amounts of firms to the sample. Swedish firms also make up a large proportion of the failure firms. However, the country where the most failure firms originate from is Norway. This is partly driven by the fact that the majority of the firms in the "Oil and Gas Extraction" industry are Norwegian.

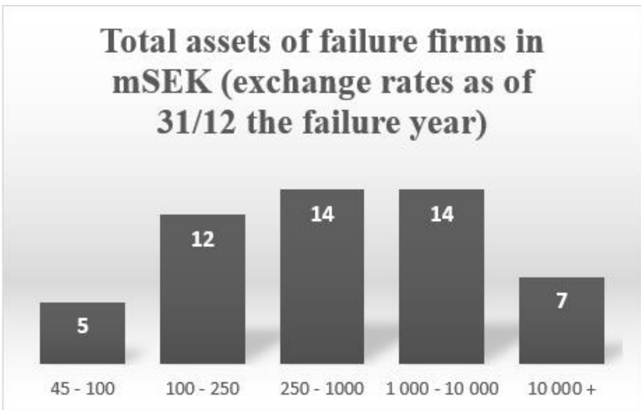
4.2.3 Yearly split

Figure 10 and 11: Yearly split of survivor and failure firms.

The most common years for having (t-1) in is 2008 and 2019 in our sample. It is worth noticing that all years between 2005-2019 are represented. As for the survivor graph, its purpose is to show that the pairing has been successful. That the staples in the survivor graph contains between 7-8 times the staples in failure firms means that every failure firm has been assigned 7 or 8 survivor firms in the pairing. See 3.2.10. for a description of how the pairing was performed.

4.2.4 Total asset size





Total assets of survivor firms in mSEK (exchange rate as of 31/12 2019)	
Mean	15 032.5
Median	1 097.0
Minimum	45.1
Maximum	524 837.0

Total assets of failure firms in mSEK (exchange rate as of 31/12 in the year of the last annual report)	
Mean	12 996.8
Median	682.7
Minimum	47.0
Maximum	152 641.6

Figure 12 and 13, table 5 and 6: Total asset sizes of survivors and failures.

For non-Swedish survivor firms, the size of total assets has been converted to SEK using the exchange rate as of 31/12/2019. This means that for example Norwegian survivor firms have been adjusted with the SEK/NOK exchange rate as of 31/12/2019. For non-Swedish failure firms, the same procedure has been performed but with the exchange rate as of 31/12 in the year of the last annual report. For both survivors and failures, the category with the most firms is the 1 000 - 10 000 mSEK category and the category with the fewest number of firms is 45 - 100 mSEK. Otherwise, the survivor sample and the failure sample differ in size distribution - here measured by asset size. For example, 10 000 + mSEK is the second most frequent firm size for survivors but the second least frequent for failures. The mean firm size is about 2 000 mSEK smaller for failures than for survivors, and the median is about 400 mSEK smaller. The largest failure firm was less than a third the size of the largest survivor firm.

4.2.5 Type of failure

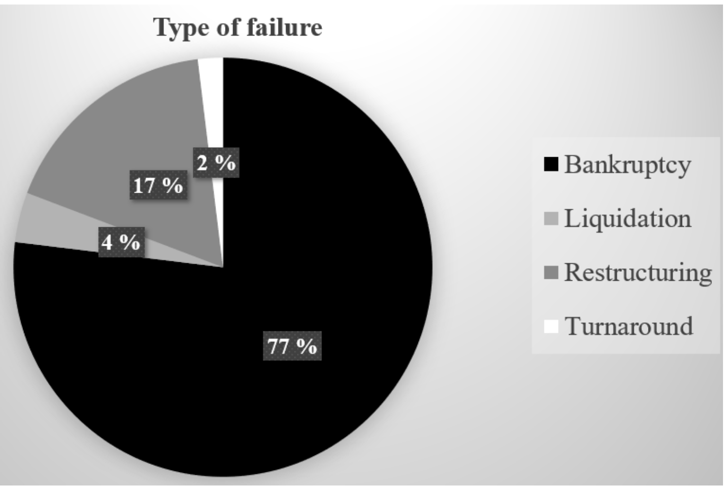


Figure 14: Type of failure.

The majority of the failure firms, 77%, failed by bankruptcy. Other types of failures represented in the sample are restructurings, liquidations and one turnaround, ref. section 3.2.1.

4.3 Descriptive statistics on financial ratios

Table 7 and 8 shows descriptive statistics regarding the ratios tested in the process of creating the Haglund and Olufsen (2021) prediction model.

Financial ratio	Mean	Standard deviation	Median	Minimum	Maximum	1st quartile	3rd quartile
R_1	-0.046	0.265	0.033	-1.407	1.312	-0.107	0.095
R_2	0.029	0.069	0.021	0	2.005	0.010	0.034
R_3	0.156	0.720	0.171	-8.459	8.728	0	0.279
R_4	0.278	1.420	0.129	0	29.001	0.053	0.193
R_5	1.186	2.747	0.283	-0.969	24.080	0.112	0.941
R_6	0.454	0.789	0.461	-17.327	0.999	0.329	0.674
R_7	0.719	7.647	0.061	-120.203	122.996	-0.096	0.284
R_8	0.044	1.751	0.172	-23.841	24.094	-0.131	0.343
R_9	0.928	0.672	0.909	0	4.337	0.357	1.356
R_{10}	2.518	3.049	1.651	0	25.874	1.143	2.603
R_{11}	0.494	0.231	0.496	0	1	0.334	0.665
R_{12}	0.344	0.237	0.335	0	0.977	0.142	0.515
R_{13}	6.129	2.334	5.905	-2.216	13.268	4.326	7.707
R_{14}	0.514	2.966	0.081	-1	47.894	-0.104	0.371
R_{15}	2.112	10.122	0	-1	57.706	-0.161	0.243
R_{16}	-0.014	2.957	0.036	-63.875	63.323	-0.007	0.134
R_{17}	0.298	0.812	0.321	-17.481	0.999	0.120	0.558
R_{18}	0.421	3.249	0	0	41.314	0	0.025
R_{19}	0.155	0.190	0.076	0	0.994	0.009	0.235
R_{20}	0.033	1.561	0	-15.025	15.048	0	0.081
R_{21}	-0.654	8.304	0.414	-69.044	68.307	0.248	0.633
R_{22}	-0.500	1.751	0	-11.892	10.874	-0.430	0.220
R_{23}	0.089	0.134	0.016	0	0.761	0	0.137
R_{24}	0.842	3.924	0	-1	20.584	0	0.012
R_{25}	0.993	4.125	0	-1	21.863	-0.072	0.177
R_{26}	0.428	2.023	0	-9.887	10.358	-0.056	0.048

Table 7: Descriptive statistics on the 26 ratios tested for the Haglund & Olufsen (2021) model, survivors and failures united.

Financial ratio	Mean values of the financial ratios (t-1)			(t-2)			(t-5)		
	Fail	Survive	t-test p	Fail	Survive	t-test p	Fail	Survive	t-test p
R_{1}	−0.198	−0.030	0.001**	−0.115	−0.022	0.003**	−0.067	−0.056	0.735
R_{2}	0.089	0.025	0.098	0.089	0.023	0.090	0.048	0.027	0.188
R_{3}	0.028	0.125	0.147	0.049	0.179	0.006**	0.107	0.175	0.439
R_{4}	0.121	0.247	0.020*	0.690	0.232	0.416	0.190	0.262	0.443
R_{5}	0.851	1.095	0.589	1.216	1.106	0.804	1.778	1.011	0.218
R_{6}	−0.215	0.514	0.023*	−0.023	0.509	0.127	0.457	0.480	0.636
R_{7}	−0.258	0.552	0.053	0.523	0.745	0.740	2.037	0.984	0.628
R_{8}	−0.251	0.055	0.654	0.426	0.068	0.456	−0.051	0.161	0.113
R_{9}	0.580	0.913	0.006**	0.563	0.951	0.000**	0.616	1.009	0.003**
R_{10}	2.286	2.461	0.804	2.301	2.408	0.836	2.811	2.493	0.646
R_{11}	0.576	0.491	0.069	0.596	0.485	0.005**	0.629	0.478	0.000**
R_{12}	0.418	0.324	0.059	0.439	0.325	0.010*	0.453	0.344	0.023*
R_{13}	5.573	6.415	0.008**	5.951	6.334	0.187	5.800	5.844	0.894
R_{14}	0.223	0.175	0.705	1.304	0.337	0.146	0.307	0.584	0.358
R_{15}	1.166	1.856	0.578	4.809	1.787	0.176	1.471	2.067	0.658
R_{16}	−0.519	0.042	0.111	−1.547	0.047	0.145	0.315	0.257	0.855
R_{17}	−0.290	0.339	0.049*	−0.128	0.336	0.183	0.325	0.331	0.903
R_{18}	0.206	0.335	0.548	0.023	0.342	0.019*	0.243	0.631	0.176
R_{19}	0.075	0.176	0.000**	0.103	0.173	0.017*	0.132	0.149	0.614
R_{20}	−0.021	0.142	0.082	−0.114	−0.020	0.446	−0.260	0.079	0.221
R_{21}	−3.976	0.322	0.066	−4.919	−0.371	0.088	−4.161	−0.568	0.131
R_{22}	−1.190	−0.449	0.046*	−1.138	−0.380	0.024*	−1.207	−0.392	0.124
R_{23}	0.014	0.105	0.000**	0.017	0.106	0.000**	0.022	0.087	0.000**
R_{24}	−0.082	0.248	0.004**	0.284	1.155	0.061	0.353	0.766	0.393
R_{25}	−0.058	0.468	0.032*	1.182	1.211	0.969	0.544	1.086	0.322
R_{26}	0.247	0.158	0.763	−0.053	0.407	0.000**	0.883	0.475	0.361

* Significant at 5% alpha-level ** Significant at 1% alpha-level

Table 8: Mean values of the 26 ratios tested in the Haglund and Olufsen (2021) model, survivors and failures divided, with t-test probabilities.

As illustrated in table 8, there is a tendency that the differences between the means of the failures and survivors is reduced as the prediction horizon increases. Whereas 11 ratios have a statistically significant difference at a 5%-alpha level in (t-1) and 10 ratios have the same in (t-2), only 4 ratios have a statistically significant difference at a 5% alpha-level in (t-5). Intuitively this is logical, as the differences between failures and survivors are expected to decrease as the prediction horizon increases.

5. Results

5.1 Results using the original Skogsvik (1987) model

In order to evaluate how well Skogsvik's (1987) original model works in more recent times, the data from our sample has been put into the original model. To assess the model's performance, the type 1, type 2 and average error rates have been calculated using both the original sample proportion of failure firms (SPOFF) threshold from Skogsvik's study and the threshold which minimizes the average error rates. In addition, graphs showing the combinations of type 1 and type 2 errors will be presented for all the prediction horizons in section 5.3. The coefficients and constants for the various prediction horizons in Skogsvik's (1987) original model are displayed in table 9 under.

Financial ratio	Prediction horizon t-1		t-2		t-3		t-4		t-5	
R_1	-4.28	(-3.59)	-3.77	(-2.78)	-	-	-	-	-	-
R_2	22.64	(4.22)	14.50	(2.77)	13.24	(2.60)	16.12	(3.12)	13.49	(2.99)
R_3	-	-	-	-	0.19	(1.82)	-	-	-	-
R_4	1.59	(2.68)	0.72	(2.03)	1.27	(2.30)	0.81	(1.37)	0.88	(1.81)
R_5	-	-	-	-	-0.51	(-1.50)	-0.79	(-1.80)	-0.99	(-2.81)
R_6	-4.46	(-4.18)	-2.91	(-3.18)	-3.27	(-3.83)	-2.50	(-3.02)	-1.76	(-2.50)
R_7	0.18	(1.54)	-	-	-	-	-	-	-	-
Constant	-1.49	(-3.53)	-1.12	(-2.97)	-1.10	(-2.94)	-1.04	(-2.81)	-1.10	(-3.39)
Likelihood ratio	115.82		79.37		56.72		51.62		42.86	

Table 9: Coefficients for financial ratios and constants for the prediction horizons from the original Skogsvik (1987) study, with t-values in parenthesis and likelihood ratio at bottom

The SPOFF from Skogsvik's (1987) study can be found in table 10 underneath. As the original coefficients are calibrated based on the data from Skogsvik's (1987) original study, the thresholds from the original study will also be used. These thresholds range from 13.0% to 13.5% depending on the prediction horizon.

Skogsvik (1987):

Prediction horizon	Number of failure firms	Number of survivor firms	Total	Proportion of failure firms
t-1	51	327	378	13.5 %
t-2	49	327	376	13.0 %
t-3	50	325	375	13.3 %
t-4	50	328	378	13.2 %
t-5	51	327	378	13.5 %

Table 10: Skogsvik (1987) sample proportions of failure firms for (t-1) to (t-5)

When running the original model and coefficients on our more recent data, the prediction results are as stated in table 11 under. The average error rates using the thresholds from table 10 range from 19.7% for horizon (t-1), up to 45.9% for horizon (t-5). The major driver behind the increasing average error rate is the increasing type 1 error rate, which increases from 26.9% in (t-1) up to 76.6% in (t-5). The type 2 error rates are more stable and range from 8.2% in horizon (t-3) up to 15.2% in horizon (t-5). This is a true holdout prediction test of the Skogsvik (1987) model, with no overlap between estimation and classification.

Type	**Skogsvik (1987) model**		
Prediction horizon	Type 1 error rate	Type 2 error rate	**Average error rate**
t-1	26.9%	12.4%	**19.7 %**
t-2	30.8%	14.7%	**22.8 %**
t-3	71.2%	8.2%	**39.7 %**
t-4	62.5%	10.8%	**36.7 %**
t-5	76.6%	15.2%	**45.9 %**

Table 11: Type 1, 2 and average error rates using Skogsvik (1987) model and sample proportions of failure firm from Skogsvik (1987) as thresholds

Applying the threshold which minimizes the average error rate gives markedly lower error rates. In general, the minimizing thresholds are lower than the proportions of failure firms above, as can be observed in table 12 under, which also includes the calculated error rates.

Type	**Skogsvik (1987) model**			
Prediction horizon	Type 1 error rate	Type 2 error rate	**Average error rate**	Minimizing threshold
t-1	13.5%	21.4%	**17.4%**	3.0 %
t-2	25.0%	17.3%	**21.1%**	8.3 %
t-3	51.9%	13.7%	**32.8%**	6.5 %
t-4	50.0%	17.0%	**33.5%**	6.5 %
t-5	55.3%	30.4%	**42.9%**	8.3 %

Table 12: Type 1, 2 and minimum average error rates using Skogsvik (1987) model

The minimum average error rates range from 17.4% in (t-1) to 42.9% in (t-5). The type 1 error rates are markedly lower when applying the minimizing threshold and range from 13.5% in (t-1) to 55.3% in (t-5). However, the type 2 error rates are higher, and range from 13.7% in (t-3) to 30.4% in (t-5). Since the reduction in type 1 error rates is greater than the increase in type 2 error rates, an overall reduction is achieved which is observed through the reduction in the average error rate. The minimizing thresholds are markedly lower than the thresholds from table 10 and range from 3.0% in (t-1) to 8.3% in (t-2) and (t-5).

Please see figure 15 in section 5.3 for the combinations of type 1 and type 2 errors using various thresholds for the five prediction horizons using the original Skogsvik (1987) model.

5.2 Results from recalibrating the Skogsvik (1987) model

In order to evaluate how well the ratios used in Skogsvik's (1987) study work on our modern sample of IFRS-applying firms, a new probit analysis has been performed to recalibrate the coefficients and constants optimally based on our data. Like in section 5.1, type 1, type 2 and average error rates will be presented both based on the SPOFF and minimizing thresholds, and the different combinations of type 1 and type 2 errors based on the cutoff chosen will be presented in section 5.3. Initially the recalibrated coefficients and constants will be presented in table 13 underneath, with the associated t-values in parenthesis.

	Prediction horizon									
Financial ratio	t-1		t-2		t-3		t-4		t-5	
R_1	-1.61	(-3.96)	-0.86	(-2.18)	-	-	-	-	-	-
R_2	7.34	(3.99)	11.58	(4.24)	4.72	(1.62)	3.30	(1.78)	5.18	(1.79)
R_3	-	-	-	-	-0.54	(-2.15)	-	-	-	-
R_4	-1.46	(-3.16)	0.08	(1.59)	0.04	(1.32)	0.07	(1.48)	-0.10	(-0.66)
R_5	-	-	-	-	0.07	(2.10)	0.06	(2.77)	0.07	(2.45)
R_6	-1.78	(-6.10)	-1.72	(-4.50)	-1.02	(-3.00)	-0.80	(-2.08)	-0.34	(-1.00)
R_7	-0.01	(-0.22)	-	-	-	-	-	-	-	-
Constant	-0.68	(-3.90)	-0.92	(-4.42)	-0.89	(-4.26)	-1.08	(-5.40)	-1.31	(-6.32)
Likelihood ratio	99.04		71.36		28.74		18.79		12.49	

Table 13: Recalibrated coefficients and constants in probit functions for the various prediction horizons, with t-values in parenthesis and likelihood ratio at the bottom.

The sample proportion of failure firms in our data can be found in table 14 below. As the recalibrated coefficients are based on the data gathered in this thesis, the sample proportions of failure firms from this thesis will be used. These thresholds range from 10.8% in (t-5) to 11.8% in (t-1) to (t-3).

Haglund and Olufsen (2021):

Prediction horizon	Number of failure firms	Number of survivor firms	Total	Proportion of failure firms
t-1	52	388	440	11.8 %
t-2	52	388	440	11.8 %
t-3	52	388	440	11.8 %
t-4	48	388	436	11.0 %
t-5	47	388	435	10.8 %

Table 14: Haglund and Olufsen (2021) sample proportions of failure firms from (t-1) to (t-5)

Rerunning the model with the recalibrated coefficients and constants yields the following results using the thresholds from table 14:

Type	**Re-estimated model**		
Prediction horizon	Type 1 error rate	Type 2 error rate	**Average error rate**
t-1	17.3 %	17.0 %	**17.2 %**
t-2	25.0 %	20.9 %	**22.9 %**
t-3	36.5 %	28.4 %	**32.4 %**
t-4	37.5 %	29.9 %	**33.7 %**
t-5	44.7 %	26.5 %	**35.6 %**

Table 15: Type 1, 2 and average error rates using the recalibrated model and sample proportions of failure firms from table 14 as thresholds

The average error rates range from 17.2% in (t-1) to 35.6% in (t-5). The average error rates gradually increase with the prediction horizon. As the prediction horizon increases, both the type 1 error rates and type 2 error rates increase along with it.

Applying the thresholds which minimize the average error rates yield a slightly different outcome. The minimizing thresholds are generally higher or close to the sample proportions of failure firms from table 14, as table 16 under shows.

Type	**Re-estimated model**			
Prediction horizon	Type 1 error rate	Type 2 error rate	**Average error rate**	Minimizing threshold
t-1	17.3 %	11.3 %	**14.3 %**	14.9 %
t-2	25.0 %	14.4 %	**19.7 %**	13.5 %
t-3	44.2 %	12.1 %	**28.2 %**	16.6 %
t-4	37.5 %	21.4 %	**29.4 %**	11.9 %
t-5	36.2 %	30.9 %	**33.5 %**	10.4 %

Table 16: Type 1, 2 and minimum average error rates using recalibrated model

The average error rates range from 14.3% in (t-1) to 33.5% in (t-5). The reduction in the average error rates compared to those obtained using the SPOFF threshold is in general not very noticeable, and one observes the same trend where the average error rates increase gradually with the prediction horizon. In (t-1) to (t-4) there is a significantly higher type 1 error rate than type 2 error rate, whereas in (t-5) the difference between the type 1 and 2 error rates is less prominent. The minimizing thresholds vary from 10.4% in (t-5) to 16.6% in (t-3), and they are significantly higher than the SPOFF thresholds in (t-1) to (t-3). In (t-4) and (t-5) the minimizing thresholds are close to the SPOFF thresholds.

Please see figure 15 in section 5.3 for the combinations of type 1 and type 2 errors using various thresholds for the five prediction horizons using the recalibrated model.

5.3 Results from the Haglund and Olufsen (2021) model

In order to see which financial ratios seem to best predict business failure in our sample, probit analysis has been performed for the various horizons as described in section 3.5. As in the two previous sections, type 1, type 2 and average error rates will be presented for the prediction horizons both for the SPOFF threshold and the minimizing threshold. In addition, graphs illustrating the combinations of type 1 and type 2 errors will be displayed. The statistically significant ratios and coefficients are presented in table 17 under for the prediction horizons in the Haglund and Olufsen (2021) model:

	Prediction horizon									
Financial ratio	t-1		t-2		t-3		t-4		t-5	
R_2	5.02	(2.78)	7.13	(2.37)	-	-	-	-	-	-
R_4	-0.97	(-2.68)	0.10	(2.06)	-	-	-	-	-	-
R_5	-0.09	(-1.60)	-	-	-	-	-	-	0.09	(2.74)
R_6	-2.18	(-7.71)	-2.35	(-5.22)	-1.85	(-3.81)	-0.96	(-2.50)	-	-
R_7	-	-	-	-	-0.31	(-2.55)	-	-	-	-
R_8	-	-	-	-	0.42	(2.21)	-	-	-	-
R_9	-0.29	(-2.28)	-	-	-	-	-	-	-	-
R_{10}	-	-	-	-	0.09	(1.83)	-	-	-	-
R_{11}	-	-	1.35	(3.02)	2.16	(4.71)	1.60	(4.25)	1.49	(3.98)
R_{12}	-	-	-	-	-	-	-	-	0.68	(2.00)
R_{14}	-	-	0.08	(2.30)	-	-	-	-	-	-
R_{15}	-	-	-	-	0.03	(3.18)	-	-	-	-
R_{17}	-	-	-	-	-	-	-	-	-0.79	(-2.54)
R_{20}	-	-	-	-	-	-	-	-	-0.11	(-1.91)
R_{22}	-0.23	(-3.01)	-0.20	(-2.68)	-0.15	(-2.49)	-0.15	(-3.07)	-	-
R_{23}	-5.01	(-2.94)	-5.30	(-3.33)	-5.12	(-3.43)	-4.19	(-3.18)	-4.65	(-3.46)
R_{26}	-	-	-	-	-0.18	(-2.10)	0.05	(1.58)	-	-
Constant	-	-	-1.08	(-3.28)	-1.54	(-4.71)	-1.55	(-5.28)	-1.92	(-6.91)
Likelihood ratio	131.44		118.39		106.51		59.58		51.66	

Table 17: Estimated coefficients and constants in the Haglund and Olufsen (2021) model for the various prediction horizons, with t-values in parenthesis and likelihood ratio at the bottom. Please note that all statistically insignificant ratios have been left out

As the table shows, 17 out of the 26 ratios are statistically significant in at least one of the prediction horizons. 9 out of the 26 are statistically significant for just one period. R_6, R_{11}, R_{22} and R_{23} seem to have a strong predictive ability, and they are all significant in at least 4 of the 5 prediction horizons. Please see appendix G for all probit functions written in equation-form.

Running the estimated prediction model yields the following prediction results using the SPOFF thresholds from table 14:

Type	Haglund and Olufsen (2021)		
Prediction horizon	Type 1 error rate	Type 2 error rate	**Average error rate**
t-1	15.4%	16.0%	**15.7%**
t-2	17.3%	19.6%	**18.4%**
t-3	23.1%	22.4%	**22.7%**
t-4	31.3%	27.6%	**29.4%**
t-5	23.4%	28.9%	**26.1%**

Table 18: Type 1, type 2 and average error rates in Haglund and Olufsen (2021) using the SPOFF threshold

The average error rates using the SPOFF threshold range from 15.7% in (t-1) to 29.4% in (t-4). The error rates tend to increase gradually as the prediction horizon lengthens, which drives the increase in the average error rates. However, a reduction is observed from (t-4) to (t-5), which is driven by a decrease in the type 1 error rate.

Applying the thresholds which minimize the average error rates yield the following results:

Type	Haglund and Olufsen (2021)			
Prediction horizon	Type 1 error rate	Type 2 error rate	**Average error rate**	Minimizing threshold
t-1	19.2%	10.3%	**14.8%**	17.8%
t-2	23.1%	11.3%	**17.2%**	18.2%
t-3	15.4%	24.5%	**19.9%**	10.7%
t-4	31.3%	24.0%	**27.6%**	12.1%
t-5	27.7%	21.1%	**24.4%**	13.8%

Table 19: Type 1, type 2 and minimum average error rates in Haglund and Olufsen (2021)

The minimized average error rates range from 14.8% in (t-1) to 27.6% in (t-4). The minimized average error rates are not very different from the ones in table 18, and the reductions range from 0.9%-points to 2.8%-points. The minimizing threshold varies from 10.7% in (t-3) to 18.2% in (t-2). The minimizing threshold is significantly higher than the SPOFF threshold in (t-1) and (t-2), while the differences are less prominent in (t-3) to (t-5).

In figure 15 on the following page, the combinations of type 1 and type 2 errors for various thresholds are illustrated for the original Skogsvik (1987 model from section 5.1, the recalibrated model from section 5.2 and the Haglund and Olufsen (2021) model from this section. Generally speaking, the closer a line is to the X- and Y-axis, the better – here in terms of prediction accuracy.

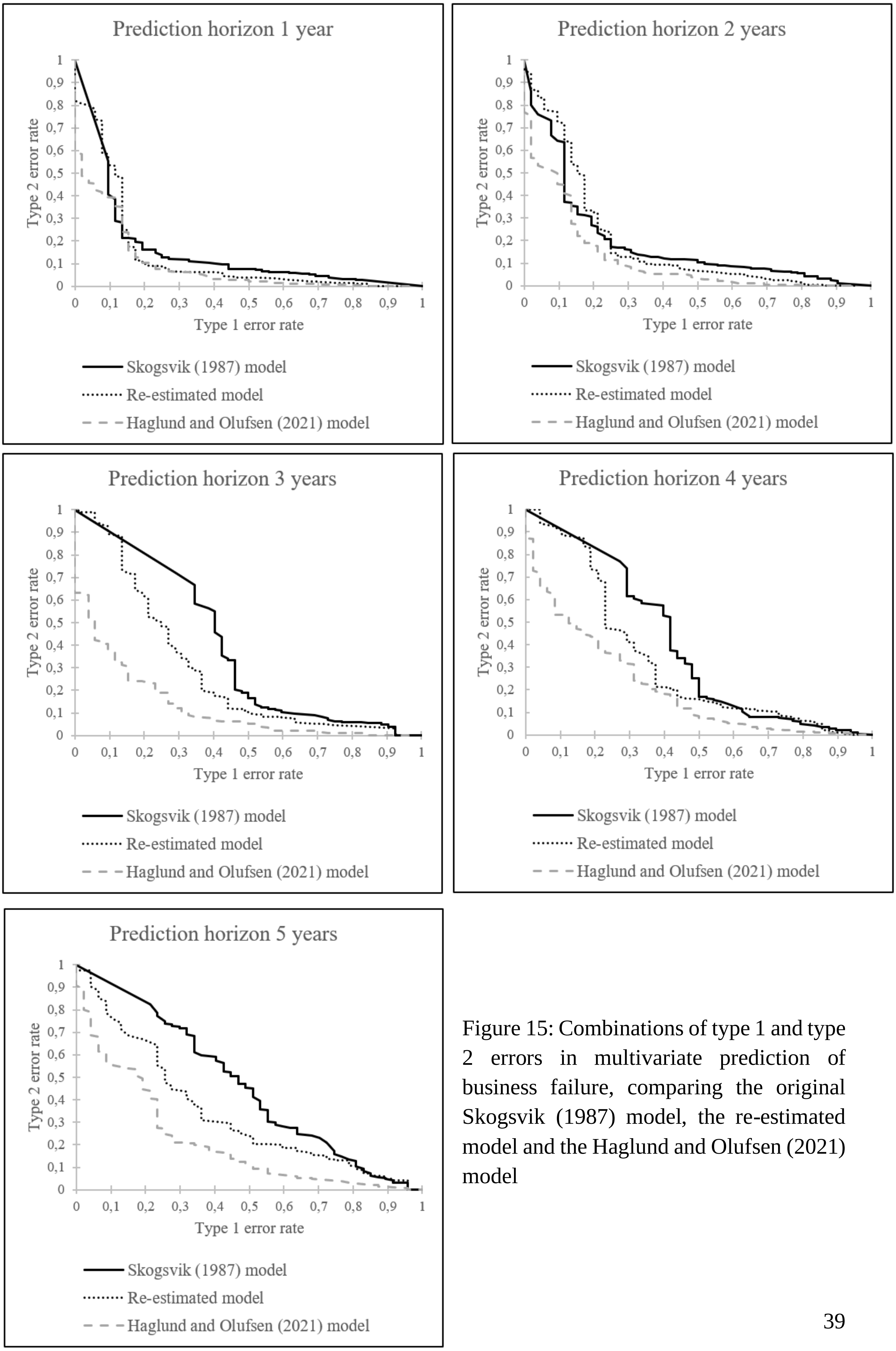


Figure 15: Combinations of type 1 and type 2 errors in multivariate prediction of business failure, comparing the original Skogsvik (1987) model, the re-estimated model and the Haglund and Olufsen (2021) model

As figure 15 illustrates, all three models work well in the shorter prediction span, (t-1) and (t-2). There are some differences between the three models, but they are not very noticeable. The Haglund and Olufsen (2021) model seems to work out slightly better than the other two models for most thresholds in the two shorter prediction spans, but the difference is minimal. The predictive ability of the models appears to be slightly better in (t-1) than (t-2), which can be observed through the lines being slightly closer to the X- and Y-axis.

However, in the longer prediction spans, from (t-3) to (t-5), there are noticeable differences in the predictive ability of the models. In all three prediction horizons, the Haglund and Olufsen (2021) model performs significantly better than the other models, regardless of which threshold is being used. There are also noticeable improvements in the recalibrated model over the Skogsvik (1987) model, and the latter model appears to have a predictive ability not very different from random chance in (t-5) - which is observed through the solid line being close to linear in figure 15 above for the prediction horizon of 5 years.

A big part of the improvement in the longer prediction horizons appears to stem from a better predictive ability in terms of the type 1 errors. In the prediction horizon (t-3) for instance, one observes a linear solid line for the Skogsvik (1987) model in the beginning, which means that as one increases the threshold from 0% to 0.1% the model incorrectly classifies about 40% of the failures. The recalibrated model and Haglund and Olufsen (2021) model offer significant improvements in these lower threshold areas in the prediction horizons from 3 to 5 years in terms of the type 1 error rates, which one can observe through the absence of linear lines from the Y-axis.

5.4 Summary of results

To ease comparison and get a better overview, the results from section 5.1 to 5.3 have been compiled in table 20 and 21 below, with the results from Skogsvik's (1987) original study in the right-most column(s).

Cutoff	Sample proportion of failure firms											
Type	**Skogsvik (1987) model**			**Re-estimated model**			**Haglund and Olufsen (2021)**			**Skogsvik (1987)**		
Prediction horizon	Type 1 error rate	Type 2 error rate	**Average error rate**	Type 1 error rate	Type 2 error rate	**Average error rate**	Type 1 error rate	Type 2 error rate	**Average error rate**	Type 1 error rate	Type 2 error rate	**Average error rate**
t-1	26.9%	12.4%	**19.7 %**	17.3 %	17.0 %	**17.2 %**	15.4%	16.0%	**15.7%**	13.7%	19.6%	**16.7 %**
t-2	30.8%	14.7%	**22.8 %**	25.0 %	20.9 %	**22.9 %**	17.3%	19.6%	**18.4%**	18.4%	24.8%	**21.6 %**
t-3	71.2%	8.2%	**39.7 %**	36.5 %	28.4 %	**32.4 %**	23.1%	22.4%	**22.7%**	30.0%	20.6%	**25.3 %**
t-4	62.5%	10.8%	**36.7 %**	37.5 %	29.9 %	**33.7 %**	31.3%	27.6%	**29.4%**	28.0%	24.1%	**26.1 %**
t-5	76.6%	15.2%	**45.9 %**	44.7 %	26.5 %	**35.6 %**	23.4%	28.9%	**26.1%**	27.5%	23.2%	**25.4 %**

Table 20: Type 1, 2 and average error rates using the SPOFF thresholds in sections 5.1 to 5.3 plus error rates from the original Skogsvik (1987) study

Cutoff	Minimizing threshold									
Type	**Skogsvik (1987) model**			**Re-estimated model**			**Haglund and Olufsen (2021)**			**Skogsvik (1987)**
Prediction horizon	Type 1 error rate	Type 2 error rate	**Average error rate**	Type 1 error rate	Type 2 error rate	**Average error rate**	Type 1 error rate	Type 2 error rate	**Average error rate**	**Average error rate**
t-1	13.5%	21.4%	**17.4%**	17.3%	11.3%	**14.3%**	19.2%	10.3%	**14.8%**	**15.2%**
t-2	25.0%	17.3%	**21.1%**	25.0%	14.4%	**19.7%**	23.1%	11.3%	**17.2%**	**21.3%**
t-3	51.9%	13.7%	**32.8%**	44.2%	12.1%	**28.2%**	15.4%	24.5%	**19.9%**	**23.9%**
t-4	50.0%	17.0%	**33.5%**	37.5%	21.4%	**29.4%**	31.3%	24.0%	**27.6%**	**23.8%**
t-5	55.3%	30.4%	**42.9%**	36.2%	30.9%	**33.5%**	27.7%	21.1%	**24.4%**	**25.1%**

Table 21: Type 1, 2 and average error rates using the minimizing thresholds in sections 5.1 to 5.3, and average error rates from the original Skogsvik (1987) study

A few findings from the tables are worth highlighting. Both using the SPOFF and minimizing thresholds, the average error rates are fairly similar in the prediction horizons (t-1) and (t-2) across all three models. The improvement from using a recalibrated model or creating an entirely new model appears to be marginal in the shorter prediction span, and all three models have fairly similar results to those of the Skogsvik (1987) study in (t-1) and (t-2) for both cutoffs.

However, for the longer prediction spans, from (t-3) to (t-5), there is a noticeable improvement from using a recalibrated or new model. The original Skogsvik (1987) model gives prediction results not very different from random chance in those forecasting horizons, but both the recalibrated and Haglund and Olufsen (2021) models give useful results. Overall, the error rates from the Haglund and Olufsen (2021) model are similar to the error rates from the original Skogsvik (1987) study, and the predictive ability of financial ratios hence seems to be about the same in this thesis as in Skogsvik's study.

6. Discussion

6.1 Robustness of Skogsvik (1987) model and ratios

As section 5 has shown, the original Skogsvik (1987) model still works remarkably well, in particular for the shorter prediction horizons (t-1) and (t-2). The error rates using both thresholds hold up well against the results from the original study, and also against the results from recalibrating the coefficients and from Haglund and Olufsen (2021) ref. table 20 and 21. In essence, this means that the five ratios used in (t-1) and the four ratios used in (t-2) in Skogsvik (1987) still appear to have a strong predictive ability on listed, Nordic manufacturing firms applying IFRS. This notion is further confirmed in the recalibrated coefficients in table 13, where four out of the five ratios have a t-value > |1.6| for (t-1) and three out of four ratios have a t-value > |1.6| for (t-2) - with the last ratio having a t-value of 1.59. These four ratios represent profitability, cost of liabilities, inventory size and solidity, and the results indicate that these four ratios still seem to have a predictive ability in the shorter prediction span.

However, in the longer prediction span, from (t-3) to (t-5), the Skogsvik (1987) model appears to be less efficient. With average error rates using the SPOFF threshold ranging from 36.7% to 45.9%, the model only marginally beats what the expected result would be by random chance - which would give an expected error rate of 50%. This implies that the five ratios used in (t-3) and four ratios used in (t-4) and (t-5) in Skogsvik's model appear to have less of a predictive ability in the current environment than they had in the 1970s and 1980s. Of the five ratios used in (t-3), four have a t-value > |1.6| in the recalibrated model in table 13. In (t-4), three out of four ratios have a t-value > |1.6|, whereas only two out of four ratios have the same in (t-5). This supports the observations in the average error rates, with the original ratios appearing to have less of a predictive ability in the longer prediction spans.

Like in Skogsvik (1987), the recalibrated coefficients for R_1 (EBIT to average assets) are statistically significant in (t-1) and (t-2). However, the coefficients are more muted, which implies that the difference between R_1 in the two subgroups are smaller than in the original study. Ref. appendix H the mean R_1 among failure firms in the sample is -11.8%, whereas the same for the survivors is -3.7%. The median R_1 is -5.9% for failures, while it is 4.6% for the survivors. This implies that there still seems to be a noticeable difference in profitability between failing and surviving firms, but with a more muted effect than in previous studies. Table 8 underlines this trend, with the gap between survivors' and failures' means narrowing the longer the prediction horizon is. A potential explanation for the more muted coefficients is given in the Fama and French (2004) study, where one saw a trend where more and more unprofitable firms with riskier payoffs were being listed on the stock market. This may drag down the profitability of the survivors and reduce the gap between failures and survivors, as long as the non-profitable survivors are able to raise capital and avoid bankruptcy.

Another strong predictor in Skogsvik's original study was R_2, the average interest cost (interest expense/average liabilities). It was significant for all five prediction horizons in Skogsvik's study, and in this thesis the coefficients are also significant for all five prediction spans ref. table 13. As was the case with R_1, the recalibrated coefficients are muted every year compared to those from Skogsvik's (1987) study. Whereas the coefficient was 22.64 in (t-1) in the original model, it is only 7.34 in the recalibrated model. For failures, the mean and median interest cost is 6.1% and 3.8% in our sample, whereas the mean and median for survivors are 2.5% and 1.9% respectively ref. appendix H. As the interest rates have declined significantly in the last decades, it could partially help explain why the interest cost seems to have less of a predictive ability today compared to in the past.

In Skogsvik's original study R_4 (average inventory to revenue) was found to be significant for all five prediction horizons with positive coefficients. In the recalibrated model, only one out of five periods have a significant coefficient (t-value > |1.6|), which is in (t-1). In (t-1) the coefficient is negative - meaning all else equal, high inventory in relation to the revenue lowers the probability of failure which may not seem all that logical. Ref. appendix H the median and mean R_4 is higher for survivors than for failures, which could explain the sign of the coefficient. Another ratio with a strong predictive ability in Skogsvik's original study was the solidity ratio, R_6 (equity to assets), which was significant for all five years. In the recalibrated model, R_6 is significant for four out of five years, with a negative coefficient every year which intuitively makes sense. Ref. table 8 and appendix H there is a larger median and mean equity from (t-1) to (t-4) for survivors compared to the failures, whereas the median R_6 for failures is higher in (t-5) which could explain why the coefficient is insignificant then. As equity is a cushion for dampening heavy losses, it is hence not surprising that the level of equity is a good predictor. The recalibrated coefficient of R_3 is significant for one period just like in the original model, and the recalibrated coefficient of R_5 is also significant in the last three periods just like in the original model. However, the recalibrated coefficients are positive, but also muted and very close to 0, meaning cash/current liabilities seems to not have as much of a predictive ability as in the past – which could be tied to the lower interest rates and easier access to liquidity.

There could be several potential explanations for the development in the predictive ability of the original ratios. It could be due to changing business models over time, where businesses have become more and more complex with remarkable changes to the asset structure for instance. Whereas intangibles represented a tiny portion of the asset base of firms in the 1970s and 1980s, it has now become the dominant asset type among listed firms. Whereas the level of intangibles is not as extreme in our sample, with an intangible asset proportion of 15.51% on average, it is an interesting observation regardless, and none of the ratios in the original Skogsvik (1987) model capture this development directly. Another explaining factor could be the changes that have happened to the business environment. The inflation, GDP growth and interest rates have declined significantly in the Nordics in the last decades, which among other things could affect how well R_2 (average interest cost) predicts failure. In addition, things tend to change more rapidly now than before in a globalized economy, which could partially explain why the predictive ability of the original seven ratios appear to be significantly lower in (t-3) to (t-5).

6.2 The Haglund and Olufsen (2021) model

Overall, the predictive ability of the Haglund and Olufsen (2021) model appears to be fairly similar to the predictive ability of the model in the original Skogsvik (1987) study. The average error rates range from 15.7% in (t-1) to 29.4% (t-4) using the SPOFF threshold, and the average error rates are slightly lower in (t-1) to (t-3) compared to those from Skogsvik's original study, but slightly higher in (t-4) and (t-5) ref. table 20. In general, these results are slightly worse than some of those reported in prior, comparable studies, but also better than some studies. The differences could here be attributed to various factors, such as methodological factors ref. section 7.3 or other factors ref. section 6.3.

The new model created from the 26 financial ratios shows that previously untested ratios appear to have a predictive ability on business failure. Out of the 17 ratios that were found to be statistically significant in at least one period, the most consistently significant ratios will be elaborated upon. The goodwill proportion, R_{23} (Goodwill / Total Assets), was the only ratio that was present in all years from (t-1) to (t-5). Not only was it present in all years, but the ratio also had the second highest coefficient (in absolute terms) for (t-1) and (t-2) and the highest coefficient from (t-3) to (t-5). It therefore seems like goodwill proportion is a strong predictor of business failure, which table 8 and appendix H support.

This contradicts the findings in Hamberg et al. (2011), as analyzing goodwill seems to enhance the decision relevance. Its negative coefficient in the models indicate that having a high proportion of goodwill on the balance sheet is a trait of a non-failing firm. One possible explanation based on previous literature would be that firms with a higher proportion of goodwill have more total assets than an equal firm without goodwill on the balance sheet, meaning that firms with goodwill are larger in size and therefore less inclined to fail. However, we find no strong evidence of this explanation. Contrary, when looking at the size distribution of the survivor and failure firms in section 4.2.4, there is little difference between survivors and failures. In addition, the ratio R_{13} (ln(A)) is insignificant for all years tested, which is a further indication that size alone cannot fully explain the strong predicting ability of the goodwill proportion in our sample.

The key to the goodwill proportion's high relevance may instead lie within the successfulness of the business model. Firms with a successful business model that generate positive cash flows have the possibility to do acquisitions to a greater extent than firms with an unsuccessful business model and/or negative cash generation. If this is the case, then the proportion of goodwill in itself would not be mitigating business failure risk. Instead, it would be the consequence of previous success, which in turn would increase the possibility of future success as there is a foundation of good business practices and cash generation to build upon.

Another possible explanation to the goodwill proportion's prevalence could be that goodwill impairment is inevitable for failing firms, no matter how long they wait to perform the impairment. Surviving firms in our sample had on average about five times higher goodwill proportion than failures (9.8% compared to 1.9% ref. appendix H), which could indicate that survivor firms may have done less goodwill impairments than failure firms. However, the change in goodwill ratio (R_{24}) was insignificant for all years tested, which contradicts this explanation. Another reason could be that there is a high degree of growth firms listed today. According to Fama and French (2004), investors today are more willing to invest in growth firms as they hope that these firms will generate high profitability in the future. As doing acquisitions is one way of growing a business, investors might be more willing to invest in firms that are doing a higher degree of acquisitions and thereby increasing their goodwill. Having investors that are willing to contribute with capital decreases the risk of bankruptcy as new financing could be obtained easily. However, we found no unambiguous evidence for this explanation.

Average interest cost, R_2, is found to play a significant role in (t-1) and (t-2), but it is not significant for (t-3) to (t-5). This indicates that the cost of liabilities still has a significant impact on business failure despite the low interest rate environment, but only in the short-term. However, its coefficients are significantly smaller than those in Skogsvik (1987), which is an indication that our hypothesis stated in section 2.1.3 that interest expense has less impact today appears to be true. There could be several reasons as to why this ratio still plays a significant role. One is that firms that are more heavily leveraged might have a more difficult time to pay their obligations than less leveraged firms. Consider the difference between equity financing and debt financing. An equity financed firm that experiences difficult times can cut dividends and thereby halt cash outflows, but a leveraged firm must pay interest on its loans, meaning that the cash outflows will be greater, leading to a higher risk of failure.

Another explanation is that more risky firms may get a higher interest rate on their debt than financially sound firms, which is supported by the mean and medians in appendix H. It could hence appear that debt providers perceive the higher failure risk, especially in (t-1) and (t-2), which is compensated for by giving the firms a higher interest cost. Renewed credits could depend on the profitability and success of the business model of a firm. In addition, equity investors might also be hesitant to invest more in a firm with an unsuccessful business model due to not expecting to get the desired return on their investment. A loss-making firm with high interest costs is typically a bad combination. Equity investors may not want to put in more capital, as they perceive it to be a negative NPV-investment. Therefore, firms can run into liquidity issues if the business model does not create enough value.

The one ratio that has prevailed the most from the original Skogsvik (1987) study is the solidity ratio, R_6 (Equity / Assets). The ratio is found to be significant in four out the five prediction spans, but also here the coefficients are more muted than in the original study. It is worth mentioning that in (t-5) the tangible equity to assets-ratio, R_{17}, is significant, which ultimately means a solidity ratio is significant in every prediction span. As table 8 and appendix H shows, there is a significant difference in mean and median solidity for failures and survivors respectively, which explains the predictive ability of the ratio. Intuitively the negative coefficient makes sense, since all else equal, higher solidity should make business failure less likely.

The long-term asset proportion (R_{11}) is significant in all years from (t-2) to (t-5), with positive coefficients above 1.35 in every year. Intuitively the sign of the coefficient may seem a bit surprising, with a higher proportion of long-term assets, all else equal, increasing the probability of failure, but the explanation could lie in the value premium from finance and asset pricing theory. Long-term assets primarily consist of PP&E, investments and intangible assets, and these assets are less liquid than most other assets. In economic downturns, firms with a high proportion of long-term assets (mostly tangible assets) suffer from excess capacity and have a harder time liquidating their assets at a favorable price. It can also be related to operating leverage, where high operating leverage typically means a firm gets issues faster when things do not go well. Operating leverage increases when the share of fixed costs rises, or the share of variable costs decreases. A high proportion of fixed assets implies high operating leverage, and hence a firm with high operating risk. This relationship derives from fixed assets requiring more fixed costs to be operational, which increases the share of fixed costs in relation to variable costs and hence increases operating leverage. High operating leverage increases risk as it limits the flexibility to reduce costs if sales are decreasing, which could lead to financial distress. Table 8 and appendix H shows that the failure firms in general had significantly higher median and mean proportions of long-term assets than their counterparts, which could explain the coefficient and the predictive ability of the ratio.

A ratio that is present in four of the years ((t-1) to (t-4)) with a slightly negative coefficient is the Free Cash Flow / Current Liabilities-ratio (R_{22}). Having a coefficient close to zero indicates that its contribution to the model is small, but yet it is significant due to the t-value > |1.6|. While this ratio is an indication of the liquidity and cash generation of the firm, comparing this ratio to the profitability ratios tested indicates that cash flow-based ratios seem to be the better predictor of the two. In total, one of the three profitability ratios tested is significant for one year (R_8 is significant for (t-3)). While we only tested one cash flow-based ratio (R_{22}), it is significant for more years than all profitability ratios combined.

A possible explanation for this could be that accounting practices have gotten complex over time, making accounting earnings have less predictive power. Free cash flow cannot be influenced by managerial decisions or accounting practices to the same degree as accounting earnings, which could mean it is more closely linked to the performance of a firm's operations and thereby more comparable from firm to firm. Following this it would be logical that free cash flow is a better predictor of firm performance than profitability ratios, which could explain its presence in our model. Another possible explanation to the lack of profitability ratios could be found in the Fama and French (2004) study. Logically, higher profitability would imply a lower risk of business failure, as profitable firms are more equipped to pay its liabilities. However, as the authors argued there has been a shift from mainly profitable firms to growth firms being listed on stock exchanges, and there is a higher share of listed firms that are not profitable. Two indications that this observation could be correct in our sample are the survivors' means of R_1 (EBIT / Average Assets) and R_8 (EBITDA / Average Equity) in appendix H. For R_1, the mean for survivors is -3.7%, meaning that the mean return on assets is negative for the survivor sample. For R_8, the mean is slightly positive (4.9%) but the standard deviation of 1.586 (158.6%) indicates that there are many survivor firms with negative returns on equity. Since there are many survivor firms with negative profitability, the predictive ability of such ratios naturally decreases.

As 28 out of the 52 failure firms in this thesis come from two industries, the mining and oil & gas industries, characteristics of firms from these industries will have a significant impact on the overall characteristics of failure firms. Both industries share certain characteristics, they both rely on extraction/upstream, mining/midstream, and processing/downstream as the core processes. In addition, both industries are capital intensive and sensitive to volatility in commodities prices. This could lead to more leveraged firms, with more volatile earnings and higher proportions of long-term assets to total assets, for instance. As these firms make up the majority of failure firms, it is inevitable that they will have a big impact on the ratios of the failure group and hence the predictions in our model.

Based on our findings, the typical failure firm seems to have certain characteristics compared to survivor firms. These characteristics include lower solidity, lower goodwill proportion, more costly debt, and more long-term assets. Using different combinations of ratios, the minimum error rates range from 14.8% in (t-1) to 27.6% in (t-4). This means that in a population with an equal number of failing and surviving firms, our model will incorrectly classify about 1 in 6 firms in (t-1). In (t-1) the seven significant ratios predict so well that the constant is insignificant, which is an interesting finding. Having a constant in a prediction model indicates that there is significant variation not explained by the ratios in the model, and the absence of such a constant implies that the chosen ratios predict well.

6.3 The decision relevance of accounting information

While the ratios used and coefficients calibrated in our model have changed significantly from the Skogsvik (1987) study, the average error rates have not, and they are quite similar across all the prediction spans. It therefore appears like accounting-based failure prediction models still can be used effectively on a modern sample of Nordic IFRS-applying manufacturing firms. There could be several potential explanations for the persisting decision relevance of accounting information.

The implementation of IFRS could be one such explanation. Initially IFRS was implemented to standardize accounting across borders and came with more detail-regulations than many of the national GAAPs. More standardized accounting across borders, which hopefully better captures the fair value of items, could enhance the decision relevance of the information provided. When accounting standards converge it is easier to pool data and make models similar to those in this thesis. The models built will then be more versatile and can be used at a lower cost. It is possible that IFRS is a contributing factor to the persisting decision relevance, but further research is needed to back this up. Ideally one would then like to compare our results to results from a setting without IFRS. For instance, we find that the goodwill proportion has a strong predictive ability in this thesis, but under many GAAPs goodwill is amortized, and one could then possibly miss out on the information content.

An explanation that could work against the decision relevance of accounting information is the gradually more complex business models of firms. While not all firms back in the 1960s and onwards were "simple", many firms nowadays have business ideas which could be quite difficult to grasp for many people. Businesses nowadays have different structures with more of the weight leaning on intangible assets, where determining the fair value is more difficult than for most tangible assets. All else equal, more complex business models should make it harder to use accounting information in making decisions.

The development in macroeconomic factors could also be a contributing factor. In the last 30-40 years there has been a significant overall reduction in the levels of interest rates, GDP growth, inflation etc. in the Nordic economic environment. It might not be clear how this could impact the decision relevance of accounting, but all else equal lower inflation should imply that historical cost accounting will be closer to current cost accounting. As Skogsvik's (1987) study pointed to however, even in a time of high inflation, current cost accounting-based prediction models did not seem to be superior to historical cost accounting-based prediction models, so one could hypothesize that macroeconomic factors do not have a significant impact on the decision relevance. The prediction accuracy of our model implies that accounting information can still be used in various situations, and this finding is of interest to various stakeholders - ranging from capital providers to employees to suppliers. While one could point to several potential explanations for the persisting decision relevance over time, further research would have to be conducted to determine the potential magnitude of these.

An interesting finding is that the original Skogsvik (1987) model works remarkably well in (t-1) and (t-2), with the recalibrated and Haglund and Olufsen (2021) models offering small improvements. For practitioners evaluating shorter-term investments, such as short-term bonds with a time to maturity shorter than two years, one could use the old Skogsvik (1987) model with good predictive results. This is the easy, low-cost solution for practitioners, and short-term it appears to be a viable solution. It could be the case that you do not need very sharp and updated models shortly prior to failure, as it may be quite clear that they are likely to fail. However, in (t-3) to (t-5) the recalibrated and Haglund and Olufsen (2021) models offer significant improvements. In the longer prediction spans the differences in means and medians are smaller, meaning failure firms look more similar to survivor firms. In order to screen out the differences that do exist, one may need to have very sharp, updated models. Intuitively it makes sense that you need a good model to separate surviving and failing firms so long before failure. For practitioners evaluating long-term investments, such as equities where a significant amount of the value typically stems from the terminal value, it appears to be worthwhile to at least recalibrate and update the model or potentially create new models for the longer prediction spans, if one has the time and knowledge necessary to do so.

7. Concluding remarks

7.1 Conclusion

The purpose of this thesis was to examine whether accounting-based failure prediction models still could be used effectively on a modern sample of firms applying IFRS. The literature contained contrasting evidence about the development of the decision relevance of accounting information over time. Some studies pointed towards a decline in decision relevance (c.f. Francis & Schipper, 1999; Brown et al., 1999; Lev & Zarowin, 1999) while other studies claimed that the implementation of IFRS helped increase the decision relevance (c.f. Gjerde et al., 2008; Bodle, 2016). With the results of this thesis at hand, our conclusion is that failure prediction models still can be used effectively. The average error rates of the Haglund and Olufsen (2021) model are similar to the error rates in the Skogsvik (1987) study. As for how the decision relevance of accounting has changed over the last roughly 40 years, the similar error rates indicates that the overall decision relevance is roughly the same, but as the ratios included in the models differ to a large extent indicates that there have been some changes as to which financial ratios that are decision relevant nowadays compared to in the past.

The ratios that are included in both Skogsvik (1987) and Haglund and Olufsen (2021) are ratios that have been included in numerous business failure prediction models throughout the years. Solidity has been and still is a stable predictor, while average interest cost still has prevailed in the short-term despite the lower interest rate levels of today. One conclusion is thereby that there are ratios that prevails throughout time with changing macroeconomic and business environments. Although one cannot know for certain, it is possible that ratios like solidity and average interest cost will still be significant factors in business failure prediction models in the future. However, it appears like profitability has a lower predictive ability than in the past, which can be supported by the findings from Fama and French (2004).

At the same time, several new ratios have emerged as strong predictors. Generally, the additional ratios tested in this thesis capture regulatory changes and a change in how business models are today compared to those of the 1960s and onwards. Keeping this in mind could be of interest for researchers of business failure in the future. The business environment is prone to change over time, and therefore a good business failure prediction model must mirror how these changes express themselves in the language of accounting. Future models will most likely include other financial ratios than in the models of this thesis, given that they could become obsolete in the future business environment. In this thesis, we find that goodwill proportion is a strong predictor for business failure, which contrasts the findings from Wu & Lai (2020) and Hamberg et al. (2011) but supports the findings from Gjerde et al. (2008). It is difficult to say what ratios future studies would find to be decision relevant, but a mix of prior successful ratios and new ratios incorporating changes to the regulatory setting and business climate is likely to make a solid foundation for building future failure prediction models.

7.2 Contributions

This thesis aims to contribute to the business failure prediction literature. As three different tests on business failure prediction models were conducted in this thesis (the robustness of an old model, the development of ratios in an old model and the creation of a new model), this thesis bridges some of the gaps between previous studies and the modern context.

A second contribution is that goodwill proportion was found to be a good predictor of failure, in contrast to findings in some prior studies. As Wu & Lai (2020) found that high goodwill intensity increased the probability of goodwill impairment and that managers tend to hoard bad news until they are released to the public, it would follow that a measure like change in goodwill would be a good predictor of bankruptcy. In contrast, this thesis did not find change in goodwill to have a significant effect, but that high goodwill intensity (or goodwill proportion) in itself had good explanatory power and was a trait of surviving firms.

This thesis also contributes by adding IFRS-specific elements to the models. The fact the error rates in the model of this thesis were comparable to the error rates in Skogsvik (1987) indicates that IFRS-based accounting information is decision relevant. A possible explanation is that IFRS is capturing some of the changes in business models well.

7.3 Limitations

While there has been an attempt to perform the analysis in a similar manner as prior studies, making direct comparisons may not be justified due to certain inevitable methodological differences. Different studies have used different samples of firms, operationalized business failure in different ways, classified the time of failure differently, and used different statistical techniques. A direct comparison of error rates may hence not be appropriate, which should be kept in mind.

This thesis has included only quantitative financial statement information as data input for the models. This is a limitation as factors that potentially could increase the predictive ability of a failure model, like macroeconomic factors, market prices of shares or bonds or other qualitative information (CEO attributes, board attributes, number of employees, CSR rating etc.), are neglected. The reason such information was left out in this thesis is that the information gathering would be extensive, hard to perform reliably and would distort from the Skogsvik (1987) study, making comparability worse. Also, the financial statement information used in this thesis is extracted solely from annual reports. This is a limitation as interim reports could be published closer to the date of failure with more current data. There are three arguments as to use annual reports rather than interim reports. One, annual financial statements are audited, ensuring a higher standard of disclosure and accuracy. Second, it is easier to extract information gathered from annual reports compared to interim reports, as it is more readily available in databases such as S&P Capital IQ. Third, as this thesis uses the Skogsvik model on a modern sample of firms, the comparability increases if the same type of data is included. The Skogsvik (1987) study used annual financial statements, making the same choice preferred for this thesis.

Compared to the study of Bodle (2016), which focused more on the type 1 error rates achieved, this thesis seeks to utilize a holistic approach to classify both survivors and failures correctly with as high accuracy as possible. This means that the results of this thesis could be of less use for practitioners who merely want to predict failures. This is not a limitation in itself, but a methodological choice. As this thesis seeks to investigate the decision relevance of accounting, we believe that focusing on average error rates gives a better understanding of the decision relevance, but we acknowledge that focusing more on type 1 errors, which have a higher misclassification cost, would have also been a viable methodological choice.

As for the selection of failure firms, finding firms from Sweden and Norway was easier than for Denmark and Finland. This was partly due to the authors understanding of the Norwegian and Swedish language as well as knowledge of where to search for data. This means that it is possible that this thesis has failed to find all Danish and Finnish failure firms that fit the selection criteria. However, the sample size found is sufficient for the purpose of this thesis. Also, there is a risk that there are restructuring and/or turnaround firms within the sample of survivors, but we believe the major restructurings have been included.

7.4 Suggestions for further research

As this thesis has purely used quantitative data from annual reports, some information with a good predictive ability might have been left out. A study integrating other types of information such as industry information, board and CEO characteristics, macroeconomic factors etc. would be of interest.

As we hypothesized in section 6.3, the persistent decision relevance of accounting information could be attributable to improvements from the implementation of IFRS. To investigate the magnitude of the IFRS impact, a more thorough study with a non-IFRS control group would be of interest. Having a non-IFRS control group in this thesis was considered, but it was perceived to increase the workload too much and was hence not included. Having research investigating the magnitude of this would however be useful.

This thesis has uncovered that goodwill intensity seems to be a good predictor of failure for Nordic manufacturing firms, and having studies investigating whether the same appears to be the case in other geographies would be of interest. As IFRS 16 has recently been implemented, a future study similar to ours investigating the impact on business failure prediction incorporating IFRS 16 changes would add to the existing literature and knowledge.

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9. Appendices

Appendix A: Time to failure with sources used

Failure number	Failure firm	Time of failure	Last financial report	Days from last report to failure
1	Siem Offshore ASA	30.10.2020	2019	304
2	Avocet Mining Plc	21.08.2019	2017	598
3	Kongsberg Automotive ASA	20.05.2020	2019	141
4	Solstad Offshore ASA	31.03.2020	2019	91
5	Seadrill Limited	02.06.2020	2019	154
6	Borr Drilling Ltd	14.04.2020	2019	105
7	Nordic Mines AB	14.04.2020	2018	105
8	Dolphin Drilling ASA	24.06.2019	2018	175
9	Ahtium OYJ	14.03.2018	2017	73
10	Sevan Drilling Ltd	02.07.2018	2017	183
11	Cybaero AB	18.06.2018	2017	169
12	Wiking Mineral AB	28.12.2018	2017	362
13	Va Automotive i Hassleholm AB	10.05.2018	2017	130
14	Norske Skog ASA	19.12.2017	2016	353
15	Takoma OYJ	21.03.2017	2016	80
16	PA Resources AB	22.12.2017	2015	722
17	Dansk Industri Invest A/S	09.09.2016	2015	253
18	REM Offshore ASA	27.06.2016	2015	179
19	Nunaminerals A/S	19.04.2015	2014	109
20	Norwegian Energy Company ASA	24.03.2015	2014	83
21	Rella Holdings A/S	13.03.2015	2014	72
22	Cecon ASA	23.04.2015	2014	113
23	Dannemora Mineral AB	13.05.2014	2013	133
24	Mineral Invest International MII AB	30.07.2015	2012	941
25	Norse Energy Corp ASA	06.02.2014	2012	400
26	Eco Byggolit AB	28.04.2014	2013	118
27	Lappland Goldminers AB	02.04.2014	2013	92
28	Northland Resources SE	19.12.2014	2013	353
29	London Mining Plc	16.10.2014	2013	289
30	Artimplant AB	01.08.2013	2012	213
31	Reservoir Exploration Technology ASA	12.06.2013	2012	163
32	Scanarc ASA	29.11.2012	2011	334
33	Remedial Plc	04.02.2011	2008	765
34	Elcoteq SE	07.10.2011	2010	280
35	PV Enterprise Sweden AB	31.10.2011	2010	304
36	Hebi Health Care AB	28.12.2010	2009	362
37	Trimera AB	11.04.2011	2010	101
38	Petromena ASA	15.12.2009	2008	349
39	Petrojack ASA	08.03.2010	2009	67
40	Obducat AB	07.04.2010	2009	97
41	Countermine Technologies AB	26.10.2010	2009	299
42	Hjellegjerde ASA	25.06.2010	2009	176
43	Scan Geophysical ASA	29.06.2009	2008	180
44	Ability Drilling ASA	26.05.2009	2008	146
45	Tandberg Data ASA	24.04.2009	2008	114
46	Tandberg Storage ASA	26.04.2009	2008	116
47	Audiodev AB	15.06.2009	2008	166
48	Tatura AB	02.09.2009	2008	245
49	TMG International AB	06.05.2008	2007	127
50	Stromsdal OYJ	30.10.2008	2007	304
51	Scanmining AB	06.12.2007	2006	345
52	Klippan AB	30.06.2006	2005	181

Table A1: Overview over time of failure and time from last financial report to failure

Failure number	Source
1	https://shippingwatch.com/Offshore/article12525816.ece
2	https://www.reuters.com/article/us-avocet-mining-liquidation-idUSKCN1VB252
3	https://e24.no/boers-og-finans/i/OpvlmV/kriseemisjon-i-kongsberg-automotive-snakker-vi-norgesrekord-i-utvanning
4	https://www.rivieramm.com/news-content-hub/news-content-hub/solstad-offshore-nears-debt-for-equity-restructuring-deal-58822
5	https://www.dn.no/bors/seadrill/john-fredriksen/rigg/15-milliarder-kroner-i-minus-for-john-fredriksens-seadrill-i-forste-kvartal-varsler-omfattende-restrukturering/2-1-817810
6	https://www.dn.no/bors/tor-olav-troims-riggselskap-forhandler-med-kreditorer-om-losning-som-vil-sikre-selskapet-i-to-ar/2-1-812137
7	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/n/nordicmines.4.69ef368911e1304a625800017110.html
8	https://www.dn.no/rigg/dolphin-drilling/gikk-dundrende-konkurs-med-nar-9-mrd-i-gjeld-kun-smuler-av-verdi-igjen/2-1-627926
9	https://www.bloomberg.com/press-releases/2018-03-14/ahtium-oyj-decision-on-ahtium-s-bankruptcy-has-become-final-and-binding-company-will-be-removed-from-the-main-list-of
10	https://www.globenewswire.com/news-release/2018/07/02/1532619/0/en/Sevan-Drilling-Ltd-Chapter-11-Plan-Effective.html?culture=fr-ca
11	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/c/cybaero.4.5947400c11f47f7f9dd80001309.html
12	https://www.allabolag.se/5566752068/svenska-bergsbruk-ab-publ
13	https://skatteverket.se/privat/skatter/vardepapper/aktiehistorik/v/vaautomotiveihassleholm.4.3f4496fd14864cc5ac9dc15.html
14	https://e24.no/boers-og-finans/i/21ak6y/norske-skogindustrier-slaar-seg-konkurs
15	https://www.avanza.se/placera/pressmeddelanden/2017/03/21/panostaja-subsidiary-takoma-oyj-and-takoma-gears-oy-have-been-filed-for-bankruptcy.html
16	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/p/paresources.4.4616442f109bb3f41f380004349.html
17	https://newsclient.omxgroup.com/cdsPublic/viewDisclosure.action?disclosureId=726749&lang=en
18	https://www.aktiespararna.se/nyheter/rem-offshore-asa-rem-offshore-asa-kunngjor-omfattende-finansiell-restrukturering
19	http://www.kamikposten.dk/global/maskinrum/rutine/leksikon.aspx?tag=emne&folder=hvadermeningen&sprog=da&punkt=Minedrift&soegestreng=&udvalgt=2015042112595874c
20	https://news.cision.com/no/noreco/r/gjennomfort-restrukturering---utstedelse-av-nye-aksjer-og-obligasjonsavtaler,c9744499
21	https://www.marketscreener.com/quote/stock/RELLA-HOLDING-A-S-1412997/news/Rella-A-S-Sale-of-shares-in-Aller-Holding-AS-20019114/
22	https://finansavisen.no/nyheter/boers-finans/2015/04/cecon-er-konkurs
23	https://www.businesswire.com/news/home/20140513005711/en/Dannemora-Mineral-AB-Dannemora-Mineral-has-filed-for-reconstruction
24	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/m/mineralinvestinternationalmii.4.400023ac12df56d65d980008750.html
25	https://e24.no/boers-og-finans/i/Mg0GkR/norse-energy-konkurs
26	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/e/ecobyggolit.4.71004e4c133e23bf6db800013157.html
27	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/l/lapplandgoldminers.4.5947400c11f47f7f9dd80004349.html
28	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/n/northlandresources.4.12815e4f14a62bc048f71c.html
29	https://phys.org/news/2014-10-uk-bankruptcy-slump-ebola.html
30	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/a/artimplant.4.4bf45f331098492fe0e8000151.html
31	https://www.dn.no/reservoir-exploration-soker-om-konkurs/1-1-1952369
32	https://www.oslobors.no/Oslo-Boers/Om-oss/Presserom/Pressemeldinger/ScanArc-strykes-fra-notering-paa-Oslo-Axess
33	https://www.oslobors.no/ob_eng/content/search/(offset)/90?SearchText=shared+jurisdiction&filter%5B%5D=meta_path_si:9055
34	https://globalinsolvency.com/headlines/finlands-elcoteq-files-bankruptcy
35	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/p/pventerprisesweden.4.58a1634211f85df4dce8000494.html
36	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/h/hebihealthcare.4.61589f801118cb2b7b280003504.html
37	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/t/trimera.4.70ac421612e2a997f8580006282.html
38	https://e24.no/norsk-oekonomi/i/K3GzX6/slutt-for-petromena-riggselskap-konkurs-med-55-milliarder-i-gjeld
39	https://www.dn.no/petrojack-konkurs/1-1-1448221
40	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/o/obducat.4.61589f801118cb2b7b280004467.html?q=obducat
41	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/c/counterminetechnologies.4.61589f801118cb2b7b280001641.html
42	https://e24.no/naeringsliv/i/Mg0Ojr/hemmelig-investorsluker-hjellegjerde
43	https://e24.no/norsk-oekonomi/i/K3G6BM/scan-geophysical-konkurs
44	http://stamdata.se/documents/NO0010354061_IB_20141031.pdf
45	https://www.dn.no/tandberg-data-er-konkurs/1-1-1304750
46	https://e24.no/norsk-oekonomi/i/opwkyg/ny-tandberg-konkurs-tandberg-storage-er-konkurs
47	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/a/audiodev.4.4bf45f331098492fe0e8000262.html
48	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/t/tatura.4.2a9d99b2110b7fcf5c080009712.html
49	https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik/t/tmginternational.4.61589f801118cb2b7b280004733.html
50	https://www.eurofound.europa.eu/observatories/emcc/erm/factsheets/stromsdal-0
51	https://www.mynewsdesk.com/se/scanmining_ab/pressreleases/scanmining-ab-ansoeker-om-konkurs-184033
52	https://www.atl.nu/skog/pappersproducenten-klippan-ab-i-konkurs/

Table A2: Overview of sources used to determine the time of failure for failure firms

Appendix B: Truncation and bounds for financial ratios

Financial ratio	Mean	Standard deviation	Lower bound	Upper bound	Number of outliers truncated	Number of DIV 0-errors	DIV 0-errors set to 0	DIV 0-errors set to upper / lower bound
R_1	−0.047	0.272	−1.407	1.312	10	0	0	0
R_2	0.039	0.393	−1.927	2.005	2	0	0	0
R_3	0.134	1.719	−8.459	8.728	7	1	1	0
R_4	0.371	5.726	−28.259	29.001	2	62	60	2
R_5	1.267	4.563	−21.546	24.080	6	5	3	2
R_6	0.353	3.536	−17.327	18.034	3	0	0	0
R_7	1.396	24.32	−120.203	122.996	6	0	0	0
R_8	0.126	4.793	−23.841	24.094	8	0	0	0
R_9	0.929	0.682	−2.479	4.337	1	0	0	0
R_{10}	2.569	4.661	−20.736	25.874	6	5	0	5
R_{11}	0.494	0.231	−0.662	1.650	0	0	0	0
R_{12}	0.344	0.237	−0.839	1.528	0	0	0	0
R_{13}	6.129	2.334	−5.542	17.801	0	0	0	0
R_{14}	0.671	9.444	−46.551	47.894	3	5	2	3
R_{15}	0.891	11.363	−55.925	57.706	7	337	276	61
R_{16}	−0.276	12.720	−63.875	63.323	3	1	1	0
R_{17}	0.200	3.536	−17.481	17.882	3	0	0	0
R_{18}	0.534	8.156	−40.247	41.314	4	62	56	6
R_{19}	0.154	0.188	−0.785	1.093	0	0	0	0
R_{20}	0.012	3.007	−15.025	15.048	9	1	1	0
R_{21}	−0.369	13.735	−69.044	68.307	5	62	38	24
R_{22}	−0.509	2.277	−11.892	10.874	9	5	0	5
R_{23}	0.089	0.134	−0.583	0.761	1	0	0	0
R_{24}	0.348	4.047	−19.889	20.584	10	933	866	67
R_{25}	0.600	4.252	−20.662	21.863	20	343	295	48
R_{26}	0.236	2.024	−9.887	10.358	24	910	861	49
					149	2732	2460	272

Total observations (obs.)	54 775
% of obs. truncated	0.27%
% of obs. with DIV-0 error	4.99%

Table B1: Overview of truncation of financial ratios. Please note that the mean and standard deviations listed for the ratios above are calculated before truncating the outliers

Appendix C: Input to financial ratios

Ratio input	Definition
Assets	Current Assets + Non-current Assets
Cash	Cash and cash equivalents
Current assets	Assets - Non-current Assets
Current Liabilities	Current Operating Liabilities + Current Financial Debt
Debt	Current Debt + Non-current Debt
EBT	Revenue - Cost of Goods Sold - Selling, General and Administrative expenses - Depreciation and Amortization - Interest
EBIT	Revenue - Cost of Goods Sold - Selling, General and Administrative expenses - Depreciation and Amortization
EBITDA	Revenue - Cost of Goods Sold - Selling, General and Administrative expenses
Equity	Common Equity
Free cash flow	Cash flow from operations after tax - Capital expenditures
Gross profit	Revenue - Cost of Goods Sold
Liabilities	Operating Liabilities + Financial Debt
Long-term Assets	Non-current Tangible Assets + Non-current Intangible Assets
Tangible Equity	Common Equity - Intangible Assets
Average	(Opening balance - Closing balance) / 2

Table C1: Overview of inputs to financial ratios

Appendix D: Correlation matrices for the Haglund and Olufsen (2021) model

(t-1)	R_2	R_4	R_5	R_6	R_9	R_{22}	R_{23}
R_2	1						
R_4	-0.0207	1					
R_5	-0.0009	0.0661	1				
R_6	0.0185	0.0514	0.1705	1			
R_9	-0.1409	-0.1704	-0.3577	-0.0101	1		
R_{22}	-0.0208	-0.2434	-0.5864	-0.0938	0.4216	1	
R_{23}	-0.0634	-0.0848	-0.1769	0.0185	0.1387	0.2667	1

(t-2)	R_2	R_4	R_6	R_{11}	R_{14}	R_{22}	R_{23}
R_2	1						
R_4	-0.0106	1					
R_6	0.0103	0.0280	1				
R_{11}	0.1645	-0.1573	0.0771	1			
R_{14}	0.0088	-0.0259	0.0164	0.0223	1		
R_{22}	-0.0136	-0.1052	-0.0966	0.0232	-0.0359	1	
R_{23}	-0.0530	-0.0639	0.0040	0.2460	-0.0144	0.2777	1

(t-3)	R_6	R_7	R_8	R_{10}	R_{11}	R_{15}	R_{22}	R_{23}	R_{26}
R_6	1								
R_7	0.0427	1							
R_8	0.0326	0.0567	1						
R_{10}	0.1791	0.0668	0.0171	1					
R_{11}	-0.0219	-0.0600	-0.0354	-0.3056	1				
R_{15}	0.0163	0.0543	-0.0065	0.0923	0.0481	1			
R_{22}	-0.0869	-0.0168	0.1662	-0.4453	-0.0078	-0.1127	1		
R_{23}	-0.0054	0.1204	0.1276	-0.2065	0.2254	0.0788	0.2186	1	
R_{26}	-0.0046	0.0313	0.0590	0.0080	-0.0411	0.2103	0.1474	0.1543	1

(t-4)	R_6	R_{11}	R_{22}	R_{23}	R_{26}
R_6	1				
R_{11}	-0.0323	1			
R_{22}	-0.1102	-0.0594	1		
R_{23}	-0.0261	0.2669	0.2013	1	
R_{26}	-0.0265	-0.0172	0.0321	0.0420	1

(t-5)	R_5	R_{11}	R_{12}	R_{17}	R_{20}	R_{23}
R_5	1					
R_{11}	-0.1713	1				
R_{12}	-0.2586	0.1936	1			
R_{17}	0.4103	-0.2275	0.0271	1		
R_{20}	-0.0298	0.0557	0.0283	-0.0293	1	
R_{23}	-0.1854	0.2410	-0.1436	-0.5136	0.0123	1

Table D1-D5: Correlation matrices for (t-1) to (t-5) in Haglund and Olufsen (2021) model

Appendix E: Survivor firms in alphabetical order

Company Name	t-1	Company Name	t-1	Company Name	t-1	Company Name	t-1
AAC CLYDE SPACE AB	2016	DOF SUBSEA ASA	2010	KONECRANES PLC	2006	RAPALA VMC OYJ	2011
AAK AB	2017	DOME ENERGY AB	2014	KONGSBERG GRUPPEN ASA	2005	RAUTE OY	2014
ABSOLENT GROUP AB	2016	DOMETIC GROUP AB	2016	KOPPARBERGS BRYGGERI AB	2015	RAYBASED AB	2017
ABSOLICON SOLAR CO	2017	DORO AB	2010	LAMMHULTS DESIGN GROUP AB	2010	REC SILICON ASA	2009
ACARIX AB	2019	DRILLCON AB	2013	LEHTO GROUP OYJ	2017	RECIPHARM AB	2010
ACCONEER AB	2019	DUNI AB	2010	LEROY SEAFOOD GROUP ASA	2013	ROBIT PLC	2017
ACTIVE BIOTECH AB	2010	EASYFILL AB	2013	LINDAB INTL AB	2012	ROBLON	2008
ADDVISE GROUP AB	2012	EDGEWARE AB	2019	LOVISAGRUVAN AB	2015	ROCKWOOL INTERNATIONAL A/S	2010
AF GRUPPEN ASA	2009	ELANDERS AB	2008	LUNDIN ENERGY AB	2009	ROTTNEROS AB	2007
AFARAK GROUP PLC	2011	ELECSTER OYJ	2008	MACKMYRA SVENSK WHISKY AB	2012	ROYAL UNIBREW	2006
AGES INDUSTRI AB	2019	ELECTROLUX AB	2007	MAGNORA ASA	2013	RTX A/S	2008
AHLSTROM-MUNKSJO OYJ	2014	ELECTROMAGNETIC GEOSERV	2014	MAGSEIS FAIRFIELD ASA	2017	SAAB AB	2013
AKASTOR ASA	2009	ELEKTA AB	2008	MAHA ENERGY AB	2019	SANDVIK AB	2005
AKER ASA	2014	ELOS MEDTECH AB	2008	MARIMEKKO OY	2013	SANIONA AB	2019
AKER BP ASA	2010	ENDOMINES AB	2017	MARTELA OYJ	2010	SANOMA CORP	2009
AKVA GROUP ASA	2009	ENEDO OYJ	2005	MEDFIELD DIAGNOSTICS AB	2014	SAXLUND GROUP AB	2010
ALELION ENERGY SYSTEMS AB	2019	ENZYMATICA AB	2016	MEDICANATUMIN AB	2016	SCA-SVENSKA CELLULOSA AB	2009
ALFA LAVAL AB	2014	EPISURF MEDICAL AB	2015	MEDISTIM ASA	2009	SCANA ASA	2010
ALIMAK GROUP AB	2019	EQL PHARMA AB	2015	METSA BOARD CORP	2014	SCANDBOOK HOLDING AB	2017
ALK-ABELLO A/S	2008	EQUINOR ASA	2009	MIDSONA AB	2011	SCANDI STANDARD AB	2018
ALLGON AB	2012	ESSITY AKTIEBOLAG	2019	MIDSUMMER AB	2019	SCANDIDOS AB	2016
ALMA MEDIA OYJ	2015	ETMAN INTERNATIONAL AS	2010	MIGATRONIC A/S	2009	SCANDINAVIAN BRAKE SYSTEM	2013
ALTIA OYJ	2011	EXEL COMPOSITES OYJ	2008	MIPS AB	2019	SCANDINAVIAN REAL	2017
ALZINOVA AB	2019	FAGERHULT AB	2008	MOBERG PHARMA AB	2016	SCANDINAVIAN TOBACCO GROUP	2013
AMBU A/S	2008	FINGERPRINT CARDS AB	2008	MOWI ASA	2008	SCANFIL OYJ	2017
AMERICAN SHIPPING CO ASA	2010	FIREFLY AB	2013	MT HOJGAARD HOLDING AS	2014	SCHIBSTED ASA	2013
ANOTO GROUP AB	2008	FISKARS OY	2010	MULTIQ INTERNATIONAL AB	2010	SCHOUW & CO A/S	2009
APETIT OYJ	2010	FLSMIDTH & CO AS	2010	MUNTERS GROUP AB	2019	SCIBASE HOLDING AB	2019
AQ GROUP AB	2009	FLUGGER GROUP A/S	2008	MYCRONIC AB	2008	SENSYS GATSO GROUP AB	2008
ARCOMA AB	2019	FM MATTSSON MORA GROUP AB	2016	MYFC HOLDING AB	2017	SENZIME AB	2009
ARCTIC MINERALS AB	2013	GABRIEL HOLDING A/S	2008	NAPATECH AS	2019	SERNEKE GROUP AB	2017
ARCTICZYMES TECHNOLOGIES ASA	2016	GAPWAVES AB	2019	NATTOPHARMA ASA	2019	SERSTECH AB	2017
ARCUS ASA	2018	GARO AB	2019	NAVAMEDIC ASA	2009	SIEVI CAPITAL OYJ	2009
ARJO AB	2019	GC RIEBER SHIPPING ASA	2005	NCC AB	2008	SIGNATUR FASTIGHETER AB	2010
ASKER OG BAERUMS BUDSTIKKE	2010	GENMAB AS	2010	NEDERMAN HOLDING AB	2012	SINTERCAST AB	2010
ASPOCOMP GROUP PLC	2013	GENOVIS AB	2010	NEKKAR ASA	2007	SIVERS SEMICONDUCTORS AB	2017
ASSA ABLOY AB	2008	GETINGE AB	2010	NEL ASA	2015	SKAKO AS	2014
ATLAS COPCO AB	2008	GLASTON OYJ	2010	NELES OYJ	2013	SKANE MOLLAN AB	2013
ATRIA PLC	2012	GLUNZ & JENSEN HLD	2007	NET INSIGHT AB	2009	SKANSKA AB	2011
AURIANT MINING AB	2014	GLYCOREX TRANSPLANTATION AB	2005	NEW NORDIC HEALTHBRANDS AB	2010	SKF AB	2014
AUSTEVOLL SEAFOOD ASA	2012	GN STORE NORD A/S	2009	NEW WAVE GROUP AB	2013	SMART ENERGY SWEDEN GROUP AB	2017
AXKID AB	2015	GOMSPACE GROUP AB	2018	NEXAM CHEMICAL AB	2014	SMART EYE AB	2019
BACTIGUARD HOLDING AB	2016	GOODTECH ASA	2006	NEXSTIM PLC	2017	SOLTECH ENERGY SWEDEN AB	2016
BALCO GROUP AB (PUBL)	2019	GOTENEHUS GROUP AB	2010	NEXT BIOMETRICS GROUP AS	2019	SOTKAMO SILVER AB	2009
BANG & OLUFSEN AS	2007	GRANGES AB	2017	NIBE INDUSTRIER AB	2008	SP GROUP AS	2009
BAVARIAN NORDIC AS	2007	GRIEG SEAFOOD AS	2011	NILORNGRUPPEN AB	2013	SPAGO NANOMEDICAL	2017
BEIJER ALMA AB	2013	GUIDELINE GEO AB	2010	NILSSON SPECIAL VEHICLES AB	2019	SPECTRACURE AB	2019
BEIJER ELECTRONICS GROUP AB	2009	GULLBERG & JANSSON	2014	NKT A/S	2008	SRV YHTIOT OYJ	2014
BERGS TIMBER AB	2009	GYLDENDAL AS	2010	NOBIA AB	2012	SSAB CORP	2005
BESQAB AB	2015	GYLDENDAL ASA	2012	NOKIA CORP	2008	SSM HOLDING AB	2016
BILLERUDKORSNAS AB	2011	H LUNDBECK A/S	2008	NOKIAN RENKAAT OYJ	2009	STILLE AB	2009
BIOGAIA AB	2014	H PLUS H INTERNATIONAL AS	2009	NOLATO AB	2009	STORA ENSO OYJ	2008
BIOHIT OYJ	2010	HALDEX AB	2014	NORAM DRILLING CO AS	2017	STRATEGIC INVESTMENTS A/S	2014
BIOSERVO TECHNOLOGIES AB	2019	HANDICARE GROUP AB	2019	NORDA ASA	2012	SUOMINEN CORP	2014
BIOTAGE AB	2008	HARBOES BRYGGERI A/S	2009	NORDIC MINING ASA	2014	SUSTAINABLE ENERGY SOLUTIONS	2019
BIOVICA INTERNATIONAL AB	2019	HAVYARD GROUP ASA	2019	NORDIC SEMICONDUCTOR	2012	SVEDBERGS I DALSTORP AB	2010
BJORN BORG AB	2007	HELIOSPECTRA AB	2015	NORSK HYDRO ASA	2010	SWEDENCARE AB	2018
BOLIDEN AB	2005	HEMCHECK SWEDEN AB	2018	NORTH MEDIA A/S	2012	SWEDISH MATCH AB	2013
BONESUPPORT HLG	2019	HEXAGON AB	2008	NORTHBAZE GROUP AB (PUBL)	2016	SWEDISH ORPHAN BIOVITRUM AB	2006
BONG AB	2014	HEXAGON COMPOSITES ASA	2014	NORWAY ROYAL SALMON AS	2008	SWEDISH STIRLING AB (PUBL)	2019
BORDING (FE) A/S	2014	HEXATRONIC GROUP AB	2015	NOTE AB	2014	SYNTHETIC MR AB	2016
BORGESTAD ASA	2013	HEXPOL AB	2010	NOVO NORDISK A/S	2007	SYSTEMAIR AB	2008
BORREGAARD ASA	2015	HKSCAN OYJ	2010	NOVOZYMES A/S	2013	TAGMASTER AB	2012
BOTNIA EXPLORATION AB	2017	HMS NETWORKS AB	2016	NRC GROUP ASA	2008	TC TECH SWEDEN AB	2019
BOULE DIAGNOSTICS AB	2010	HOFSETH BIOCARE ASA	2016	NTR HOLDING A/S	2014	TCM GROUP A/S	2017
BRAINCOOL AB	2019	HOLMEN AB	2008	OASMIA PHARMACEUTICAL AB	2009	TELEFONAKTIEBOLAGET LM ERICS	2014
BRAVIDA HOLDING AB	2013	HONKARAKENNE OYJ	2008	OCEANTEAM ASA	2014	TELESTE OYJ	2009
BRIGHTER AB	2017	HOVDING SVERIGE AB	2019	ODD MOLLY INTL AB	2010	TGS-NOPEC GEOPHYSICAL CO ASA	2013
BRODRENE HARTMANN A/S	2006	HUHTAMAKI OYJ	2009	OLVI OYJ	2007	THE LEXINGTON COMP	2019
BULTEN AB	2016	HUSQVARNA AB	2013	OREXO AB	2007	THULE GROUP AB	2014
BYGGMA ASA	2008	IDEX BIOMETRICS ASA	2019	ORGANOCLICK AB	2019	TIKKURILA OYJ	2015

BYGGPARTNER I DALARNA HLDG	2019	ILKKA-YHTYMA OYJ	2009	ORION CORP	2007	TOBII AB	2019
C-RAD AB	2012	IMAGE SYSTEMS AB	2009	ORTOMA AB	2017	TOMRA SYSTEMS A/S	2009
CAMURUS AB	2017	IMPACT COATINGS AB	2008	OUTOKUMPU OY	2006	TRELLEBORG AB	2008
CARGOTEC OYJ	2009	INCAP OYJ	2008	OXE MARINE AB (PUBL)	2019	TRENTION AB	2013
CARLSBERG A/S	2013	INDUTRADE AB	2008	PANDORA AS	2015	TROAX GROUP AB	2019
CELL IMPACT AB	2017	INISSION AB	2019	Panoro Energy ASA	2015	TULIKIVI OYJ	2011
CELLAVISION AB	2013	INSTALCO AB (PUBL)	2019	PEAB AB	2010	UPM-KYMMENE CORP	2014
CHEMOMETEC A/S	2017	INTERMAIL AS	2008	PER AARSLEFF HOLDING AS	2008	UPONOR OYJ	2008
CHR.HANSEN HOLDINGS AS	2015	INTERVACC AB	2016	PGS ASA	2014	VAISALA OYJ	2008
CLEAN MOTION AB	2019	INVISIO AB	2010	PHILLY SHIPYARD ASA	2014	VALMET CORP	2016
CLEMONDO GROUP AB	2015	INWIDO AB	2015	PHOTOCURE ASA	2012	VALOE OYJ	2014
CLOETTA AB	2017	IRISITY AB	2017	PIEZOMOTOR UPPSALA AB	2019	VBG AB	2014
COLOPLAST A/S	2007	IRRAS AB	2019	PIIPPO OYJ	2019	VEIDEKKE A/S	2005
CONCEJO AB	2013	ITAB SHOP CONCEPT AB	2013	PLC UUTECHNIC GROUP OYJ	2019	VESTAS WIND SYSTEMS A/S	2014
CONCENTRIC AB	2015	IZAFE GROUP AB (PUBL)	2015	PLEJD AB	2017	VISTIN PHARMA ASA	2018
CONSTI OYJ	2017	JLT MOBILE COMPUTERS AB	2009	POLARIS MEDIA ASA	2014	VITROLIFE AB	2007
COPPERSTONE RESOURCES AB	2017	JM AB	2008	POLYGIENE AB	2015	VOLVO AB	2013
CORLINE BIOMEDICAL AB	2018	JOSAB WATER SOLUTIONS AB	2010	PONSSE OYJ	2013	WARTSILA OYJ ABP	2013
CORTUS ENERGY AB	2013	KABE GROUP AB	2009	POWERCELL SWEDEN AB	2016	WAYSTREAM HOLDING AB	2019
CTT SYSTEMS AB	2013	KARO PHARMA AB	2012	PRECISE BIOMETRICS AB	2013	WONDERFUL TIMES GROUP AB	2014
DANTAX	2007	KEBNI AB	2019	PRECOMP SOLUTIONS AB	2016	XANO INDUSTRI AB	2014
DEMANT AS	2014	KEMIRA OY	2007	PREMIUM SNACKS NORDIC AB	2017	XVIVO PERFUSION AB	2018
DETECTION TECHNOLOGY OYJ	2017	KESKISUOMALAINEN OYJ	2014	PRICER AB	2008	YARA INTERNATIONAL ASA	2010
DIGNITANA AB	2017	KESLA OYJ	2006	PROFILGRUPPEN AB	2013	YIT CORP	2008
DNO ASA	2013	KITRON ASA	2006	PUNAMUSTA MEDIA OYJ	2009	ZENERGY AB	2017
DOF INSTALLER ASA	2017	KONE OYJ	2008	RAISIO PLC	2013	ZETADISPLAY AB	2015

Table E1: List of survivor firms and what year the last financial report is from (t-1)

Appendix F: Failure firms in alphabetical order

Company name	t-1	Company name	t-1	Company name	t-1	Company name	t-1
ABILITY DRILLING ASA	2008	ELCOTEQ SE	2010	NUNAMINERALS A/S	2015	SEADRILL LIMITED	2019
AHTIUM OYJ	2017	HEBI HEALTH CARE AB	2010	OBDUCAT AB	2009	SEVAN DRILLING LTD	2017
ARTIMPLANT AB	2012	HJELLEGJERDE ASA	2009	PA RESOURCES AB	2016	SIEM OFFSHORE INC	2020
AUDIODEV AB	2008	KLIPPAN AB	2005	PETROJACK ASA	2009	SOLSTAD OFFSHORE ASA	2019
AVOCET MINING PLC	2019	KONGSBERG AUTOMOTIVE AS	2019	PETROMENA ASA	2009	STROMSDAL OYJ	2007
BORR DRILLING LTD	2019	LAPPLAND GOLDMINERS AB	2013	PV ENTERPRISE SWEDEN AB	2010	TAKOMA OYJ	2016
CECON ASA	2014	LONDON MINING PLC	2013	RELLA HOLDINGS A/S	2014	TANDBERG DATA ASA	2008
COUNTERMINE TECHNOLO	2009	MINERAL INVEST INTERNATIONAI	2014	REM OFFSHORE ASA	2015	TANDBERG STORAGE ASA	2008
CYBAERO AB	2017	NORDIC MINES AB	2019	REMEDIAL (CYPRUS) PLC	2010	TATURA AB	2008
DANNEMORA MINERAL AB	2014	NORSE ENERGY CORP ASA	2013	RESERVOIR EXPLORATION TECHNO	2012	TMG INTERNATIONAL AB	2007
DANSK INDUSTRI INVEST A	2015	NORSKE SKOGINDUSTRIER ASA	2016	SCAN GEOPHYSICAL ASA	2008	TRIMERA AB	2010
DOLPHIN DRILLING ASA	2018	NORTHLAND RESOURCES SE (TIDI	2013	SCANARC ASA	2011	VA AUTOMOTIVE I HÄSSLEF	2017
ECO BYGGOLIT AB	2013	NORWEGIAN ENERGY COMPANY A	2014	SCANMINING AB	2006	WIKING MINERAL AB	2017

Table F1: List of failure firms and what year the last financial report is from (t-1)

Appendix G: Optimal functions of the Haglund and Olufsen (2021) model

t-1:

$$V = 5.02 * R_2 - 0.97 * R_4 - 0.09 * R_5 - 2.18 * R_6 - 0.29 * R_9 - 0.23 * R_{22} - 5.01 * R_{23}$$

t-2:

$$V = -1.08 + 7.13 * R_2 + 0.10 * R_4 - 2.35 * R_6 + 1.35 * R_{11} + 0.08 * R_{14} - 0.20 * R_{22} - 5.30 * R_{23}$$

t-3:

$$V = -1.54 - 1.85 * R_6 - 0.31 * R_7 + 0.42 * R_8 + 0.09 * R_{10} + 2.16 * R_{11} + 0.03 * R_{15} - 0.15 * R_{22} - 5.12 * R_{23} - 0.18 * R_{26}$$

t-4:

$$V = -1.55 - 0.96 * R_6 + 1.60 * R_{11} - 0.15 * R_{22} - 4.19 * R_{23} + 0.05 * R_{26}$$

t-5:

$$V = -1.92 + 0.09 * R_5 + 1.49 * R_{11} + 0.68 * R_{12} - 0.79 * R_{17} - 0.11 * R_{20} - 4.65 * R_{23}$$

Figure G1: Overview of optimal probit functions estimated in the Haglund and Olufsen (2021) model

Appendix H: Financial ratios for each forecast horizon split on failures and survivors

Financial ratio	Mean values of the financial ratios									
	(t-1)		(t-2)		(t-3)		(t-4)		(t-5)	
	Fail	Survive	Fail	Survive	Fail	Survive	Fail	Survive	Fail	Survive
R_1	−0.198	−0.03	−0.115	−0.022	−0.098	−0.03	−0.105	−0.044	−0.067	−0.056
R_2	0.089	0.025	0.089	0.023	0.036	0.025	0.038	0.025	0.048	0.027
R_3	0.028	0.125	0.049	0.179	0.026	0.187	0.181	0.166	0.107	0.175
R_4	0.121	0.247	0.69	0.232	0.683	0.272	0.727	0.241	0.19	0.262
R_5	0.851	1.095	1.216	1.106	1.466	1.099	2.511	1.387	1.778	1.011
R_6	−0.215	0.514	−0.023	0.509	0.052	0.513	0.098	0.504	0.457	0.48
R_7	−0.258	0.552	0.523	0.745	−0.297	0.659	3.029	0.504	2.037	0.984
R_8	−0.251	0.055	0.426	0.068	−0.06	−0.069	−0.012	0.028	−0.051	0.161
R_9	0.58	0.913	0.563	0.951	0.594	0.992	0.575	0.994	0.616	1.009
R_{10}	2.286	2.461	2.301	2.408	2.61	2.404	3.582	2.708	2.811	2.493
R_{11}	0.576	0.491	0.596	0.485	0.639	0.475	0.624	0.466	0.629	0.478
R_{12}	0.418	0.324	0.439	0.325	0.481	0.326	0.451	0.335	0.453	0.344
R_{13}	5.573	6.415	5.951	6.334	5.996	6.197	5.963	6.032	5.8	5.844
R_{14}	0.223	0.175	1.304	0.337	2.46	0.577	0.633	0.58	0.307	0.584
R_{15}	1.166	1.856	4.809	1.787	6.179	1.966	2.552	2.128	1.471	2.067
R_{16}	−0.519	0.042	−1.547	0.047	−1.56	0.099	−0.908	0.034	0.315	0.257
R_{17}	−0.29	0.339	−0.128	0.336	−0.053	0.35	−0.025	0.356	0.325	0.331
R_{18}	0.206	0.335	0.023	0.342	0.037	0.439	0.037	0.561	0.243	0.631
R_{19}	0.075	0.176	0.103	0.173	0.102	0.162	0.121	0.148	0.132	0.149
R_{20}	−0.021	0.142	−0.114	−0.02	0.081	0.072	−0.041	−0.04	−0.26	0.079
R_{21}	−3.976	0.322	−4.919	−0.371	−7.976	−0.009	−3.259	0.103	−4.161	−0.568
R_{22}	−1.19	−0.449	−1.138	−0.38	−1.47	−0.38	−1.481	−0.383	−1.207	−0.392
R_{23}	0.014	0.105	0.017	0.106	0.02	0.1	0.024	0.089	0.022	0.087
R_{24}	−0.082	0.248	0.284	1.155	0.717	1.257	0.649	1.079	0.353	0.766
R_{25}	−0.058	0.468	1.182	1.211	1.147	1.301	1.358	1	0.544	1.086
R_{26}	0.247	0.158	−0.053	0.407	−0.005	0.59	0.998	0.532	0.883	0.475

Table H1: Mean values of the financial ratios split on survivors and failures and by time horizon

Financial ratio	Median values of the financial ratios									
	(t-1)		(t-2)		(t-3)		(t-4)		(t-5)	
	Fail	Survive	Fail	Survive	Fail	Survive	Fail	Survive	Fail	Survive
R_1	−0.101	0.042	−0.063	0.053	−0.056	0.049	−0.042	0.047	−0.014	0.042
R_2	0.044	0.019	0.038	0.019	0.033	0.02	0.038	0.019	0.036	0.022
R_3	0	0.206	0	0.194	0	0.182	0	0.222	0	0.218
R_4	0.034	0.14	0.048	0.14	0.041	0.13	0.062	0.138	0.066	0.128
R_5	0.117	0.304	0.19	0.284	0.254	0.288	0.232	0.305	0.301	0.279
R_6	0.11	0.49	0.281	0.488	0.348	0.491	0.358	0.464	0.399	0.447
R_7	−0.345	0.053	−0.227	0.058	−0.117	0.08	−0.038	0.102	−0.069	0.086
R_8	−0.069	0.173	−0.031	0.195	−0.024	0.192	−0.028	0.197	0.048	0.209
R_9	0.161	0.91	0.186	0.953	0.208	0.939	0.291	0.974	0.209	0.987
R_{10}	0.858	1.7	1.083	1.711	1.13	1.691	1.185	1.743	1.251	1.694
R_{11}	0.654	0.499	0.614	0.484	0.653	0.483	0.621	0.475	0.672	0.473
R_{12}	0.425	0.303	0.425	0.309	0.495	0.316	0.447	0.325	0.512	0.343
R_{13}	5.682	6.091	5.991	5.953	5.94	5.916	5.916	5.818	5.834	5.632
R_{14}	0.069	0.054	0.11	0.071	0.12	0.125	0.084	0.119	0	0.065
R_{15}	−0.031	0	0.02	0	0.035	0	0	0	0	0
R_{16}	−0.186	0.039	−0.046	0.041	−0.007	0.039	0	0.035	0.078	0.043
R_{17}	0.069	0.34	0.202	0.317	0.252	0.335	0.272	0.345	0.291	0.319
R_{18}	0	0.005	0	0.003	0	0	0	0	0	0
R_{19}	0	0.108	0.017	0.104	0.014	0.091	0.024	0.075	0.035	0.071
R_{20}	0	0	0	0	0	0	0	0	0	0
R_{21}	0.315	0.408	0.473	0.409	0.293	0.423	0.283	0.432	0.377	0.432
R_{22}	−0.225	0.054	−0.275	0.02	−0.229	0.046	−0.16	0.022	−0.358	0.019
R_{23}	0	0.038	0	0.041	0	0.025	0	0.018	0	0.013
R_{24}	0	0	0	0	0	0	0	0	0	0
R_{25}	0	0	0	0.001	0	0.005	0	0.003	0	0
R_{26}	0	0	0	0	0	0	0	0	0	0

Table H2: Median values of the financial ratios split on survivors, failures and time horizon

	Failures			**Survivors**		
Ratio	**Mean**	**Standard deviation**	**Median**	**Mean**	**Standard deviation**	**Median**
R_1	-0.118	0.244	-0.059	-0.037	0.266	0.046
R_2	0.061	0.184	0.038	0.025	0.029	0.019
R_3	0.076	0.490	0	0.166	0.744	0.201
R_4	0.484	3.159	0.046	0.251	0.993	0.135
R_5	1.545	4.050	0.209	1.140	2.529	0.292
R_6	0.066	2.203	0.301	0.504	0.237	0.477
R_7	0.954	10.226	-0.112	0.689	7.252	0.074
R_8	0.012	2.712	-0.026	0.049	1.586	0.193
R_9	0.585	0.762	0.201	0.972	0.647	0.950
R_{10}	2.702	4.735	1.083	2.495	2.759	1.717
R_{11}	0.612	0.272	0.647	0.479	0.221	0.482
R_{12}	0.448	0.306	0.456	0.331	0.223	0.316
R_{13}	5.856	1.935	5.859	6.165	2.380	5.910
R_{14}	1.005	4.933	0.080	0.450	2.602	0.082
R_{15}	3.281	12.854	0	1.961	9.709	0
R_{16}	-0.866	7.120	-0.002	0.096	1.799	0.039
R_{17}	-0.042	2.208	0.229	0.342	0.314	0.334
R_{18}	0.108	0.814	0	0.462	3.439	0
R_{19}	0.106	0.196	0.010	0.162	0.188	0.087
R_{20}	-0.068	0.919	0	0.047	1.625	0
R_{21}	-4.897	17.78	0.346	-0.105	5.877	0.419
R_{22}	-1.296	2.871	-0.244	-0.397	1.520	0.034
R_{23}	0.019	0.050	0	0.098	0.139	0.026
R_{24}	0.380	2.964	0	0.901	4.029	0
R_{25}	0.832	4.133	0	1.013	4.126	0
R_{26}	0.396	2.269	0	0.432	1.990	0

Table H3: Mean, median and standard deviation of financial ratios split on failures and survivors